Chair of Waste Processing Technology and Waste Management

Doctoral Thesis

Increasing Efficiency in Sensor-Based Sorting Processes for Waste Streams consisting of Plastics

Dipl.-Ing. Karl Friedrich, BSc

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MONTANUNIVERSITÄT LEOBEN
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Affidavit

I declare on oath that I wrote this thesis independently, did not use other than the specified sources and aids, and did not otherwise use any unauthorized aids.

I declare that I have read, understood, and complied with the guidelines of the senate of the Montanuniversitaet Leoben for "Good Scientific Practice".

Furthermore, I declare that the electronic and printed version of the submitted thesis are identical, both, formally and with regard to content.

Date: 26.10.2023

Friedrich

Author's signature
Karl Friedrich
01131954

Dedicated to

My Family

Danksagung

„Wenn ich die Strecken und Baue durchquer', das Haupt gebeugt vor den Firsten,
die Brust von schwülem Brodem schwer, der Gaumen vertrocknend vor Dürsten,
da ist mir's, als wären es tausend Jahr, daß ich in den Bergen da droben,
daß ich Student in Leoben war, im alten, trauten Leoben.“

Erste Strophe des Leobener Lieds, Dr. Karl Jirsch

Beim Hören und Singen der ersten Strophe des Leobener Lieds schlägt nicht nur mein Herz höher, sondern es stimmt mich auch ein wenig melancholisch und treibt mir Tränen in die Augen. Nicht nur, weil sie mich an die wunderschöne Bergstadt Leoben erinnert, sondern auch weil ich hierbei an die Studienzeit, welche ich an der Alma Mater Leobiensis verbringen durfte, zurückdenke. Es sind fast sieben Jahre geworden, welche der Weg vom Finden eines Dissertationsthemas, eines Betreuers, den Abschluss des Gleichwertigkeitsverfahrens, der Abgabe der Dissertation bis hin zum Rigorosum gedauert hat. Diese Zeit mit Arbeitskollegen, Kommilitonen und Freunden möchte ich nicht missen und ich konnte in dieser enorm hinsichtlich fachlicher Kompetenz, aber vor allem in der Fähigkeit der Resilienz – der Fähigkeit nach dem Fall wiederaufzustehen – sehr wachsen und mich weiterentwickeln.

Nun ist es an der Zeit, jenem Personen Danke zu sagen, welche mich auf diesem prägenden, formenden aber auch steinigen Weg unterstützt haben.

Als erstes möchte ich mich bei meiner Frau Katica bedanken. Du bist mir in den schwersten Zeiten während meines Doktorats beigestanden und hast mich wiederaufgebaut, unabhängig davon wie sich meine Stimmungen und Launen gestaltet haben. Du hast mich nicht nur unterstützt, sondern mir den notwendigen Antrieb gegeben, den ich brauchte, um das Doktoratsstudium abzuschließen. Für Dinge, für die ich oft nur eine eingeschränkte Sicht hatte, hast du mir den Weitblick ermöglicht. Dinge, wo der Blick so weitgehend war, dass ich die Nähe nicht mehr wahrnehmen konnte, hast du relativiert und mich auf den Ausblickspunkt zurückgeholt. Durch dich durfte ich lernen, was im Leben wirklich zählt und dafür bin ich dir am meisten dankbar. Das Leben besteht nicht nur aus Beruf und Studium, sondern aus Familie, Freunden und Heimat. Wir beide teilen nicht nur die Liebe zur Heimat, sondern wir haben auch dasselbe Werteverständnis im Leben. Du hast mir deine Hand für den Bund der Ehe gereicht und damit haben wir beide gemeinsam schon das, was für mich im Leben das Wichtigste geworden ist, unsere eigene Familie. Wir beide haben schon vieles gemeinsam geschafft und ich bin mir bei jedem Mal, wenn ich dich ansehe oder an dich denke, sicher, dass wir im Leben gemeinsam alles schaffen können, komme was wolle.

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Vertrag in der Industrie zu kündigen, um ab März 2017 eine auf sechs Monate befristete Anstellung an der Montanuniversität Leoben anzunehmen, wo die Aussicht auf ein Doktoratsstudium in dieser Anstellung noch mehr einem Wunschdenken als einer realistischen Möglichkeit entsprach. Ich möchte nun jedem von euch beiden einzeln danken.

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Ein weiterer Dank gilt meinem Bruder, Florian Friedrich. Wir beide haben gemeinsam viel – und ich würde auch sagen, mit dir habe ich am meisten – erlebt und auch durchgestanden. Ich möchte nun jedoch einen Punkt hervorheben, für welchem ich dir besonderen Dank aussprechen möchte. Du hast mir ganz zu Beginn meiner bisherigen akademischen Laufbahn beigestanden und mich wesentlich dazu bestärkt, diesen Weg zu gehen. Nun habe ich ein Doktoratsstudium abgeschlossen, aber ich könnte bis heute nicht sagen, ob ich ohne dich überhaupt das damalige Bakkalaureatsstudium begonnen hätte.

Großer Dank gilt dem Betreuer meiner Dissertation, Professor Roland Pomberger. Du hast mich fachlich aufgebaut und mir die herausfordernde Aufgabe übertragen, den Fachbereich „Sensorgestützte Sortierung“ am Lehrstuhl für Abfallverwertungstechnik und Abfallwirtschaft zu entwickeln. Für diese Chance, die du mir hiermit gegeben hast, bin ich dir sehr dankbar. Dank deiner Unterstützung konnte ich nicht nur über mich hinauswachsen, sondern es konnte auch noch eine Dissertation in meiner Zeit am Lehrstuhl für Abfallverwertungstechnik und Abfallwirtschaft (und darüber hinaus) entstehen.

Zuletzt möchte ich mich noch bei Professor Helmut Flachberger bedanken. Du hast es mir ermöglicht, in der Königsdisziplin der Montanuniversität Leoben, der Rohstoffaufbereitung, Fuß zu fassen und mir auch die zeitlichen Ressourcen für die Verfassung der Dissertation zur Verfügung gestellt. Ich möchte hier schriftlich meinen Dank an dich festhalten, da ich glaube, dieses Werk hätte ohne deine Unterstützung nicht vollendet werden können.

Vielen Dank euch allen, ohne euch wäre ich heute nicht da, wo ich jetzt bin.

Kurzfassung

Effizienzsteigerung von sensorgestützten Sortierprozessen für kunststoffhaltige Abfallströme

Das Ziel dieser Doktorarbeit ist die Validierung neuer Methoden, die zu Effizienzsteigerung in der sensorgestützten Sortierung von kunststoffhaltigen Abfällen führen. Die Abgrenzung dieser Arbeit ist die Aggregatebene, die Anlagenebene wird nicht berücksichtigt. Bei dem verwendeten Aggregat handelt es sich um den Versuchstand für sensorgestützte Sortierung am Lehrstuhl für Abfallverwertungstechnik und Abfallwirtschaft der Montanuniversität Leoben. Die verwendete Sensortechnologie ist Nahinfrarotspektroskopie.

Eine Steigerung der Sortiereffizienz kann entweder durch eine Optimierung der Erkennung oder des mechanischen Partikelaustrags erfolgen. Als eine Lösung wird die Datenanalytik aufgezeigt, daher liegt ein Schwerpunkt auf der Verwendung statistischer Methoden.

Zur Optimierung der Identifizierung von Partikeln werden Forschungsarbeiten in den folgenden Bereichen durchgeführt:

- Einfluss der Oberflächenrauheit
- Einfluss von Reflektoren als Hintergrundmaterial
- Einsatz maschineller Lernansätze

Zur Optimierung des mechanischen Austrags von Partikeln werden Forschungsarbeiten in den folgenden Bereichen durchgeführt:

- Korrelationen zwischen den Input-Parametern (Input-Zusammensetzung, Durchsatzrate) und den Output-Parametern (Reinheit, Ausbringung, Wertstoffausbringung, fehlerhaft ausgeschleuste Partikel) eines sensorgestützten Sortierprozesses
- Mathematische Ansätze zur Beschreibung des optimalen Betriebspunkts einer sensorgestützten Sortiermaschine zur Erzielung eines bestimmten Sortierergebnisses

Als zentrales Ergebnis lässt sich festhalten, dass es einer Sortieranlage möglich ist, die Reinheit zu erhöhen, indem sie Ansätze des maschinellen Lernens zur Optimierung der Erkennung nutzt oder die Anlage im optimalen Betriebspunkt betreibt - Beides ohne wesentliche Modifikationen der Anlage. Diese Lösungen tragen dazu bei, die Menge an recyceltem Kunststoff zu erhöhen, sodass weniger Kunststoffabfälle thermisch behandelt werden müssen.

Schlagwörter

Sensorgestützte Sortierung, Sortiereffizienz, NIR-Sortierung, Datenanalytik,
Maschinelles Lernen, Regressionsmodell, Optimaler Betriebspunkt, Durchsatz,
Transflektion, Oberflächenrauigkeit

Abstract

Increasing Efficiency in Sensor-Based Sorting Processes for Waste Streams consisting of Plastics

This doctoral thesis aims to validate new methods that increase the efficiency of sensor-based sorting processes for waste streams consisting of plastics. It deals with set boundaries on aggregate level; the plant level is not considered. The used equipment is the experimental sensor-based sorting setup at the Chair of Waste Processing Technology and Waste Management at Montanuniversität Leoben and the used sensor technology near-infrared spectroscopy.

Increasing the sorting efficiency can be done by optimizing the identification of the mechanical discharge of particles. Data analytics is shown as a solution to achieve optimization, therefore this thesis focuses on using data-analytics-related methods.

For optimizing the identification of particles, research is conducted in the fields:

- Influence of surface roughness
- Influence of reflectors as background material
- Usage of machine learning approaches

For optimizing the mechanical discharge of particles, research is conducted in the fields:

- Correlations between the input parameters (input composition, throughput rate) and the output parameters (purity, recovery, yield, incorrect discharged particles) of a sensor-based sorting process
- Mathematical approaches to describe the optimal operation point of a sensor-based sorting machine to achieve a specific sorting result

It is stated that this outcome allows a sorting plant to increase purity by using machine learning approaches to optimize the identification or running the plant on the optimal operation point, both without substantially adapting the plant. Superordinate considered these solutions help to increase the amount of recycled plastic so that less plastic waste is thermally treated.

Keywords

Sensor-Based Sorting, Sorting Efficiency, NIR-Sorting, Data Analytics,
Machine Learning, Regression Model, Optimal Operation Point, Throughput Rate,
Transflection, Surface Roughness

Contents

1 Compilation of the doctoral thesis

In this chapter, the organization of this doctoral thesis, "Increasing efficiency in sensor-based sorting processes for waste streams consisting of plastics", is the first part. The second part consists of the complied publications and the scope of investigations. All publications of this doctoral thesis are available **"Open access"**. A graphical abstract (Figure 1-1) at the end of chapter 1.1 of this doctoral thesis visualizes the compilation and content.

1.1 Thesis organization

The thesis starts with an **"Introduction"** to sensor-based sorting and corresponding regulations for recycling plastic waste with **Publication I, Review Article,** *"Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review".* Further, the superordinate research questions in increasing the efficiency in sensor-based sorting for plastic waste streams are defined in **Publication II, Mini Review Article,** *"Challenges to Increase Plastic Sorting Efficiency".*

Environmental Analysis

After the State-of-the-Art is evaluated in **Publication I** and the overall scientific imperative is elucidated, it is necessary to perform two environmental analyses. The first is to discover which qualities of sorted plastic waste are required for recycling processes of different plastic types in Austria. The corresponding environmental analysis is done in **Publication III, Original Article,** *"Benchmark Analysis for Plastic Recyclates in Austrian Waste Management"*.

Furthermore, suitable solutions need to be found on how it can be possible to increase the plastic sorting efficiency in sensor-based waste sorting plants. The evaluation if data analytics is a suitable option for increasing plastic sorting efficiency and how this can be done is performed in **Publication IV, Original Article,** *"Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants".*

Experimental Design

Since the required qualities to be achieved in a plastic sorting process and the possibilities of implementing data analytics to increase the plastic sorting efficiency are known, the next steps are to develop experimental designs to achieve this goal.

At the beginning of the chapter "Experimental Design", the equipment and the physical principles of sensors used in this thesis is introduced. The used equipment for (most of) the trials is the experimental sensor-based sorting setup at the Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben. This setup, the used method near-infrared spectroscopy, as well as the parameter throughput rate, purity, recovery, yield and incorrectly discharged particles are introduced in **Publication V, Method Article,** *"Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup".*

Sensor-based sorting is mainly based on two steps: the identifying of particles and the mechanical discharge of particles. For this reason, the chapter experimental design is split up into two subchapters, "Identification" and "Mechanical Discharge".

Experimental design: Identification

Increasing the sensor-based sorting efficiency by improving the identification of plastic particles or getting plastic particles identified, which are unable to be recognized in a sensor-based sorting machine yet, is the goal of this chapter. This is evaluated in the following three publications.

Publication VI, Original Article, *"Influences and consequences of mechanical delabelling on pet recycling",* deals with whether surface modification influences the identification of particles.

Publication VII, Original Article, *"Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials",* covers the use of transflection, the combination of light reflection and transmission, to identify thin foils which are currently difficult to be identified by sensor-based sorting machines.

Publication VIII, Original Article, *"Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches",* shows the possibility of improving the identification of mono- and multilayer films with machine learning approaches.

Experimental design: Mechanical discharge

Optimizing the mechanical discharge of a sensor-based sorting machine is the second step to increase plastic sorting efficiency. Target plastic particles, which are overlapping or running too fast through the sorting machine, are lost instead of sorted. Running a sensor-based sorting machine on the optimal operation point for mechanical discharge of the target plastic particles maximizes the quality and quantity of sorted material. This is evaluated in the following two publications.

Publication IX, Original Article, *"Influence of material alterations and machine impairment on throughput related sensor-based sorting performance",* analyses the influences of several properties and parameters on the sensor-based sorting efficiency in mechanical discharge.

Publication X, Original Article, *"Feasibility study for finding mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste",* relates to finding the optimal operation point for mechanical discharge with mathematical approaches.

The doctoral thesis is closed with the chapters **"Conclusions"** to summarise the findings of all publications and **"Outlook and further research"** to forecast how results can be implemented and what further research needs to be done to implement them in the industry. The graphical abstract, which visualizes the compilation of the doctoral thesis is shown in Figure 1-1.

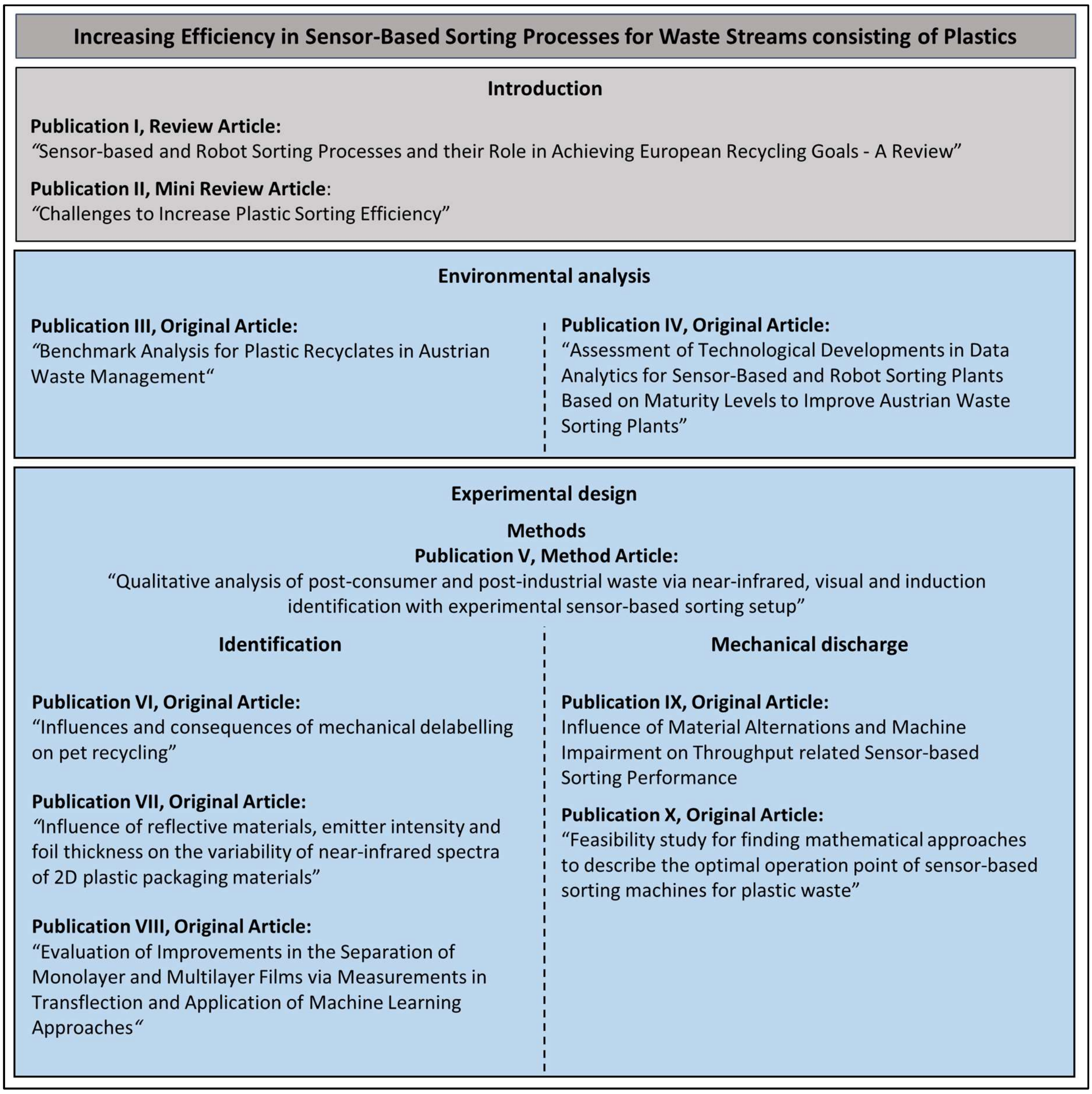

Figure 1-1: Graphical abstract of the doctoral thesis "Increasing efficiency in sensor-based sorting processes for waste streams consisting of plastics"

1.2 Compiled publications

This chapter gives an overview about the compiled publications within this doctoral thesis. The item numbers point to those sections where the publications are shown.

Introduction

2.1 Publication I, Review Article
Friedrich, K., Koinig, G., Fritz, T., Pomberger, R., Vollprecht, D. (2022). *Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review.* In AJOP 5 (4). DOI: 10.19080/AJOP.2022.05.555668.

2.2 Publication II, Mini Review Article
Friedrich, K., Koinig, G., Tschiggerl, K., Pomberger, R., Vollprecht, D. (2021). *Challenges to Increase Plastic Sorting Efficiency.* In Int J Eng Tech & Inf. 2021;2(4):114–118. DOI:10.51626/ijeti.2021.02.00023.

Environmental Analysis

3.1 Publication III, Original Article
Friedrich, K., Möllnitz, S., Holzschuster, S., Pomberger, R., Vollprecht, D., Sarc, R. (2019). *Benchmark Analysis for Plastic Recyclates in Austrian Waste Management.* Detritus, 9, 105–112. DOI: 10.31025/2611-4135/2019.13869.

3.2 Publication IV, Original Article
Friedrich, K., Fritz, T., Koinig, G., Pomberger, R., Vollprecht, D. (2021). *Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants.* Sustainability 2021, 13, 9472. DOI: 10.3390/su13169472.

Experimental Design: Methods

4.1 Publication V, Method Article
Friedrich, K., Koinig, G., Pomberger, R., Vollprecht, D. (2022). *Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup.* In MethodsX 9, p. 101686. DOI: 10.1016/j.mex.2022.101686.

Experimental Design: Identification

4.2 Publication VI, Original Article
Küppers, B., Chen, X., Seidler, I., **Friedrich, K.**, Raulf, K., Pretz, T., Feil, A., Pomberger, R., Vollprecht, D. (2019). *Influences and consequences of mechanical delabelling on pet recycling.* Detritus, Volume 06-June 2019(0), 1. DOI: 10.31025/2611-4135/2019.13816.

4.3 Publication VII, Original Article
Koinig, G., **Friedrich, K.**, Rutrecht, B., Oreski, G., Barretta, C., Vollprecht, D. (2022). *Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials.* In Waste management (New York, N.Y.) 144, pp. 543–551. DOI: 10.1016/j.wasman.2021.12.019.

4.4 Publication VIII, Original Article
Koinig, G., Kuhn, N., Barretta, C., **Friedrich, K.**, Vollprecht, D. (2022). *Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches.* In Polymers 2022, 14(19), 3926. DOI: 10.3390/polym14193926.

Experimental Design: Mechanical Discharge

4.5 Publication IX, Original Article
Küppers, B., Schlögl, S., **Friedrich, K.**, Lederle, L., Pichler, C., Freil, J., Pomberger, R., Vollprecht, D. (2021). *Influence of material alterations and machine impairment on throughput related sensor-based sorting performance.* Waste Management & Research. 2021;39(1):122-129. DOI: 10.1177/0734242X20936745.

4.6 Publication X, Original Article
Friedrich, K., Kuhn, N., Pomberger, R., Koinig, G. (2023). *Feasibility study for finding mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste.* In Polymers 2023, 15(21), 4266. DOI: 10.3390/polym15214266.

1.3 Scope of Investigations

This chapter describes the boundaries of the doctoral thesis, the research publications and the research questions to be answered in respective publications.

Boundaries

The scope of investigations in waste processing technology and waste management is mainly set by the waste processing technology, the waste to be processed and the waste processing technology's "Technology Readiness Level" (TRL). Table 1-1 shows the scope of investigation, which are waste streams consisting of plastic, sensor-based sorting and TRL 2 to TRL 4.

Table 1-1: Scope of investigations for the doctoral thesis "Increasing efficiency in sensor-based sorting processes for waste streams consisting of plastics"

Waste processing technology	Sensor-based sorting
Waste to be processed	Waste streams consisting of plastics
TRL	2 to 4

TRL 1 means "Fundamental Research", while TRL 2 to 4 means "Industrial Research". In Figure 1-2, the TRL definitions in dependence on European Commission (2012) are transformed into "TRL definitions in sensor-based sorting" to be brought into relation to the boundaries of this doctoral thesis. It aims to increase the efficiency of sensor-based sorting machines from TRL 2 to TRL 4. TRL 1 means that "Physical principles in sensor-based sorting" are examined; for TRL 2 to 4 "Technology concept for sensor-based sorting machines approved on laboratory scale". According to these boundaries, the doctoral thesis ends with approving the found opportunities on the aggregate level - the sensor-based sorting machine as a stand-alone equipment. Basic research on TRL 1 is seen as approved for starting at TRL 2.

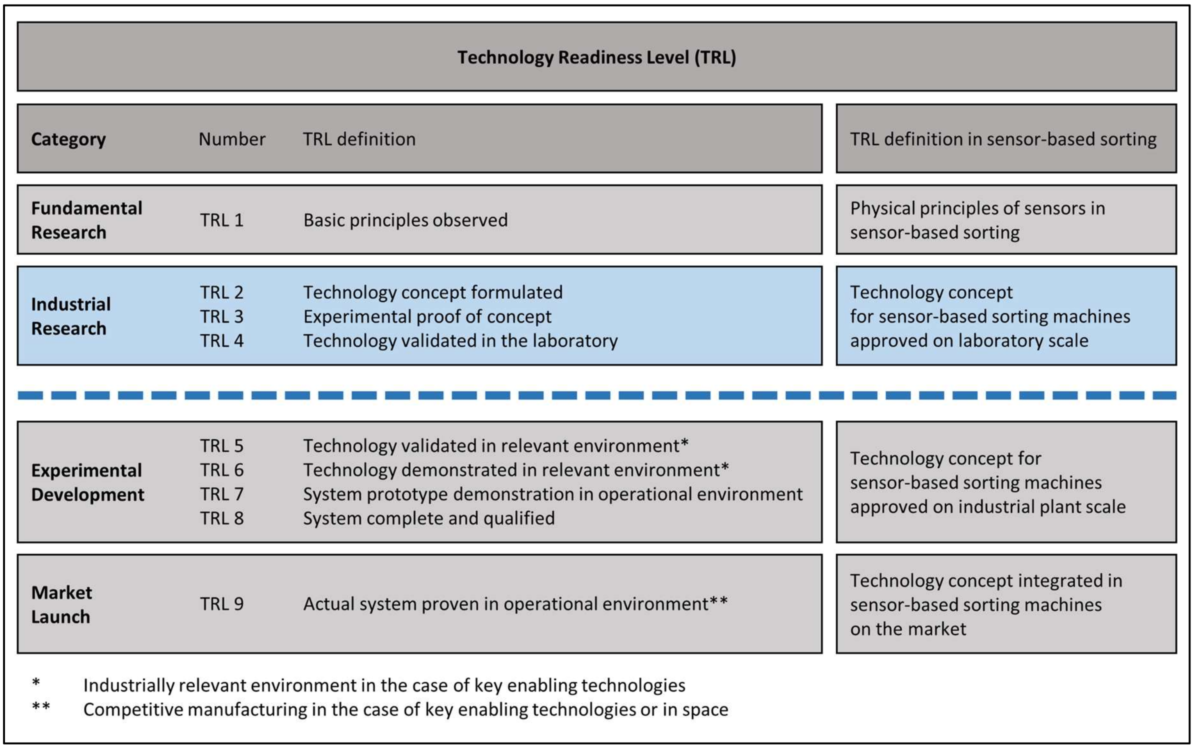

Figure 1-2: TRL definitions in dependence on European Commission (2012) are transformed in "TRL definitions in sensor-based sorting"

TRL 5 to TRL 8 meaning, "Technology concept for sensor-based sorting machines approved on industrial plant scale", are not in the doctoral thesis's scope. These levels would approve new technology concepts on industrial plant scale. The set boundary of this doctoral thesis related to TRL are marked as a blue area for the scope and as a blue line for the border in Figure 1-2. The categories “Experimental Development” and “Market Launch” (TRL 9) are not part of this thesis’ focus.

Publications and research questions

Within this chapter, the research questions, which are answered in each of the ten research publications, are expressed.

Introduction

Publication I, Review Article, "Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review"

The topic of sensor-based sorting and robot sorting, as well as current technological and political developments in the waste management sector, are introduced in this publication. As a review paper, it outlines not only an introduction to the topic, it gives detailed information about the application possibilities, best-practice examples and how these technologies potentially help achieving the European recycling goals. The overview outlines which technologies are mainly used for the sensor-based sorting of waste streams consisting of plastics to choose the sensor technology for this doctoral thesis.

Research question 1 (RQ 1): What is the State-of-the-Art in sensor-based sorting of waste streams consisting of plastics?

Publication II, Mini Review Article, "Challenges to Increase Plastic Sorting Efficiency"

Finding the current challenges to increase plastic sorting efficiency is the topic of this publication. The found challenges are obligatory to define the current necessity of research to increase the plastic sorting efficiency in sensor-based sorting plants. The found research gaps in this publication are formative to define the research questions and develop the experimental design of this doctoral thesis.

Research question 2 (RQ 2): What are the current research gaps for increasing the sorting efficiency of plastic waste streams?

Environmental Analysis

Publication III, Original Article, "Benchmark Analysis for Plastic Recyclates in Austrian Waste Management"

The correlation between different quality features and how they affect the pricing policy for recyclates is the focus of this publication. Therefore, quality parameters for the sorted plastic waste as an input for plastic waste recycling companies and manufactured recyclates are included. This environmental analysis shows that purities of sorted waste are expected from recycling plants for different types of waste. This doctoral thesis outlines the threshold values for the purities of sorted waste, defining the least sorting result to be achieved in sensor-based sorting of waste streams consisting of plastics.

Research question 3 (RQ 3): What are the expected sorted waste qualities for different types of plastic?

<u>Publication IV, Original Article, "Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants"</u>

This publication aims to give novel insights into the degree of implementation of data analytics in the Austrian waste management sector. The degree of implementation is defined in maturity models developed for stakeholders, referred to sensor-based sorting. Furthermore, the interviewed stakeholders were asked about their appraisal of data analytics usage in sensor-based sorting. This leads to the decision to research methods for more efficient data analatics in sensor-based sorting methods.

Research question 4 (RQ 4): Can data analytics be seen as a solution to make sensor-based sorting processes more efficient?

Experimental Design: Methods

<u>Publication V, Method Article, "Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup"</u>

This publication describes the experimental sensor-based sorting setup applied in upcoming publications of this doctoral thesis and details all installed sensors and their specifications. Moreover, the selected method, near-infrared spectroscopy, used in further publications of this doctoral thesis, is outlined in detail. The parameters throughput rate, purity, yield and recovery – which outline the efficiency of a sensor-based sorting process – are defined.

Research question 5 (RQ 5): Which parameters define the efficiency of a sensor-based sorting process?

Experimental Design: Identification

Publication VI, Original Article, "Influences and consequences of mechanical delabelling on pet recycling"

Whether the use of mechanical delabelling of polyethylene terephthalate (PET) bottles influences near-infrared identification is examined in this publication. With the change in surface roughness of the PET bottles in the label scratching process of the delabeler, it is assumed that the identification changes as well. For the doctoral thesis, this publication finds out if the surface roughness influences near-infrared identification, which increases the efficiency of sensor-based sorting.

Research question 6 (RQ 6): Does surface roughness influence the near-infrared identification of sensor-based sorting processes?

Publication VII, Original Article, "Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials"

For thin 2D plastic packaging, near-infrared spectroscopy often brings fluctuating spectra and some particles cannot be recognized by the sensor. This paper aims to improve the spectral quality, which can be achieved by installing reflectors behind the material made up of copper or aluminium. This setup enables identification in transflection – a combination of transmission and reflection - rather than only reflection mode. In addition to that, the influence of the emitter intensity and the foil thickness is further evaluated. The use of transflection to increase the identification and continuative sorting efficiency is the part considered to be found in this doctoral thesis.

Research question 7 (RQ 7): Is the usage of transflection for near-infrared spectroscopy for 2D plastic packaging enhancing the identification in sensor-based sorting processes?

Publication VIII, Original Article, "Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches"

Machine learning approaches are developed for sorting monolayer and multilayer materials without requiring manual adaption of the near-infrared sorting model. The amount of correctly identified particles can be enhanced automated by machinal adaption of the sorting model. Supplementary frequency analysis methods increase spectral information by eliminating spectral noise. For the doctoral thesis, the validation to use machine learning for getting sensor-based sorting processes more efficient is the main output of this publication.

Research question 8 (RQ 8): Is the usage of machine learning algorithms suitable to enhance correct identification of particles in sensor-based sorting processes?

Experimental Design: Mechanical Discharge

Publication IX, Original Article, "Influence of material alterations and machine impairment on throughput related sensor-based sorting performance"

The sorting efficiency of a sensor-based sorting setup using near-infrared technology in dependence on throughput rate and various input compositions is studied with four parameters: purity, yield, recovery and incorrectly discharged share of reject particles. The aim is to find the dependency of the sensor-based sorting input parameters throughput rate and input composition on the output results purity, yield, recovery and incorrectly discharged particles. The influences on the parameters of 2D particles in the input of a sorting stage and failing air valves were evaluated for various input compositions at different throughput rates. The resulting graphs correspond to this doctoral thesis since they show the dependence of the input parameters of a sensor-based sorting process on the sorting efficiency in the output parameters.

Research question 9 (RQ 9): How do the input parameters of a sensor-base sorting process (throughput rate and input composition) depend on the sorting efficiency in the output parameters (purity, yield, recovery, incorrect discharged particles)?

Publication X, Original Article, "Feasibility study for finding mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste"

The optimal operation point of sensor-based sorting machines is mostly not occupied; machines are either overrun or underrun depending on the availability of waste streams. Mathematical approaches in regression models define the dependence on the input stream composition and the throughput rate on the sorting result. Four hypotheses are validated, whether the same mathematical approaches can be transferred to different types of waste, whether they can be transferred individually to further sensor-based sorting machines or whether there are other limitations. For a sensor-based sorting plant, the main effort of validated mathematical approaches in their area of validity would be to increase the sorting efficiency, e.g. enhance the purity without substantially adapting the sorting plant. The validation of the area of validity for mathematical approaches describing the sorting efficiency is the main result of this doctoral thesis. This defines how and under what conditions a sensor-based sorting plant can run automated on the optimal operation point depending on the throughput rate and the input composition.

Research question 10 (RQ 10): In what area of validity can mathematical approaches be used so that sensor-based sorting machines can run automated on the optimal operation point?

2 Introduction

The "Introduction" chapter consists of two peer-reviewed publications. These two publications are presented below.

2.1 Publication I, Review

"Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review"

Review Article
Friedrich, K., Koinig, G., Fritz, T., Pomberger, R., Vollprecht, D. (2022). *Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review.* In AJOP 5 (4). DOI: 10.19080/AJOP.2022.05.555668.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 2-1.

Table 2-1: Annotation on the doctoral candidate's contribution to Publication I

Conceptualization	**Friedrich, K.**, Vollprecht, D.
Methodology	**Friedrich, K.**
Software	-
Validation	**Friedrich, K.**, Fritz, T., Koinig, G.
Formal Analysis	**Friedrich, K.**, Koinig, G.
Investigation	**Friedrich, K.**, Fritz, T., Koinig, G.
Resources	-
Data Curation	Fritz, T., **Friedrich, K.**
Writing: Original Draft Preparation	**Friedrich, K.**, Fritz, T., Koinig, G.
Writing: Review and Editing	**Friedrich, K.**, Koinig, G.
Visualization	**Friedrich, K.**, Fritz, T., Koinig, G.
Supervision	Vollprecht, D., Pomberger, R.
Project Administration	Pomberger, R.
Funding Acquisition	-

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Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review

Friedrich Karl*, Koinig Gerald, Fritz Theresa, Pomberger Roland and Vollprecht Daniel

Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Austria

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***Corresponding author:** Karl Friedrich, Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Franz Josef-Straße 18, 8700 Leoben, Austria.

Abstract

A circular economy is the stated aim of current technological and political developments in the waste management sector. Achieving the goal of a circular economy requires significant improvements in waste treatment technologies. For this reason, this paper summarises the relevant technologies, detailing the developments in the significant sensor-based sorting technologies. This review analyses the key spectral analysis methods like Near-Infrared Spectroscopy, Visual Spectroscopy, X-ray transmission, X-ray fluorescence analysis and Laser-Induced Breakdown Spectroscopy. This study further contains a detailed analysis of the standard sensor-based sorting construction types chute sorter, belt sorter and robot-aided sorting. Further insights in the branch of sensor-based sorting are permitted by describing the key players and stakeholders in sensor-based sorting, detailing the area of expertise and current fields of study for primary sensor and sorting machine suppliers. A convenient lookup table detailing the capabilities of these significant suppliers is provided. The last chapter summarises relevant trends and developments in digitalisation and Industry 4.0 in the waste and recycling sector, elaborating on relevant technology like digital waste management, sorting robots in waste management, smart villages and recyclable materials scanners. The reviewed data portrays the waste management industry's substantial developments. While new technologies, like machine learning, convolutional neural networks and robot sorting, are increasingly implemented, a substantial discrepancy exists between technological capabilities and the current State-of-the-Art.

Keywords: Sensor-based Sorting; Robot Sorting; Recycling Goals; Digitalisation; Circular Economy

Introduction

This study aims to research developments in sensor-based sorting and robotics and their effects on waste management. The implementation and further development of sensor-based sorting and robotics has great potential to change waste management over the long term. In addition, research is performed on the technologies currently available on the market to determine their future potential. Furthermore, possible solutions are derived from achieving the circular economy package's new European resource efficiency targets. Developments in waste technology and management are based on solving technical problems within the given legal framework. In the following, the essential regulations guide the waste management sector, cause trends and significantly influence their developments by changing parameters.

Circular Economy Package

The Circular Economy Action Plan of the European Union (EU) was introduced in December 2015 and it is intended to lead to a more resource-efficient future. In Europe, there has been a continuous growth of recycled materials to total raw materials from 2008 to 2016. However, secondary raw materials only account for 12 % of the total demand for raw materials in the EU, which provides a broad basis for innovation in waste management. A new legal basis came into force in July 2018, requiring, among other things, recycling rates of 70 % for packaging waste by 2030 and 65 % for municipal waste by 2035. In addition, the landfilling of municipal waste hass to be reduced to 10 % [1]. Furthermore, the harmonisation of definitions and calculation methods for recycling rates and new requirements for the separate collection of the waste types defined in the Waste Framework Directive (WFD) are included. These new regulations strengthen the market for secondary raw materials and create a uniform system to ensure their quality and make them comparable. The basis for this is always the most efficient waste separation and sorting possible [1]. Central objective is increasing the recycling quota by overcoming the plethora of challenges opposing this development [2].

Plastics strategy

The strategy for plastics, adopted in 2018, states that from 2020 onwards, all plastic packaging on the EU market must be recyclable and the consumption of single-use plastics should be reduced. The EU states that about 150,000 to 500,000 tonnes of plastic waste ends up in the sea every year. In order to prevent this, the plastics strategy aims at setting the path towards a circular economy of plastics. An important factor is the cost efficiency of recycling plastic waste, which can be achieved through changes in production and the design of packaging and products. Close cooperation between packaging manufacturers and the recycling industry as well as communication between the waste management and chemical industries is required to find a broader field of applications for recycled packaging waste. The EU expects a fourfold increase in demand for recycled plastics when the Plastics Strategy is fully implemented, which reduces the dependence on imported fossil raw materials. The resulting carbon dioxide (CO_2) savings are expected to help meet the targets of the Paris Agreement [3].

For the waste management sector, this means opportunities for innovation, growth and new business models based on the circular economy. The expected increase in the market value of recycled plastics is based on evaluations of the automotive and construction industries, and economic incentives from the EU are also currently under discussion. Furthermore, increasing volume and better separate collection are expected to make recycling more lucrative. In order to achieve these goals, investments in infrastructure and innovation, which the EU estimates at 8,4 to 16,6 billion Euros, are needed. The strategy of plastics as an ambitious vision can become a job provider if the main actors take concrete actions towards a circular economy ("Towards a Circular Economy") [3].

Single-Use Plastics Directive

The directive on reducing the impact of certain plastic products on the environment was designated as part of the Plastics Strategy only eight months after it was presented and came into force on 2 July 2019. The directive is based on a census that traced the pollution of European beaches to 15 products. According to litter counts, the main component of marine litter is plastics, at around 80-85 %, and these consist of 50 % single-use plastic and 27 % fishing gear. The single-use plastic problem can also be illustrated very well by measured numerical data. Between 1950 and 2015, more than one tonne of plastic was produced per capita of the world's population, of which not even ten per cent was recycled. Half of the plastic ever produced worldwide has been produced since 2000. The market restrictions imposed by this directive mainly affect single-use plastic items. Unlike bio-based and biodegradable plastics, this directive does not cover microplastics, glass and metal beverage containers. The aim is to reverse the trend, as consumption is expected to increase from single use items to more sustainable alternative items. The member states should set as ambitious measures as possible to comply with the waste hierarchy. It is also essential to consider the product life cycle and a harmonised standard in product design, which the waste management industry has demanded for a long time. In addition to increased producer responsibility, consumer decisions are also to be steered in a more sustainable direction to achieve a measurable quantitative reduction in the consumption of single-use plastics in the EU by 2026 compared to 2022. The directive focuses on marketing restrictions, product requirements, labelling requirements, extended producer responsibility, separate collection and consumer awareness measures. Further specifications concern the coordination of measures, guidelines on single-use plastic articles, information systems and reporting and finally, sanctions as well as evaluation and review. In principle, the directive's contents must be complied with by 3 July 2021, although individual articles will not come into force until later. Market restrictions on products will come into force by the end of 2024 and the increased recycled content in beverage bottles by 2030 [4,5].

Sensor-based sorting as a key player

Developing a sustainable circular economy would be unthinkable without sensor-based sorting technology, especially if the ambitious EU targets shall be achieved. For example, solutions already exist for almost all industrial waste sorting tasks in polymer materials, which the actors in the recycling chain have also adopted [6].

Sensor-based sorting: Sensor technologies

Sensor-based sorting technology can automatically sort materials according to various material properties to divide the material flow into different product groups [6]. The upswing in sensor-based sorting is due to the rapid development in non-contact sorting technology, which has opened up new areas of application in recent years. This development, which continues to be dynamic, leads more efficient devices and thus to new areas of application in waste management [7]. Due to the increasingly complex requirements for the quality of the end products, the more valuable fractions and higher recovery of these fractions' materials, sensors with different measuring principles are being combined more frequently to meet the prevailing trends in this direction [8]. The complexity of the technical design and the number of sensors is decisive for the possible applications. Especially in dry sorting, this technology has led to redesigns of processing methods and new application possibilities. Comparisons with the still widespread manual sorting showed that human eyesight was often insufficient to identify the properties of waste components and that machine systems were more efficient in this respect [9].

The learning ability of modern sensor-based systems, which is achieved through software-controlled data processing, is seen as an unique advantage, especially in changing the feed material's composition or quality requirements. The decoupling of the sorting criterion from the actual separation process reduces the

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risk of false outputs due to mutual interference and the carry-over of different components. The units are very compact and can also be used in mobile plants. In addition, materials can be separated, which would otherwise be impossible to separate, such as minerals of the same density and magnetic properties in the coarse range. In addition, multiple sorting criteria like e.g. wettability or conductivity can be used in one process stage to achieve better separation efficiency. Due to considerable savings in water, energy and reagents compared to other separation methods, non-contact sorting can make the recovery of previously uneconomic deposits economical. Possible pre-enrichment by sensor technology also helps, which saves resources and, since it can already be used on-site, also space and transport costs [9,10].

However, good separation results can only be achieved by suitable preconditioning of the feed material. Pre-classification to the narrowest possible particle size range and separation of fine and coarse material that cannot be sorted is essential for achieving a certain separation accuracy, depending on the performance of the sorting system. The material mixture to be processed must be pre-treated so that the concentration of the material to be separated is as high as possible. At the same time, disturbing components such as easy dispersible particles with low densities are separated beforehand. Particularly important in preparing the feed material is separating the particles to create at least a monolayer. This means that the individual particles do neither touch nor overlap each other. Some sensor types require clean surfaces, which are generally produced by a washing process. This requirement leads to a certain amount of water consumption in the dry technique, which is less than wet separation methods. In addition to very light, flyable materials, composites and agglomerates also present particular challenges [9,10]. In principle, it is possible to use all non-contact physical measurement methods as separation methods. Factors such as resolution, measuring speed and environmental influences determine the possible applications, and so there is still potential for optimisation even with the sensor types already in use [10].

Sensors are differentiated according to whether they can detect superficial properties or "look inside" the material. The essential types belong to the former group and include the optical (colour) line scan cameras, which measure colour, brightness, transparency, reflection and shape. Fluorescent materials can also be detected after UV excitation [10]. 3D sensors, which function via laser triangulation, can consider the shape and structure of the material [6]. The wavelengths of the sensors, which are installed for sensor-based sorting, explain different fields of application. The terahertz range in the electromagnetic spectrum, as shown in Figure 1, is a part that is not yet fully exploited [11]. The sensors' non-contact detection of object properties and characteristics consists of an object feeder, a separation system, and intelligent sensor technology consisting of an emitter, a detector, an evaluation and a discharge unit [12]. Table 1 presents an overview of the typical sensor types installed in waste management [13]. Near-infrared spectroscopy (NIR) for detecting material properties works via a light source placed above the conveyor belt that irradiates the material with infrared light. The irradiated molecules are excited to vibrate by specific wavelengths corresponding to the resonance frequency and reflect the other wavelengths diffusely. The respective spectrum is compared with a database and each one is assigned a material class as shown in Figure 2; this is called classification. The absorption lines important for plastic recognition are between 1,200 and 2,000 nm [14]. Spectroscopy works analogously to NIR spectroscopy in the visual (VIS) frequency range for colour sorting. Digital images are assigned different numerical values per pixel, exactly one for grey-scale images and three numerical values per pixel (red, green, blue) for colour images. In contrast to these red-green-blue (RGB) cameras, several hundred numerical values are assigned to a pixel in hyperspectral imaging (HSI) [15].

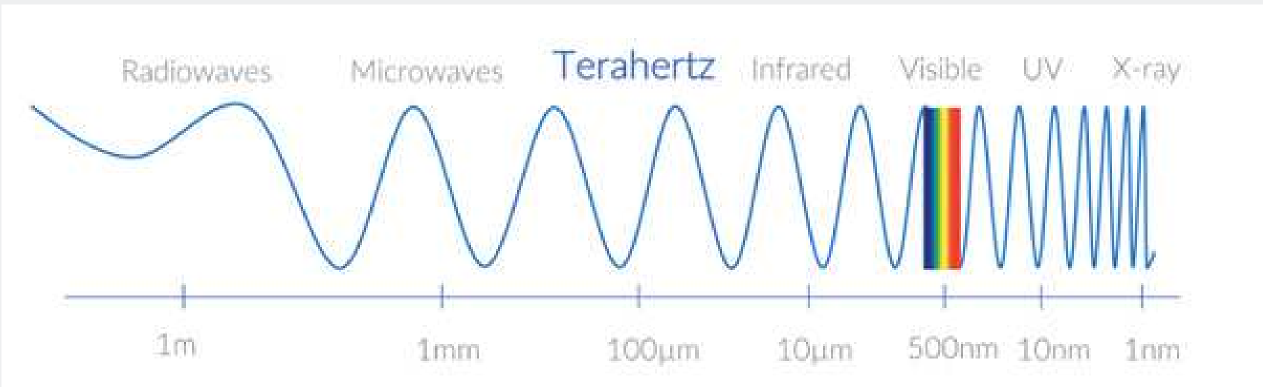

Figure 1: Embedding the terahertz range in the electromagnetic spectrum [11].

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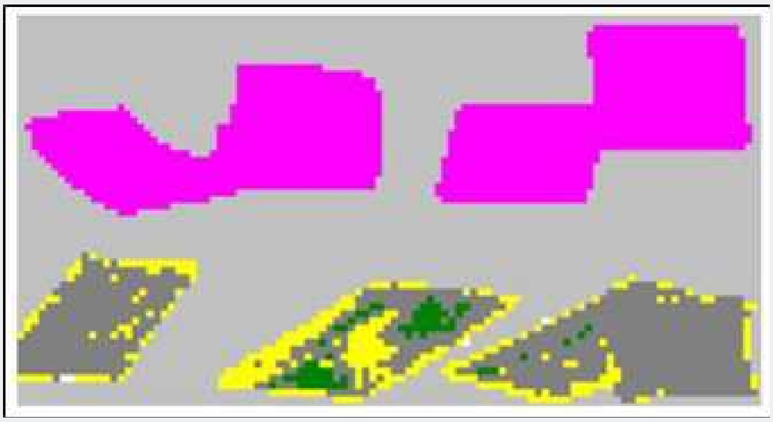

Figure 2: Polypropylene (PP) (pink) and High-Density-Polyethylene (HDPE) (grey), Non-Classified (yellow) and Polyethylene-Terephthalate (PET) (green) - Particles coloured according to their material [14].

Table 1: Overview of sensor technologies [8,13].

Sensor technology	Material property	Measurement principle	Waste stream
Electromagnetic Induction	Electrical Conductivity	• Generation of an electromagnetic field • If a metal passes through the electromagnetic area, the field is changed in a substance-specific manner • Detection of this change and assignment to a type of metal	• Scrap processing • Electronic waste • Construction site mixed waste • Commercial waste • Waste glass
Laser-Induced-Breakdown-Spectroscopy (LIBS)	Elemental Composition	• By heating a sample surface with a pulsed laser, sample portions are converted into a so-called plasma • The plasma light spectrum assigns the material type	• Differentiation and sorting according to metal alloys • Sorting of aluminium scrap
Near-Infrared Spectroscopy (NIR)	Molecular Composition	• Molecular excitation by near-infrared radiation • Absorption of specific wavelength ranges by the molecules, a reflection of the remaining wavelength ranges • A spectrum of reflected radiation can be assigned to a substance	• Packaging waste • Household waste • Waste paper • Commercial waste • Pre-sorting of recyclables • End-of-life vehicle recycling • Mixed construction waste
Visual Spectroscopy (VIS)	Colour (reflection and transmission); Shape	• Imaging sensor • Separation of the sample according to colour, brightness, reflection and transparency	• Waste paper • Pre-sorted recyclables • Chipboard • Construction site mixed waste
X-ray Fluorescence Spectroscopy (XRF), Laser	Elementary Composition; Colour; Fluorescence; Scattering;	• X-rays excite atoms in a sample, resulting in substance-specific fluorescence. • The spectrum of the emitted fluorescence provides information about the material's elemental composition.	• Copper from iron scrap • Glass sorting • Compost processing
X-ray Transmission (XRT)	Atomic Density	• X-rays shine through the sample • Absorption of part of the radiation, depending on sample density and thickness • Comparison of the non-absorbed rays with a given initial value for the density	• Scrap processing • End-of-life vehicle recycling • Electronic waste • Household waste • Commercial waste

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The spectral decomposition of the signal happens before the detector and results in a complete spectrum for each pixel. However, the passband wavebands of an RGB colour camera are much wider for the three colours red, green and blue. Combining both principles, the entire wavelength range from 400 to 1,000 nm can be covered, in that the HSI camera can represent parts of the VIS and the NIR range, and the RGB camera can cover the VIS range from 400 nm to 700 nm, at least in three bands. Figure 3 shows the transmittance curves of an RGB colour camera equipped with a filter for wavelengths above 650 nm and the HSI camera equipped with a passband of a bandpass from 600 to 1,000 nm to avoid ambiguous information [15]. Typical HSI cameras can operate between 250 to a maximum of 2500; an example for waste management imaging is shown in Figure 4 [15,16]. Hard plastics, paper, films, wood, biomass or fuels are separated with this method. In order to achieve the quality requirements for higher-quality recycling, multi-stage sorting is more frequently used than positive and negative sorting combinations. In positive sorting, the recyclable material is enriched in the discharged product, and in negative sorting, interfering components are separated. By switching between these two types of sorting, it is possible to react to the waste sector's often highly fluctuating input compositions. NIR or VIS spectroscopy are increasingly used in commercial waste, electrical and electronic scrap, bulky waste, biowaste and mineral waste. The secondary raw materials industry is a significant development driver, demanding innovations with more complex sorting requirements and higher quality standards [8,9].

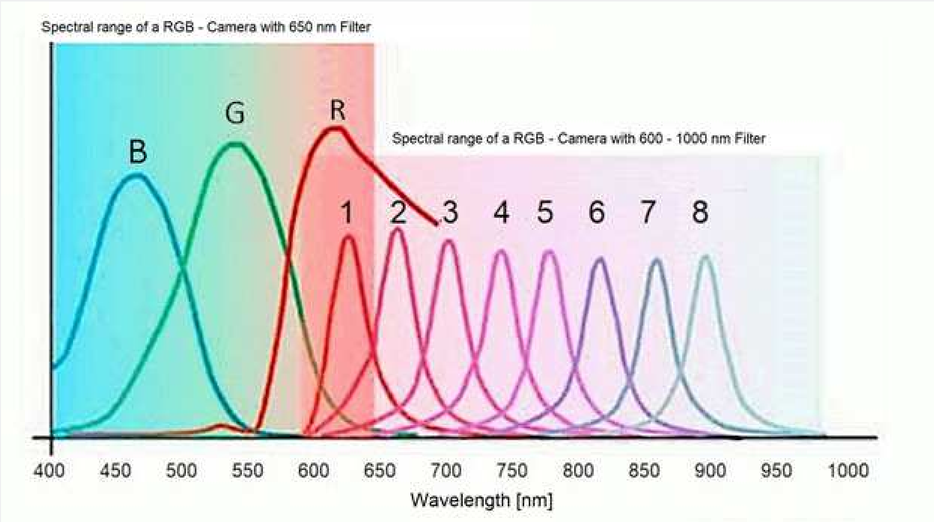

Figure 3: Transmittance curves of an RGB colour camera as well as a 9-band HSI camera for the range of 630 to 920nm [15].

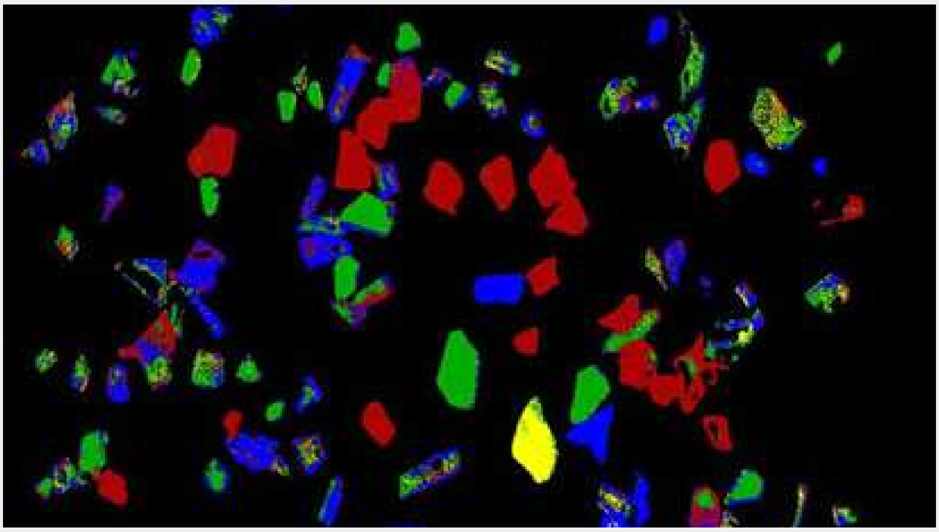

Figure 4: HSI detection on a conveyor belt in waste management and recycling [16].

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The second large group is electromagnetic sensors. These sensors are located transversely to the belt's direction under the conveyor belt. Each generates a high-frequency electromagnetic field through a coil, which is changed by introducing conductive materials. The coil induces eddy currents in the material, which extract energy from the emitting field. The energy is detected by the electromagnetic sensor and leads to metal detection. For this reason, electromagnetic sensors are often used in shredder plants and electronic scrap processing. After using classic metal separators such as magnetic separators and eddy current separators, up to 10% of metals can still be contained in the material stream. These can be recovered with additional sensors. It is also helpful for sorting construction waste or incineration ashes, especially with digital image processing. In addition to metal recovery, purification of metallic fractions is also possible, for example, in PET bottle sorting [8].

The third large group of sensor types is relevant for recycling work with X-ray radiation. Here, a distinction is made between X-ray transmission and X-ray fluorescence.

X-ray transmission (XRT) divides the material according to density differences by measuring the degree of absorption of the X-ray radiation. The degree of absorption depends on the thickness and density of the material. The influences of the material size and thickness are compensated to determine the material-specific absorption of the individual parts with the help of software. For this purpose, the X-ray source is placed below the material flow and the scanner area for determining the residual radiation is placed above. Based on the information from the scanner and the sorting specifications, two products result [6].

X-ray fluorescence analysis (XRF) divides the material stream based on its atomic composition. The scanner unit and the X-ray source sit above the material stream, passing through a low-energy X-ray field. The chemical elements are excited to emit element-specific energy by shell jumps of the electrons. The evaluation software outputs energy spectra that can be used to separate different product groups [6].

The use of laser technology is suitable for cleaning compost/structural material by removing glass and plastics. Due to the 'scattering' effect, which occurs depending on the degree of hardness and water content, laser technology is particularly applicable in this area. Depending on the wavelength range of the laser, different properties such as colour, structure or, for example, fluorescence can be detected together or separately [8].

LIBS is shorthand for Laser-Induced Breakdown Spectroscopy, and this technology is used to determine the elemental composition of the specimen. LIBS uses high-focused light amplification by stimulated emission of radiation (laser) to remove the surface of the specimen [12].

It causes the electronic excitation of atoms, which form a plasma. As these fall decay back into their original state, they emit light of specific wavelengths. These wavelengths are characteristic of the element composition in question, forming a "fingerprint" used for qualitative and quantitative evaluation. The detection technology in collecting waste is less widespread and less researched than sorting waste. Reasons for this are the high decentralisation of waste accumulation and the influences of weather, vibrations, and dirt. An example of a waste stream that requires high purity for recycling is biowaste for composting plants. The German company Maier & Fabris has developed a metallic value or contaminant detection system based on eddy current induction directly on the collection vehicle. Further development is an automatic feedback system for citizens to inform them directly about the analysis result and, in the worst case, to block emptying at the collection vehicle. In addition to imaging techniques, research is currently being done on a detection method for odour, using 'electronic noses'. Although significant progress can be seen, this technology is not yet employed commercially. However, data generation has new possibilities, such as weighing waste bins [12].

Sensor-based sorting: Construction type

Generally, a distinction can be made between the two systems of material feeding, namely feeding by chute and by belt. Both types are used in recycling and they differ according to their material feed. As shown in Figure 5, the chute machines are used mainly in the fine-grain range and with bulk materials that flow well. An oscillating conveyor trough (A) ensures uniform distribution over the entire width of the conveying chute and sufficient separation. The feed is then transferred to an inclined chute for further separation and acceleration. A detection device (B) inspects the feed material below the chute by a detection device (B) in free fall.

With the help of a computer, a real-time image of the material flow is classified according to various properties such as colour information, position and size. This image activates compressed air valves of a nozzle bar (C), which discharge the detected components (D). This type of construction is often combined with a colour line scan camera with an associated illumination unit and can distinguish colours in a vast spectrum [9]. With two or three sorting paths, the chute system is designed for the raw materials industry and the recycling industry to sort used glass, plastics, used electrical appliances, incineration ash, and construction and demolition waste [9].

As exemplified in Figure 6, belt sorters were developed for coarse and irregular feed material and can be used in combination with a NIR wavelength range detector. The feed material is again fed via an oscillating conveyor trough (A) and is pre-collected by continuously increasing conveyor speeds. Above the belt conveyor is an NIR sensor (B) which monitors the entire belt width and compares the characteristic spectrum of the objects with those in a computer database. Classification is also done according to size and position. The actual sorting is done using an air nozzle bar (C), which targets and separates the object (D) under investigation with one or more nozzles [9]. The belt sorting systems are used in the recycling industry to sort paper, plastics, RDF, and household

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and commercial waste with two sorting paths [17]. Various companies, also offer multiway sorting systems, which provide up to six sorting paths. Areas of application are packaging waste from household and commercial waste [17].

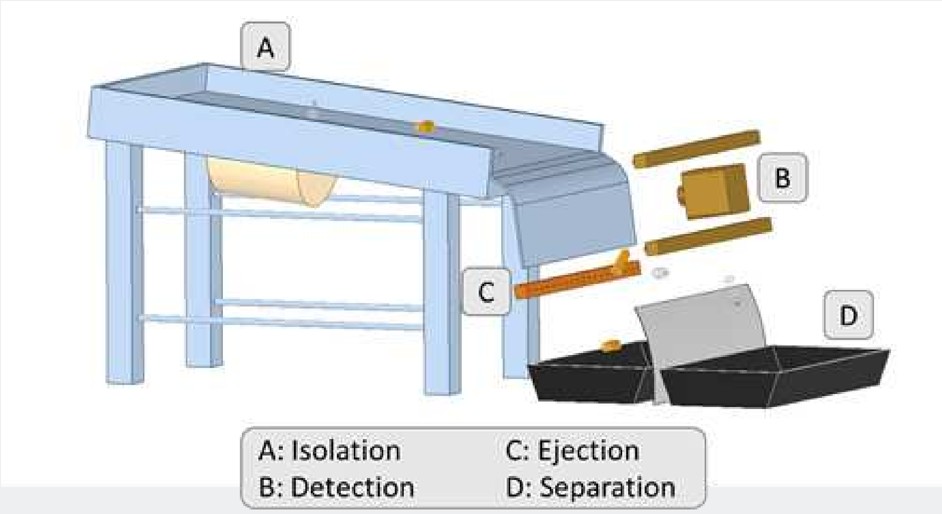

Figure 5: Principle sketch of chute sorters (authors' depiction).

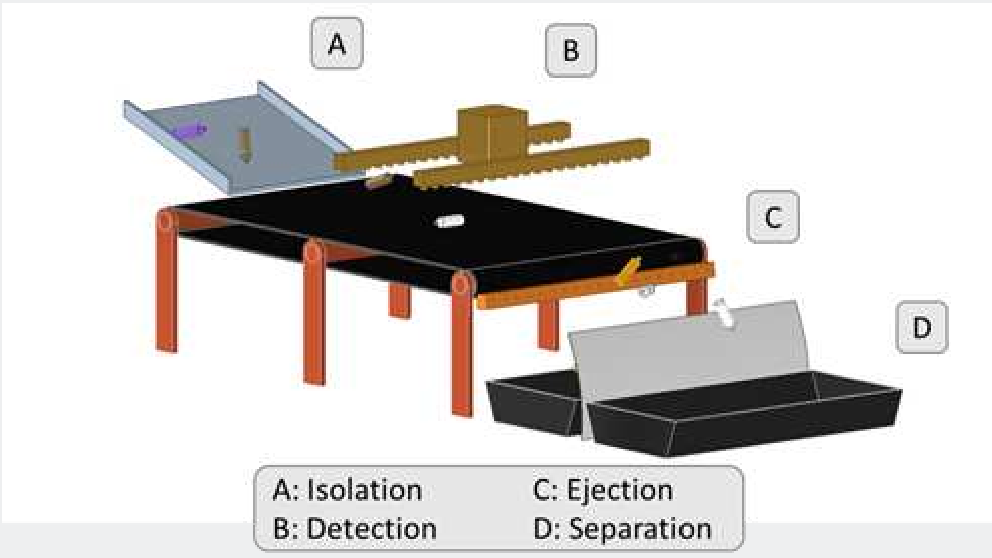

Figure 6: Principle sketch of belt sorters (authors' depiction).

Robotics

The Robotic Industries Association (RIA) defines robots as follows (Inc 2020): "A robot is a reprogrammable, multifunctional manipulator designed to move material, parts, tools or specialised devices through variable programmed motions for the performance of a variety of tasks. Recently, however, the industry's current working definition of a robot has come to be understood as any piece of equipment that has three or more degrees of movement or freedom." [18]. Many industries have been using robotics and automated work processes for many years to take over physically demanding tasks from humans and make processes more efficient and more manageable. Especially in the industrial sector, collaborative robots, i.e. robots built to

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work with and alongside humans, are becoming increasingly important [19]. Human-robot collaborations refer to humans and machines working simultaneously on the same object, and cooperation refers to working reciprocally. Without the protective concepts such as nets or grids, it requires a unique design of the robot arms, which do not have sharp edges and rigid material. This concept combines the hand-eye coordination, force dosage and independent problem-solving ability of humans with the advantages of robotics such as freedom from fatigue, path fidelity and precision [20]. Table 2 shows a classification of common robot types including their functions [21].

Table 2: Classification of robot types [21].

Robot type	Characteristics and field of application
Industrial robots	Industrial robots have a wide range of applications in manufacturing and carry out various processes. They are used as welding robots, painting robots, palletising robots, assembly robots, etc.
Service robots	Service robots provide services to humans in various forms, which is the reason why they must be able to move autonomously in a wide variety of environments. Another feature of these robots is the easy-to-use user interface. Since the robots move close to people, human safety must be guaranteed at all times. Examples are as hoover robots, lawnmower robots, pool cleaning robots, assistance robots for persons with walking disabilities, etc.
Mobile robots	Mobile robots can move independently in their environment without human assistance and have many similarities with service robots. See service robots or driverless transport robots for application areas for logistics systems, toy robots, exploration robots, etc.
Micro- and Nan-orobots	Microrobots are only a few millimetres in size and can move autonomously in small structures and carry out actions there, e.g. inside the body. Another development direction aims to let many microrobots acts as swarms, e.g. for exploration. Nanorobots are autonomous machines and structures down to the size of molecules.
Humanoid robots	Humanoid robots have a human-like appearance and are programmed or equipped with actuators that enable them to commu-nicate or act directly with humans. They are used as a multifunctional working machine, assistant for humans etc.

Roughly categorised, industrial robots can take on tasks in the areas of production (robot carries tool), assembly and handling (robot carries gripping system), as well as checking and measuring (robot carries measuring device). They consist of arm parts connected by joints and can vary in size and number depending on the type of application. The entire robot arm is referred to as the manipulator, the foremost part as the effector, to which a wide variety of tools and grippers can be attached. Most systems for waste management fall under mechanical separators using grippers (pneumatically, electrically or hydraulically controlled), use suction pads or vacuum cups. The former robotic systems sort, for example, construction waste and the latter are used for sorting packaging. An important part is the control system, through which connected sensors can also be used in some circumstances. The robotic system also includes safety devices if needed, for example, to protect labourers. The kinematics (spatial relationship between the workpiece or tool and the manufacturing device) determines the design of the robot, which influences the working area, the load-bearing capacity, speed and repeatability [22].

Industrial robots usually have six degrees of freedom, which allow them to grasp objects independently of their positioning. The term kinematics describes the movement axes resulting from the degrees of freedom. Two types of kinematics are distinguished: serial kinematics, where the robot arm gets its mobility from joints but is connected to the base at one point (drives in the joints are also moved), and parallel kinematics, where several arms are connected to a fixed drive and can be moved simultaneously. Depending on the task, fewer degrees of freedom can be achieved using rotational, linear and translational joints, leading to the goal. The joints determine the operating range, shown in Figure 7 [22,23]. According to the kinematics, the following classification of industrial robots in Figure 8 is suggested.

According to the IFR - International Federation of Robotics statistics, an average of 106 new robots were installed per 10,000 employees in Europe in 2017. The record year 2017 saw a 30 % increase worldwide compared to the previous year [25]. One reason for the increased use of robotics is undoubtedly the rapid development in artificial intelligence, i.e. the ability of robots to perform so-called 'deep learning'. Deep learning uses a particular type of information processing that functions via artificial neural networks. Using artificial neural networks and large amounts of data, machines can imitate the human brain in its decision-making processes and thus independently improve their abilities without human assistance. The more data is available and combined with the progress already made, the more complex the problems and the machine's approaches to solving them. The use of robotics has limitations in that material can be heterogeneous, dirty and have different properties such as structure, size and shape. Limitations of the technique include non-optimised material flow, position changes between detection and gripping of the robot, poor pre-sorting, sensor failures, and limitations of the robotic arm such as size, reaction speed and the number of parts selected per hour [19].

Challenges for the use of robotic systems are also currently still unclear legal obligations in the event of damage. In some cases, existing laws, such as waste management laws, further hinder the progress of digitalisation. Lack of acceptance, for example, due to quality problems, is not to be expected because of the rapidly developing technology [26]. The fear of job losses can be calmed

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by the fact that robotics is accompanied by a reduction of stresses and dangers in manufacturing and that new professions are constantly being created in automation and data processing. At present, it is mainly menial labour, or tasks that are monotonous, heavy or hazardous to health that have been lost [22].

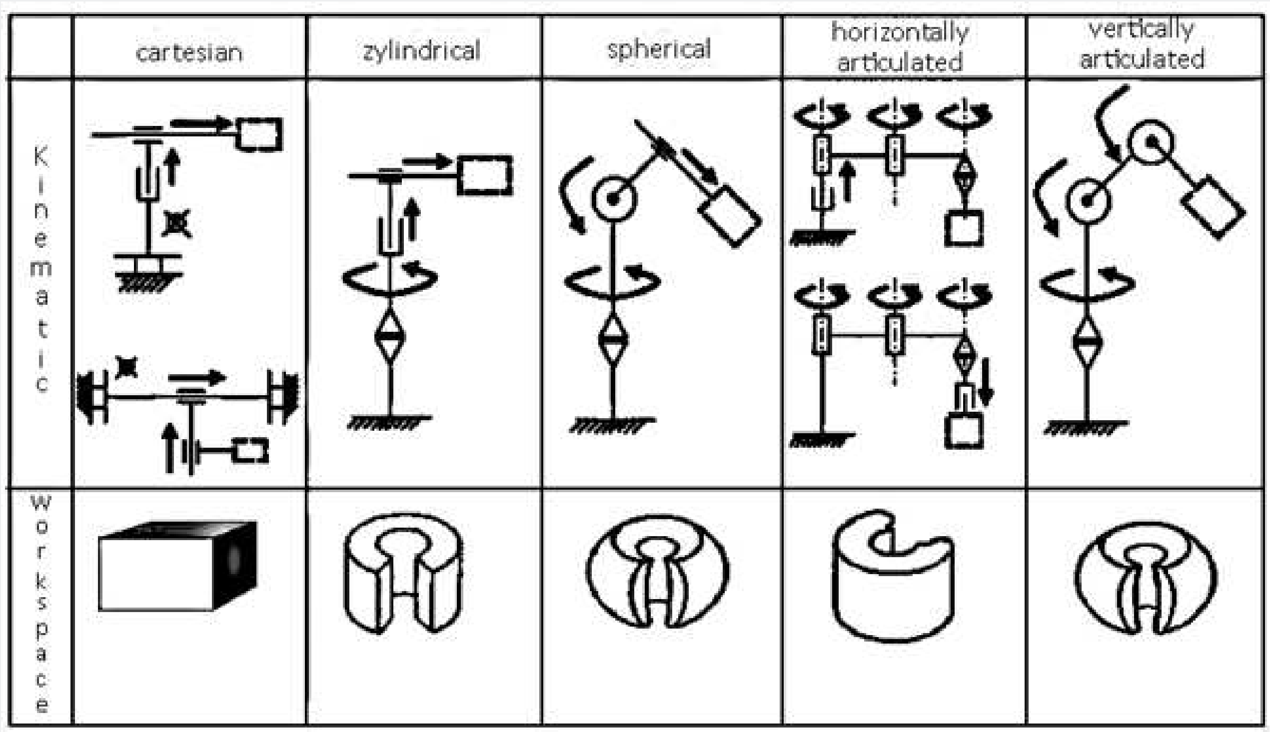

Figure 7: Positioning axes of robot systems in the industry including working range [23].

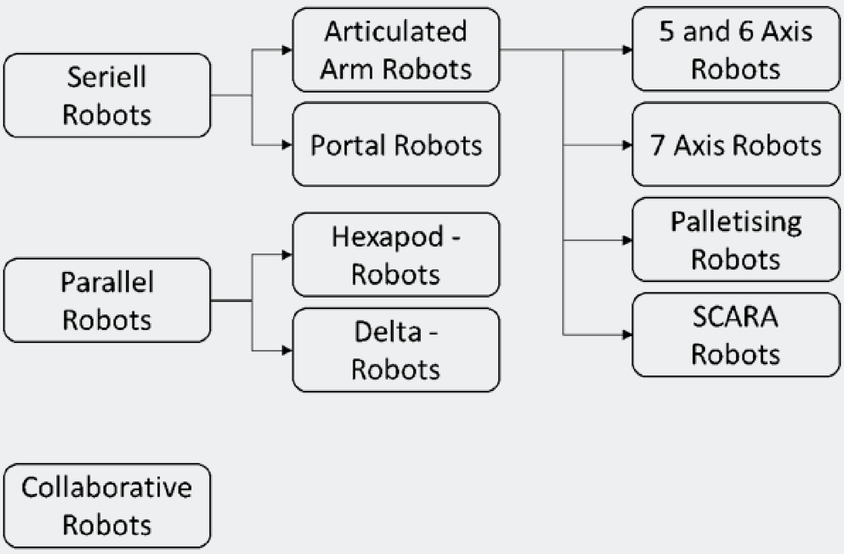

Figure 8: Classification of robots according to kinematics (authors depiction according to Induux 2021 [24]).

Materials and methods

In order to achieve the objectives of this study, several methods described below were used to provide the most comprehensive possible picture of waste management and its future developments. The scope of this study ranges from the description of the legal and technological framework conditions

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to a comprehensive analysis of future technologies and trend developments.

Evaluation of the stakeholders and current development projects in waste management

After extensive research on the most crucial technology, sensor-based and robot sorting suppliers are found and divided into the categories sensor suppliers, sorting machine manufacturers, and sorting robot manufacturers. In addition to the descriptions of the interest groups, some current projects in the field of sensor-based sorting and robotics are presented.

Deriving the effects of trend developments

Literature research on future developments in waste management serves as the basis for deriving the trends. After the subsequent evaluation, trend developments are deduced.

Results and Discussion

At first, the technology supplier's market study results are reflected, and it is described which technology suppliers make a significant contribution to today's developments in sensor-based sorting and robotics and the essential products in their portfolio.

Sensor suppliers

In the following, two companies are presented that have contributed to the numerous advances in sorting technology in the field of waste management and recycling (list in alphabetical order):

EVK DI Kerschhaggl GmbH

In addition to applications in the pharmaceutical industry, food processing and mining, this company based in Raaba near Graz also offers sensors for the recycling industry. Sensors are offered for polyethene terephthalate (PET) separation, RDF sorting, bulk material separation in heterogeneous waste and material flows, plastic flake sorting with hyperspectral imaging systems and conductivity imaging technologies. The EVK product portfolio includes colour, hyperspectral and inductive sensor systems. Hyperspectral imaging systems are intelligent camera systems of the 'Helios' product range that use spectral ranges adapted to the application (VIS, VIS/NIR, NIR and short-wave infrared "Short Wavelength Infrared" (SWIR)). These systems classify objects according to their chemical composition. EVK offers the possibility of combining this technology with inductive sensors or colour camera systems for sorting, inspection or monitoring purposes [27].

SLOC GmbH

The company has gained a foothold in waste management through cooperation with Saubermacher Dienstleistungs AG in level sensors. In addition to the initial level sensors, information on the location, movement patterns, lid positions, container/bin openings and fire warnings are also possible in the context of a smart waste bin and rubble bin. The sensors are equipped with computer, power and storage systems independent of the manufacturer. The product portfolio also offers solutions for intralogistics in which forklifts are digitised and smart load carriers are made possible. Lifting height, usage profile, amount counts and load status are information that can be called up [28].

Sorting machine manufacturers

In the following chapter, companies acting worldwide in the manufacture of sensor-based sorting machines are presented and their sensor technologies for waste management sorting tasks are described. Meanwhile, it is reserved for a few established companies to dominate the world market for sensor technologies in the circular economy. Some offer 'complete packages' as system planners, whereas the individual components do not necessarily come from the same company. The list below does not claim to be exhaustive as there are other manufacturers on the market. The excluded manufacturers were not mentioned since they only offer a few units (e.g. LIBS) for waste management. Table 3 shows the sensor technologies of the various companies in 2018 [13].

Table 3: Selected manufacturers of sensor-based sorting machines [13].

Manufacturer	Binder+Co	Pellenc	REDWAVE	Sesotec	Steinert	TOMRA
Electromagnetic Induction	x	x	x	x	x	x
Laser-Induced-Breakdown-Spectroscopy (LIBS)					x	
Near-Infrared Spectroscopy (NIR)	x	x	x	x	x	x
Visual Spectroscopy (VIS)			x		x	
X-ray Fluorescence Spectroscopy (XRF)		x			x	x
X-ray Transmission	x	x	x	x	x	x

Binder+Co

The machine manufacturer located in Gleisdorf, Austria, offers various processing units and sensor-based sorting machines. These include the CLARITY product line, which sorts recyclable from non-recyclable waste, and the MINEXX line, which is primarily used to process raw materials [29]. Sensor fusion allows sorting by material type and colour simultaneously through a link with

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specially developed software. In this way, more individual tasks can be solved than simply by combining different sensors [17].

Pellenc

Pellenc Selective Technologies (ST) is part of the Pellenc group. The optical sorters for household and commercial waste are manufactured at the company's headquarters in Pertuis, France, and sold under the product name MISTRAL+. These systems use NIR, VIS and induction sensors [30].

REDWAVE

Another company that offers sensor-based sorting machines is REDWAVE, a division of BT Wolfgang Binder, located in Gleisdorf, Austria. In addition to sorting plastics, glass and paper, the sorting of minerals is also offered. As a company, REDWAVE is active as a machine supplier and provides system planning [31].

Sesotec

The development and production of the sorting systems of the company founded in 1976 still takes place in Schönberg, Germany, although it now operates globally with seven subsidiaries. Modular sorting systems for plastics, electronic waste, glass, household waste and metal are offered, which combine different sensors, detectors and separators in one device depending on the application. Up to three combined sensors can be used in the recycling systems: a high-resolution line scan camera, near-infrared sensors and inductive metal detectors. The units are offered with a conveyor belt or a chute [32].

Steinert

The subsidiary Steinert Unisort bundles the resources for the sorting technologies for the waste management of the Steinert Group. The Steinert Group has been based in Köln, Germany, since it was founded in 1889, although there are subsidiaries in the USA, Australia and Latin America [33]. The product range for recycling with NIR is called 'Unisort'. There is the option of a combination system of up to four sensors in one unit, called the Steinert KSS. The Steinert KSS contains 3D, colour and induction recognition. The fourth installed sensor is either a near-infrared, an X-ray transmission or an X-ray fluorescence sensor. Typical application areas would be separating heavy metal concentrates into copper, brass and grey metals [34].

TOMRA Systems

The company, based in Mülheim-Kärlich, Germany, offers sensor-based sorting solutions for various industries. Formerly TOMRA Sorting was called TiTech, till it was integrated in the Norwegian company TOMRA Systems in 2004. The AUTOSORT product range, which covers almost all waste streams, uses NIR, VIS or induction sensors or a combination of these. Furthermore, besides waste sorting machines and waste collection automats, TOMRA Sorting offers sorting systems for different applications in food or mining [35]."

Sorting robot manufacturers

The future of robotics in waste management has not yet been defined and offers room for innovative ideas. The following is a brief overview of the leading robotics manufacturers in the waste management sector and their current products.

Apple Inc.

Apple revealed their first dismantling robot in 2016. Apple claimed that this robot, called 'Liam', could dismantle 1.2 million iPhones 6 per year in eleven seconds each. The further development of 'Daisy', which replaced 'Liam' in 2018, can dismantle 200 iPhones per hour and differentiate between nine models [36,37]. Although there was a lot of media attention, it must be mentioned that Apple knows the location of recyclables in their devices and how they can be dismantled. This knowledge is usually absent in the everyday waste management business, which struggles with heterogeneity and variable degrees of pollution. The first waste sorting robot entered the market in 2011 from ZenRobotics and uses optical systems [37]. Since then, there have been attempts to use haptic because the sense of touch gives the operator much additional information. Therefore, a robot called 'RoCycle' was equipped with capacitive sensors by the Artificial Intelligence (AI) Lab at the Massachusetts Institute of Technology (MIT). It measures size and stiffness by touch. It is not yet a real competition to optical systems because of its low throughput, but combining the sensor systems would be conceivable [38].

OP Teknik

The waste sorting system from OP Teknik specialises in the fully automatic separation of construction and industrial waste into metals, plastic, wood, construction waste, stones and paper. With six robots used, as recommended by the manufacturer, up to 14,400 picks per hour are possible, selected by sensors and cameras in real-time according to material type, colour, size and shape. A single-arm can handle 2,400 picks per hour. For comparison, various manufacturers stated that a person could manage 20 to 40 picks per minute, correspondingly 1,200 to 2,400 picks per hour [39,19].

ZenRobotics

Founded in 2007 and based in Helsinki, Finland, the company was the first to focus on robotics sorting by launching its Heavy Picker in 2009. The robot system with up to three arms contains various detection units such as NIR, VIS and 3D sensors, metal detectors and an RGB camera. The Heavy Picker is designed for heavy and unwieldy objects weighing up to 30 kg. Therefore, it can simultaneously separate up to four different fractions with one arm without extensive pre-sorting or shredding. The various material flows for which it can be used are: commercial and industrial waste, construction and demolition waste, wood, inert materials, plastics, metals (scrap) and different coloured "plastic bags" collected from household waste. The Heavy Picker manages up to 2,000 picks per hour on a conveyor belt controlled by the

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robot. The AI software that ZenRobotics combines with their products is called Zenbrain [19,40].

The ZenRobotics Fast Picker has a maximum speed of 4,000 picks per hour and consists of an arm with a gripper that works via suction and a sensor unit for the software. This robot is designed for light materials such as packaging waste, dry mixed recyclable materials and household waste with a maximum weight of 1 kg [19,40].

AMP Robotics

The AMP Robotics company from Colorado achieves up to 3,600 picks per hour with its sorting system Cortex. The Cortex system introduced in 2017 uses VIS sensors and machine learning to sort mainly packaging waste. Sorting plants that use this system are mainly found in the USA. Figure 9 shows the basic functional principle: The vision system records data processed using AI-based learning and then sorted by the robot arm [19,41].

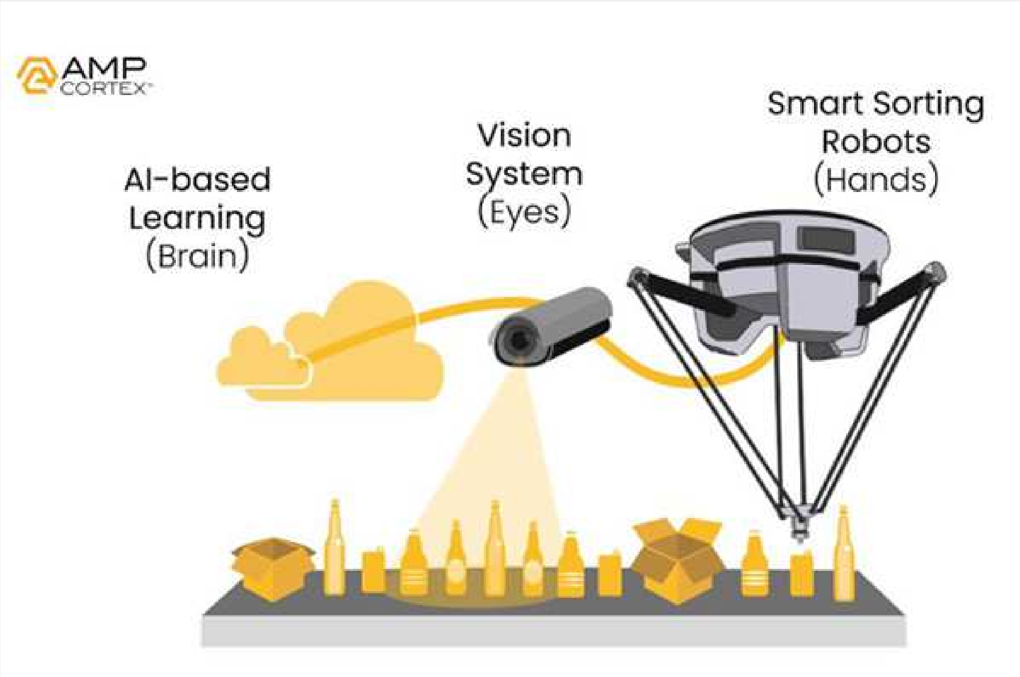

Figure 9: AMP Cortex [41].

Sadako in cooperation with BHS

Since it was founded in 2012, the Spanish company Sadako has focused on artificial intelligence and robotics. Together with BHS - Bulk Handling Systems, their waste sorting system, Max-AI, was used for the first time in California in 2017. Max-AI uses deep learning and an optical system to act as quality control. Using suction mechanisms, up to six different fractions can be recognised simultaneously and sorted with the gripper arm. According to the manufacturer, the system can reach up to 3,900 picks per hour [19,42].

Bollegraaf Recycling Solutions

The company from the Netherlands has been providing waste sorting systems for 55 years and has installed over 3,500 recycling systems in Europe, North America, Mexico and Canada. In 2013, the artificial intelligence-provided waste sorting robot RoBB-AQC was presented, separating recyclable materials in the final sorting step. The system is equipped with NIR sensors, an RGB camera and laser units for height detection and separates the detected materials automatically with a suction head. Up to four materials can be sorted out simultaneously per unit at a very high rate of 12,000 picks per hour if an installation with four vacuum grippers is available. However, the materials are mainly paper/cardboard and various plastics made from mixed waste [19,43]. The Bollegraaf Cogni was presented in 2018 which uses the same technologies as RoBB-AQC and is also mounted on a portable overbelt construction. The suction head is on a delta robotic arm [19,43].

Machinex

The sorting robot from the Canadian company Machinex called SamurAI has been available since 2018 and operates with artificial intelligence from AMP. With one of its four suction heads on four robot arms, it can lift up to 6 kg and manage up to 4,000 picks per hour. SamurAI sorts plastics positively and negatively for quality control or separates from mixed waste. The system is used in nine plants in the USA and Canada and is mainly used to sort plastics. The manufacturer offers software called 'MACH Vision'. It can create databases for material identification in advance, receive software updates and also use the 'MACH Cloud', which can obtain optimisations from other systems [19,44].

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Relevant Trends and Developments

This chapter describes the influence of digitalisation and Industry 4.0 on the waste and recycling industry and elaborates on robotics and the sensors used in this industry.

Digital Waste Management

There are various definitions of the term digital transformation. In sum, it can be said that the networking of individual stakeholders (companies, customers, products, etc.) succeeds through using the latest technologies (computers, internet, etc.) and the processing, collection and analysis of information. The so-called 4th Industrial Revolution - better known as Industry 4.0 - thus involves using IT and automation to pass on real-time information to all actors in the value chain and network them [45].

These developments do not stop at the waste management industry. They offer great opportunities, as 63 % of the companies surveyed in a study by the Montanuniversitaet Leoben in cooperation with HTL Leoben confirm. Of the 400 companies surveyed in the green tech sector in German-speaking countries, 75 % said they were involved in digital transformation and 84 % of the companies that were not yet involved said they planned to do so in the future. Moreover, the global circular economy and waste management market volume is expected to rise from around 100 billion euros in 2013 to 170 billion euros by 2025, further encouraging becoming involved in the digital transformation [26,46]. This conclusion is supported by another recently published survey in which 83 % of all surveyed companies announce that they have implemented a company strategy for managing data and 75 % make efforts to ensure high qualities in their transaction data [47].

At the same time, companies in the green tech sector must face new challenges summarised by Roland Berger in 2016 for the German market in five areas. One challenge is securing customer access, as traditional trade is losing importance and sales platforms are becoming increasingly important for customer contact. In order not to lose touch, it is recommended for companies to initiate their platforms and to integrate value-added partners for system solutions [48].

An example is the 'Daheim' app of Saubermacher Dienstleistungs AG, which is available individually designed for 230 municipalities. It implements information and reminder functions for collection calender, which is a Austrian calender that states on which days specific waste streams like light-weight packaging, paper or biological waste are collected by the waste collection system. Furthermore, it is a free communication platform for associations, schools and it offers e-car rental or swap [49].

In order to keep up, the need to increase flexibility and agility to follow the fast innovation cycles is mentioned. One characteristic of agility is to involve customers in the early phases of new developments and to obtain feedback. A further challenge is the development of digital competence. Digital transformation is a cross-sectional undertaking in many areas and does not stop at established processes and structures. In order to exploit the full potential of existing skills, interdisciplinary teams and cloud solutions for rapid information exchange are advantageous. Another recommendation is to adapt financing along the entire value chain. The digital economy relies on intangible assets such as employee know-how, digital strategies and data, whose monetary value is hard to estimate. It is essential to design individual solutions and evaluate the feasibility of renting, leasing, and pay-per-use options. The final challenge of digital transformation is developing the digital mission statement. That means not looking at the challenges individually but developing a comprehensive digitalisation strategy. The digitalisation strategy should be constant evaluation and adaptation to remain proactive [48]. Disruptive innovations in the waste and circular economy are currently taking place and will take place in the future in four identified areas. Collection and logistics face a revolution through 'smart waste bins' and intelligent route optimisation. Generally speaking, the customer is coming into focus, with more and more personalisation in terms of collection cycles, for example, which should increase recycling rates [50].

Sensor technology in waste management

With the increased demand for recycled material and increased demands on the quality and purity of this, the pressure on waste management to innovate towards real-time quality control is growing. The goal in the future will undoubtedly be digitised waste treatment, with individual treatment plants communicating with each other and various sensors providing real-time data. For example, to run conveyor belts at the right speed and in turn, adjust pre-treatment equipment such as shredders. Robotics will play a significant role in sorting in combination with real-time statistical modelling, improved object recognition and perpetual optimisation for tasks too dangerous or strenuous for human workers [26].

Quality plays a significant role in recycling plastics for energy use as RDF. Up to now, controls have mainly been carried out manually or by automated sampling. This approach became increasingly impractical due to the delay in the results, as the product had already been manufactured. Various sensors (e.g. NIR sensors) can remedy this situation and determine parameters in the waste stream such as degree of contamination, moisture content, etc. If these parameters are compared with the material group-specific properties in a database or additional parameters such as calorific value, chlorine or ash content are collected, the production line can be adapted in real-time. This fast influence offers the possibility of intervening in the process and optimising the plant to market-specific requirements [19]. In addition to ensure the quality of the RDF, increasing focus is being placed on the recovery of metals to identify and quantify valuable alloying elements [13].

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Sorting robots in waste management

In Germany, only 30 % of waste management companies state that they are ready for digital transformation, following the global trend towards green technologies and digitisation [48]. Digitisation and automated processes should help make processes run faster and more precisely by exchanging human work for machine work. In addition, robotics is widely used to reduce human effort. For waste management, only robots for industrial use are considered. Robots differ significantly in their properties, such as speed, gripping system, and the size of their working area or range of the gripper [19]. In the field of waste sorting, collaborative robots (so-called "cobots") would be conceivable. However, compared to other branches of industry, such as the automotive industry, their use has not yet arrived in waste management. Mechanically separating structures such as fences, light barriers, or laser networks can separate work areas. The latest concepts are based on cooperation and collaboration between man and machine without such restrictions, so robots can directly support employees [20].

With the introduction of Industry 4.0 and the rapidly developing digitisation, more and more applications of robotics technology are emerging. The learning ability of robotic systems means that sorting can be carried out more efficiently. One application of this learning ability is the use of the case-dependent speed of the conveyor belt. Regulating the speed of conveyor belts is a big issue in waste management as the heterogeneity of waste in type, size, and shape has presented a challenge for automated systems. In addition, waste streams have the problem of surface pollution, which impedes detection by sensors. The task for sorting robots includes the need to grasp objects of various shapes and sizes that occur in randomly distributed locations and quantities in the waste stream. Error-free work is also made more difficult by the change in position of objects due to vibrations of the conveyor belt, centrifugal forces or drafts. The computed inverse kinematic of the robotic arm has become wrong since the presumed position of the object has been altered. The failure to grab the object results in misthrows or loss of valuables, which poses the need for continuous monitoring and tracking of objects to be ejected [19].

If the software is connected to the appropriate hardware and artificial intelligence is stored, a robotic system can perform several operations simultaneously and thus perform different sorting tasks. Of course, new waste streams to be sorted out can also be teached in, which makes this technology fundamentally promising, because of the possibility of separating a wide variety of fractions. Figure 10 shows the detection of different materials by the AMP sorting robot Cortex. Robots are used to replace manual sorting or to sort for areas that were previously not sortable [19]. Furthermore, these technologies allow an automatic quality recording and increase sorting efficiencies (e.g. plastics), if necessary. Manual sorting is limited by weight, size and the extension of work environment that robotics is not [19].

Figure 10: Classification of the material flow of a sorting robot [41,51].

The developers do not see robotics as the only future solution for waste treatment and sorting, but especially in packaging and residual waste combined with other technologies such as optical sensors with pneumatic separation. Automated systems are often seen as a quality guarantee at the discharge of a plant. Another topic of utmost importance during the discourse about digitalisation is the protection against cybercrime. The stored software for detecting objects and the associated algorithms are essential and must be adequately protected against manipulation and exploitation. Adequately protecting intellectual property and shielding networks against attacks demands financial resources and know-how [19].

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Smart Waste

The circular economy targets stated by the EU and 90 % of the German population agree that waste separation significantly impacts environmental protection. From the consumer's point of view, the producers or manufacturers of goods substantially influence establishing a well-functioning recycling system. Assuming that these findings can be transferred to Austria, this could explain why the proportions of recyclable materials in the residual waste bin in Styria have hardly changed in the last 20 years. In order to meet the recycling quotas of the EU, citizens must be involved additionally to the expansion of the sorting technology in plants [52,53]. The smart garbage bin, for example, with level measuring sensors from SLOC leads to less traffic, traffic jams, noise and CO_2 emissions through dynamic route planning. Austria Glas Recycling expects a potential saving of up to 30 % of the costs and the effort of the collection through the high-tech sensors in public glass containers after the pilot project with Saubermacher in December 2018 in the municipality of Horn in Lower Austria [54]. This example is intended to show that the detection options using sensors, in addition to level measurement, can determine location, movement pattern, several lid openings and a temperature increase of a barrel and thus enable a need-based collection tour planning in addition to increasing comfort for the citizens [12,53].

Recyclable materials scanner

In 2018, the Saubermacher Dienstleistungs AG presented the 'recyclable material scanner', a multisensor, multi-spectral image recording system that detects the empty contents of a residual waste bin on the collection vehicle. The generated visual output is displayed in Figure 11. The system evaluates the collected waste in real colours, 3D, and various spectral channels to classify the material. A waste bag opener is used to further increase the visibility of the waste for the convolutional neural network. Test runs have shown that the announcement of the use of this procedure led to a significant reduction in missed throws. Before this announcement, incorrect throws were detected in 65 % of the garbage cans; after the project was publicised, the rate immediately fell to 38 % and could be further reduced through direct feedback. The supplementary resource scanner portal can display and evaluate the detection results and can thus be used as a feedback portal for citizens. The citizens communicate with the disposal company and vice versa via SMS or Saubermacher's app 'Daheim'. The proportion of incorrect throws in the municipalities' residual waste could be reduced by up to 80 %; on average, incorrect throws were halved. The technologies developed in Austria are to be used in another larger region in 2020 [55,56,57].

Figure 11: Classification of waste using the recyclable material scanner [58].

Smart Villages

The recyclable material scanner and the intelligent waste bin are part of the "Smart Village" project. Energie Steiermark and Saubermacher Dienstleistungs AG included around 150 households in the communities of Riegersburg and Feldkirchen. In addition to the measurements necessary for generating key figures to quantify correct waste separation, street lights were equipped with sensors and vehicles of the road service in winter with GPS route recording and ice sensors. The project was presented in mid-2018, and the first positive results were presented in July 2019, which suggest an expansion of smart technologies in the municipal waste sector [56,57].

Conclusion

The presented data depicts the waste management industry's rapid developments. While new technologies, like machine learning and convolutional neural networks and robot sorting, are increasingly implemented, a substantial discrepancy exists between technological capabilities and the current State-of-the-Art. Stakeholders in the industry expressed their willingness to adapt their current approaches and implement emerging technologies into their current approaches; these developments take time. Further investments must be made to acquire the knowledge, technology, and human resources needed for such a transmission. These investments need a dependable political and

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economic foundation to be made, and further political guidelines will be needed to ensure the sustainability of these investments. The increasing attention lawmakers and political institutes currently give to the waste management industry are a welcome enticement to facilitate the implementation of improved sorting technologies in the sector.

When combined with these new emerging technologies, the existing technologies mentioned in this study applied to sensor-based sorting can substantially impact the feasibility of reaching the goal of a circular economy. The active participation in the studies mentioned in this survey reflects the consumers' and manufacturers' interest in enhancing current waste management techniques and implementing and adapting to technologies like robotic sorting and applying neural networks for the classification in waste collection. These changes were shown to increase the efficiency of the collection of post-consumer waste by announcement alone. However, while these results motivate further research and these technologies see widespread employment in the automotive and pharmaceutical industry, the operating conditions in this field differ significantly from those in waste management. More comprehensive employment of technologies like robot sorting, live in-line sensor-based measurements of manufacturing and machine learning approaches need to be evaluated in their adaptability to the inherent problems their application in waste management entails.

The employment of these new technologies will need coherent legal and political guidelines. This lack of coherent legal guidelines extends not only to the sector of waste management but to the industrial application of robotics, data science and machine learning in general. Without legal guidelines regulating the liability issues arising from human labourers sharing working space with machines and defining safety regulations adapted to this new development, further growth of this technology will be stunted. It is further to be expected that the emergence of these new technologies will significantly impact the existing labour market, as the need for menial labour is decreasing, and arduous and dangerous jobs may soon be undertaken by machinery. The labour market's needs will increasingly shift to skilled technicians, able to maintain, program and control the machines substituting the human workforce. Since digitisation and digitalisation are comparable new topics in the waste industry, there is great potential for improvements. The rising interest in this topic is also reflected by the increased market volume of products affiliated with green production and the circular economy, prompting all significant stakeholders in the manufacturing of sorting systems to become involved in applying these emerging technologies in their product portfolio to be on the leading edge of these developments.

Author Contributions

Conceptualization, Karl Friedrich and Daniel Vollprecht; methodology, Karl Friedrich; validation, Karl Friedrich, Theresa Fritz and Gerald Koinig; formal analysis, Karl Friedrich and Gerald Koinig; investigation, Karl Friedrich, Theresa Fritz and Gerald Koinig; data curation, Theresa Fritz and Karl Friedrich; writing - original draft preparation, Karl Friedrich, Theresa Fritz and Gerald Koinig; writing - review and editing, Karl Friedrich and Gerald Koinig; visualization, Karl Friedrich, Theresa Fritz and Gerald Koinig; supervision, Daniel Vollprecht and Roland Pomberger; project administration, Roland Pomberger. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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2.2 Publication II, Research Gaps

"Challenges to Increase Plastic Sorting Efficiency."

Mini Review Article
Friedrich, K., Koinig, G., Tschiggerl, K., Pomberger, R., Vollprecht, D. (2021). *Challenges to Increase Plastic Sorting Efficiency.* In Int J Eng Tech & Inf. 2021;2(4):114–118. DOI: 10.51626/ijeti.2021.02.00023.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 2-2.

Table 2-2: Annotation on the doctoral candidate's contribution to Publication II

Conceptualization	**Friedrich, K.**, Vollprecht, D.
Methodology	**Friedrich, K.**
Software	-
Validation	**Friedrich, K.**
Formal Analysis	**Friedrich, K.**, Koinig, G.
Investigation	**Friedrich, K.**, Koinig, G.
Resources	-
Data Curation	**Friedrich, K.**
Writing: Original Draft Preparation	**Friedrich, K.**, Koinig, G., Tschiggerl, K.
Writing: Review and Editing	**Friedrich, K.**, Koinig, G., Tschiggerl, K.
Visualisation	**Friedrich, K.**
Supervision	Vollprecht, D., Pomberger, R.
Project Administration	Pomberger, R.
Funding Acquisition	-

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Challenges to Increase Plastic Sorting Efficiency

Mini Review

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Author Details

Karl Friedrich[1]*, Gerald Koinig[1], Karin Tschiggerl[2], Roland Pomberger[1], Daniel Vollprecht[1]

[1]Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Austria

[2]Department Economic and Business Management, Montanuniversitaet Leoben, Austria

*Corresponding author

Karl Friedrich, Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Franz Josef-Strasse 18, 8700 Leoben, Austria

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Abstract: The recycling rate for plastics results as a factor, mainly based on multiplying the collection quote, the sorting quote and the recycling process quote of a plastic waste stream. This paper gives insights into sorting rates, challenges to enhance these values and perspective opportunities on how to improve the sorting rate for the future. As a result, the challenges are contrasted with the opportunities to develop future strategies and elevate research necessities to increase the sorting rate.

Keywords: Recycling rate; Sorting rate; Sensor-based sorting; Recycling; Waste treatment; Waste management

Introduction

Plastics are an indispensable part of everyday objects of use and application, both in households and in industry, where they are a central raw material for a wide variety of areas - from packaging material, in medical care, to electronic components, to construction and Transportation Industry - Represent [1]. Around 8.3 billion tons of plastic have been produced globally since 1950. Only nine percent have been recycled; twelve percent were incinerated, and the majority (79%) ended up in landfills or the environment [2]. In 2015, 322 million tons of plastic were produced worldwide [3], and this amount is expected to double by 2035 and quadruple by 2050 [4].

It is undisputed that the resulting plastic waste is an enormous burden for the public and the environment - keyword microplastics in the oceans. Consequently there is an endeavour by business, politics and society to force the recycling of raw materials and to increase the proportion of recovered valuable materials. In this context, recycling rates have the task of providing statistical information on the proportion of waste recycled and fulfilling legal requirements within the framework of national and European sustainability policy. In addition to ecological intentions, economic aspects of recycling must also be considered from a business point of view - the issues of resource efficiency and life cycle considerations in particular, are becoming increasingly important. Bunge [5] states that the usefulness of recycling has to be judged through an economic as well as an ecological perspective. As a recycling rate approaches the 100 percent mark, recycling becomes more and more inefficient in terms of costs/benefits. The ecological yield from recycling increases linearly with the degree of recycling, while the ecological recycling effort increases exponentially [5].

Against this background, questions and hitherto unsolved problems arise concerning the determination and collection of recycling rates, including the extent to which these contribute to sustainable development goals. For example, in plastics recycling, the aim is to show the consequences of rate regulations along the value chain and whether the implementation of such rate can contribute to the recovery of processed material flows. Further, the inherent potential of rate implementation needs to be evaluated.

Framework Conditions for the Definition of Recycling Rates

The Austrian Waste Management Act [6] defines recycling as "any recovery process through which waste materials are processed into products, things or substances, either for their original purpose or other purposes. It includes the processing of organic materials, but not energy recovery and processing into materials that are intended for use as fuel or for backfilling." Accordingly, recycling is recovery, not reuse. Waste is considered completely recycled if it is fed into a process recognized as recycling. No distinction is made between which parts are actually recovered for use as secondary raw materials [7].

Based on the definition mentioned, specific proportions of the reusable or recycling rates are determined but the method of calculating of these rates is open to interpretation, this can yield different outcomes - even within the same material fractions. Further, no specifics for determining the total amount of waste and partial amount of recycling are stated, this leads to different measuring points for each different group of waste, hampering the comparability of results. This lack of definition is further evident in the interchangeable use of the terms "recovery" and "recycling" in official and legal documents, showing the confusion present when discussing the subject.

Recycling Rate – Definition of the Term

In waste management, the recycling targets are based on rates. The essential requirement for calculating a rate is knowledge of the population of the recyclable material available on the market. Uniform definitions and calculation methods are not available at the national level (e.g. differences in federal states) or European Union level. From a global perspective, this raises considerable problems concerning collecting and determining recycling rates against the background of exports (e.g. through packaging materials) [8]. In this context, Bothe [9] states about the dual systems that "a calculation that compares only a mixture 'x' with an unknown composition and only partially known whereabouts to a mixture 'y' of another and also unknown composition as a reference variable is not even a rate."

There are two main distinctions to be made when defining recycling rates [7]:

a. **Production-related recycling rate (input-related):** Indicates the recycling rate in the material input of a production process;

b. **Waste-related recycling rate (output-related):** Refers to the proportion of materials or valuable materials recycled from the waste during disposal.

It must be considered that a high waste-related recycling does not necessarily lead to a high production-related recycling rate since the import and export of waste also enable the secondary material to be used in other economies [7].

The following distinction is also essential in this context: While the recovery rate includes the thermal recovery of valuable materials from waste (i.e. the incineration of the same, including their processing into fuel), the recycling rate excludes this type of recovery. Therefore, the recovery rate is greater than the reuse or recycling rate [10].

European and National Case Law on the Rate Regulation for Plastics Recycling

At the European Union level, plastic waste is dealt with through several legal provisions, but none specifically designed for plastic. Plastics are indirectly addressed by the following directives: Waste Framework Directive (2008/98/EC) [11], Directive on waste electrical and electronic equipment (2012/19/EU) [12], Directive on end-of-life vehicles (2000/53/EC) [13], and in the Packaging and packaging waste directive (94/62/EC) [14].

The target for the reuse and recycling of municipal waste is set in Article 11 of the Waste Framework Directive at 50% by 2020 (preparation for reuse and recycling). The rate for preparation for reuse, recycling and another material recovery will be increased to 70% by 2020. The only plastic-specific target in European waste legislation concerns the recycling rate of 22.5% for plastic packaging waste [15].

At the national level, plastic is specifically dealt with in the AWG 2002 or the AWG Amendment Packaging (2013) and the Austrian Packaging Regulation (2014) [16]. In the latter, the recycling rate for plastic packaging is also defined as 22.5% to comply with the EU requirement.

The new amendments to the European waste package came into force on July 4, 2018. The essential elements of the new EU waste law set new binding targets, including an increase in the target rates for the recycling of municipal waste and packaging waste and an adjustment of definitions [17]. Furthermore, new calculation methods for the recycling rate of municipal waste are used to measure the actually recycled waste and make the data comparable. However, these rates mainly relate to quantity and not to quality [8].

Table 1 gives an overview of current and planned recycling rates for plastic packaging material. According to this (EU and national), 22.5% of the mass of plastic packaging placed on the market must be brought into a recycling plant.

Table 1: Overview of current and planned recycling rates for plastic packaging material.

	EU			Austria
	Packaging Directive Article 6	Change Policy of Packaging Directive (2018) Article 1		Packaging Regulation § 5
Year	2009	2025	2030	2014
Recycling rate in %	22,5	50	55	22,5

The currently implemented recycling rate for plastic packaging are less than 30% at the EU level in 2018 [18]; 31% are landfilled, 39% are incinerated [19]. According to the Austrian Waste Management Plan (2017) 33.6% of plastic packaging was recycled in 2015, the recovery rate was 100% [20].

Sustainable Recycling of plastic Recyclates

Thermal recovery should only be considered if qualitative plastic processing is no longer possible, it is essential to focus on the recycling of plastics.

Looking at the value-added lifecycle of plastics recycling in Figure 1, it can be seen that this begins with the consumer as a waste producer (1) and is then treated (2), sorted (3) and recycled (4). In the following steps, the recyclate is fed into a production process (5) by the producer and used by the plastic consumer (6) before the cycle closes with waste generation (1). According to Wilts et al. [7], with the definition of the recycling rate for the waste-related recycling rate (output-related), those plastics available as valuable or materials after the recycling process will contribute to the rate fulfilment.

Due to the lack of a uniform legal definition of the recycling rate, a "non-closing" value chain can nevertheless contribute to positive fulfilment. If a recycler processes a material flow from a plastic collection in his plant, the completion of the processing would be sufficient to contribute to the recycling rate. At the end of the recycling process, plastic granules are obtained to be used for processing into new products. It is currently not legally stipulated in what quality the resulting recyclate should be.

The quality assessment of recyclates shows that the sole focus on recycling rates cannot be expedient to close the value chain. The usability of a manufactured recyclate has to be ensured to guarantee

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sustainable recycling. Recycling rates that are not specific to the material flow contrast the usability of the recovered recyclate, which means that the proportion of primary new plastics in products is a multiple of the proportion of recycled material [20].

This means that every generated recyclate that can be fed into a production process can positively contribute to the recycling rate. Whether the use of a given recyclate results in the production of high-quality or low-quality product is not regulated. Neither is the required proportion of new and recycled plastics fed into a production process regulated. When a small proportion of low-quality recyclate is mixed with a high proportion of new plastics the quality for the production of plastic products can usually be maintained, but without having to guarantee sustainable recycling. Another problem that arises from the poor quality and the volatility of the recyclates is that it is more difficult to find buyers for the secondary raw material produced. Forming a market for plastic recyclates or prices based on the quality of the recyclate also proves to be difficult without statutory quality specifications.

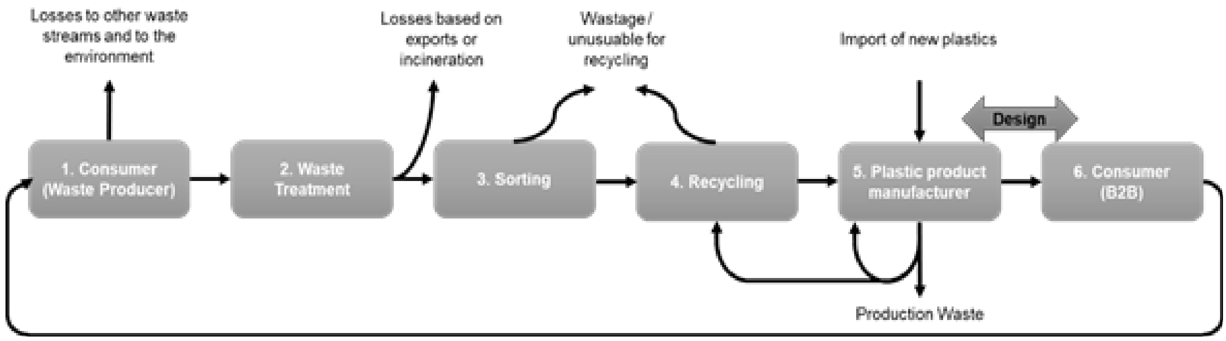

Figure 1: Value-added lifecycle of plastics recycling.

According to Treder [8], the following core requirements must be met in order to solve the rate problem: (1) The definitions of terms and valid data must be standardized, (2) a uniform calculation of rates must be defined. The current procedure for recycling is not appropriate, as it does not consider "high-quality recycling", which can counteract the spread of pollutants. Finally, (3) rates are used to achieve the target if the population (the amount of waste) is known, which is currently not always the case. In addition, it would make sense to adopt rates to dynamic market conditions - e.g. by specifying strategic raw materials - and considering the eco-efficiency of alternative scenarios over the entire life cycle.

Furthermore, an integrated view of economic and ecological aspects over the entire life cycle and the entire supply chain of plastics - from product design to treatment with intermediate sorting and processing systems - is necessary in order to achieve sustainable, resource-efficient waste management and use the possibilities of plastic recycling in an ecologically and economically sensible way.

The Influence of the Sorting Rate on the Recycling Rate

Following Figure 1 it can be seen that there are three types of losses, which negatively influence the output-related recycling rate technologically or socially:

- The **collection rate** is negatively influenced by the losses through incorrect disposal of waste into other waste collection streams like municipal waste or the losses through waste disposal into the environment, mainly known as littering.
- The **sorting rate** is decreased by the losses during the waste sorting process. This includes reject in the last sorting step, wastage, and materials that are unusable for recycling. The lost material during the plastic sorting process is incinerated.
- The **recycling process rate** is reduced by the losses during the recycling process itself based on the wastage and unusable materials for recycling.

Losses caused by exports and incineration are not part of this evaluation because these are regulated politically and are not as affected by technological innovations or social research as other losses mentioned above.

Expecting a collection rate R_{WC} of 70 % for lightweight packaging waste, there are still further losses of 40 % during sorting, which is known as a typical value for the sorting rate R_{WS} and further 40%, which is known as a typical value for the recycling process rate R_{WR} these results in a recycling rate of 25,2% (Formula 1). When the recycling rate of 55 % for lightweight packaging has to be reached by 2030, many steps have to be set.

Since this paper covers only the increase of the sorting rate R_{WS}, it will be expected that a feasible collection rate $R_{WC,}$ for Austria in 2025 is 85 %. The recycling process rate R_{WR} is expected to reach 75 % because of increased process efficiency. This would mean that by 2030, Austria has to increase its sorting rate to 90 % to reach the European goal of a 55 % recycling rate for lightweight packaging waste (Formula 1). Increasing the sorting efficiency to raise the sorting rate is obligatory to achieve this target value.**Status quo:** $R_{WC} * R_{WS} * R_{WR} = 0.7 * 0.6 * 0.6 = 25.2$ %

Requirement: $R_{WC} * R_{WS} * R_{WR} = 0.85 * 0.9 * 0.75 = 57.4$ %

Formula 1: Calculation of the recycling rate: Status quo and requirement

Challenges and Research Question to be Answered to Increase the Sorting Efficiency

Regardless of the significant, as yet unused secondary raw material potential, there are currently few incentives on the plastics market to increasingly redirect recyclable plastics (mainly polyolefin packaging) from thermal utilization to recycling. Soon, based on the European Union in preparation for the circular economy package [21], a new dynamic in plastics recycling is to be expected. In addition to a gradual increase in the recycling targets for plastic waste, which is currently at 22.5 % should reach 50 % in 2025 and will increase incrementally over the next decade to reach 65 % in 2035. (2020 22.5% | 2025 50% | 2030 55% | 2035 65%, [18]. In addition to the gradual increase of recycling targets, the calculation of the recycling rate will be changed to be based on output related considerations rather than input related considerations.

Increasing the flexibility of the processing technology, concerning the input quality and a growth in the recovery of valuable materials can improve the value-added lifecycle of plastics and the recycling rate.

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Additionally, the economic risk in the field of plastic sorting can be reduced.

Fluctuations in the waste stream composition resulting from changes in the collection can be better cushioned with a more flexible processing technology. Furthermore, increased added value can be realized with alternative plastic input streams beyond the packaging plastic.

Through direct processing in the plastics recycling companies after sorting, the value chain can be extended accordingly, or an integration of the value chain of plastic waste sorting and plastic recycling can be achieved.

Challenge: Necessity to Achieve Purities with Possibly Poorer Input Quality

The requirements of the secondary plastics market tend to be higher with the increasing volume of secondary plastics, as is to be expected based on environmental and resource policy requirements. This is due to additional products to be developed for the use of secondary plastics. At the same time, it can be assumed that the quality of the collected plastic waste (input flows for the sorting) becomes worse due to the quantitative goals to be achieved. This development has to be offset by improved sorting technology.

Research question: How can sensor-based sorting processes be improved regarding the identification of known material types?

Challenge: Lack of Structured Knowledge of Complex Products/Material Combinations

Due to a lack of knowledge concerning complex products / material combinations, there are currently no approaches to a differentiated licensing policy based on the recyclability of the system operators of plastic collection and recycling systems. Through a structured gain in knowledge, legislators and manufacturers can be influenced, on the one hand, under the aspect of EcoDesign and, on the other hand, the system operators of plastic collection and recycling systems can establish a differentiated licensing tariff scheme with the corresponding steering effects in the direction of increasing recyclability.

Research question: Which products or material combinations are problematic to be detected, and what are possible solutions to identify them correctly in sensor-based sorting?

Challenge: Increase in the Yield of Recyclable Materials and Purity with Feedback Loops between the Sorting Result to the Plant Operation

The flexibility concerning the sorting input while increasing the recovery of recyclable materials and ensuring the quality of the recyclates required by the secondary raw material market requires the combination of different sorting criteria and their linking within the scope of the sorting decision at a property level. An input-dependent system operation can also ensure that the potential of valuable materials is optimally exploited.

One challenge is the coordinated, clear identification of the signal values provided by various sensors. For clear material identification, signals that sensors can detect must be correlated with specific material properties, which require extensive material investigations on the relevant material systems and access to the sensor-based data. By implementing a feedback loop between the quality of the input and the plant operation, it is possible to adapt the plant operation to the potential of recyclable materials and optimize the recovery of recyclable materials. Such approaches have not yet been implemented.

Research question: How can the sorting efficiency be improved by implementing feedback loops between the sorting result and the plant operation?

The main task for the future is to answer all these research questions with innovative solutions to increase the sensor-based sorting efficiency and further increase the sorting rates to achieve the threshold values of the European recycling goals.

Author Contributions

Conceptualization, Karl Friedrich and Daniel Vollprecht; methodology, Karl Friedrich; validation, Karl Friedrich; formal analysis, Karl Friedrich and Gerald Koinig; investigation, Karl Friedrich and Gerald Koinig; data curation, Karl Friedrich; writing—original draft preparation, Karl Friedrich, Gerald Koinig and Karin Tschiggerl; writing—review and editing, Karl Friedrich, Gerald Koinig and Karin Tschiggerl; visualization, Karl Friedrich; supervision, Daniel Vollprecht and Roland Pomberger; project administration, Roland Pomberger. All authors have read and agreed to the published version of the manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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3 Environmental Analysis

The chapter "Environmental Analysis" is structured into two peer-reviewed publications. These two publications are presented below.

3.1 Publication III, Sorted plastic waste

"Benchmark Analysis for Plastic Recyclates in Austrian Waste Management"

Original Article

Friedrich, K., Möllnitz, S., Holzschuster, S., Pomberger, R., Vollprecht, D., Sarc, R. (2019). *Benchmark Analysis for Plastic Recyclates in Austrian Waste Management.* Detritus, 9, 105–112. DOI: 10.31025/2611-4135/2019.13869.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 3-1.

Table 3-1: Annotation on the doctoral candidate's contribution to Publication III

Conceptualization	**Friedrich, K.**, Möllnitz, S., Vollprecht, D., Sarc, R.
Methodology	**Friedrich, K.,** Möllnitz, S., Vollprecht, D., Sarc, R.
Software	-
Validation	**Friedrich, K.,** Holzschuster, S.
Formal Analysis	**Friedrich, K.,** Holzschuster, S.
Investigation	**Friedrich, K.**, Möllnitz, S.
Resources	-
Data Curation	**Friedrich, K.,** Holzschuster, S., Möllnitz, S.
Writing: Original Draft Preparation	**Friedrich, K.**, Holzschuster, S., Möllnitz, S.
Writing: Review and Editing	**Friedrich, K.**, Möllnitz, S.
Visualization	**Friedrich, K.,** Holzschuster, S.
Supervision	Vollprecht, D., Pomberger, R., Sarc, R.
Project Administration	Pomberger, R., Sarc, R., Möllnitz, S.
Funding Acquisition	Pomberger, R., Sarc, R.

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BENCHMARK ANALYSIS FOR PLASTIC RECYCLATES IN AUSTRIAN WASTE MANAGEMENT

Karl Friedrich *, Selina Möllnitz, Stephan Holzschuster, Roland Pomberger, Daniel Vollprecht and Renato Sarc

Montanuniversitaet Leoben, Department of Environmental and Energy Process Engineering, Chair of Waste Processing Technology and Waste Management, Franz-Josef-Straße 18, A-8700, Leoben, Austria

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ABSTRACT
Plastic recyclates are granulates which are produced by the processing of plastic wastes. The circular economy package of the EU, especially the amendment of the Waste Framework Directive, sets a new goal for the use of different types of these recyclates. Corresponding primary raw materials can assure reliable qualities with respect to stable physical and chemical properties. Besides, the production of recyclates is often even more expensive than the production of primary raw material granulates. Several quality assurance measures are carried out along the value chain from plastic waste to final plastic products. Recyclates are evidently priced based on the price of primary raw material granulate. Pricing also correlates with different quality parameters, however, such as degree of mixing, degree of degradation and presence of impurities. This paper examines the correlation between different quality features and how they affect the pricing policy for recyclates. Experts and Stakeholders along the value chain of plastic recycling in Austria and Germany have been interviewed about the most important quality assurance parameters and how they (would) affect prices of recyclates. Therefore, quality parameters for the sorted plastic waste as an input for plastic waste recycling companies and manufactured recyclates are included in this paper. Experts from the plastic waste recycling industry confirmed that there is a profound correlation between price and quality that is presented and discussed in the paper: The higher the quality of the recyclates, the lower the level of impurities and the purer the recyclates, the higher the price.

1. INTRODUCTION

The European plastic strategy presented by the European Commission, to be implemented in the Recycling Sector Package, poses an enormous challenge for the European waste management and the plastics processing industry. The circular economy package sets a recycling rate of 55 wt.% by 2030 for plastic packaging waste (European Union, 2018). The European Commission has not stipulated a compulsory percentage of recycled plastics in the manufacturing process of new consuming products, i.e. substitution rate on a primary raw material level. Moreover, the Commission appeals to the responsibility of manufacturers to achieve its objectives regarding circular economy.

Currently, recyclates are applied with a content lower than 10% in new plastic packaging products (Reitz, 2019). This suggests that recyclates are either too expensive or of too low quality. Although scientific studies (Klumpp & Su, 2018; Martel, 2018; Pauwels & D'Aveni, 2014; Voros, 2019; Zhe Gin & Kato, 2010) have already focused on the correlation of quality and price for other goods, this paper does not only examine such correlations but also includes quality parameters for the sorted plastic waste and recyclates to provide a practical guideline for quality assurance. In the course of the applied survey for this paper, experts gave a comprehensive overview of how quality is assessed in the field and which parameters are significant for high quality material. Furthermore, this data will support assessing the economic feasibility of certain stages of plastic packaging waste treatment (European Committee, 2019).

Wide range of composited materials and problematic additives can lead to sales difficulties for recyclates too, since recycled materials from "older" waste plastics may still contain substances that are no longer permitted in new plastics due to their negative effects on the environment and health (Wilts et. al., 2014). Plastic recycling is also limited by a lack of quality and constant supply of raw materials required by the industry (Vilaplana & Karlsson, 2008). Quality criteria for recyclates for the final plastic processing companies are not standardised but defined individu-

* Corresponding author:
Karl Friedrich
email: karl.friedrich@unileoben.ac.at

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ally by the recycling and processing companies. Criteria include exceptionally pure colour and low content of contaminations (Vilaplana & Karlsson, 2008). Besides the lack of quality, the poor image of recycled plastics in the public also impairs plastic recycling (Moser et. al., 2016). As a result, recyclates are not used in new plastic products to the desired extent or not at all.

Despite the number of obstacles, however, recyclates are increasingly applied by the industry to pursue a sustainable strategy (Polymer Comply Europe, 2017). The market for primary raw plastics is characterized by:

- A close correlation with the price of crude oil, resulting in comparatively high volatility of prices. As a result, when the price of primary raw plastic significantly decreases, recyclates will be increasingly substituted by primary raw material granulate, as well as
- Easy substitutability of products of different suppliers and also by oligopolistic market structures, inspiring strategic behaviour of suppliers (Rothgang et. al., 2017).

The main question raised by this paper is based on these two findings and seeks to establish a correlation between the price and the quality of plastic recyclates. In addition, the quality requirements for sorted plastic waste and produced recyclates are examined. The importance of quality assurance and its practical implementation are treated in a separate section. Furthermore, the market for primary raw plastics and recyclates is examined in detail and pricing developments are analyzed.

2. MATERIALS AND METHODS

2.1 Materials

The following plastic types are being investigated in the study as they represent 57% of the demand for the plastic packaging waste processing industry in Austria (Stoifl et. al., 2017):

- High-density polyethylene (HDPE) foils and hollow bodies (emptied);
- Low-density polyethylene (LDPE) foils and hollow bodies (emptied);
- Polypropylene (PP) foils and dimensionally stable PP (bucket, canister, emptied);
- Polyethylene terephthalate (PET) bottles (emptied);
- Polystyrene (PS) foils (thermoforming film).

This paper mainly discusses recyclates since regrind materials do not undergo extensive quality assurance and, frequently, only the impurity content is of importance.

2.2 Methods

All relevant stakeholders along the value chain from plastic wastes to the finished products are shown in Figure 1. This figure also shows all the terms used in this paper along the presented value chain.

A market analysis of secondary plastic granulates was conducted to identify the quality benchmark in plastic recyclates, performed by observing the development of pricing, identifying drivers to the increase or decrease of value and verifying whether the value depends on recyclate quality or on other economic features.

To analyse the correlation between price and quality, several packaging plastic waste processing companies and plastic waste recycling companies were provided with a specially designed assessment guide. In addition to personal discussion with plastic waste recyclers and the plastic waste processing industry in Austria, the plastics recyclers and the plastics processing industry in Germany was approached with short and targeted e-mail questions. Altogether, 19 different stakeholders responded. Six phone calls were made, reaching two plastic recyclers, three plastics processing companies and one association. In addition, about 80 e-mails were sent to plastic waste collectors, plastics recyclers and plastics processing companies, resulting in a return rate of approximately 20%. Four plastics recyclers, five plastic processing companies and four other stakeholders responded. Figure 2 shows the distribution of the consulted companies by industry. 32% of plastic re-

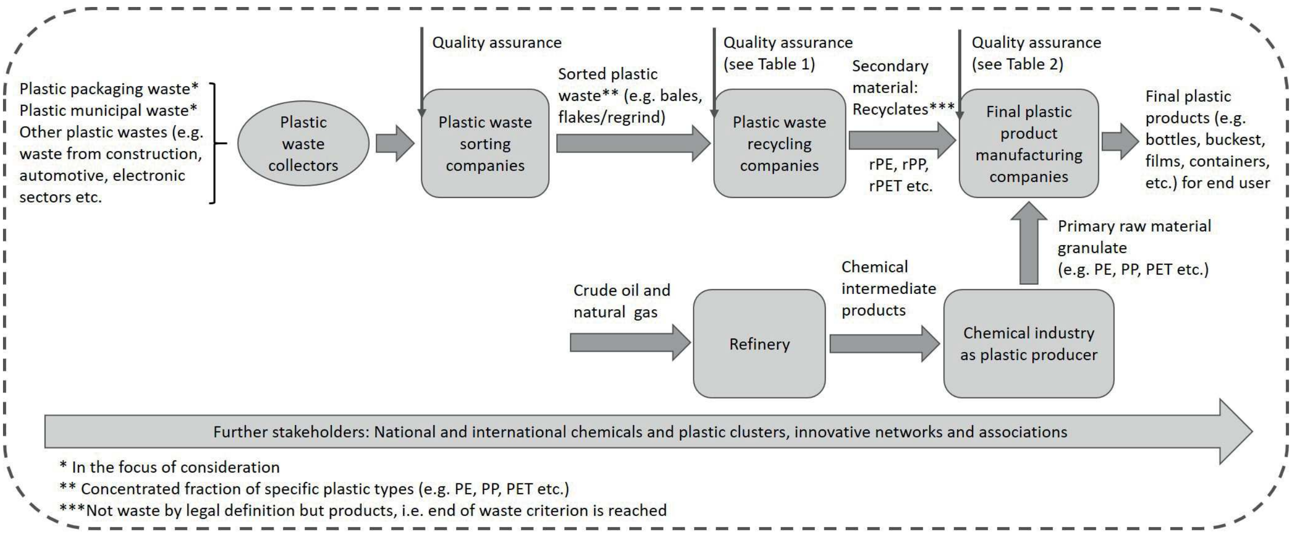

FIGURE 1: Stakeholders along the value chain from plastic waste to final plastic products.

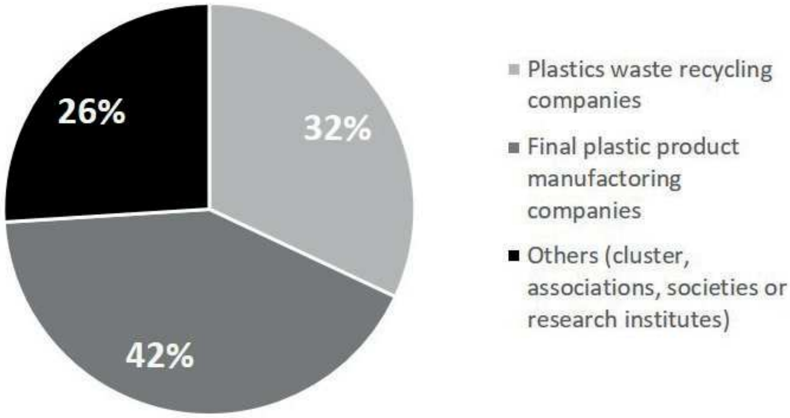

FIGURE 2: Distribution of the consulted companies by industry.

cyclers, 42% of plastic processing companies and 26% of other stakeholders along the plastic value chain participated the survey. The other stakeholders are cluster, associations, societies or research institutions operating in the field of plastics processing.

3. RESULTS AND DISCUSSION

The following section is divided into five subsections. First, the quality requirements for the sorted plastic waste and the plastic recyclates are shown. Second, the section "Quality Control" is describing, which parameters are significant for reliable quality control for the sorted plastic waste and manufactured recyclates. Additionally, price development for the polymer types mentioned above has been done. Furthermore, the most relevant questions of this study are answered in a separate section. Finally, to fulfil the titles of this paper, the quality benchmark in plastics recyclates are described.

3.1 Quality Requirements

Requirements for sorted plastic waste qualities:

In Germany, quality standards for sorted plastic waste applied in the plastic waste recycling companies have evolved within the plastic industry (Grüner Punkt, 2019), summarized in Table 1.

Quality requirements for produced recyclates:

Provided specification sheets or datasheets of produced recyclates include limit ranges (see Table 2) for the following properties:

- The density of non-cellular plastics (DIN EN ISO 1183-1)
- Melt volume-flow rate (MVR), melt-mass flow rate (MFR) and flow rate ratio (DIN EN ISO 1133-1)
- Tensile properties, in particular, modulus of elasticity (E-Modul) (DIN EN ISO 527-1)
- Notch impact strength (DIN EN ISO 179/1eA)

3.2 Quality assurance

3.2.1 Quality assurance of plastic waste

The key competence in the quality assurance process of the delivered mixed plastic waste material to the plastic waste sorting plant is found with the material acceptance staff. Based on their experience, the quality of supplied plastic waste bales can be assessed by visual inspection. Attention is paid to coarse impurities. The collective experience of the stuff is decisive. An essential part of the input control is the colour distribution of the bale because a majority of pure plastics is a requirement for the production of high-quality recyclates and their use in new products.

Furthermore, the origin of waste affects the assessment of the sorted plastic waste quality. Hence, the materi-

TABLE 1: Quality standards for sorted plastic wastes for recycling (Grüner Punkt, 2019).

Sorted plastic wastes	Metal items [wt.%]	Other plastic particles [wt.%]	Other residues [1] [wt.%]	Dimensionally stable PE articles [wt.%]	Foamed plastics incl. EPS* [wt.%]	Plastic Foils [wt.%]	PVC [wt.%]	Dimensionally stable PP [wt.%]
Plastic Foils (mostly LDPE)	< 0.5	< 4.0	< 4.0	-	-	-	-	-
Plastic hollow body (mostly HDPE)	< 0.5	< 3.0	< 3.0	-	-	-	-	-
PP	< 0.5	-	< 3.0	< 1.0	< 0.5	< 2	-	-
PET bottles	< 0.5	< 2.0	< 2.0	-	-	-	< 0.1	-
PE	< 0.5	-	< 3.0	-	< 0.5	< 5.0	-	< 3.0
PS	< 0.5	< 4.0	< 2.0	-	< 1.0	-	-	-

*Compostable waste (foods, garden rubbish). * EPS: expanded polystyrene*

TABLE 2: Physical, chemical and rheological properties of the investigated recyclates (Grüner Punkt, 2019).

Properties	LDPE	HDPE	PP	PET	PS
Density [g/cm³]	0.920 - 0.945	0.940 - 0.970	0.895 - 0.920	1.360 - 1.390	1.050 - 1.290
Melt-mass flow rate (MFR) [g/10 min]	0.5 – 0.9[(1)]	0.1 - 30.0[(1)]	0.1 - 30.0[(2)]	20.0 - 30.0[(3)]	2.3 - 8.2[(4)]
Tensile properties (modulus of elasticity) [MPa]	220 - 380	1 170 - 1 350	850 - 1 450	3 400 - 3 700	3 000 - 3 400
Notch impact strength [kJ/m²]	8.00 - 15.00	4.85 - 5.15	3.00 - 5.50	2.00 - 4.00	8.0 - 12.0

[(1)] 190°C | 2,16 kg [(2)] 230°C | 2,16 kg [(3)] 280°C | 5,00 kg [(4)] 200°C | 5,00 kg

al flow can be assessed using empirical values depending on the origin.

There are interesting arguments why deliveries of sorted plastic waste bales are rejected. Cartridges for sealing compounds repeatedly lead to rejection. The moisture of bales is another argument. Increased moisture can affect the surface of the particles and foaming processes during injection moulding may occur. Basically, however, non-conformity with quality requirements usually leads to a price reduction. If the content of contaminants is too high, the processing is impaired (material variations).

3.2.2 Quality control of recyclates

The quality of random samples of recyclates is controlled in a laboratory. The physical, rheological and mechanical properties of the recyclates are of great interest. The following characteristics are analysed in the course of a random sample inspection:

1. Physical properties
   a. density determination (DIN EN ISO 1183-1)
2. Rheological properties
   a. melt-mass flow rate (MFR) (DIN EN ISO 1133-1)
3. Mechanical properties
   a. tensile properties, especially modulus of elasticity (DIN EN ISO 527-1)
   b. notch impact strength DIN EN ISO 179/1eA

Frequently, further parameters of the recyclates are determined. These include:

- Melting temperature
- Colour distribution and colour composition
- Size and form of the granulated material (e.g. lenses, cylinder)
- Moisture content
- Filtration fineness
- Ash content
- Heavy metal content

In addition, there is often a continuous control of recyclates and an inspection for any specks, gas emissions, mechanical values and the colour of the recyclates.

The hardness of recyclates allows initial prediction of the foreign plastic content, the shape of the granulates and the bulk density indicating potential gas inclusions or vacuoles. The colour and odour of granulates may indicate previous thermal degradation of the material. The following devices or test methods are frequently used in quality assurance refers to the previously mentioned standard specifications: Melt index testers, differential scanning calorimetry (DSC), ash furnaces, residual moisture scales, density analysers, capillary rheometers, tensile testing and notched-bar impact test machine.

3.3 Price Development

The plastic trading market is currently shifting and, as mentioned before, increasingly developing into a buyer's market. A high dollar exchange rate (1,1008 $/€ on 24-Sept-2019) (Wallstreet-online, 2019) and weak crude oil prices (62.90 $/barrel on 24-Sept-2019) (Tecson, 2019) result in a preference for primary raw material over recyclates. Moreover, the European plastic market has changed due to the ban of exports to China that has previously been one of the largest importers of European plastic waste.56% of all plastic waste worldwide and 87% of all European plastic waste has been sent to China in recent years (Uken, 2018). The plastic waste streams, which are heavily contaminated and poorly sorted are most seriously affected. As a result, there is an oversupply of this plastic wastes in the European plastic recycling market. It follows that the plastics processing industry will favour high quality of plastics available.

Plastic wastes with low extraneous and pollutant contents and lower humidity are demanded. This oversupply of polluted plastic waste enables customers to select highest-quality plastic waste, ultimately affecting the pricing. Low-quality plastic waste losing market shares used to a great extent for thermal treatment or recovery (Sarc et. al., 2019).

3.3.1 Price development for sorted plastic waste

The price developments for HDPE and LDPE (A), PP (B), PET (C) and PS (D) regrinds and bales over the last years are shown in Figure 3. The average selling price for regrinds of commodity plastics (e.g. PE, PP, PET, PS) is about 538 €/t, varying by 92 €/t (Plasticker, 2019).

For the PE types, it is stated that the average regrind price is very similar for HDPE and LDPE with approximately 0.6 €/kg (Plasticker, 2019). The HDPE regrind price fluctuated significantly more than LDPE in the years 2014 to 2017. The LDPE regrind price is on average three times higher than the prices for the LDPE bales. This can also be observed for PP and PET. At 0.56 €/kg, the average regrind price for PP is 2.5 times higher than for PP bales, and at 0.37 €/kg, the average regrind price for PET is 1.9 times higher (Plasticker, 2019). The reason for this is the higher processing depth and the associated higher costs for the production of regrinds compared to bales. The different

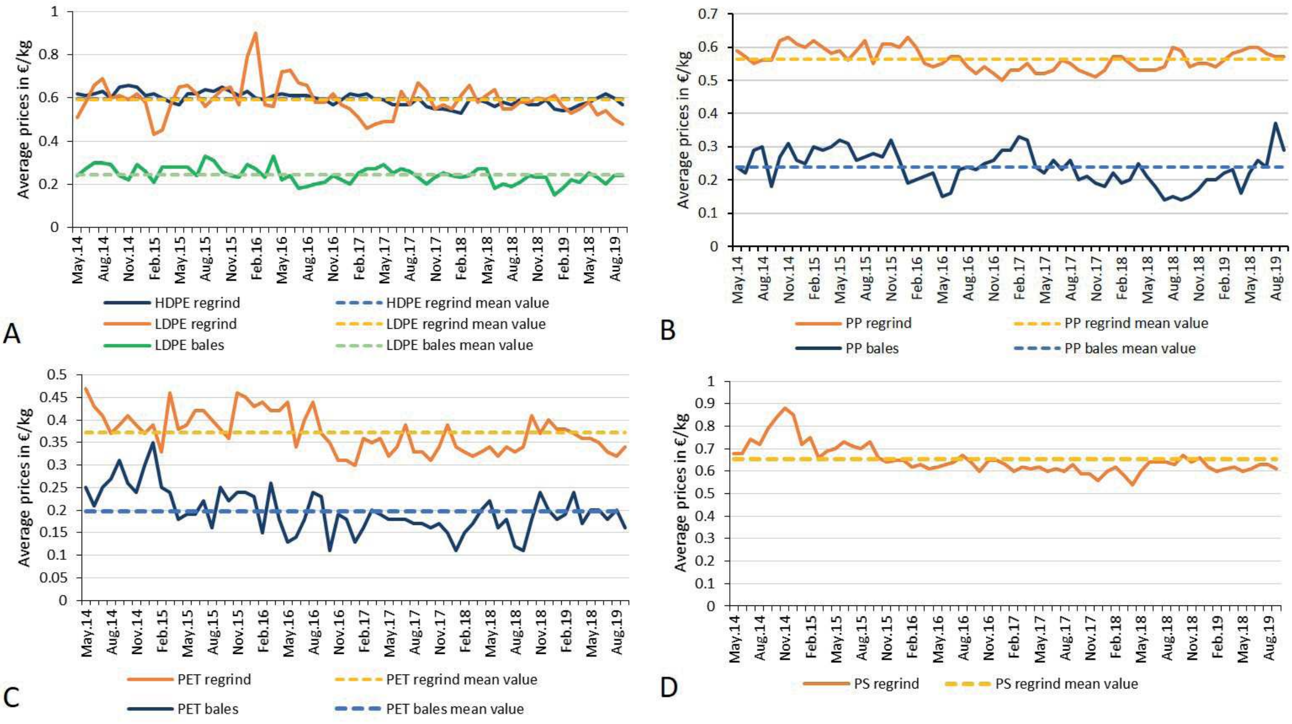

FIGURE 3: Price development for regrinds and bales of PE types (A), PP (B), PET (C) and PS (D) (Plasticker, 2019).

price differences between regrinds and bales of the plastic types can be explained by the different processing costs.

3.3.2 Price development for recyclates

The price developments for LDPE (A), HDPE (B), PP (C) and PS (D) granulates of primary raw materials and recyclates are shown in figure 4. No reliable price development could be collected for PET. The average selling price in July 2019 of primary raw material granulates of standard plastics (e.g. PE, PP, PS, PET) was around 1.17 €/t and 0.537 €/t (Plasticker, 2019) was the average selling price of recyclates of standard plastics. This means that granulates produced of primary raw material are on average twice as expensive as recyclates.

A comparison of the price developments of the primary raw materials with those of recyclates shows that there is a certain dependency between both price developments. If the price of a primary raw material rises or falls, the recyclate price of this plastic type also reacts with a price rise or fall. This fact can be seen for example well for LDPE in Figure 4 (A).

3.4 Market Study

The following section provides a summary of the most important statements:

Is there a correlation between price and quality of the sorted plastic waste?

First, the general market balance of supply and demand is pointed out. This provides the basis for any pricing. Where supply and demand meet, a corresponding market for goods develops.

The respondents 'affirm' the question, though. There is indeed a strong correlation between the quality and price of the sorted plastic waste. In addition, better application options are made accessible by purer sorted plastic waste, higher-priced. Surveyed plastic processing companies also reported the dependence of co-payments, i.e. a negative price for recyclates. If the sorted plastic waste can be purchased for a higher additional price, then the recyclates may be offered for less. When co-payments decline, however, the prices in sales have to rise. Additional payments depend primarily on the quality of the sorted plastic waste. If the material is dirty and includes high amounts of extraneous plastic, additional payments are higher. It the material is clean, on the other hand, and has a low level of extraneous plastics, additional payments will be lower.

It was also mentioned that the quality of the sorted plastic waste is primarily defined by its colour. The higher its purity, the higher the price that can be achieved on the plastic trade market. This is mainly due to its broader application range, say, in subsequent colouring, foil thickness and mechanical properties.

As mentioned above, the staff is crucial for sorted plastic waste price. They ultimately control the quality and their wealth of experience facilitates a reliable quality level and, accordingly, adequate pricing.

Is there a correlation between price and quality of the recyclates?

Regarding this question, there is again a general agreement on a higher quality of recyclates leading to higher prices. It is backed by the argument that higher quality of the recyclate reduces the risk of failures or bad batches from contamination for final plastic processing companies. Furthermore, it was mentioned that the quality of the

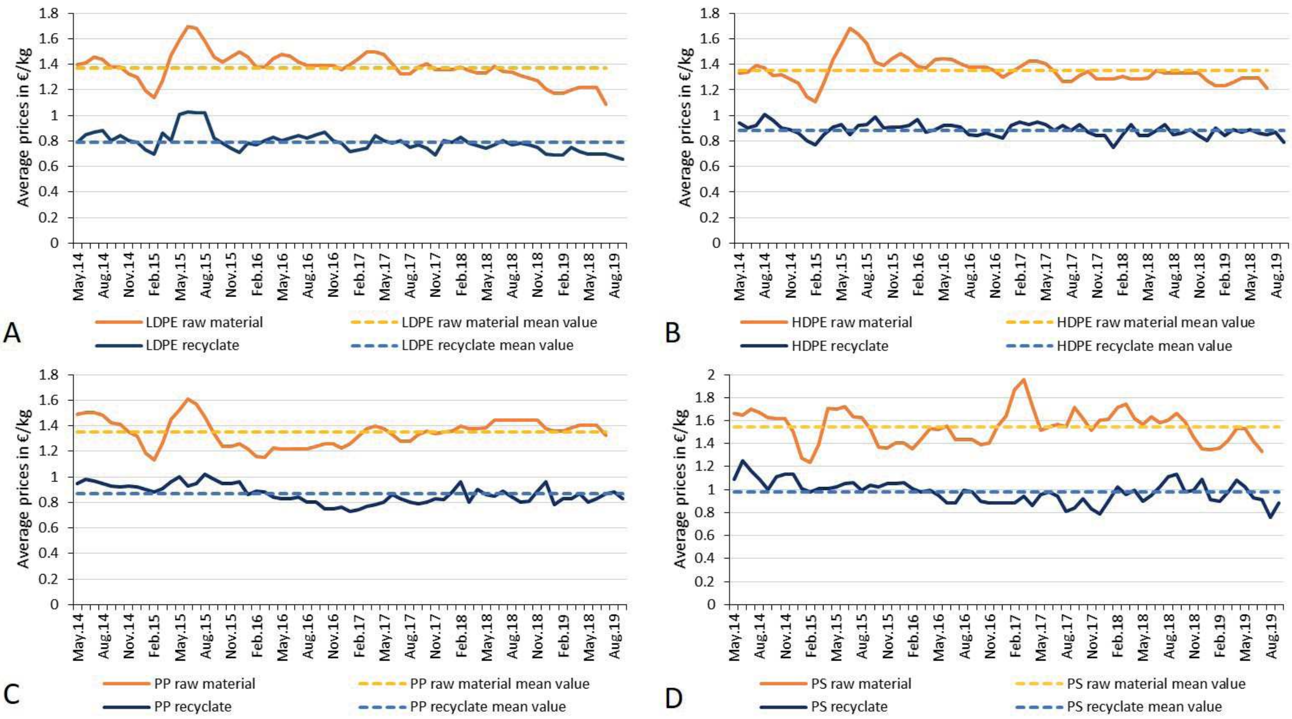

FIGURE 4: Price development for primary raw material and recyclates of LDPE (A), HDPE (B), PP (C) and PS (C) (Plasticker, 2019).

sorted plastic waste strangely affects the quality of the produced recyclates.

Pricing of recyclates

Basically, the market mechanisms of supply and demand apply. In addition, the following criteria were identified for pricing recyclates:

- Purity: the purer a material, the broader its range of application and the higher the price potentially achieved;
- Colour purity: the purer the colour of recycled material, the broader its range of application and the higher the price potentially achieved;
- A function of the primary raw material prices: Pricing polymer types is a function of the respective commodity price. If the price of primary raw material decreases, the price of polymers will drop as well. Recyclate prices are usually following the trend.

Other pricing contributors are melt filtration in the context the lower the melt filtration (measured in µm), the higher the quality and cost supplement for masterbatches. When plastic is dyed, a certain amount will be charged for this procedure, raising the price.

3.5 Quality benchmark in plastics recyclates

Market analysis has not produced any evidence for plastics recyclate benchmark. Therefore, producers of recyclates were asked to give one.

The surveys indicated that the quality standards for recyclates from Grüner Punkt (2019) are considered as a benchmark in the industry. For the recyclate quality, two levels are distinguished: mean quality for standard products like flower pots or buckets in 'standard plants' and high quality surpassing defined threshold values from Grüner Punkt (2019).

The demand for plastic recyclates is higher now than the recycling market is able to provide. For this reason, primary raw plastic granulates are mostly about 40 to 60% (see Figure 4) more expensive than plastic recyclates compared by the market data. The quality of recyclates is below that of primary raw plastic granulates regarding material properties but the consumers would tolerate it for the sake of sustainability. Better recyclability of plastics might reduce the market value of plastic recyclates. As best plastic recyclate quality, i.e. the benchmark, is met by plastic recyclates applied to food packaging like 'cap-to-cap' or 'bottle-to-bottle' production referring to the surveyed plastic processing companies.

4. CONCLUSIONS

The essential question was whether a correlation between price and quality of plastics recyclates is perceived. Experts from the plastics product manufacturing companies and plastics recyclers confirmed it unequivocally: The higher the quality of the material, the lower the impurities and the purer the material, the more applications for the material exist.

For sorted plastic waste, the plastic waste recycling companies quality standards defined by Grüner Punkt (2019) are considered a benchmark while recyclates applicable as food packaging (like cap-to-cap or bottle-to-bottle) constitute a benchmark for plastic recyclates.

In addition to the general market mechanisms of supply and demand, the pricing of secondary plastics is mainly a function of the purity of the recyclate, the purity of the colour and the respective price of raw materials. The purer and the cleaner the material, the higher the price that can be achieved on the market. The impact of respective commodity prices is also linked to the crude oil price and the dollar exchange rate.

Furthermore, the key competence of the staff in terms of quality control must be underlined. Their experience allows fast and reliable control, essential for successful further processing. For the quality control of recycled material, physical, rheological and mechanical properties are identified. In addition to density and melt flow rate, tensile properties and impact strength are identified to assure the required quality.

Plastic waste recycling companies would very much welcome a stipulation of minimum requirements for sorted plastic waste and recyclates by legislation.

Finally, it can be stated that, although the use of recyclates is facing some obstacles, many plastic product manufacturing companies are using plastic recyclates in their spite. There is a need for further changes at the political level (note: very positive example is "plastic strategy" of the EU) to help achieve a breakthrough. Many stakeholders along the plastic value chain would favour the further international introduction of quality standards. In addition, raising public awareness of the value of plastic waste is of key importance for further developments in the use of recycled plastic. Therefore, a package of measures and tools is needed to reduce obstacles and to promote high-quality plastics recycling as well as the use of recyclates.

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3.2 Publication IV, Data Analytics

"Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants"

Original Article
Friedrich, K., Fritz, T., Koinig, G., Pomberger, R., Vollprecht, D. (2021). *Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants.* Sustainability 2021, 13, 9472. DOI: 10.3390/su13169472.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 3-2.

Table 3-2: Annotation on the doctoral candidate's contribution to Publication IV

Conceptualization	**Friedrich, K.**, Vollprecht, D.
Methodology	**Friedrich, K.**
Software	-
Validation	**Friedrich, K.**, Fritz, T., Koinig, G.
Formal Analysis	**Friedrich, K.**, Fritz, T.
Investigation	**Friedrich, K.**, Fritz, T.
Resources	-
Data Curation	Fritz, T.
Writing: Original Draft Preparation	**Friedrich, K.**, Fritz, T.
Writing: Review and Editing	**Friedrich, K.**, Fritz, T., Koinig, G.
Visualisation	Fritz, T.
Supervision	Vollprecht, D.
Project Administration	Pomberger, R.
Funding Acquisition	-

sustainability

MDPI

Article

Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants

Karl Friedrich *, Theresa Fritz, Gerald Koinig, Roland Pomberger and Daniel Vollprecht

Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, 8700 Leoben, Austria; theresa.fritz@unileoben.ac.at (T.F.); gerald.koinig@unileoben.ac.at (G.K.); roland.pomberger@unileoben.ac.at (R.P.); daniel.vollprecht@unileoben.ac.at (D.V.)

* Correspondence: karl.friedrich@unileoben.ac.at; Tel.: +43-3842-402-5139

Abstract: Sensor-based and robot sorting are key technologies in the extended value chain of many products such as packaging waste (glass, plastics) or building materials since these processes are significant contributors in reaching the EU recycling goals. Hence, technological developments and possibilities to improve these processes concerning data analytics are evaluated with an interview-based survey. The requirements to apply data analytics in sensor-based sorting are separated into different sections, i.e., data scope or consistency. The interviewed companies are divided into four categories: sorting machine manufacturers, sorting robot manufacturers, recycling plant operators, and sensor technology companies. This paper aims to give novel insights into the degree of implementation of data analytics in the Austrian waste management sector. As a result, maturity models are set up for these sections and evaluated for each of the interview partner categories. Interviewees expressed concerns regarding the implementation such as a perceived loss of control and, subsequently, a supposed inability to intervene. Nevertheless, further comments by the interviewees on the state of the waste management sector conveyed that data analytics in their processes would also be a significant step forward to achieve the European recycling goals.

Keywords: sensor-based sorting; robot sorting; data analytics; maturity model; recycling; waste treatment; waste management

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1. Introduction

Sensor-based sorting, being one of the newest technologies for the recycling industry, is hoped to improve waste sorting enough to lead the way into a digitalized future and subsequently help meet the goals presented by the EU in 2018. These are 70% for packaging by 2030 and municipal waste in 5-year steps to a minimum of 65% by 2035. In addition, landfilling of municipal waste must be ensured to decrease to a maximum of 10% [1].

In recent years sensor-based sorting became increasingly popular due to the numerous possible applications and advancements in sensor technology as micro technologies enabled mass production of low cost and high-reliability sensors [2,3]. Sensor-based sorting is a contactless automated separation of particles based on specific features. Applications of this method can vary depending on the complexity of the technical design and the number of sensors. The detected features include color, composition, density, and conductivity, and the detection units, while following similar principles, vary in their construction. Comparisons with the still widely applied manual sorting show that sensor-based systems can identify characteristics of waste components more accurately [4–6]. An additional advantage related to mechanical waste sorting is the reduced health risk for workers [7]. The option to combine sensors with different characterization principles [8] especially results in a better quality of the final product, higher product yield and improved valuable recovery [9], which are aspects that can correlate directly with a recycling plant's revenue [10,11]. Due to the dynamic development of sensor-based sorting in recent years, new areas for use were and still are found [12–14]. Some sensors detect the superficial properties of the material, others give information about internal characteristics [15]. Visible spectroscopy (VIS) and near-infrared-sensors (NIR) belong to the first group and the other group comprises X-ray-transmission, X-ray-fluorescence, and inductive sensors [16].

Industry 4.0, the IoT, and rapidly increasing digitalization will enable the individual stakeholders (companies, customers, products, among others) to share valuable information amongst themselves in real time [17]. At the same time, the use of IT and automation will ensure the processing, analysis, and collection of vast amounts of information [18].

Implementing Industry 4.0 into the existing value chain of producers and stakeholders, though necessary for remaining responsive and adaptive to increasingly dynamic markets [19], comes with its own set of challenges and demands. When implementing Industry 4.0 technologies, challenges such as implantability, embedment, flexibility, and, especially in the field of waste management, robustness need to be considered [20].

Among the four dimensions of Big Data, namely, the variety of data, the velocity of generation and analysis of new data, the value of data, and the volume of data [21], one of the most pressing issues when adapting an existing plant to an Industry 4.0 approach is the emergence of vast amounts of data that must be processed and transmitted.

Transmission under the current industrial wireless network protocol is infeasible due to the limited bandwidth, which is unsuited to the necessary transmission rates for large scale Industry 4.0 applications [19]. Industry 4.0 needs transmission protocols able to handle the expected increase in data transmission volume.

In addition to the transmission issue, data processing needs to be implemented in a manufacturing-specific manner to ensure high quality and fidelity in the processed data and cohesion among different data acquisition models has to be ensured to allow for big data analytics [22].

Lastly, Industry 4.0 calls for standardized communication protocols and interconnectivity. This increase in connectivity and ease of access through standardized connections leads to issues concerning cybersecurity. The need to protect critical infrastructure, sensitive manufacturing data, and classified information stored in local servers or cloud-based IT platforms [23] increase dramatically with the use of Industry 4.0 settings [24].

The central aspect of Industry 4.0, apart from gaining insight into current industry procedures, is determining the differences in handling data [25] along the sensor-based sorting value chain in waste management. This value chain starts with the sensor manufacturer, which produces the sensor. Next comes the sorting machines manufacturer or the sorting robot manufacturer who installs the sensor in his equipment. At the end of this value chain, the sorting plant operator shows up and installs the sorting machine or sorting robot in his plant.

The definition of data as well as the perceived important aspects and usages may vary between individual stakeholders, thus resulting in unrealized potential concerning the possibilities and advantages of a sound data analytics strategy. Therefore, this study aims to explore the different approaches to and goals of the data handling part of digitalization in each of the four stakeholder categories.

The scientific research questions that are answered in this paper are:

1. How mature is the sensor-based and robot sorting area in Austrian waste management in the use of data analytics?
2. Where are the current limitations in technologies or in the willingness to be able to use data analytics in sensor-based or robot sorting in Austria?
3. What are the risks and chances in the specific area of sensor-based and robot sorting in the Austrian waste management sector?

Scientific literature reviews were performed to find a suitable evaluation method, searching for approaches to similar overarching questions.

Graninger executed an interview-based survey in his master's thesis to monitor the current status of the interpretation, implementation and obstacles for Industry 4.0 in Austria's industrial sector. In Graninger´s study, 34 companies out of over 300 participated in an email-based survey, so the return rate was approximately 10%. Furthermore, only 26 of them filled out this survey completely. The expert interviews were evaluated with bar charts and key figures such as a score factor or the weighted average [26].

Another analogical study was brought up by the German federal ministry of economics and technology in 2013. An online survey to evaluate the innovation potentials of big data was created and sent out to companies over decision makers, providers, users and scientists. It is not stated how many surveys were sent or where the contacted companies are located, but it is mentioned that 185 assessments were returned. The evaluation was done with percentages in bar charts [27].

Schuhmacher et al. created a study for an Industry 4.0 maturity model with expert interviews, practitioner workshops, and literature research. It was evaluated with spider diagrams and weighing of influence factors [28]. A maturity level is a step with predefined characteristics, with each level having more advanced characteristics on the way toward a mature process. In the case of this study, a data analytics strategy embracing all later specified aspects was used.

The last reference study was published by Gonçalves et al. and evaluates the readiness for Industry 4.0 of manufacturing companies. An online self-check tool was created and sent to an unknown number of companies, of which a total of 602 companies responded [29].

All these studies only consider Industry 4.0 in general but do not consider sensor-based sorting as a special technology within Industry 4.0. Therefore, in this study, for the first time ever, a maturity level assessment for sensor-based sorting in waste treatment is carried out with a focus on the Austrian waste sorting sector.

2. Materials and Methods

The state-of-the-art in waste sorting plants compared with a literature review revealed that a lot of information on sensor-based sorting in waste treatment is not accessible in the literature and is only known and traded by industrial experts in this field. For this reason, instead of a literature review, expert interviews were selected as an appropriate methodology.

After analyzing the previous stated four studies [26–29], it was decided that an interview-based survey would fit best since more information may be gathered in a personal conversation than from evaluating answers to predefined survey questions alone.

The interview-based survey consisted of questions regarding data analytics in general and in sensor-based/robot sorting. Due to COVID-19, all the interviews were conducted via video calls from March 2020 until May 2020.

The interviewed stakeholder experts were separated into four categories along the sensor sorting value chain: sensor manufacturers, sorting machine manufacturers, sorting robot manufacturers, and sorting plant operators. These categories were selected because only they can provide original data, whereas other stakeholders such as public authorities or research institutions could only provide secondary data obtained from the same group of experts. According to the working hypothesis, the highest maturity level should occur at the sensor technology sector, and at every step of utilization it will decrease, i.e., the sorting robot manufacturer is technologically behind the sensor producer, and so on.

Twenty-eight stakeholder experts were contacted, but due to reduced working hours in many companies, 12 interviews were held. The interview length varied from 45 min to 2.5 h. These 12 interviewed stakeholder experts cover mainly the whole Austrian waste sorting sector, although the companies are located all in Europe, because their equipment is the most commonly installed in Austrian waste sorting plants. The interviewed stakeholder experts were two sensor manufacturers located in Europe, four sorting machine manufacturers located in Europe, two sorting robot manufacturers located in Europe, and four sorting plant operators located in Austria.

In this section, it has to be stated that two sensor manufacturers cover the Austrian waste sorting sector because some sorting machine manufacturers produce their own sensors for their sorting machines. The two sorting robot manufacturers also cover the Austrian waste sorting sector since there are only a few sorting robots installed currently.

At the beginning of the interviews, the interviewers introduced themselves (the Chair of Waste Processing Technology and Waste Management), the research area of sensor-based sorting in the industry, as well as the aim and the focus of the survey. Next, the interviewee introduced himself, described his job and responsibilities in his company, and had the opportunity to bring in some questions of interest for the study. An example for such a question would be how the acquired data in the assessment is processed, which was in most of the interviews as the first open question. After it was agreed that the acquired data is only allowed to be published in an anonymous way—which was the precondition for each of the companies to participate—the survey questioning itself started. In some cases, one answer flipped to another question, but it was decided to follow the survey strictly and discuss topics twice instead of assuming the risk of missing any information. Nevertheless, when additional questions came up for some answer, they were discussed and appended to the study's results.

The evaluation of the data acquired in the study is done with individual critical analysis for each of the expert interviews and graphically visualized with bar charts since the number of participants is straightforward and enables going into details with each of the interviewees.

The data analytics survey was primarily based on the doctoral thesis of Bernerstätter [30]. It consisted of general questions, a self-evaluation, and detailed questions, i.e., concerning the consistency and amount of data needed to calculate the degree of data analytics maturity [30]. Bernerstätter stated that a maturity for the use of data analytics cannot be determined with one overall maturity level that is detailed enough because the maturity for data analytics consists of many sectors which need to be determined individually to calculate an overall maturity level. These sectors are data collection, data provision and transfer, data formats, data encoding and presentation, data scope, data consistency, and data usage [30]. In his models, the maturity level 1 is the lowest level and the maturity level 4 the highest, which is also the basis for this study [30]. For this study there was also a new sector considered, which is the commitment to change, to bring in a perspective on whether applying data analytics is not a technical problem but a mental one when employees fear losing their jobs with increasing digitalization.

The first set of introductory questions covers data of sensor-based sorting systems, namely, which data are collected and where they are stored, and aims to determine a degree of occupation with the topic of the data in general Table 1.

The averaged data analytics maturity level is calculated via the summation of the answers divided by the number of questions, with a possible 0.5 gradation if the participants felt that the company was on the way to a higher level but not quite there yet. The self-assessment, which is an estimation of the overall maturity level based on the four possibilities given (Table 2) was done prior to the detailed questions which were used to calculate an average data analytics maturity level with all of the data analytic sectors (Table 3) to compare. Lastly, it was inquired if the industry experts trusted their recorded data.

Table 1. Questions concerning data collection by the sensor-based sorting system and the general approach to data.

What Data is Collected by the Sensor-Based Sorting System?	
Production data	83% (10/12)
Maintenance data	75% (9/12)
Quality data	58% (7/12)
Machine data	83% (10/12)
Other data	8% (1/12)
Where is the data recorded?	
Right at the plant	92% (11/12)
Measuring room	50% (6/12)
Not on site	8% (1/12)
Others	0% (0/12)
Has the company implemented a strategy for managing data?	83% yes (10/12)
Are data owners assigned for data governance?	50% yes (6/12)
Are efforts made as well to ensure high quality of transaction data?	75% yes (9/12)

Table 2. Self-assessed data analytics maturity level.

How Would You Assess the Degree of Maturity of Data Analysis for Sensor-Based Sorting or Robot Sorting in Your Company Using the Following Scale?	
Hardly any digitization in data analysis has been implemented. There is no actual concern about the subject.	1
An analysis of interrelationships has been implemented showing the reasons for an incident.	2
Partially automated recording and specific formatting standards have been implemented. However, there is no consistency across data sources.	3
Continuous data and information management have been implemented based on established standards. In addition, prescriptive analysis helps the system act autonomously and appropriately.	4

Table 3. Detailed data analytics maturity level to portray a more accurate state of the art.

Data Collection	
Data collection does not adhere to any standards and objectives and, in addition, is incomplete. Paper-recording predominates, the amount of data collected is generally relatively small.	1
Digital data collection is triggered manually or irregularly. Fault remedy measures and logic connecting the process generated and collected data are available.	2
Irregular predefined triggers constitute automated data collection. Manual records are regularly digitized.	3
No more manual data input, only confirmation of values is required. Automated data acquisition is made in regular intervals.	4
Data provision and transfer	
Data is not available in any format utilizable by analysis tools, so substantial data aggregation is not ensured.	1
Local server systems cause interface and compatibility problems. Manual transmission is sparse due to high effort and not in real-time.	2

Table 3. *Cont.*

Data provision and transfer	
A centralized database system prevents interface problems and enables real-time analysis. Unstructured data from measurement processes are immediately reduced to relevant characteristics.	3
Pre-processing steps are provided to immediately present data in a structured manner ready for analysis. Data is stored in a Data Warehouse.	4
Data formats	
It takes high effort to convert the data into a standard format.	1
Standard data formats are used (xls, PDF, . . .) but not consistently, so that compilation takes a lot of time and effort.	2
Data formats do not limit the common data stock. Large amounts of data can be stored.	3
Data formats are irrelevant because the file transfer passes through an interface straight to an analysis tool. Alternatively, file formats suitable for Big Data are available.	4
Data encoding and presentation	
Text-only or incomprehensible codes characterize this unstructured form of data collection.	1
Codes can be interpreted clearly and entries are comparable.	2
Unambiguous interpretability is standard; essential attributes are scaled metrically, enabling transformation into nominally scaled values.	3
Metadata facilitates the automatic interpretation of the standardized codes from all data sources.	4
Data scope	
Data collected is unstructured, partly irrelevant, and too little in number. Spreadsheet software is sufficient.	1
The amount of data collected is too large to be interpreted by staff. The recording period is at least nine months.	2
The recording period is at least one year.	3
For at least 1.5 years, data has been entirely recorded and its relevance checked by precise allocation to the relevant observation units.	4
Data consistency	
Manual recordings provide inadequate or no consistent time reference.	1
Consistent time reference cannot be ensured across data sources but can be achieved using time stamps.	2
Diagnostic purposes can be satisfied by a defined reliable interval between surveys (to provide forecasts). Consistent time reference is ensured even across data sources.	3
A consistent system ensures time stamp integrity and traceable quality by association with ID data (e.g., order numbers).	4
Data usage	
Data is not used, i.e., records are kept without interpretation, or no adjustments are performed after interpretation.	1
Individual records are converted into a format ready for interpretation. Problems with data quality/consistency are known but not remedied in a standardized way. The IT department is solely responsible.	2

Table 3. *Cont.*

Data usage	
Data is interpreted to remedy faults and to make decisions on a regular basis. Data management processes are documented and discussed with data protection and security. Data is considered a resource.	3
Both an archiving strategy and a disposal strategy are implemented. The use and expense of data can be financially evaluated. Data-based systems intervene in the process.	4
Commitment to change	
Staff and/or management resist real-time digital measurements, preferring paper-based recording or simultaneous digital and paper-based data recording. New technologies are faced with skepticism and no serious measures are taken to overcome resistance.	1
Individuals or mid-level management are voicing a desire for change. Change management is not systematic, but the relevance of data used as a resource is discussed.	2
Easy data access and fast interpretation, as well as automated process tracking, are key elements. Handling of data loss or insufficient data is improved. The entire management supports change projects and embraces new technologies.	3
New digital systems are embraced to support staff and to maintain and optimize the process. Change projects can be initiated top-down and bottom-up.	4

2.1. Types of Data Recorded

During the interviews, additional information about the nature of the data collected has been gathered. Despite varying amongst the different stakeholders, similar types of data are being collected across all participating companies. These types of recorded data and a detailed description to them is listed in Table 4. The data will be categorized into four groups, namely machine, production, maintenance, and quality data.

Table 4. Types of data collected across all participating companies.

Production Data
Occupation density Since the sorting efficiency is highly dependent on the occupation density (quote), many stakeholders opt to record the occupation density. The calculation is done by dividing the number of pixels detected by the area of the specific sorting aggregate. Throughput rate The throughput rate is defined as the amount of material in kg or m^3 passing through the sorting aggregate in a specified amount of time. Recording the throughput rate can help calibrate the sorting process to reach the ideal trade-off between yield and purity, highly dependent on the throughput rate [31].
Maintenance data
Operating hours Currently, the operating hours of the sorting equipment are being recorded. Nevertheless, so far, none of the interviewees intend to use this data set for advanced maintenance techniques such as prospective or predictive maintenance.
Quality data
Purity and Yield Purity is the quotient of valuables in the ejected material. This value, along with yield, is the defining factor for the evaluation of separation success. The yield is defined as the quotient material fraction mass (e.g., PET) in eject multiplied with the related eject concentration and divided by input mass, which is first multiplied with the concentration of the material fraction mass in the input (e.g., PET) [25].

Table 4. *Cont.*

Machine data
Object statistics The number of objects recognized by the sensor-based sorting setup defines the object statistics. Objects are defined as areas of coagulated pixels of a specified minimum area. Pixels statistics The number of pixels detected for each specified material. This statistic yields the basis for more advanced statistics such as area density or occupation density. Bad pixel replacement Sensors may exhibit defective pixels caused by production. Many sorting software packages come with the ability to exclude or filter those pixels to minimize their effect on the sorting efficiency. However, in most cases, the number of these faulty pixels is not recorded or not available to the software's user. Areal density By calculating the average mass of an object and correlating this with the average amount of pixels detected per object, e.g., a given PET bottle, the areal density of said material can be calculated. This measurement can be used to estimate the number of valuables in the input without the necessity of costly hand sorting or input analysis. Detection rate The detection rate defines the number of correctly identified pixels and objects with a custom sorting model relative to the standard settings of the given sorting aggregate. Valve activity According to the questioned stakeholders, the activation statistics of the pressurized air valves are being saved in most machine statistics. These may be used to recognize one-sided loading of the sorting aggregate in addition to the pixel statistics.
Other data
When the customer wants to record individual data in his sensor-based sorting machines, this option can be additionally enabled. This data could be, e.g., the used spare parts or how many remote maintenance accesses have been performed since the commissioning of the sensor-based sorting machine.

2.2. Validation of Results

In order to validate the answers of the companies, site visits were conducted at every second company. During these site visits, selected sorting machines and sensors were conducted to confirm the given maturity level.

3. Results

Since 28 stakeholder experts were contacted and 12 interviews were held, a return rate of 43% could be achieved. As not all the 12 participants own a sensor-based sorting system directly, some answers refer to industry partners or customers. Most of the data collected regards the production and machine data, and nearly all of it is collected right at the plant. The introductory questions showed that most of the surveyed companies have a data managing strategy implemented, but only half have a designated person responsible for it. Transaction data, meaning the continual evaluation of data quality, was important to 75% of the participants. Questions and answers are listed in Table 1.

The self-assessed data analytics maturity level compared to the calculated average for each sector is shown in Figure 1. Sensor manufacturers have estimated their overall maturity level approximately one degree lower than the assessment resulted, and the same was true of the sorting plant operators. The sorting machine manufacturers' self-assessed maturity level is lower than calculated for two stakeholders and higher for another two stakeholders. In contrast, the sorting robot manufacturers self-assessed themselves higher than the calculation result. The average for all of the stakeholders would be an overall data maturity level between 2.0 and 3.0, which would also be the similar to the self-assessed average.

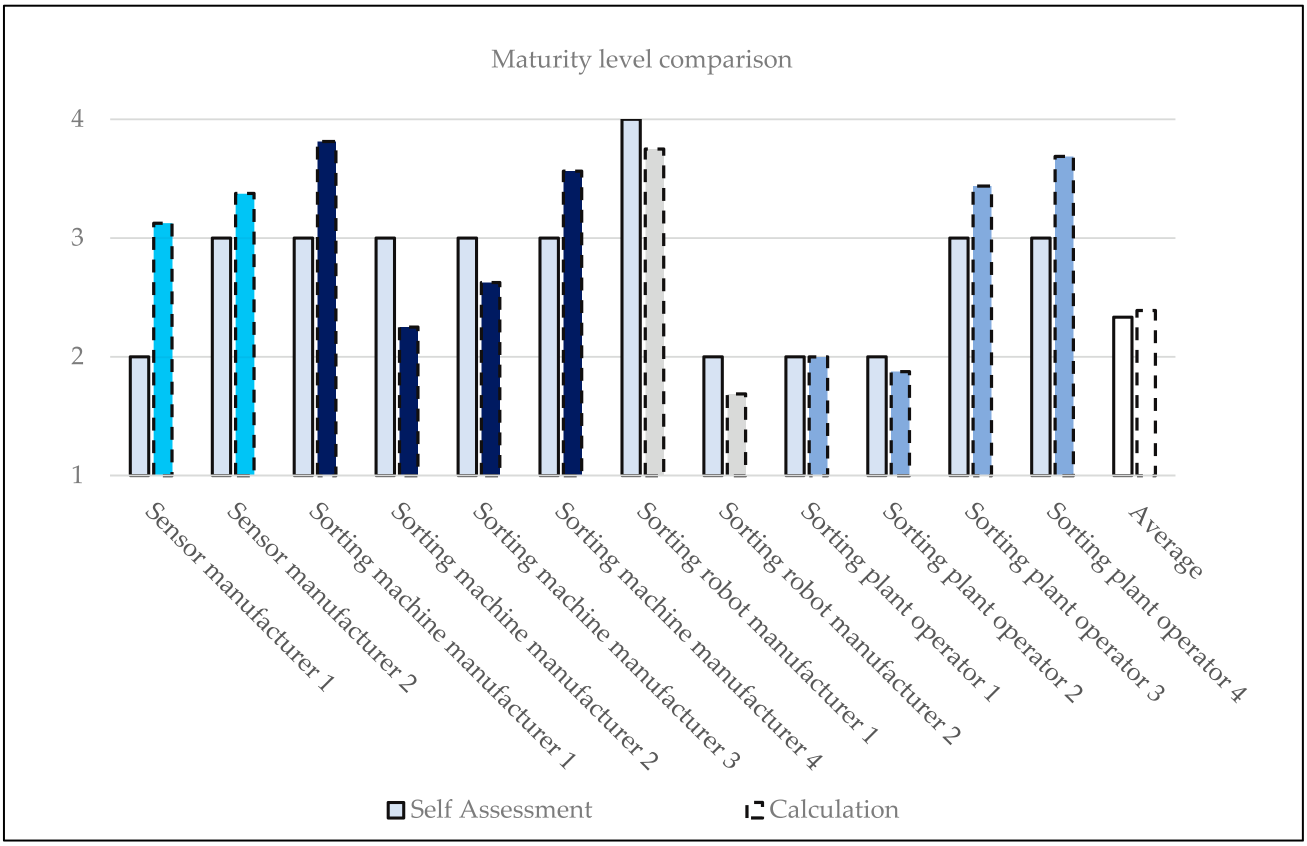

Figure 1. Data analytics maturity level split up into the individual answers of all participants and comparison to the self-assessment.

It was mentioned by the stakeholder experts that smaller and younger companies often do not have the means to build a data management strategy yet and, in addition, presently do not need it. However, all the questioned companies found data analytics to be an important topic that cannot be overlooked in the future and pledged to improve their approach to data handling. The following text will go into detail about which maturity level was calculated for each sector from the overall calculated data analytics maturity level. Figure 2 shows the results for each data analytics sector split up for each stakeholder expert.

Primarily following the data analytics maturity assessment of Bernerstätter [24], the first question for the calculated data analytics maturity level concerns data collection. Most of the participants were identified as being on the third step or higher. The area of data collection was generally considered to be the most digitized, especially for three sorting machine manufacturers and one sorting robot manufacturer, which reached level 4. Table 3 contains detailed descriptions of all maturity levels for each sector. The third level for data collection is described as 'Irregular predefined triggers constitute automated data collection. Manual records are regularly digitized'. Data use is evidently not automated in plants to optimize efficiency. It is only used manually to optimize the sorting machine efficiency in periodic maintenance or troubleshooting when sorting machines face problems.

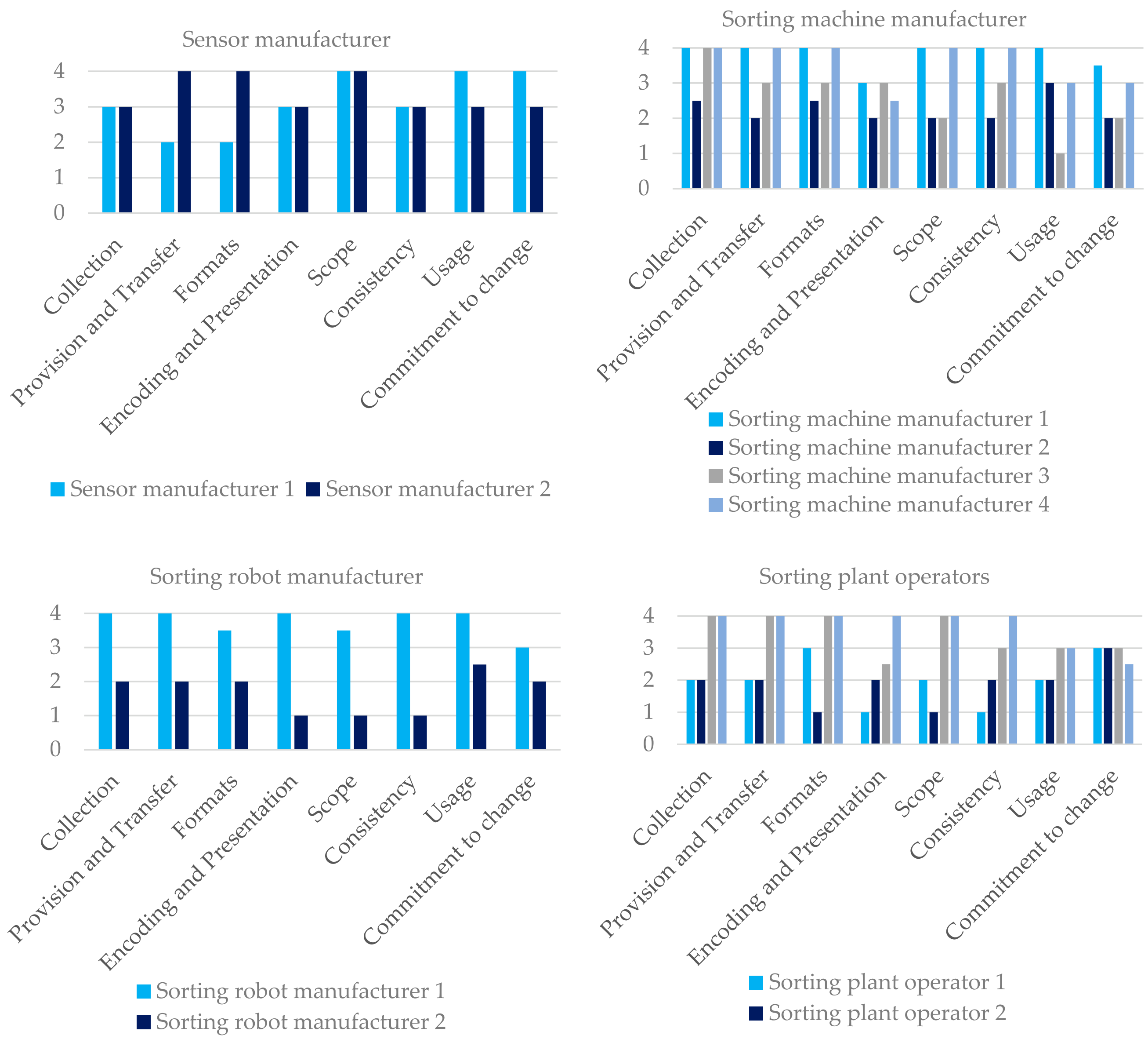

Figure 2. Comparison of the stakeholder answers in maturity levels from one to four in each data analytics category.

Question 2 concerns data provision and transfer and was estimated to be a level 4 for half of the interviewed stakeholder experts through the sensor-based sorting value chain. The description of the fourth level is 'Pre-processing steps are provided to immediately present data in a structured manner ready for analysis. Data is stored in a Data Warehouse'.

Data formats, as a sector of data analytics, show similar results to data provision and transfer instead of sorting machine manufacturer 2, which faces a maturity level of 2.5. The fourth maturity level, which is the dominant one, is defined as 'Data formats are irrelevant because the file transfer passes through an interface straight to an analysis tool. Alternatively, file formats suitable for Big Data are available'.

Generally, there is no visible trend seen for all four stakeholder categories in data encoding and presentation. The most established maturity level in this sector was level 3 (four times), which is defined as 'Unambiguous interpretability is standard; essential attributes are scaled metrically, enabling transformation into nominally scaled values'.

On the data scope, half of the participated stakeholders are on the fourth step with the description 'For at least 1.5 years, data has been entirely recorded and its relevance checked by precise allocation to the relevant observation units'. The maturity level 3 could not be achieved by any interviewed stakeholder, and all of them had either a lower or a higher level.

Regarding data consistency, four participants are on the fourth level. The sensor manufacturers are both on second step, defined by the following statement: 'Consistent time reference cannot be ensured across data sources, but can be achieved using time stamps'. An interesting result is that the maturity level of all four interviewed sorting plant operators varies from the lowest level to the highest level.

Consistent with the other maturity levels, the data usage also strongly depends on each interviewed stakeholder individually. The most determined maturity level was level 3 at five stakeholders. The definition for this level is 'Data is interpreted to remedy faults and to make decisions on a regular basis. Data management processes are documented and discussed with data protection and security. Data is considered a resource'.

The last maturity level deviates from the work of Bernerstätter [24] but is also considered to be of interest and concerns the commitment to change. This maturity level does not deal with data but is essential to be considered on the way to a digitized future that does not start and stop at the IT department. Most of the participating stakeholder experts took a second to think about this part and changed their answers at least once. Only sensor manufacturer 1 found himself on the fourth maturity level and sorting machine manufacturer 1 was on the way to the fourth. The other stakeholder experts consider themselves to be on the way to the third, at the second level, or in between. Maturity level 3 is described as follows: 'Easy data access and fast interpretation, as well as automated process tracking, are key elements. Handling of data loss or insufficient data is improved. The entire management supports change projects and embraces new technologies.'

The last question, "Do you trust the recorded data?", received positive answers for 11 out of 12 interviewees (92%), emphasizing the need to verify data permanently. Considering the different maturity levels for each sector and each stakeholder, it cannot be claimed to determine a trend for each sector. However, advancement can be attempted for the whole European waste management industry as the interviewed stakeholders in the categories of sorting machine manufacturers and sorting robot manufacturers hold a considerable share of the market in Europe. Nonetheless, of interest, Figure 2 shows the individual sectors of data analytics in sensor-based sorting and the commitment to change for each stakeholder.

Finally, as a supplementary question, it was asked where there are currently still barriers to the use of data analytics in sensor-based sorting. Ten out of 12 participants stated that, currently, no mathematical relationships or models between the recorded data had been investigated. Whether there can be mathematical models, e.g., describing the influence of the processed data on one another, would first have to be examined. Furthermore, the area of validity for newly found relationships in the recorded data is still not exactly known. Since these mathematical relationships in recorded data are still not investigated on an industrial level, these 10 participants see the use of data analytics as a risk, which can either be a chance or a hazard to a machine and, in the end, may weaken its performance instead of optimizing it. It would be a significant step to investigate the mathematical relationships in the recorded sensor-based sorting machine data to handle this industry's risk correctly.

Furthermore, although the influences of different machine settings are known, they have not yet been investigated on a level that a sensor-based sorting machine can automatically adapt its sorting settings to the material flow to achieve the best sorting results. These settings would be, e.g., the illuminance of the used emitter(s), the used pressure for ejecting, the minimum object area and object height that is discharged, or the delay time for the activation of the compressed air nozzles.

At last, the stakeholders are interested in making sensor-based and robot sorting processes more efficient, either by improving the identification to characterize more particles correctly or by improving sorting efficiency with, e.g., mathematical models.

4. Discussion

The introductory questions generally show high interest in keeping the quality of data high with a minimal tendency to monitor machine and production data in contrast to data concerning the maintenance and quality of the product. In this chapter, the research questions of the study are discussed and interpreted.

4.1. How Mature Is the Sensor-Based and Robot Sorting Area in Austrian Waste Management in the Use of Data Analytics?

In Figure 1, the comparison between the self-assessed and averaged data analytics maturity level, sensor manufacturers and sorting plant operators have estimated their overall maturity level lower than it was calculated in the assessment. Two sorting machine manufacturers self-assessed lower than the results of the assessment and two self-assed higher than the results. Sorting robot manufacturers tend to self-assess themselves a bit higher than the calculated maturity level. The overall average data maturity level for all stakeholders would be between 2.0 and 3.0, which would also be the similar to the self-assessed average.

The maturity levels of each stakeholder in each data analytics sector differ from each other with slight to no correlations, and there is no derivable trend, as can be seen in Figure 2. The maturity level of each data analytic sector strongly depends on the company itself, so the stakeholder categories need to be analyzed individually.

4.1.1. Sensor Manufacturers

Sensor manufacturer 1 has been in the market for waste sorting sensors for years and has a broader product portfolio than the sensor manufacturer 2. Sensor manufacturer 2 has a slighter product portfolio, which might be the reason that the data analytic sectors are in the scope and the usage higher for 1. In provision and transfer, as well as for the formats, the maturity level might be higher for sensor manufacturer 2 since all their sensor portfolio is new and they have already thought about the relevance of these sectors in their product development. Meanwhile, sensor manufacturer 2 still has also "older" sensors in their equipment, which are not supplied with functions of the higher maturity levels. It can be said that new developed sensors are mostly supplied with the opportunity to provide data so that they can be used in sorting plants to develop a smart waste sorting plant.

4.1.2. Sorting Machine Manufacturers

For the sorting machine manufacturers, it can be seen that number 1 and number 4 are the leaders for all of the technical categories. The reason for this might be that these two companies are far older than the other two, so the global size of the companies as well as the amount of sold sorting machines result directly in a high maturity level for using data analytics in sensor-based sorting.

Sorting machine manufacturers 2 and 3 are in the lower maturity levels for the sectors, especially sorting machine manufacturer 3, which has the maturity level of 1 in data usage: 'Data is not used, i.e., records are kept without interpretation, or no adjustments are performed after interpretation'. Taking a closer look on the company itself, it can be determined that this company supplies mostly smaller plants with their equipment, which might be the reason for their lower level: that customers do not favor this option was one of the answers that was given during the interviews. If the customer would have a demand for these options, they would of course integrate such opportunities in their new sorting machine generations. This leads to the next statement, which is that larger sorting machine manufacturers are on a higher data analytics maturity level in nearly all of the sectors than the smaller ones.

4.1.3. Sorting Robot Manufacturers

For the sorting robot manufacturers, the same statement as for the sensor manufacturers is valid, but in the other way around. Sorting robots are quite new technologies in the waste management branch, so they are developed in a way that data analytics can be used in smart waste sorting plants. The main difference between sorting robot manufacturer 1 and sorting robot manufacturer 2 is that manufacturer 1 developed his robots so that it can be easily integrated in a plant and all of the data can be elected and used by other plant equipment. That is not the intention of sorting robot manufacturer 2: he does not want to share all the data from the robot with other machines, he only provides predefined selected data, which are mostly only finished calculations of objects and pixel statistics. It can be stated that sorting robots are able to provide data so that it can be used in sorting plants to develop a smart waste sorting plant, but this depends—as is also valid for the sensor manufacturers and the sorting machine manufacturers—on which data and how far the supplier is willing to hand over the access to his customer/sorting plant operator.

4.1.4. Sorting Plant Operators

The maturity level results of the category of the sorting plant operators shows that sorting plant operators 3 and 4 are further developed than the others. Sorting plant operator 4 is one of the largest waste sorting plants in Austria, which leads to this high maturity level in each category. Sorting plant operator 3 is has new sorting lines and old sorting lines installed and is also much bigger compared to the other sorting plants in Austria. The two smaller sorting plant operators 1 and 2 are not sorting fractions. They only sort out contaminants for waste, which is thermally treated after the sorting. A high maturity level of the data analytic sectors is not required for them since the sorting task is not to obtain a maximized pure sorted output product. They focus is on the legal threshold values for contaminants, which requires, in the worst case, a second sorter to reach the threshold values, but no intelligent plant, which works with cascade connections, uses intelligent circuits or scavenger concepts. In the case of the smaller sorting plants, the investment in a high digitalization level is not required since the tasks are different. For the sorting plant operators, it can be said that there are two main factors: one is the goal of the sorting tasks (high purity of output product or depose contaminants) and the size of the plant, measured in the yearly throughput rate.

In summary, it can be said that new developed sensors are able to provide all requirements to use data analytics in sensor-based and robot sorting. In any case, whether all of these options can be used depends strongly on the knowledge and willingness to share data of the sorting machine or sorting robot manufacturer. Here, as it can be seen in Figure 2, the data analytics sector's commitment to change will be most important for the future. When these two criteria are fulfilled, the last criterion is whether the sorting plant operator wants or needs new innovations to achieve better sorting results as well as the plant size.

4.2. Where Are the Current Limitations in Technologies or in the Willingness to Be Able to Use Data Analytics in Sensor-Based or Robot Sorting in Austria? What Are the Risks and Chances in the Specific Area of Sensor-Based and Robot Sorting in the Austrian Waste Management Sector?

Supplementary questioning discovered the unused potential for further use of data analytics by developing mathematical models and the use of machine learning algorithms. However, the realization of this potential is inhibited by concerns about the reliability of these machine learning technologies. In addition, interviewees voiced their concerns about diminishing control over their machinery, which could lead to adverse effects on the sorting success without them being able to intervene promptly to alleviate the problem. These are viable concerns and must be dealt with in further evaluation of the applicability of machine learning based on mathematical models in the waste processing industry. Simultaneously, further studies have to be conducted to assess the essential machine parameters, e.g., the intensity of the emitters, the used pressure for ejecting, the minimum object area and object height that is discharged or the delay time for the activation of the compressed air nozzles to be controlled. Integrating data analysis systems and intelligent machinery control algorithms backed by mathematical models successfully into the processes would be a significant step into the future for the waste processing industry. The main objective of all stakeholders is to make sensor-based and robot sorting processes more efficient by improving either the identification or the mechanical operation with mathematical models.

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Conflicts of Interest: The authors declare no conflict of interest.

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4 Experimental Design

The chapter "Experimental Design" describes the experiments performed in this doctoral thesis. It is divided into three parts consisting of three publications:

- Publications 5 presents the methods and equipment used.
- Publications 6, 7, and 8 present experiments on optimizing the identification of particles
- Publications 9 and 10 present the optimization of mechanical particle discharge.

4.1 Publication V, Methods

"Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup"

Method Article
Friedrich, K., Koinig, G., Pomberger, R., Vollprecht, D. (2022). *Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup*. In MethodsX 9, p. 101686. DOI: 10.1016/j.mex.2022.101686.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 4-1.

Table 4-1: Annotation on the doctoral candidate's contribution to Publication V

Conceptualization	**Friedrich, K.**, Koinig, G., Pomberger, R., Vollprecht, D.
Methodology	**Friedrich, K.**, Koinig, G., Pomberger, R., Vollprecht, D.
Software	-
Validation	**Friedrich, K.**, Koinig, G.
Formal Analysis	**Friedrich, K.**, Koinig, G., Pomberger, R., Vollprecht, D.
Investigation	**Friedrich, K.**, Koinig, G.
Resources	-
Data Curation	**Friedrich, K.**, Koinig, G.
Writing: Original Draft Preparation	**Friedrich, K.**, Koinig, G.
Writing: Review and Editing	**Friedrich, K.**, Koinig, G., Pomberger, R., Vollprecht, D.
Visualization	**Friedrich, K.**, Koinig, G.
Supervision	Pomberger, R., Vollprecht, D.
Project Administration	-
Funding Acquisition	-

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journal homepage: www.elsevier.com/locate/mex

Method Article

Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup

K. Friedrich*, G. Koinig, R. Pomberger, D. Vollprecht

Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Franz Josef-Strasse 18, 8700 Leoben, Austria

A B S T R A C T

Sensor-based sorting in waste management is a method to separate valuable material or contaminants from a waste stream. Depending on the separation property different types of sensors are used. Separation properties and their corresponding sensors are e.g. molecular composition with near-infrared sensors, colour with visual spectroscopy or colour line scan cameras, or electric conductivity with electromagnetic sensors.

The methods described in this paper deal with the development of **sorting models** for a specific **near-infrared, a visual spectroscopy and an induction sensor**. For near-infrared and visual spectroscopy software is required to create sorting models, while for induction only machine settings have to be adjusted and optimized for a specific sorting task. These sensors are installed in the **experimental sensor-based sorting setup** at the Chair of Waste Processing Technology and Waste Management located at the Montanuniversitaet Leoben. This sorting stand is a special designed machine for the university to make experiments on sensor-based sorting in lab scale. It can be used for a variety of waste streams depending on the grain size and the pre-conditioning for the sensor-based sorting machine. In detail the methods to create these sorting models are described and validated with plastic, glass and metal waste.

- Near-infrared spectroscopy measures the molecular composition of near-infrared-active particles.
- Visual spectroscopy measures the absorption of visible light by chemical compounds.
- Induction sensors use induced currents to detect nearby metal objects.

Abbreviations: ALU, Arbitrary light units; AVAW, Chair for Waste Processing Technology and Waste Management; HDPE, High density polyethylene; HSB, Hue-saturation-brightness; HSI, Hyperspectral imaging; HSV, Hue-saturation-value; LDPE, Low density polyethylene; LLDPE, Linear low density polyethylene; MMI, Man-Machine-Interface; NIR, Near-infrared spectroscopy; PET, Polyethylene terephthalate; PLC, Programmable logic controller; PMMA, Polymethylmethacrylate; PP, Polypropylene; RDF, Refuse derived fuel; RGB, Red-green-blue; SBS, Sensor-based sorting; TPU, Thermoplastic polyurethane; VIS, Visual spectroscopy.

* Corresponding author.
E-mail address: karl.friedrich@unileoben.ac.at (K. Friedrich).

https://doi.org/10.1016/j.mex.2022.101686

A R T I C L E I N F O
Method name: Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup
Keywords: Sensor-based sorting, Identification model, Near-infrared sorting (NIR Sorting), Visual-spectroscopy sorting (VIS Sorting), Induction sorting
Article history: Received 26 November 2021; Accepted 29 March 2022; Available online 2 April 2022

Specifications table

Subject Area;	Environmental Science
More specific subject area;	*Sensor-based Sorting*
Method name;	*Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup*
Name and reference of original method;	• *Near-Infrared Spectroscopy: Ozaki, Y.; Huck, C.; Tsuchikawa, S.; Engelsen, S.B. Near-Infrared Spectroscopy: Theory, Spectral Analysis, Instrumentation and Applications, 1st Edition, Springer, Singapore, 2021, ISBN: 978-981-15-8648-4.* • *Visual-Spectroscopy: Perkampus, H.-H. UV-VIS Spectroscopy and Its Applications, 1st Edition, Springer, Berlin, Heidelberg, 1992, ISBN: 978-3-642-77477-5.* • *Electromagnetic Induction: Morris, N.M. Electrical Principles II, 1st Edition, Palgrave, London, 1977, ISBN: 978-0-333-22062-7.*
Resource availability;	• *Hardware, Main Configuration: CLARITY Sorting System MONTANUNI-01, custom-made product constructed by Binder+Co AG* • *Software, Control Cabinet: Man-Machine-Interface (MMI) by Binder+Co AG* • *Hardware, Near-Infrared Technology: EVK HELIOS NIR G2-320 by EVK DI Kerschhaggl GmbH* • *Software, Near-Infrared Technology: EVK Helios Optimizer; Version 3.4.2017.1* by EVK DI Kerschhaggl GmbH, *08-2017 - Hardware, Induction Sensor: MESEP FS3 by Pulsotronic Anlagentechnik GmbH* • *Hardware, Visual Spectroscopy: AViiVA® SC2 CL Camera Link® Color Linescan Camera by e2v* • *Software, Visual Spectroscopy: FraunhoferICC by Fraunhofer IOSB, Version 2.5.0.0 by Fraunhofer IOSB, 2012*

Method details

Sensor-based sorting is used in waste management for sorting and analysing waste streams and bulk materials. It is a non-contact, non-destructive process that offers a great deal of flexibility to cope with a wide variety of tasks. The Chair for Waste Processing Technology and Waste Management (AVAW) has an experimental sensor-based sorting setup for university and industrial research projects designed as a two-way machine. A grain size range from 5 to 300 mm can be processed. The feed takes place via a vibrating conveyor (1) followed by a glass chute (2) (see Fig. 1). The experimental sensor-based sorting (SBS) setup contains three sensors (referred to Fig. 1) that can be used for different waste streams:

- Near-infrared sensor (NIR) (5): waste glass, paper and cardboard, plastics, electronic scrap as well as construction and demolition waste.
- High-resolution colour line scan camera with the measurement principle of visual spectroscopy (VIS) (5): plastics, wood, paper and cardboard, waste glass as well as construction and demolition waste.
- Electromagnetic induction sensor (3): electric conductors, e.g. metallic waste.

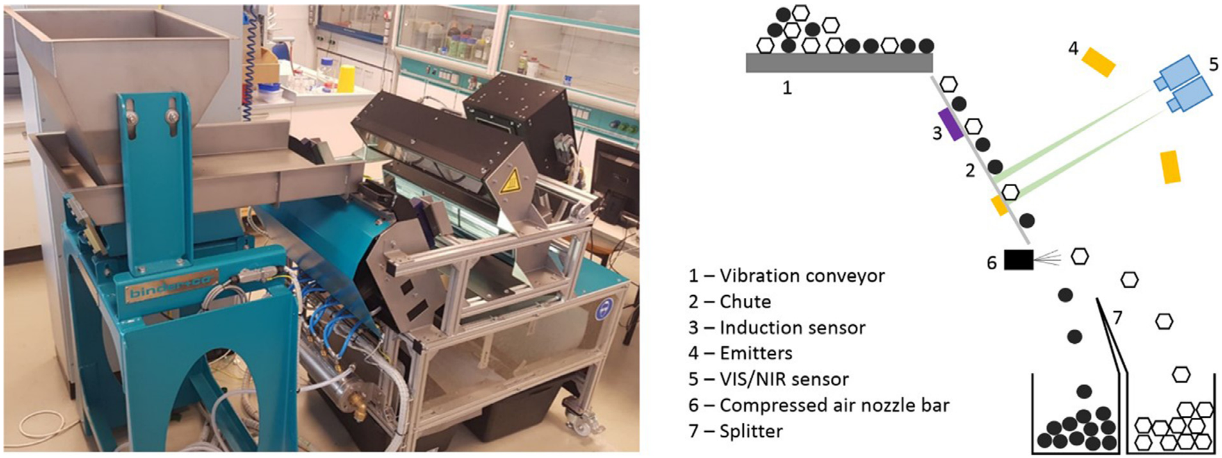

Fig. 1. Functional schematic of the experimental sensor-based sorting setup at AVAW [3].

Table 1
Technical Parameters of the EVK Helios NIR G2-320 Near Infrared Sensor.

Technical Data	Value
Spectral Range	930 – 1700 nm
Scan Rate	500 Hz full frame
Spectra Resolution	9 nm
Spectral Sampling	3.1 nm
Spatial Resolution	312 Pixels
Pixel Size	30 × 30 μm
Optical Coupling	C-mount lens
Slit	100 μm (80μm optionally)
Interfaces	GigE Vision, CamLink 2
Trigger Input	RS-485

Table 2
Key Technical Properties of the AViiVA® SC2 CL Camera Link® Color Linescan Camera VIS Sensor.

Technical Data	Value		
Sensor Characteristics at Maximum Pixel Rate			
Resolution	1365 Red-Green-Blue (RGB) patterns or 4096 pixels		
Pixel pitch	10 µm		
Maximum line rate	14 kHz		
Anti-blooming	X 100		
Radiometric Performances (Maximum Pixel Rate, T_{amb} = 25°C)			
Output Format	12 bits (also configurable in 8 bit or 10 bit)		
Linearity (G = 0)	< 2 %		
Gain range (steps of 0.035 dB)	G_{min} -2 dB	G_{nom} 0 dB	G_{max} 22 dB
Peak response (1)(2) Blue Green Red	16.6 LSB/(nJ/cm²) 24.4 LSB/(nJ/cm²) 31.3 LSB/(nJ/cm²)	21.5 LSB/(nJ/cm²) 31.5 LSB/(nJ/cm²) 41 LSB/(nJ/cm²)	263 LSB/(nJ/cm²) 383 LSB/(nJ/cm²) 496 LSB/(nJ/cm²)
Dynamic Range	66 dB	64 dB	42 dB
Photo Response Non-Uniformity	± 4 % (± 15 % max)		

It is also possible to combine several sensors to solve complex tasks with so-called sensor fusion.

Currently, norms are existing how to interpret NIR spectra with standard test methods like ASTM D 1925 Determination Yellowness Index or ASTM D 1003 Haze and Luminous Transmittance of Transparent Plastics, but none how to record all the data (VIS, NIR, induction, senor fusion) for such a setup, which is the focused method in this research paper [1,2].

In order to reproduce all applicable methods with the experimental SBS setup, the specifications of the sensors are listed. The first of the sensors used for classification via NIR Spectroscopy is the EVK Helios NIR G2-320, a high-speed hyperspectral imaging system. The main specifications of the EVK Helios NIR G2-320 are listed in Table 1.

The second sensor in application for the separation and classification trials conducted with the SBS setup explained above is the sensor for visual spectroscopy, the AViiVA® SC2 CL Camera Link® Color Linescan Camera. In the following, the essential key specifics of the sensor are depicted. The main specifications of the EVK Helios NIR G2-320 are listed in Table 2.

The third sensor used during trials at the sensor-based sorting stand is an induction-based sensor to detect metallic objects. It delivers a sensitive and accurate detection of small metal fragments. It

Table 3
Technical Properties of the Induction Sensor MESEP FS3.

Technical Data	Value
Interface	Ethernet RJ45; 10/100Mbit, RS485; 57.600 - 6.000.000 Baud; CAN; EtherCAT**
Sample rate	1 kHz
Resolution	12 - 100 mm
Protocol	UDP; HTTP(Ethernet); ASCII(RS485)
Number of Channels	4 - 124

delivers the detection results in real-time via Ethernet to a PC or a programmable logic controller (PLC), where the data can be evaluated. This way, the sensor's data can be coupled with the data delivered by other sensors like the NIR or VIS sensor to achieve complex sorting tasks. The main specifications of the Induction Sensor MESEP FS3 are listed in Table 3.

Since correct illumination is vital for the detection with NIR, a halogen lamp is employed since halogen lamps deliver a flat spectrum in the NIR range. This specific illumination device, the Helen Dr. Fischer 15026Z with reflector, delivers a maximum illumination output in the detection area of 6.5 mW/mm^2 and is adjustable. It means the illumination setting allows dimming the lamp.

The complete data sheets of all employed sensors are found in the chapter "Additional Information" for further reference.

Tasks and applications that have been worked on in research projects on the experimental SBS setup are:

- Sample characterisation and determination of the composition,
- Creation of a digital grain size distribution,
- Discharge of contaminants,
- Enrichment of valuable substances,
- Sorting of bulk goods according to substance groups and
- Validation of sorting/separation results.

All of these tasks require the same method of qualitative analysis for sensor-based sorting, but the objective of the task is different.

Requirements to get respectively good sorting results

Sorting results are influenced by internal and external factors, which have an impact on the process control. The internal factors are based on the construction of the sensor-based sorting setup, adjustments and settings on the machine:

- Belt velocity: throughput rate, relative velocity
- Air pressure: to blow out objects according to the sensor signal with the compressed air nozzle bar
- Valve diameter: influences the compressed air flow rate through one valve
- Valve distance: defines possible grain ranges to be sorted
- Splitter position: influences the sorting because of object weight and flight characteristics
- Position of the compressed air nozzle bar: influences the sorting because of object weight and ejection trajectories

The external factors which influence the sorting result are based on the properties of the material stream to be sorted:

- Grain size distribution: should be between 3 to 4 referred to the smallest and the biggest object in the fraction.
- Content of valuable material: the more valuable material in the input, the lower the influence of object overlapping.
- Grain form: agglomerates or objects, which are deformed, influence the sorting result either positively or negatively.

- Area density: too low can lead to incorrect sorting because of bad flight characteristics and too high can lead to incorrect sorting because the air pressure is not able to push the object over the splitter and into the reject fraction.
- Dust or steam between sensors and emitters can influence the identification of objects negatively; either objects are not identified, not recognised or the dust/steam cloud is identified as an object, which leads to an incorrect sorting result.
- Surface contamination: contaminations on the objects can cause that objects are incorrectly identified and wrongly sorted.
- Reflective surfaces: influence the transfer of the sensors light beam, it can cause positive or negative effects in the sorting result depending on the application. Positive: Reflective bands behind the specimen can enable measurement in transflection. Negative: Reflective materials can cause direct reflection into the sensorś lense, causing misclassification or since direct reflection cannot be used by the NIR detector.

Further parameters, which influence the sorting result, can be set up on the man-machine-interface (MMI). For the correct identification of various materials, the correct calibration of the illumination is necessary. This is achieved by three illumination parameters in the MMI, namely the background light, in incident light and the intensity of the NIR emitters. These parameters can be set in a range of 0 - 100, corresponding with the percentage of the maximum intensity.

The background light is used for detecting the particles for ejection. Decreasing the background illumination can allow for the ejection of transmissive materials such as glass or clear PET bottles. This is necessary since excessive intensity may cause these materials to be ignored since the high intensity does not cause sufficient shadows for them to be identified. The background illumination should not be set higher than 20 %, because this leads to an overexposure of light which results in incorrect material identification.

Similarly, the identification for the VIS sensor can benefit from manipulation the incident illumination intensity in correlation to the surface properties of the material. Materials which absorb light very well may need a higher intensity than reflective materials whose glare can become an issue with excessive illumination.

The third illumination source to be calibrated is the NIR emitters intensity. Here a similar problem arises. Distinct materials can cause glare when illuminated with sufficient intensity, e.g. smooth PS containers. Here a reduction in NIR intensity can improve classification. Other materials with worse reflective properties, e.g. thin foils and multi-layered plastic packaging materials, benefit from increased NIR intensity. The reason for this is their thin material thickness, which limits the amount of radiation that can be reflected. With thin materials like plastic packaging foils most of the radiation emitted by the NIR illumination is lost to transmission because of the low material thickness. An increase in emission intensity can increase the overall radiation arriving at the specimen and therefore increase the amount of radiation reflected by the material, overall improving the detectability of these materials.

Some sorting tasks require the prioritisation of distinct materials over others present in the waste stream. In these applications, purity takes priority over yield. Here, the ejection of a particle that might be contaminated of wrongly classified is treated as more severe than the loss of a valuable particle. To achieve this prioritisation the sorting software allows for a weighing of material class pixels. This allows the user to multiply material pixels in the detection. Through this, the number of pixels of a contaminant might be counted tenfold, therefore ensuring the ejection of a contaminated or misclassified particle or an agglomerate containing a valuable particle, that might otherwise be ejected, reducing the purity of the valuable fraction.

Further parameters which have to be optimized for maximized sorting efficiency are:

- Delay time [ms]: Defines the time from the sensors object detection to the activation of the valve and needs to be set up so that the sorted objects can be blown out efficiently. It is mainly depended on the sorted objects weight.
- Minimum blow-out time [ms]: Defines how long the valve are minimum opened
- Minimum object width [mm]: Defines the minimum width of an objects, it can be set from 1 to 100 mm

- Valve activity [%]: Defines how far an object has to reach in a path so that the associated valve is activated, it can be set from 10 to 100 %.

In order to understand the principle for the explained methods in sensor-based sorting there are some definitions and statistics, that are mandatory to be understood:

- Pixel: A pixel is the smallest unit of recognition by the detector, determined by the detectorś resolution. These pixels make up the spectral image and are the basis for spectral evaluation. Each pixel contains information about its location and the intensities inherent at its location in all evaluated wavelengths. With this information each pixel is assigned a material class, which is then used to create objects for separation.
- Object: An object is a cluster of pixels. Whether an object is assigned to material class A or material class B is determined by the abundance of pixels making up the object. E.g. if an object consists of 49 % pixels classified as A and 51 % pixels classified as B, then the object is assigned to material class B. For separation purposes only, the objects classification is considered, therefore correct weighing of material classes is important in order to achieve a given sorting task at hand.
- Pixel statistics: Pixel statistics are the distribution of pixels between material classes, i.e. if an object consists of 50 pixels of material class A and 8 pixels of material class B, these proportions are assigned to the relevant classes separately.
- Material statistics: Material statistics are the classification of objects according to the dominant material class, e.g. if an object consists of 50 pixels of material class A and 8 pixels of material class B, the object is evaluated as material class A and all pixels (here 58 pixels) are assigned to material class A.
- Object statistics: The object statistics are the distribution of objects between material classes. If 58 pixels of class A are assigned to the object in the material statistics, this object is counted in material Aś object statistic, raising the object count by one.

The most crucial parameter in terms of plant settings from an operator's point of view is the throughput-rate $\dot{m}$. This parameter influences the economic performance of the sorting plant. The throughput rate determines the amount of material passing the experimental SBS setup during a specific time. The chute has a width of 0.5 m. The following formula is used to calculate the **throughput-rate** $\dot{m}$ [4]:

$$\dot{m}\left[\frac{kg}{h*m}\right] = \frac{m_{input}\ [kg]}{t\ [s]/3600\left[\frac{s}{h}\right]*0.5\ [m]}$$

where m_{input} is the mass of the input material, and t the time of the sorting experiment. Additionally, four quality parameters should be determined to evaluate the performance of the sorting trial [4]:

- The **purity** is the quality of the product fraction (ejected fraction) and is calculated according to the following formula:

$$Purity\ [\%] = \frac{m_{target\ \ fraction,\ \ eject}[kg]}{m\ _{eject}[kg]} * 100\%$$

- The **yield** determines the efficiency of the ejection process and is calculated according to the following formula:

$$Yield\ [\%] = \frac{m_{eject}[kg]*\ c_{target\ fraction,\ eject}[\%]}{m_{input}[kg]*\ c_{target\ fraction,\ input}[\%]} * 100\%$$

- **Recovery** is the mass of ejected material relative to the mass of input material and calculated according to the following formula:

$$Recovery\ [\%] = \frac{m_{eject}[kg]}{m\ _{input}[kg]} * 100\%$$

- **Incorrect discharges** are material pieces, which are wrongfully ejected and their share is calculated according to the following formula:

$$Incorrect\ [\%] = \frac{m_{eject}[kg]*\ c_{non-target\ fraction,\ eject}[\%]}{m_{input}[kg]*\ c_{non-target\ fraction,\ input}[\%]} * 100\%$$

where m_{input} is the input mass, t *is* the time of the experiment, $m_{\text{target fraction,eject}}$ is the mass of the target material in the ejected material, m_{eject} is the mass of ejected material, $c_{\text{target fraction,eject}}$ is the percentage of the target material in the ejected material, $c_{\text{target fraction,input}}$ is the percentage of the target material in the input material, $c_{\text{non-target fraction,eject}}$ is the percentage of the non-target material in the ejected material and $c_{\text{non-target fraction, input}}$ is the percentage of the non-target material in the input.

Sorting with VIS technology

Method principle

With the assistance of VIS-based sorting, materials can be sorted according to their colour. VIS-based sorting is the oldest sensor-based sorting technique, which was previously used mainly for waste glass. In polymer recycling, this sensor technology is often used for polyethylene terephthalate (PET). Its primary operating principles are well understood and thoroughly explained [5]. Nowadays, it is mainly used in combination with other sorting techniques.

The method is based on the interaction of electromagnetic radiation from the visible range (380 nm - 750 nm) with the sample. The colour of an object is determined by the absorption or reflectance of light in the visible range. The absorption of a specific wavelength is based on the excitation of valence electrons. The excitation of the valence electrons causes electron transitions between the energy orbitals of different energy. The resulting energy difference leads to the absorption of specific wavelengths according to the following equation:

$$\lambda = \frac{h \cdot c}{\Delta E}$$

where λ is the wavelength, E is the energy, h is the Planck constant ($6{,}626*10^{-34}$ J*s) and c is the speed of light [6]. The smaller the energy difference, i.e. the easier it is to excite the electrons, the longer the wavelengths of light absorbed.

In the sorting process, the sample is exposed to electromagnetic radiation from a light source. Part of the light is absorbed and other parts are diffusely reflected on the surface of the object. These reflected parts are directed onto a detector. In this detector, the incident light is split into its components. The result is a spectrum of wavelengths as a function of intensity. With this sorting technique, only the range of visible light is analysed [7]. The colours can be defined either according to the red-green-blue (RGB) method or the hue-saturation-brightness (HSB) method. The RGB method defines the colour by parts of the primary colours red, green, and blue.

In comparison, the HSB method defines colour by hue saturation and brightness. The hue is displayed in a 360° circle representing a colour wheel, with each degree representing a specific colour. A saturation of 100% is the most intense version of the colour, regardless of the hue selected. In comparison, a saturation of 0 % represents the grey version of that colour. Brightness is also expressed as a percentage. A brightness of 0 % is black, no matter the hue or saturation. A brightness of 100 % means the light is at full strength [8].

With the VIS-based sorting technique, manual sorting by colour can be replaced. Compared to manual sorting, smaller grain sizes can be sorted with a higher throughput rate. The technique also enables the sorting of materials that are only slightly different in colour and would no longer be distinguishable by the eye (e.g. different shades of blue). However, successful sorting requires much preparatory work in defining the various colour classes and configuring the system correctly (lightning settings) [9]. The lighting settings must be adapted correctly, as they react very sensitively to external influences. When creating the colour classes, it must be ensured that no reflections occur in the picture of the reference material or that these are not considered when defining the colour class. The method works very well with materials that differ significantly in colour. When the colour differences are minor, the effort required to create the colour classes is very high [10,11].

Since materials vary in their ability to transmit visible light, the setup consists of two individual illumination arrangements. They are split up into two separate lighting modes, incident light and

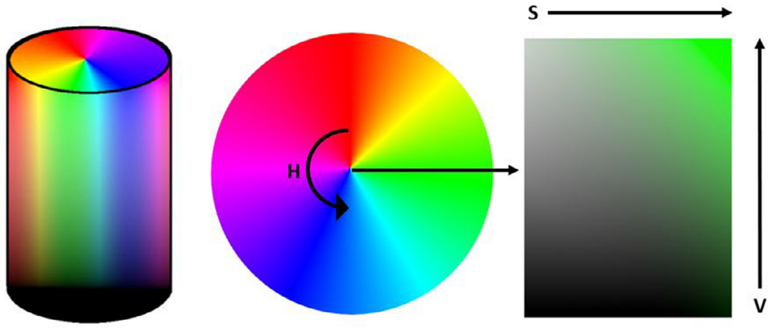

Fig. 2. Colour cylinder for creating the VIS sorting model according to the colour sector (Hue, H), the brightness level (Value, V) and the saturation circle (Saturation, S) (authors depiction).

background light. Incident light is used with materials whose density does not permit light to be transmitted. The illumination source, therefore, needs to be on the same side as the detector. These materials include building materials like bricks which need to separate from the mortar according to their colour. The other category includes materials like glass, which are highly reflective and translucent. Their high reflectivity can inhibit the incident illumination by reflecting light directly into the detector lenses, causing glare. This glare can prohibit the detector from gathering sufficient information about the colour of the particle. Illuminating the particles from behind using background illumination can circumvent and alleviate these problems. Through background illumination, the particles tendency to cause glare is reduced and finer differentiation in the material's colour can be made. This allows good separation between different shades of the same colour, e.g. separating light blue glass from blue glass.

Method description

The first two steps of a VIS sorting trial are typically adjusting the lighting settings and determining the white calibration and the black calibration to ensure optimal light that allows an equally good identification of the different colours and does not lead to overexposure.

White and black calibration aims to adjust and determine the spectroscope's colour response to a known colour composition under experimental circumstances like artificial light in the laboratory. It is done by taking an image of a standard colour before the experiments and calibrating the sensor's response. The object used for this is a white ceramic plate provided by the manufacturer specifically for this purpose. An image of this ceramic plate is taken which serves as a benchmark for what the sensor and the post-processing software regard as pure white or all detectable colours' similar composition in the visible wavelength range. Similarly, the black calibration is performed by shielding the detectors lense with a non-permissive plate, prohibiting stray light from entering the lens. This state sets the lower boundaries of brightness. These calibrations need to be performed before every measurement since changes in the ambient light due to changes in the daytime, weather and similar conditions can alter the colour of the specimen and render the prepared sorting model worse.

In order to separate and differentiate plastic parts by colour, the VIS sensor needs to be trained **in a third step** through creating a basic classification program. This program is developed by registering different colour types according to the Hue-saturation-value (HSV) system. Therefore, the HSV system settings need to be configured: The hue component, which represents the colour variations on a pie chart of 360°C, is divided into 48 units to differentiate between colours. The saturation parameter depicts the richness of the colour, and the brightness component defines how bright the colour is [8], as seen in Fig. 2. Both parameters are measured on a scale from 0 % to 100 % and divided into 200 saturation units and 250 brightness units, respectively. The more subdivisions into units of the HSV, the better is the resolution of the sorting trial, but the more complex and time-consuming the sorting system is capturing the different colours and training.

Fourth, some pieces of each chosen material – in the current example, a red low density polyethylene (LDPE), a white LDPE and a grey high density polyethylene (HDPE) – are inserted separately into the experimental SBS setup to picture the material. The picture allows the classification of the colour and consequently the detection and sorting using the VIS sensor for the sorting trial. The material stream, which goes through the chute, is classified by the colour of the targeted fraction in the HSV system in step **five**.

The software depicted and used to create the colour separation model is Teachin ICC. A teachin file defines the mapping of colours to specific classes. The file is read in by the sorting system so that during sorting it can be decided which colour classes are present for the pixels of an object detected in the camera image, in order to determine which material is to be assigned to the object based on the majority of colour classes present.

Fig. 3 shows exemplarily this procedure for the white LDPE fraction. After loading the picture (or a part of it) into the software Teachin ICC, a range of pixels is selected (A), which fits the material's colour. It shows little reflections and it is not situated at the edge of the material to avoid transparency. The hue pie then locates the colour in the respective segments (B). It also indicates other segments where previous materials have been localised. For example, the orange section in the pie represents the segments and saturation where the grey HDPE material is situated. By clicking on the different segments, the saturation (x-axis) and brightness (y-axis) diagram for the respective segment opens (C), showing where the corresponding area of the target material is located for the different selected pixels. In order to classify this range, the area is selected and saved for the respective colour. This procedure has to be repeated for all relevant hue segments (in the picture according to the segments, where the "x" is located).

In order to have an effective classification, in a **sixth step,** it needs to be verified to what extent the selected HSV parameters can serve to detect and ultimately eject the targeted material by determining the coverage rate of the registered classification with the original picture of the material. These coverage ratios for three materials are visible in the following Fig. 4.

It is visible that the coverage ratio for red is optimal as it covers almost the whole surface of the three different material pieces. In contrast, the white and grey materials have a lower coverage ratio due to reflections and different exposure to the lighting system. The VIS sensor's inability to identify the material needs to be remedied. For this reason, the coverage ratio is optimised by adding more pixel and HSV ranges to the material classification in iterative procedure by repeating step five. Additionally, the parts that were successfully identified can be weighted with a higher factor. In this trial, grey and white are both being weighed twice as much as the other colours.

Step seven: After finishing the setup and configuration of the classification program, the program is transferred to the man-machine interface (MMI) of the experimental SBS setup and the target material for sorting is selected. The MMI is connected to the VIS sensor and ultimately controls the air nozzles that mechanically eject the selected material pieces through an air blast. The pressure applied as air blast from the valves in the air nozzle bar is defined, reflecting sufficient pressure to move the target material pieces over the splitter. The time delay between detection and ejection, Δt, is defined to consider the distance between the classification area on the chute and the air nozzle bar and reflect on the density and falling behaviour of the material. For the trials the white LDPE material is the target material for ejection.

In **step eight**, the actual sorting trial is conducted by inserting the test fraction into the experimental SBS setup, thus, putting it on the vibration conveyor and running the system. The pieces fall down the chute where the VIS sensor detects the targeted fraction, which activates a specific valve in the air nozzle bar according to the position of the targeted material piece. This airflow ultimately sorts the material detected as white over the splitter into the target box, whereas the non-target fraction falls into the reject box.

As the final and **ninth step**, the two sorted fractions are manually sorted and weighed per target and non-target material content to determine the performance parameters of the sorting trial.

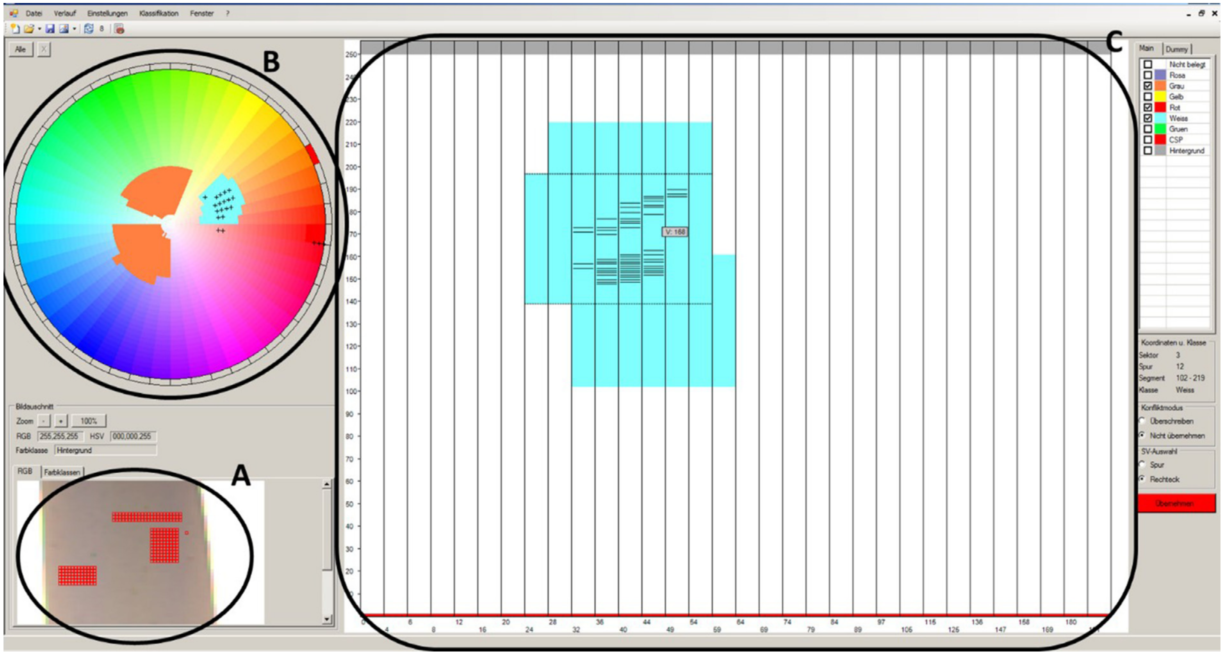

Fig. 3. Creating the classification program in Teachin ICC by configuring the colour parameters according to the HSV system, here exemplary for the white LDPE material (authors depiction).

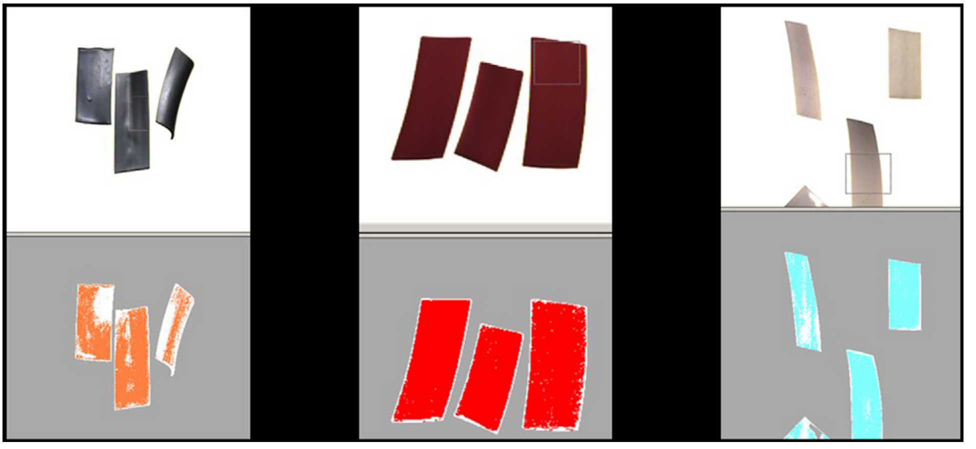

Fig. 4. Verification of the coverage ratio for three different materials in Teachin ICC (left picture colour "grey" marked in orange, centred picture colour "red" marked in red, right picture colour "white" marked in turquoise) (authors depiction).

Table 4
Material and corresponding colour of the feed material components.

Material	Colour
LDPE	red
LDPE	white
LLDPE	green
HDPE	grey
PP	purple
TPU	yellow
PET	clear

Method application

The feed material is a mixed fraction of different plastic components with a corresponding colour, see Table 4. A high-resolution line scan camera (VIS technology) is used as the sensor. The aim is the purest possible extraction of white material from the feed material. Following Fig. 1, the material is separated using a vibration conveyor (1) and moved into the sensor's exposure area via a slide or chute (2).

This sensor assembly (4 - 5) consists of an emitter (4) and a detector (5). In this case, halogen lamps, fluorescent tubes, or LED strips are usually chosen as emitters. The emitter's radiation is partially reflected by the individual pieces of plastic and measured by the detector. The detector is connected to a computer that records the detected colour in the “colour cylinder”. In terms of the colour sector (Hue, H), the brightness level (Value, V) and the saturation circle (Saturation, S) in a previously created colour cylinder model (see Fig. 2) are compared and thereby assigned to a defined group.

According to the task, if a piece of plastic belonging to the “white” group is recognised, it must be separated from the remaining fragments. That is done using a compressed air blast. A valve strip (6) downstream of the sensor opens one or more valves when the white piece is in front of the valve strip. The piece is "shot out" over the separating edge (7). All different coloured plastics are deliberately not ejected.

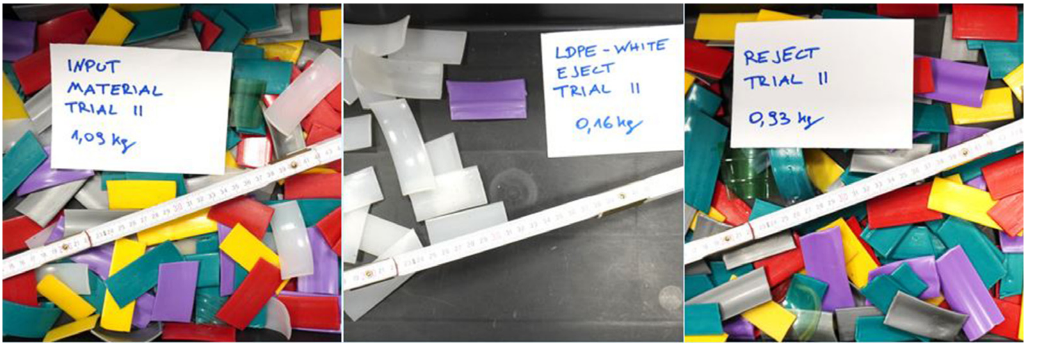

Fig. 5. Feed material (left), separated white LDPE – Eject (centre) and coloured plastic – Reject (right) (Trial 2 in Table 5) (authors depiction).

Table 5
Data of the VIS experiments.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Time of experiment	*s*	34	38	42	42	42	40	42	41	40	38
Input mass	*kg*	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09
Mass of eject	*kg*	0.16	0.16	0.18	0.17	0.17	0.16	0.15	0.17	0.15	0.17
Mass of reject	*kg*	0.93	0.93	0.91	0.92	0.92	0.93	0.93	0.92	0.93	0.92
Target material in eject	*kg*	0.15	0.15	0.16	0.16	0.17	0.16	0.14	0.16	0.14	0.16
Target material in reject	*kg*	0.02	0.02	0.01	0.01	0.00	0.01	0.02	0.01	0.03	0.01
Non-target material in eject	*kg*	0.01	0.01	0.02	0.01	0.00	0.01	0.01	0.01	0.02	0.01
Non-target material in reject	*kg*	0.91	0.92	0.90	0.91	0.92	0.91	0.92	0.91	0.91	0.91

Table 6
Results of the VIS experiments.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Throughput-rate	*kg/(h*m)*	230,6	206,3	186,7	186,7	186,7	196,0	186,7	191,2	196,0	206,3
Purity	*%*	93.8	96.8	86.6	93.9	97.7	94.5	94.1	93.6	90.3	92.0
Yield	*%*	90.5	89.2	92.3	93.9	100.0	92.3	88.9	95.2	83.7	95.2
Recovery	*%*	14.9	14.1	16.4	15.2	15.8	15.1	14.0	15.7	14.1	16.0
Incorrect discharges	*%*	1.1	0.5	2.6	1.1	0.4	1.0	1.0	1.2	1.6	1.5

Method validation

The validation use-case is to separate “white” as target fraction from the feed material described in Table 4 and the left picture of Fig. 5.

Table 5 sums up the data from the trials in the VIS experiment. The white LDPE material was targeted for ejection in all sorting trials. Table 6 provides the consequent sorting trial results in terms of plant and quality performance parameters. The resulted fractions from the trial are shown in the centred and right picture of Fig. 5.

Sorting with NIR technology

Method principle

Nowadays, near-infrared (NIR) sorting systems are state-of-the-art in plastic waste sorting plants [4]. The basic working principles of NIR spectroscopy were the subject of a plethora of scientific studies, so they are well understood and can be used and modified to achieve a variety of tasks [12]. The NIR spectroscopy is based on the partial absorption of light in the NIR region (750 – 2500 nm) by the molecules in a material. Other than photons of UV and visible light, IR photons lead to vibrational and rotational movements of molecules or molecule parts. Suppose the frequency of the incident IR light correlates with the resonance frequency of molecular vibration. In that case, the IR light is absorbed, resulting in the molecule's or functional groups' vibrations. However, IR light can only be absorbed if the vibration changes the dipole moment in the molecule or functional group. By detecting the reflected or transmitted light of the irradiated material, absorption bands in specific spectral regions can be located. Based on these bands' position and intensity, the functional groups within the material and, therefore, the material itself can be identified [13].

Methods based on NIR spectroscopy are characterised by the fast, non-destructive and non-invasive principle. Additionally, they are more suitable for in-line use than the mid-range infrared systems because of their lower price and higher robustness [14,15].

The basic principle behind NIR systems in sorting plants is irradiating the objects with NIR light and detecting the reflected light by a sensor. For successful sorting, the system has to be trained beforehand with the spectra of different materials. The detected spectrum is then pre-processed, which entails normalisation and derivation to emphasize their specific characteristics. These processed spectra are then compared with the spectrum of the previously defined material to be ejected. If the similarity is high enough, the respective object is identified as the defined material and ejected. The similarity necessary for assigning the material to an existing class can be defined by the user via the threshold parameter in EVK SQALAR. In most cases, specific wavelength regions in the spectra are defined for comparison rather than the entire spectrum. In this way, the computing time can be reduced.

This sorting method also has its disadvantages as it is a binary sorting system that can only target one fraction to be sorted out. Thus, several NIR systems have to be connected in series or cascades to sort out multiple fractions. Another point that should be kept in mind is that moisture, dirt, or other residues can influence the NIR-spectra, leading to mis-sorting [4]. Furthermore, it is impossible to sort black or very dark plastics as they show high absorbance and, therefore, low reflectance [16]. An alternative to NIR sorting systems are tracer-based or water-mark sorting systems, which can sort a waste stream into several fractions in one step. Nevertheless, these two technologies also have their challenges, e.g. in technical feasibility and economic performance.

Method description

Similar to the proceeding in the VIS experiment, the NIR sorting trial starts with classifying the different target materials for the program's configuration. As for the VIS experiment, the light settings and the white calibration and black calibration for the NIR experiment are set up for the sorting task.

Before a measurement can take place, the sensor's white and black calibration needs to be performed. The reasoning behind this calibration is that the software needs to know the maximum and minimum radiation intensity to expect, setting the upper and lower boundaries for spectral evaluation. The white calibration is performed as follows. Firstly, a reflective material is placed on the chute, a white ceramic plate provided by the manufacturer for this purpose. Then the user sets the white calibration target in the EVK SQALAR software, in this case, 2000 Arbitrary Light Units (ALU), which is the unit for radiation intensity used by EVK in all their software and detection applications. This target correlates to the reflected intensity by the ceramic plate. The software will use this calibration target as a reference to order the detected radiation according to its intensity. If any pixels' reflected radiation exceeds this threshold, its intensity will be capped to the white calibration setting.

After the white calibration has been performed, the black calibration follows. All incoming light into the detector must be blocked with a non-NIR permissive shielding, usually made from black polymers, coloured with carbon. Then the user starts the black calibration process in EVK SQALAR, defining the bottom threshold, 0 ALU, of incoming light. After both processes, black and white calibration, have been completed, the intensity range under the given experimental circumstances has been defined. This intensity range is used to plot and evaluate the spectral information of the evaluated materials.

In addition, the backgroundś reflection intensity needs to be defined in SQALAR. The glass chute (2 in Fig. 1) is transmissive, leading to low reflected intensity if no object is present to reflect the incident

NIR radiation. This lack of reflection is exploited by defining a lower boundary of intensity under which all pixels are classified as background. All background pixels are omitted from classification.

The next step is the setup of the system. In this case, three materials for creating the classification program are chosen: Polypropylene (PP), PET and thermoplastic polyurethane (TPU). Several pieces are taken and inserted into the experimental SBS setup to acquire an image and the corresponding NIR-spectra for each material. From the images of the pieces, several pixels are selected over which the respective NIR-spectrum is averaged. Fig. 6 shows the spectra of five selected pixels of a PP specimen. It can be seen that the spectra vary amongst those pixels although it is the same material. When selecting the areas of the particles, areas with reflections and edges should be avoided. The received spectrum is then assigned to the respective material. For the following comparison between the materials, the first derivative of the spectrum is used. The scattering of the spectra of the three materials is shown in Fig. 7 and Fig. 8. As visible in the Fig.s, PET exhibits a relatively high scattering compared to the other two plastics. However, due to its characteristic peak in the area of 1650 nm, PET is usually easy to detect, especially in this case compared to PP and TPU.

The spectra can be evaluated using their depiction in a cartesian coordinate plane. The x-axis of this plane depicts the relevant wavelength in nanometres. This relevant wavelength represents the wavelengths the detector acquires, in this case, 930 nm - 1700 nm. This label does not change, regardless of the post-processing, the spectra undergo. The y-axis depicts the intensity of the reflected radiation acquired by the sensor. The y-axis' unit is the arbitrary light unit (ALU). As mentioned, this unit is used by all operating systems created by EVK and represents the detected intensity in relation to the white and black calibration. The range of this is set by the user or the manufacturer when setting the target for white calibration. In the case of this study, the white calibration target is set to 2000 ALU, representing the maximum intensity of the radiation reflected by the specimen used for white calibration. In this case, the background used for the calibration was a white ceramic plate supplied explicitly by the manufacturer for white calibration. As mentioned, the label of the x-axis does not change with progressing processing of the spectral data, e.g. derivation. It is not applicable for the y-axis, as its label changes with processing the spectral data, depicting the relevant information for the current processing application, e.g. the gradient of the raw spectra when displaying the first derivative. In this example, the unit of the y-axis changes to depict the change in intensity over the given wavelength, represented as arbitrary light units per nanometre (ALU/nm). However, this is not represented in the current version of the used classification software. The representation of the y-axis increases the range to permit the representation of the derivatives of the raw spectra. This part of the software can confuse when interpreting the spectra and needs to consider when preparing spectra for publication and use compared to other spectra, taken under different circumstances and with different levels of processing applied to them. With knowledge of this peculiarity in the analysis software, caused complications can be successfully circumnavigated. E.g., by using external software to analyse and compare spectra, a MATLAB script translates the raw spectral hyperspectral imaging (HSI) cube into a spectral image. Out of this cube, suitable spectra can be selected, processed, evaluated and plotted.

The code used in the comparison of spectra takes the HSI Cube, exported as a .mat file. This HSI cube's dimensions represent the size of the spectral image taken and the number of spectral evaluation points linearly spaced over the relevant wavebands. In this case, the detector can assess 220 spectral points in the detectable range from 930 nm - 1700 nm. Therefore, the dimensions of this HSI cube are [Width of the spectral image in pixels x Height of the spectral image in pixels x 220]. The code converts this HSI Cube into a black and white image, representing the average reflected NIR intensity at every recorded pixel. This average produces an interpretable representation of the spectral information contained in the HSI Cube from which pixels for spectral evaluation can be selected. This selection process is depicted in Fig. 9, which shows the representation of a spectral recording taken of seven PP specimens.

After selection, the user can process the spectral information as needed. For example, apply smoothing, normalisation and derivation, enabling the user to exert more control over the data processing. An example of three evaluated pixels from the spectral image mentioned above is depicted in Fig. 10. This Fig. depicts three PP spectra of the specimen after applying the first derivative, gaussian smoothing with a smoothing interval of 10 and normalisation using the z-score method,

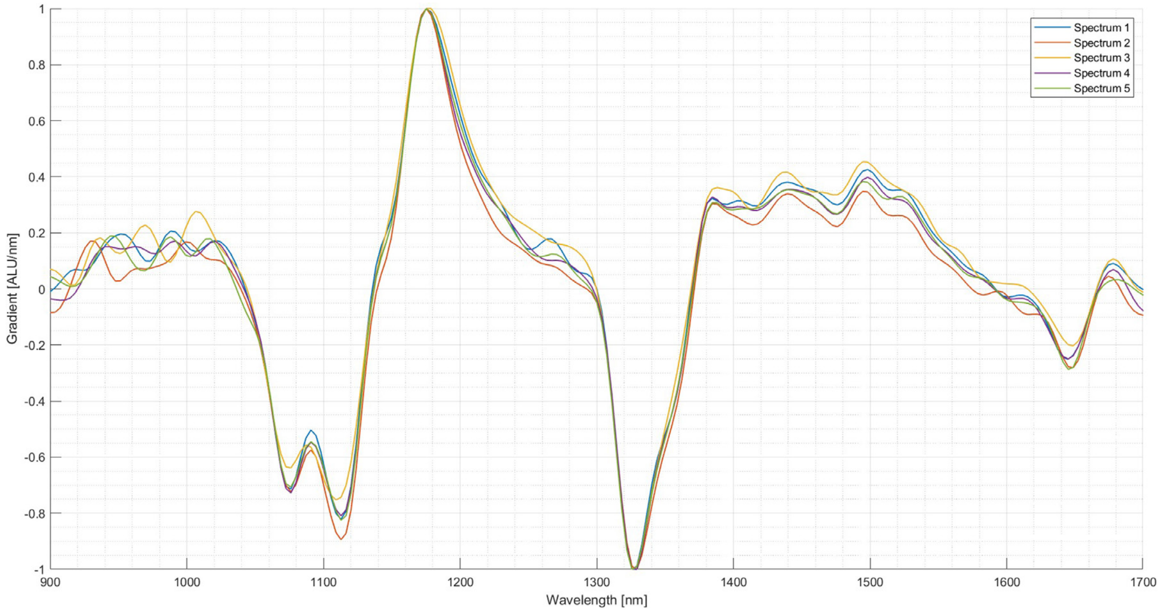

Fig. 6. Scattering of the first derivative of the NIR-spectrum of PP amongst different Pixels (evaluation performed in MATLAB, authors depiction).

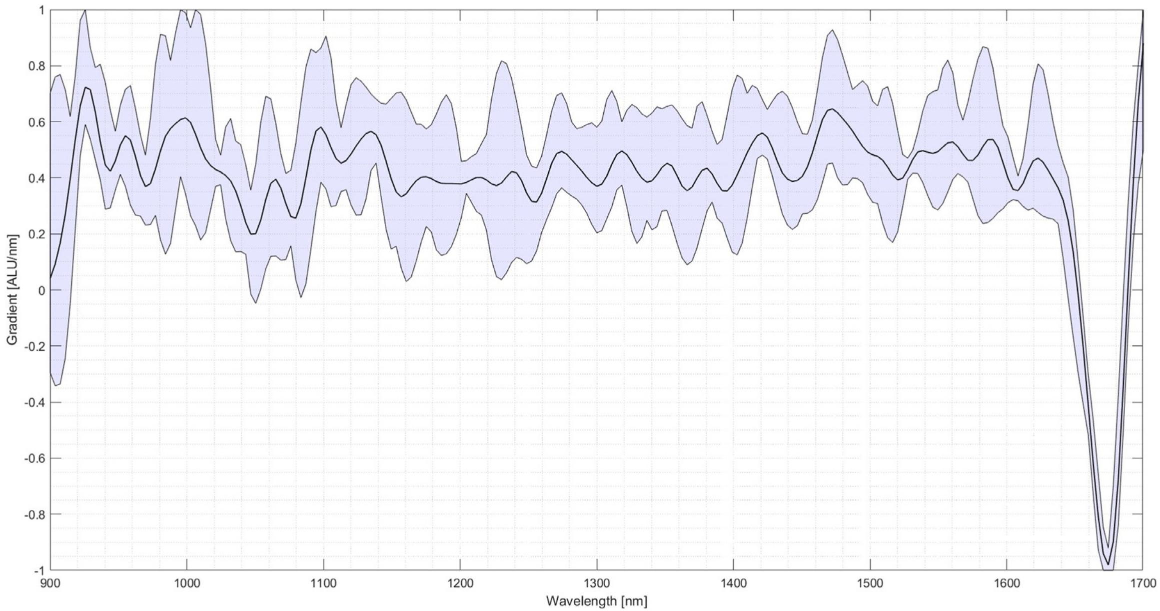

Fig. 7. Scattering of the first derivative of the NIR-spectrum of PET (blue) (evaluation performed in MATLAB, authors depiction).

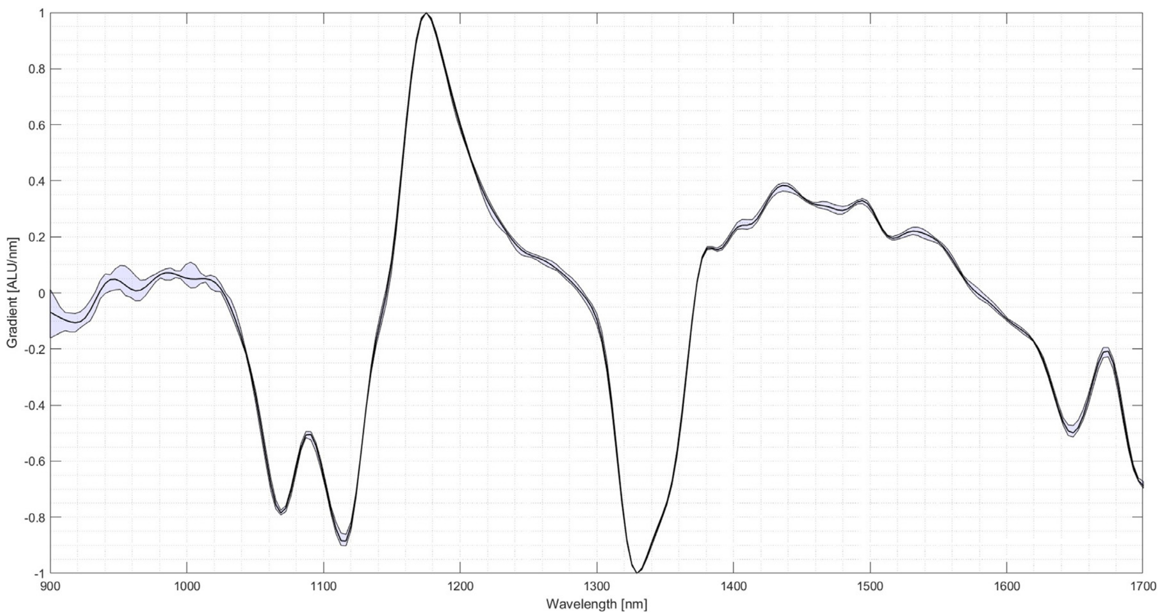

Fig. 8. Scattering of the first derivative of the NIR-spectrum of yellow TPU (evaluation performed in MATLAB, authors depiction).

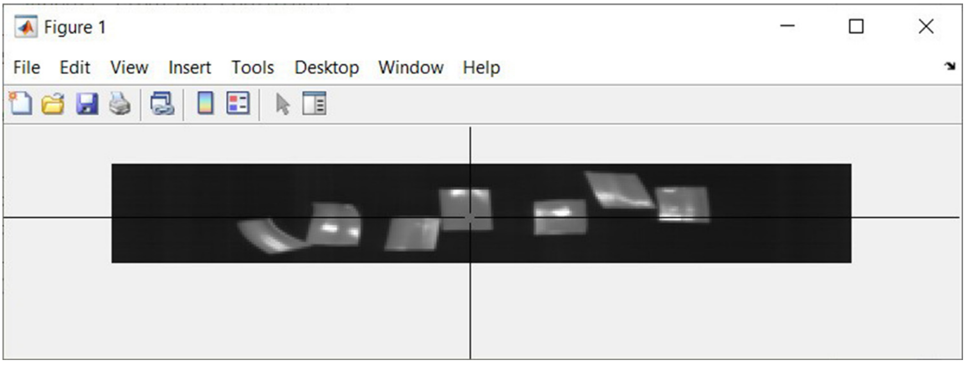

Fig. 9. Selection of pixels for evaluation from the visualised HSI Cube in SQALAR (authors depiction).

which normalises the data to have a mean of 0 and a standard deviation of 1. A smoothing interval of 10 means the smoothing was applied taking the median over a ten-element sliding window.

These spectra are used as labelled input for the machine learning algorithm underlying the spectral classification. These spectra serve as the training data for the supervised machine learning approaches used to label new spectra or in other words, to classify materials into pre-defined groups. In order to achieve this, partial least square regression is used. This approach allows the classification of material without the need to explicitly program every spectrum which could likely be encountered when sorting materials. The rigor, with which spectra which deviate from the training set are discarded, or counted as “not classified”, can be determined by the user via the previously mentioned threshold parameter.

Once the spectra have been successfully assigned to the materials, the wavelength range is selected in SQALAR for usage in the following sorting process to select specific ranges in which the spectra differ significantly. Fig. 11 shows the chosen wavelength ranges in the left side of the Figure (1). The images on the right side of the Figure (2) show the pieces and the classified material type, visualised by the respective colour. It is shown that PP is covered best. PET is also well covered, except for some small areas at the edges assigned to unclassified material (yellow). The yellow lines in the frames can be attributed to dirt on the chute. The third image shows TPU, which has larger misclassified edge areas identified either unclassified or PP. Since the coverage ratio is greatly exceeding 50%, sorting should be feasible. The higher weighting of the successfully identified parts can further improve the sorting.

After finishing the classification program and transferring it to the MMI, the settings of the air nozzles are adjusted as described previously for VIS technology. For the sorting experiment, PP is the target material for ejection.

The sorting trial is started by putting the test fraction on the conveyor and running the system. The principle of the sorting process is the same as for the VIS sorting. After the sorting is finished, the two separated fractions are manually sorted by target and non-target material and then weighed to evaluate the sorting process’s quality.

Method application

The feed material is a mixed fraction of different plastic components with a corresponding colour, see Table 4. NIR spectroscopy is used as sorting technology. The aim is to achieve the purest possible output of PP (following Fig. 1).

The material is separated using a vibration conveyor (1) and moved into the sensor’s exposure area via a slide or chute (2).

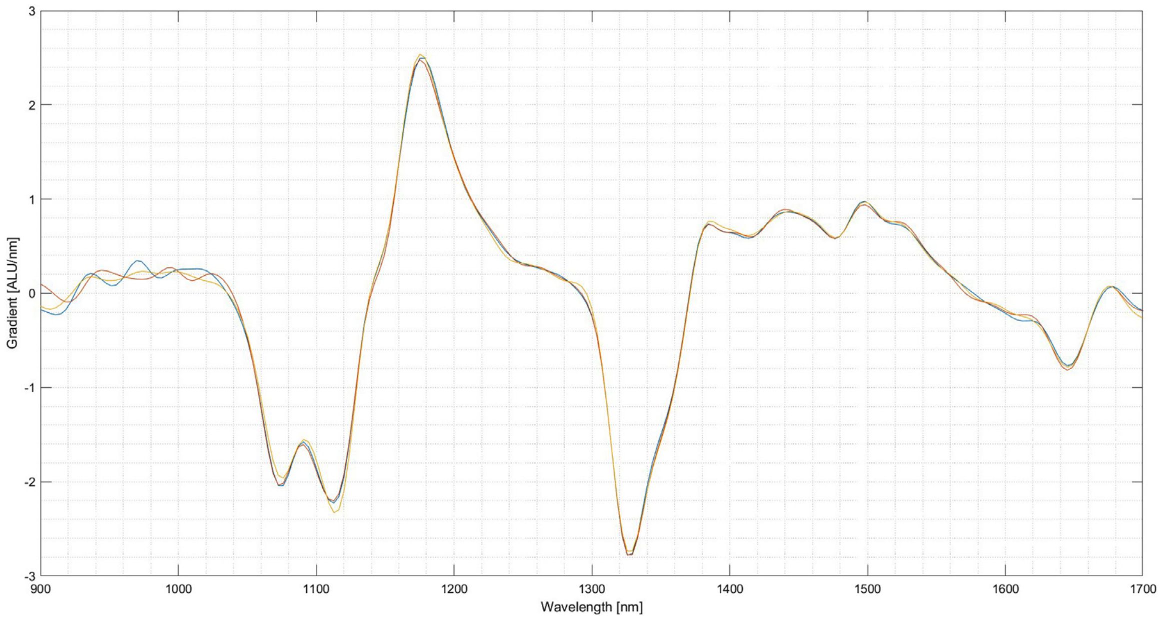

Fig. 10. Spectral evaluation of PP pixels after processing (evaluation performed in MATLAB, authors depiction).

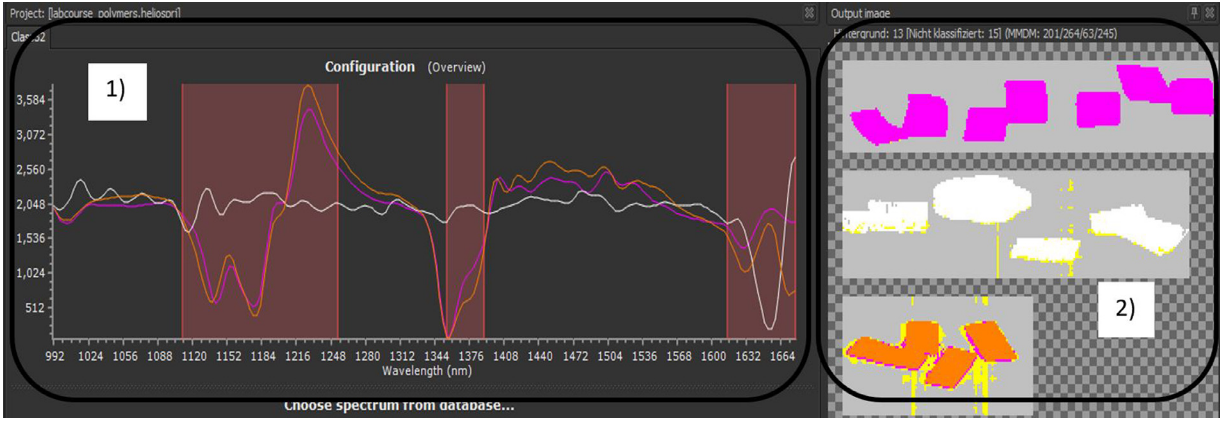

Fig. 11. Creating the classification program in SQALAR for the NIR experiment: 1) selecting three wavelength sections visualised by the red areas, 2) coverage ratios of the used pieces (PP purple, PET white, TPU orange) (authors depiction).

Table 7
Data of the NIR experiment.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Time of experiment	*s*	41	41	36	38	38	40	38	40	37	38
Input mass	*kg*	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09	1.09
Mass of eject	*kg*	0.11	0.02	0.11	0.13	0.10	0.11	0.12	0.10	0.14	0.14
Mass of reject	*kg*	0.98	0.98	0.98	0.96	1.00	0.98	0.97	0.99	0.95	0.95
Target material in eject	*kg*	0.10	0.01	0.10	0.10	0.09	0.10	0.10	0.09	0.10	0.10
Target material in reject	*kg*	0.00	0.00	0.00	0.00	0.01	0.00	0.00	0.01	0.00	0.00
Non-target material in eject	*kg*	0.01	0.01	0.01	0.03	0.01	0.01	0.02	0.01	0.04	0.04
Non-target material in reject	*kg*	0.98	0.98	0.98	0.96	0.99	0.98	0.97	0.98	0.95	0.95

Table 8
Results of the NIR experiment.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Throughput-rate	*kg/(h*m)*	191.2	191.2	217.8	206.3	206.3	196.0	206.3	196.0	211.9	206.3
Purity	*%*	91.7	66.7	90.8	76.3	93.9	89.4	84.9	92.2	69.9	74.1
Yield	*%*	100.0	100.0	100.0	100.0	92.1	100.0	100.0	93.1	100.0	100.0
Recovery	*%*	10.0	1.4	10.0	12.0	9.1	10.4	10.9	9.4	13.1	12.4
Incorrect discharges	*%*	0.9	0.5	1.0	3.1	0.6	1.2	1.8	0.8	4.4	3.5

Modern NIR sensors (5) cover a wavelength range from around 1000 to 2500 nm. Halogen lamps, for example, can be used as emitters (4). This spectrum contains information that allows conclusions about the chemical composition of the investigated objects.

NIR technology makes it possible to recognise different types of plastic based on specific molecule groups - in the application example PP. Fig. 12 shows the spectra of PET (blue) and PP (red) and the differences between the two materials which are used to separate them from each other. These waves are excited to vibrate by the incident radiation. The wave oscillation energy is split in the reflected and transmitted radiation so that a corresponding absorption band results in the resulting spectrum. The detected spectrum is converted into an electrical signal and processed in an associated evaluation unit. The measured spectrum is compared with several reference spectra from a database. If the spectrum matches one of these spectra, the particle is recognised as the related material and can be sorted. The detection of dark (soot-blackened) materials is a limiting factor that plays a role in plastic processing in particular. These particles usually do not reflect a spectrum detected by the NIR sensor of a sensor-based sorting machine [17].

According to the task, if packaging from the "PP" group is recognised, it must be separated from the rest of the fraction. That is done using a compressed air blast. A valve bar (6) downstream of the sensor opens one or more valves when the PP is in front of the valve bar. The PP is ejected over the separating edge (7). All other types of plastic are deliberately not ejected.

Method validation

The validation use-case is to separate PP as target fraction from the feed material described in Table 4 and Fig. 13.

The throughput rate and the quality parameters are evaluated according to the equations shown for VIS technology. In Table 7, the data from the NIR sorting trial are summarised, where the PP material fraction was targeted for ejection. Table 8 provides the consequent results of the sorting trial in terms of plant and quality performance parameters. Both trials were performed with a different amount of input stream out of the same input fraction. The resulted fractions from the trial are shown in the centred and right picture of Fig. 13.

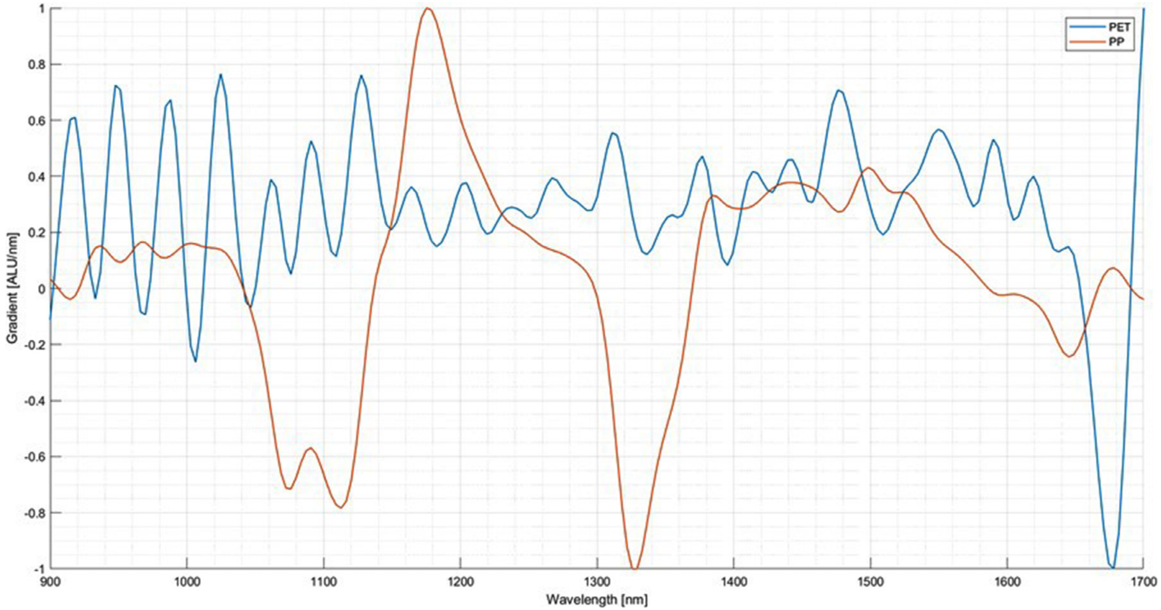

Fig. 12. Recorded spectra using NIR technology on the experimental sensor-based sorting setup and further evaluated in MATLAB: The blue line represents the characteristic PET spectrum while red represents the characteristic PP spectrum (authors depiction).

Fig. 13. Feed material (left), separated PP – Eject (centre) and coloured plastic – Reject (right) (Trial 10 of Table 7) (authors depiction).

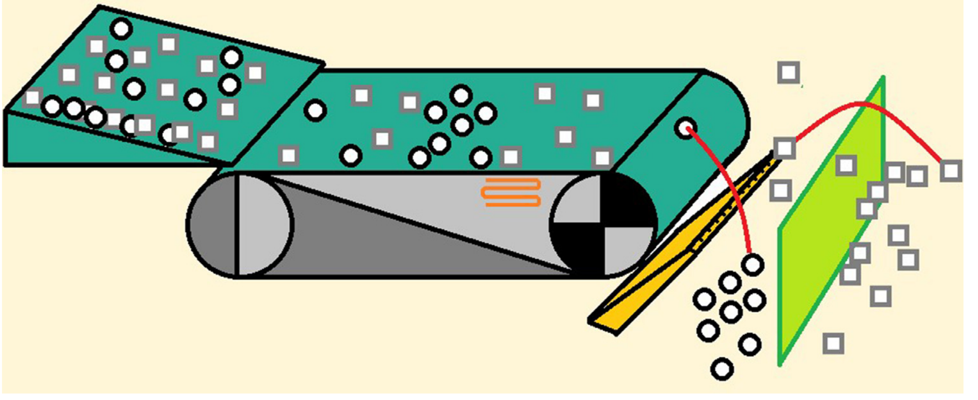

Fig. 14. Typical working schemata of induction sorting with compressed air bar and sorting screen (authors depiction).

Induction Sorting

Method principle

The principal workings of induction sorting are well explained and understood. Therefore, the following will be a summary of the methods working principles [18]. Valuable metal content can be separated from the non-metallic waste stream by deploying three different methods. One of those, apart from eddy current sorting and magnetic sorting, are induction sorting systems. These sensors identify metallic objects in the waste stream via magnetic induction. Coils in the sensor generate a magnetic field, which, once a metallic object, or, in broader terms, a conductive object, moves past, it induces an electric current. According to the programming, this electronic signal is sent to a computing unit that activates an ejector mechanism, usually in the form of a compressed air nozzle array. This compressed air pushes the detected metal objects over a diverting screen, separating them from the material flow and generating a metallic fraction.

The size of the coils depends on the grain size of the material to be sorted and has to be chosen accordingly. Fig. 14 shows the working principle of an induction separating unit.

Method description

In contrast to develop sorting models for the VIS and NIR sensor, the sorting model for induction consists only on the setup of parameters for the induction sensor. These parameters can be set on the man-machine-interface (MMI) of the experimental sorting setups control cabinet. These parameters are the follows:

- Delay time [ms]: Defines the time from the sensors object detection to the activation of the valve.
- Minimum blow-out time [ms]: Defines how long the valve are minimum opened.
- Minimum object size [mm]: Minimum size of an object that the valves from the air nozzle bar opens.
- Scaling [%]: Object scaling can either stretch or compress the object, it can be set from 50 to 100 %.
- Edge valve: A button to be activated, when the edge valves of the compressed air nozzle bar should be activated.
- Sensitivity: Defines the threshold value when the metal sensor should detect metal objects as metal objects, this threshold can be set from 5 to 750.

Table 9
Data of the induction experiment.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Time of experiment	*s*	52	53	52	55	47	53	53	49	57	55
Input mass	*kg*	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00	1.00
Mass of eject	*kg*	0.27	0.27	0.26	0.26	0.25	0.24	0.24	0.26	0.24	0.24
Mass of reject	*kg*	0.73	0.73	0.74	0.74	0.75	0.76	0.76	0.74	0.76	0.76
Target material in eject	*kg*	0.19	0.2	0.19	0.2	0.2	0.19	0.18	0.19	0.18	0.19
Target material in reject	*kg*	0.06	0.05	0.06	0.05	0.05	0.06	0.07	0.06	0.07	0.06
Non-target material in eject	*kg*	0.08	0.07	0.07	0.06	0.05	0.05	0.06	0.07	0.06	0.05
Non-target material in reject	*kg*	0.67	0.68	0.68	0.69	0.70	0.70	0.69	0.68	0.69	0.70

Table 10
Results of the induction experiment.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Throughput-rate	*kg/(h*m)*	138.5	135.8	138.5	130.9	153.2	135.8	135.8	146.9	126.3	130.9
Purity	*%*	70.4	74.1	73.1	76.9	80.0	79.2	75.0	73.1	75.0	79.2
Yield	*%*	76.0	80.0	76.0	80.0	80.0	76.0	72.0	76.0	72.0	76.0
Recovery	*%*	27.0	27.0	26.0	26.0	25.0	24.0	24.0	26.0	24.0	24.0
Incorrect discharges	*%*	10.7	9.3	9.3	8.0	6.7	6.7	8.0	9.3	8.0	6.7

Method application

The induction sorting system complements magnetic sorting and eddy current separation for recovering residual metals from a mix of materials. It is particularly suitable for stainless steel and composite materials such as cables or circuit boards. It can be used to focus on the production of recoverable metal concentrates, such as a stainless-steel fraction. However, the goal of processing can also be to produce a metal-free residual fraction with less than 1% metal to meet acceptable qualities and purities, e.g. in the production of residue derived fuels. Both tasks are the core applications of induction sorting systems.

Metallised foils can be separated from their unmetalled counterparts because the detection sensitivity of the induction sensor can be increased until the minute amount of metallisation can be detected. This approach allows the detection of metallised 2D materials and permits their ejection. Metallised foils are inherently difficult to be detected with a NIR sensor. There is a high probability that the metallised layer will be the side facing the NIR detector, prohibiting any form of NIR detection since the NIR inactive metal layer reflects most radiation. It is, therefore, useful to detect those metallised particles by induction sorting. Further, the reaction time between detection and ejection can be modified to account for the aerodynamics of the material. Metallised foils drop comparatively slowly, so the reaction time could be increased while sensitivity and reaction time had to be decreased when separating refuse derived fuel (RDF) from metallic contaminants.

Method validation

The induction sensor settings for the following trial are a delay time of 65 ms, a minimum blow-out time of 15 ms, a minimum object size of 3 mm, a scaling of 100 %, activated edge valves and a sensitivity of 35. The throughput rate and the quality parameters are evaluated according to the equations shown for VIS technology. In Table 9, the data from the induction sorting trial are summarised, where the metals in a refuse-derived fuel stream were targeted for ejection. Table 10 provides the consequent results of the sorting trial in terms of plant and quality performance parameters. The resulted fractions from the trial are shown in the centred and right picture of Fig. 15.

Fig. 15. Feed material (left), separated metal – Eject (centre) and refuse-derived fuel – Reject (right) (Trial 4 of Table 9) (authors depiction).

Fig. 16. Input composition of sensor fusion trial (authors depiction).

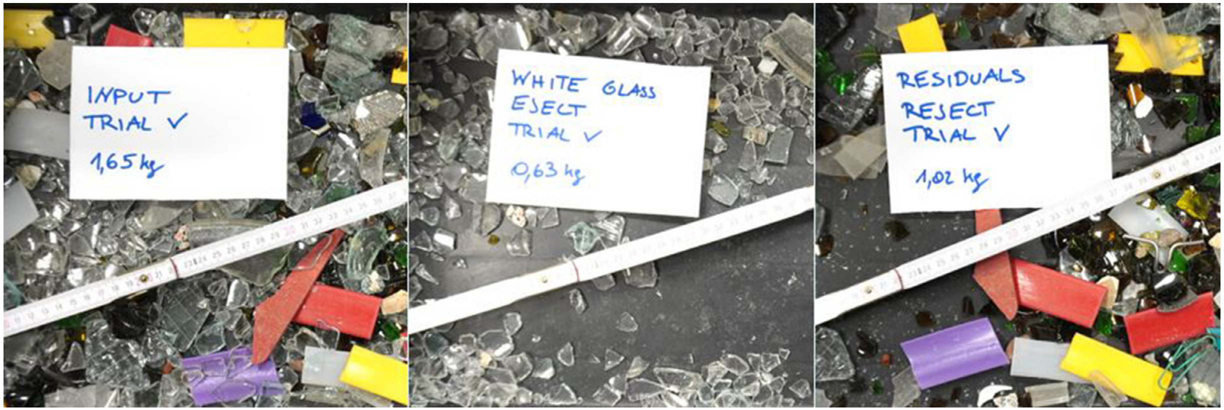

Fig. 17. Feed material (left), separated white glass – Eject (centre) and residuals – Reject (right) (Trial 5 of Table 12) (authors depiction).

Table 11
Input composition of sensor fusion trial.

Input Material	Unit	Mass
PP	*kg*	0.01
HDPE	*kg*	0.01
TPU	*kg*	0.02
LLDPE	*kg*	0.01
LDPE - Red	*kg*	0.03
LDPE - White	*kg*	0.04
PMMA	*kg*	0.04
White Glass	*kg*	0.63
Wire Glass	*kg*	0.31
Coloured Glass	*kg*	0.46
Ceramics	*kg*	0.02
Metals	*kg*	0.03

Table 12
Data of the sensor fusion experiment.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Time of experiment	*s*	57	47	54	50	52	56	50	53	48	50
Input mass	*kg*	1.66	1.66	1.66	1.65	1.65	1.65	1.65	1.65	1.65	1.65
Mass of eject	*kg*	0.63	0.62	0.61	0.63	0.63	0.63	0.60	0.61	0.61	0.60
Mass of reject	*kg*	1.02	1.04	1.09	1.02	1.02	1.02	1.05	1.04	1.04	1.05
Target material in eject	*kg*	0.63	0.62	0.61	0.62	0.63	0.63	0.60	0.61	0.61	0.60
Target material in reject	*kg*	0.02	0.04	0.04	0.02	0.02	0.01	0.05	0.03	0.03	0.04
Non-target material in eject	*kg*	0.00	0.00	0.00	0.01	0.00	0.00	0.00	0.00	0.00	0.00
Non-target material in reject	*kg*	1.00	1.00	1.05	1.00	1.00	1.00	1.01	1.00	1.01	1.01

Table 13
Results of the sensor fusion experiment.

	Unit	Trial 1	Trial 2	Trial 3	Trial 4	Trial 5	Trial 6	Trial 7	Trial 8	Trial 9	Trial 10
Throughput-rate	*kg/(h*m)*	209.1	253.5	220.7	237.9	228.7	212.1	237.9	224.0	247.1	237.5
Purity	*%*	100.0	100.0	100.0	98.9	100.0	100.0	100.0	100.0	100.0	100.0
Yield	*%*	97.4	93.9	93.8	96.9	97.4	97.8	92.7	94.7	95.9	93.8
Recovery	*%*	38.3	37.3	36.7	38.2	38.1	38.2	36.0	36.9	37.1	36.6
Incorrect discharges	*%*	0.0	0.0	0.0	0.7	0.0	0.0	0.0	0.0	0.0	0.0

Sensor fusion

Method principle and method description

In principle, all separation characteristics that can be measured without contact using sensors, such as shape, color, gloss, molecular composition, density or electrical conductivity are used. Today, various detection methods are mostly used combined to ensure simultaneous detection of multiple material properties, this is called multi-sensor technology or sensor fusion [17,19]. This approach is useful for sorting material compositions. An example is the fusion of previously described technologies NIR, VIS and induction, to eject white glass from a mixed waste fraction composed of plastics, mixed coloured glas, wire glass and metals).

Further sensor fusion techniques currently employed and under development, like X-Ray or marker-based sorting can further increase the efficiency of sensor fusion by increasing the number of physical and chemical properties and manmade markers by which sorting of refuse can be undertaken.

Method application

The method described here utilises the aforementioned technologies, NIR, VIS and induction combined to generate a valuable product of pure white glass from an input consisting of LDPE, HDPE, PP, TPU, linear low density polyethylene (LLDPE), polymethylmethacrylate (PMMA), mixed coloured glass, wire glass and metals (Table 11 and Fig. 16). In one trial, NIR combined with VIS spectroscopy is used to eject only the valuable white glass by combining detection of the characteristic plastic NIR fingerprints to sort out plastics with the inclusion of the respective VIS model for white glass. Further, induction classification of the particle is set up negative, assuring the white glass fraction is not polluted by wire glass particles which would be ejected alongside the white glass. This sensor fusion ensures, that only white glass is ejected.

Method validation

The validation use-case is to sort white glass as target fraction from the feed material described in Table 11 and Fig. 17.

The throughput rate and the quality parameters are evaluated according to the equations shown for VIS technology. In Table 12, the data from the sensor fusion trials are summarised, where the white glass was targeted for ejection. Table 13 provides the consequent results of the sorting trial in terms of plant and quality performance parameters. Both trials were performed with a different amount of input stream out of the same input fraction. The resulted fractions from the trial are shown in the centred and right picture of Fig. 17.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.mex.2022.101686.

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4.2 Publication VI, Identification, Surface Roughness

"Influences and consequences of mechanical delabelling on pet recycling"

Original Article
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The annotation on the doctoral candidate's contribution to this publication is listed in Table 4-2.

Table 4-2: Annotation on the doctoral candidate's contribution to Publication VI

Conceptualization	Küppers, B., Chen, X., **Friedrich, K.**, Raulf, K., Pretz, T., Feil, A., Pomberger, R., Vollprecht, D.
Methodology	Küppers, B., Chen, X., **Friedrich, K.**
Software	Chen, X.
Validation	Küppers, B., Chen, X., Seidler, I., **Friedrich, K.**
Formal Analysis	Küppers, B., Chen, X., Seidler, I. **Friedrich, K.**, Raulf, K., Pretz, T., Feil, A., Pomberger, R., Vollprecht, D.
Investigation	Küppers, B., Chen, X., Seidler, I., **Friedrich, K.**, Pretz, T.
Resources	-
Data Curation	Küppers, B., Chen, X., Seidler, I., **Friedrich, K.**
Writing: Original Draft Preparation	Küppers, B., Seidler, I., **Friedrich, K.**
Writing: Review and Editing	Küppers, B., Seidler, I., **Friedrich, K.**
Visualization	Küppers, B., Seidler, I., **Friedrich, K.**
Supervision	Raulf, K., Pretz, T., Feil, A., Pomberger, R., Vollprecht, D.
Project Administration	Küppers, B.
Funding Acquisition	Raulf, K., Pretz, T., Feil, A., Pomberger, R., Vollprecht, D.

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INFLUENCES AND CONSEQUENCES OF MECHANICAL DELABELLING ON PET RECYCLING

Bastian Küppers [1,*], Xiaozheng Chen [2], Irina Seidler [1], Karl Friedrich [1], Karoline Raulf [2], Thomas Pretz [2], Alexander Feil [2], Roland Pomberger [1] and Daniel Vollprecht [1]

[1] *Montanuniversitaet Leoben, Chair of Waste Processing Technology and Waste Management, Austria*
[2] *Rheinisch Westfalische Technische Hochschule Aachen, Department of Processing and Recycling, Germany*

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ABSTRACT
The recycling of polyethylene terephthalate (PET) is an important issue of today's society. Mechanical recycling makes more sense from an ecological point of view than chemical PET recycling. However, mechanical recycling still is highly susceptible to defilements. Therefore, intensive pre-treatment is necessary to ensure the mechanical production of high-quality recycled PET. An important step in this process is to separate the PET bottles from their labels/sleeves. For this purpose, a newly developed label remover was studied. In this study, it was found that the machine had a delabelling efficiency of 90 w%. The PET bottles that were not sufficiently delabelled (10 wt.%) on average had a significantly smaller bottle size. This means that a sharp screening step, prior to delabelling, could improve the delabelling efficiency furthermore. Additionally, the applicability of near-infrared sorting technology was tested to find out, whether it can be used for quality control. Tests showed that state-of-the-art technology could differentiate between labelled and delabelled PET bottles, enabling separation of labelled PET bottles from delabelled bottles via sensor-based sorting. Hence, the proportion of contaminated PET bottles could be reduced furthermore with additional processing steps.

1. INTRODUCTION

Polyethylene terephthalate (PET) is one of the most common and prevalent thermoplastic polymers in today's society. It is used for the production of beverage bottles, fibres, moldings, sheets and other packaging material. Especially its worldwide usage as a container for beverages can be explained by the, in comparison to other plastic types, superior properties such as chemical, physical, mechanical, oxygen and carbon dioxide barrier features. The high clarity of PET constitutes a major advantage in comparison to many other packaging polymers. These properties contributed to the increased consumption of PET since the 1950s (Shen et al., 2010; Burat et al., 2009; Welle, 2011).

Due to the high quantities of PET bottles, this material presents a significant amount of today's waste. Since PET is not degradable under normal conditions and therefore occurs in aged waste excavated during landfill mining, expensive procedures would be needed in order to degrade PET biologically. In contrast, recycling processes constitute a relatively cost-effective method to reduce landfilling or incineration of PET waste. Therefore, its recycling is driven forward constantly (Awaja and Pavel, 2005).

Usually for recycling, first, mechanical pre-processing steps are applied to generate PET flakes that can be recycled chemically via depolymerisation or mechanically via extrusion. Chemical recycling offers the advantage that the recycled PET (RPET) has better properties than mechanically recycled PET, enabling a wide-ranging variety of possible applications. These superior properties come at the cost of a worse environmental profile of the chemical recycling process. During this process, the PET polymer is stripped down into monomers or oligomers using depolymerisation, resulting in an economically inferior process (Shen et al., 2010).

To receive better product qualities of mechanically manufactured recycled PET (RPET), the quality of their PET flakes must be improved. One of the main influencing factors on quality is the number of contaminants that enter RPET. These contaminants can be reduced by sorting out other materials, such as polyethylene (PE), polypropylene (PP) as well as metals. In order to separate PE and PP that are used for labels and sleeves from PET, pre-conditioning in form of delabelling can be necessary. (Awaja and Pavel, 2005).

Especially due to marketing requirements, labels and sleeves become more popular and their size is often in-

* Corresponding author:
Bastian Küppers
email: bastian.kueppers@unileoben.ac.at

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creased for promotional actions like enhancing packaging decoration. The variety of labels used on PET bottles is significant. Mainly low-density polyethylene (LDPE) and/or polyvinyl chloride (PVC) labels are used. Nevertheless, also labels and sleeves made out of 2-phenylphenol, polypropylene, and polystyrene can be found on the market. Such labels cannot only have an enormous effect on the quality of RPET but also affect the mechanical processing and sorting of PET bottles resulting in decreased machine efficiencies and recycling rates. If labels and sleeves are successfully removed from the PET bottles, they can be sold as by-products or be incinerated. The separation of labels/sleeves and bottles can also be accomplished by a washing process (Shen et al. 2010; Cotrep, 2012).

In this work, the separation efficiency of an innovative delabelling stage is tested and assessed at the pilot scale. Furthermore, its intelligent utilization in combination with sensor-based sorting machines is discussed. At last, the effects of the delabelling stage on the efficiency of downstream sensor-based sorting machines, applying near-infrared (NIR) technology, are studied.

2. PET RECYCLING - AN OVERVIEW

In order to recycle PET bottles, they have to be collected first. In Europe, this usually happens under schemes which follow the rule of producer responsibility. In some countries, PET bottles are collected within the household waste or via deposit-refund systems like in Germany. Either way, the collection of PET bottles is carried out on a local scale to transport the PET bottles to separation centres (Arena et al., 2003).

In waste separation centres, the bottles undergo several mechanical processing steps. Since the bottles often arrive in bales, a bale opener is used to disperse the bottles. Afterwards, either pre-washing or delabelling is necessary to remove labels and sleeves, enabling successful and efficient sorting of the bottles. In case of a washing step, an 80°C hot solution with 2% NaOH can be used. In the dry mechanical delabelling step, assessed in this study, mechanical friction is applied to tear the label or sleeve of the PET bottles (Awaja and Pavel, 2005).

The sorting of the material is often conducted via sensor-based sorting machines but can also be done manually. Magnetic and eddy current separators can be used to separate ferrous and non-ferrous metals. After separating undesirable materials and contaminants, the bottles can be sorted, e.g. according to their colour. At last the bottles are shredded into flakes, washed and have to be dried carefully. For the final washing step of the PET flakes, solvent washing with tetrachloroethylene is suitable. Since the minimization of the moisture content is most important to reduce hydrolytic degradation, the drying stage is essential after washing. Usually drying temperatures between 140 and 170°C, with a retention time between 3 and 7 hours are chosen in order to reach < 50 ppm water in PET flakes. To ensure the required purity of the PET flakes, a sensor-based sorting step might be necessary (Shen et al., 2010; Kranert, 2017; Awaja and Pavel, 2005; Assadi et al., 2004).

In this way, about 75 w.% of the baled PET bottles are processed to PET flakes and can be used for mechanical or chemical recycling. Losses occur during mechanical treatment, e.g. in the form of defilements, plastic and paper labels/sleeves, PE-/PP-caps and metals. 11-14 w.% of these fractions can be sold as by-products (PE caps, PVC/LDPE sleeves, etc.) while 14-18 w.% resemble solid waste and have to be treated furthermore (Shen et al., 2010).

The described mechanical pre-processing steps are necessary to prepare the PET for its further processing. Especially the quality characteristics of PET flakes must be achieved to ensure successful mechanical recycling. In Table 1, the minimum requirements for RPET flakes are given.

The degradation of RPET is increased by contaminants such as polyolefins or PVC, causing a reduction of the molecular weight and intrinsic viscosity of PET. This leads to a deterioration of the RPET properties. Reinforcing fillers and toughening modifiers then have to be applied to counteract the drop in molecular weight. (Srithep et al., 2011; Awaja and Pavel, 2005)

Once the minimum requirements for RPET flakes are met, they can be converted to granules or finished products at 280°C via melt extrusion. In comparison to chemical recycling, extrusion is a relatively simple, environmentally friendly and cost-effective process. However, to reduce the main disadvantage of mechanical recycling (reduction of molecular weight), mechanical processing must be improved (Shen et al., 2010).

In accordance with the topic of this study, a special focus lies on the influence of labels and sleeves on the recycling process of PET bottles despite their negative impact on RPET quality. During the sorting stage, labels and sleeves often remain on the PET bottles and can end up in the PET stream as well as in the PE or waste stream. Depending on the type of plastic used for the labels/sleeves, their thickness and size, PET bottles might not be identified correctly as PET and could be sorted out wrongly as undesirables. In this case, the PET yield would be significantly decreased since e.g. all full-sleeve PET bottles might be lost. Because of this reduction of the PET yield Cotrep (the technical committee for recycling of plastic packaging in France) recommends the use of partial labels and sleeves (Cotrep, 2012).

PVC labels are classified as unfavourable because PVC has a significant negative impact on RPET. It decomposes

TABLE 1: Minimum requirements for post-consumer-PET flakes to be reprocessed (Awaja and Pavel).

Property	Value
Viscosity [η]	> 0.7 dl g^{-1}
Melting point [Tm]	> 240°C
Water content	< 0.02 wt.%
Flake size	0.4 mm < D < 8 mm
Dye content	< 10 ppm
Yellowing index	< 20
Metal content	< 3 ppm
PVC content	< 50 ppm
Polyolefin content	< 10 ppm

during extrusion, clogs extruder fillers and causes further quality problems. Hence, if a PVC flake is detected in the PET flake stream, the separation of PVC has to be ensured. For a singular separated PVC flake up to 100 flakes are ejected. Because of this, more losses are generated and the amount of waste to be disposed of is rising (Cotrep, 2012). Cotrep recommends that labels and sleeves that are made out of polystyrene (PS) and PET-G should be substituted because they tend to deteriorate, form impurities (PS) and create yellowing (PS and PET-G) in RPET. Shrink LDPE labels are classified as favourable since they do not disrupt the recycling process significantly (Cotrep, 2012).

3. MATERIAL AND METHODS

PET bottles from a public collection system were obtained as input material for the delabelling trials. To generate reliable data, only empty bottles with fully attached labels were chosen for the trials. In total 98 kg of PET bottles with labels or sleeves were handpicked. An exemplary picture of the handpicked PET bottles is given in Figure 1. One can be seen that most of the bottles are deformed or crushed. The samples had a bulk density of around 50 kg/m³.

FIGURE 1: Input material for delabelling trials - PET bottles from the public collection system.

Delabelling trials were conducted with the "STADLER label remover" (max. throughput 8 t/h, dimensions 2,733 × 1,862 × 2,317 mm (L x W x H) stator diameter of 1,600 mm and drive power of 37 kW, rotor speed of 200 rpm) at the Stadler Technology Centre in Krško, Slovenia. As can be seen in Figure 2, the label remover is equipped with rotating arms that have jagged knives made from high-tensile steel. The length of these arms can be adjusted via slot holes. So, the distances between the knives on the rotating arms and the knives on the inner wall can be adjusted to fit the size of the input material. The general principle is that less space between the knives causes more delabelling at the risk of bottles being torn. Two types of knives are mounted to the inner wall:

- Vertically mounted knives
- Knives with an adjustable angle

The knives with adjustable angle enable the machine operator to modify the retention time of the input material: the more obtuse the angle, the longer the retention time.

For the trials, the input material was divided into two equally sized samples each weighing 49 kg. Two trials were run at a throughput of about 4 t/h. In the first and last seconds of each round, a continuous feed into the label remover could not be ensured. Particles at the beginning and the end of a round could falsify the results due to higher retention times. Therefore, only the delabelled product that was generated while a steady feed of the machine could be ensured was further studied. As a result of this approach, of the 49.0 kg input material per trial, 33.2 kg and 34.9 kg could be analysed respectively. It has to be mentioned, that

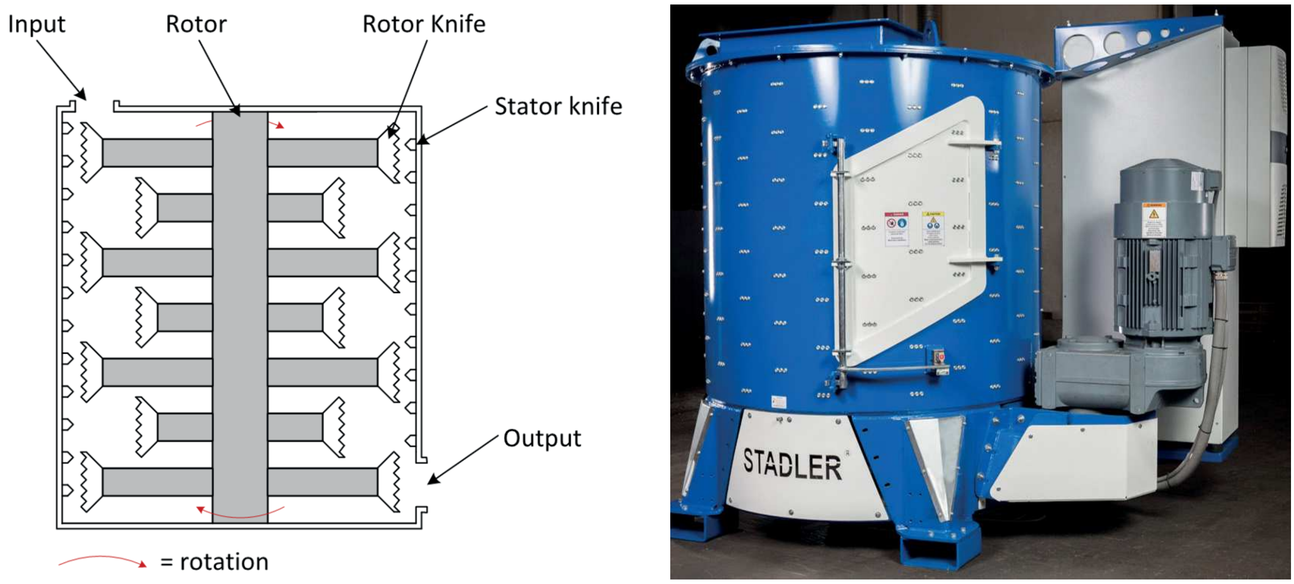

FIGURE 2: Scheme of the grinding chamber and picture of the "STADLER label remover".

the separated labels were not weighed after the trials since too many of them would remain in the delabeller or be lost throughout the trials to make sufficiently sound conclusions.

To evaluate the influence of the delabelling process, samples were taken before as well as after the trials and screened with a laboratory polygonal drum sieve. These screenings were conducted at a mesh size of 80 mm for 90 seconds since this is the typical screening time of packaging material in a technical drum screen of 10 m length (Go et al., 2018). The mesh size of 80 mm was chosen because this screen cut is used industrially to enrich PET bottles in the coarse fraction. PET bottles with a volume of 0.5 l and less can be lost into the fines. Therefore, the number of bottles in the coarse and fine fraction provides information about the predominant bottle size in the screened sample and potential shredding effects of the delabeller. Additionally, the delabelled bottles were sorted manually after the trials and divided into three different categories:

- Good: > 98% of the labels/sleeves were separated from the respective bottles (sufficient)
- Middle: 90-98% of the labels/sleeves were separated from the respective bottles (sufficient)
- Bad: < 90% of the labels/sleeves were separated from the respective bottles (insufficient)

The allocation of the delabelled bottles to these three categories was carried out by manual separation after the trials. Bottles that ended up in category 1 either contained no label at all or only small label pieces at the joins. Category 2 mainly contains bottles with label pieces on the joins. Bottles in category 3 primarily showed labels that were ripped open or sleeves that were sliced in pieces but not separated from the bottle. After the delabelling trials, samples of each category were taken and a screening analysis was conducted with a mesh size of 80 mm.

Before and after the delabelling process, samples of bottles were taken for further investigations with NIR (near infrared) technology. For these analyses, a sensor-based sorting machine from Binder+Co AG, equipped with a hyperspectral imaging (HIS) NIR sensor from EVK (HELIOS NIR G2 320) with a wavelength range from 950 nm to 1700 nm was used. Pictures of the samples, taken before and after the delabelling trials, were captured to analyse the raw spectra of the samples and to classify the different materials contained in the samples using state of the art algorithms. These algorithms consist of the processing steps given in Table 2.

For a classification of each object pixel, the y-values of each spectral band (width of one band is approx. 3.2 nm) were compared with the material specific spectral information implemented in the algorithm. This way, each pixel can be provided with a false colour and less computing power for the evaluation of each particle is necessary. Hence, the classification of each bottle can be performed.

TABLE 2: Preprocessing and spectral processing steps of spectra for classification.

Preprocessing	Spectral Processing
Spatial correction	1st Derivative
Bad pixel replacement	Normalization
Intensity Calibration	Smoothing
Noise suppression	

4. RESULTS AND DISCUSSION

The delabelling efficiency results from the composition of the output of the delabelling trials. The results are given in Table 3.

After visual inspection of the output, it could be found that about 90 wt.% of the bottles were delabelled sufficiently (60 wt.% Good, 30 wt.% Middle), meaning, the number of labels on PET bottles was reduced drastically. About 10 wt.% of the bottles were not delabelled successfully. The visual result can also be withdrawn from Figure 4.

An apparently large number of small bottles was sorted into category 3 (Figure 3). The visual observation can be confirmed with the results of the screening analyses presented in Figure 4. It can be seen, that compared to the

TABLE 3: Output composition - label remover.

	Good	Middle	Bad
Trial 1	62 wt.%	29 wt.%	9 wt.%
Trial 2	59 wt.%	33 wt.%	8 wt.%

FIGURE 3: Output fraction of the delabeller - from left to right: category 1 (Good), category 2 (Middle), category 3 (Bad).

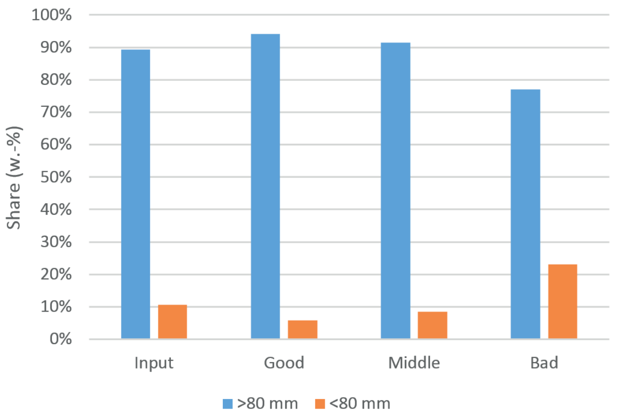

FIGURE 4: Results of screening analyses before and after delabelling.

input analysis, bottles in categories 1 and 2 (Good and Middle) show smaller amounts of material <80 mm (less than 10 wt.%) while category 3 contains more than 20 wt.% of bottles <80 mm.

It must be stated, that no shredded or compacted bottles were found. This suggests that most small bottles were delabelled insufficiently while most big bottles (>0.5 l) were processed successfully. The inverse conclusion of this is that a sieving step prior to the delabelling step would increase the efficiency of the delabeller furthermore, which is in accordance with findings of Go et al., 2018. Additionally, it must be mentioned that the input for the above-shown trials consisting of 100% labelled bottles is not the case in reality. This affects the quality of the output positively by increasing the percentage amount of label-free bottles in the output of the delabelling stage. Besides that, fully affixed paper labels underwent little to no change during the treatment. An example is given in Figure 5.

To determine the impact of labels and of the delabeller on the detection as well as classification of PET bottles, HSI NIR pictures of the bottles, prior and after delabelling, were taken. The different average spectra that were used to distinguish PET from PET covered with a label (PETL) and bottle caps are given in Figure 6. Significant differences between HDPE and the other spectra can be registered. To distinguish PET from PETL pixels, two different spectra for PETL had to be included due to variations concerning the intensity of the peaks, typical for PETL. Therefore, a

FIGURE 5: Impact of delabeller on the fully affixed paper label.

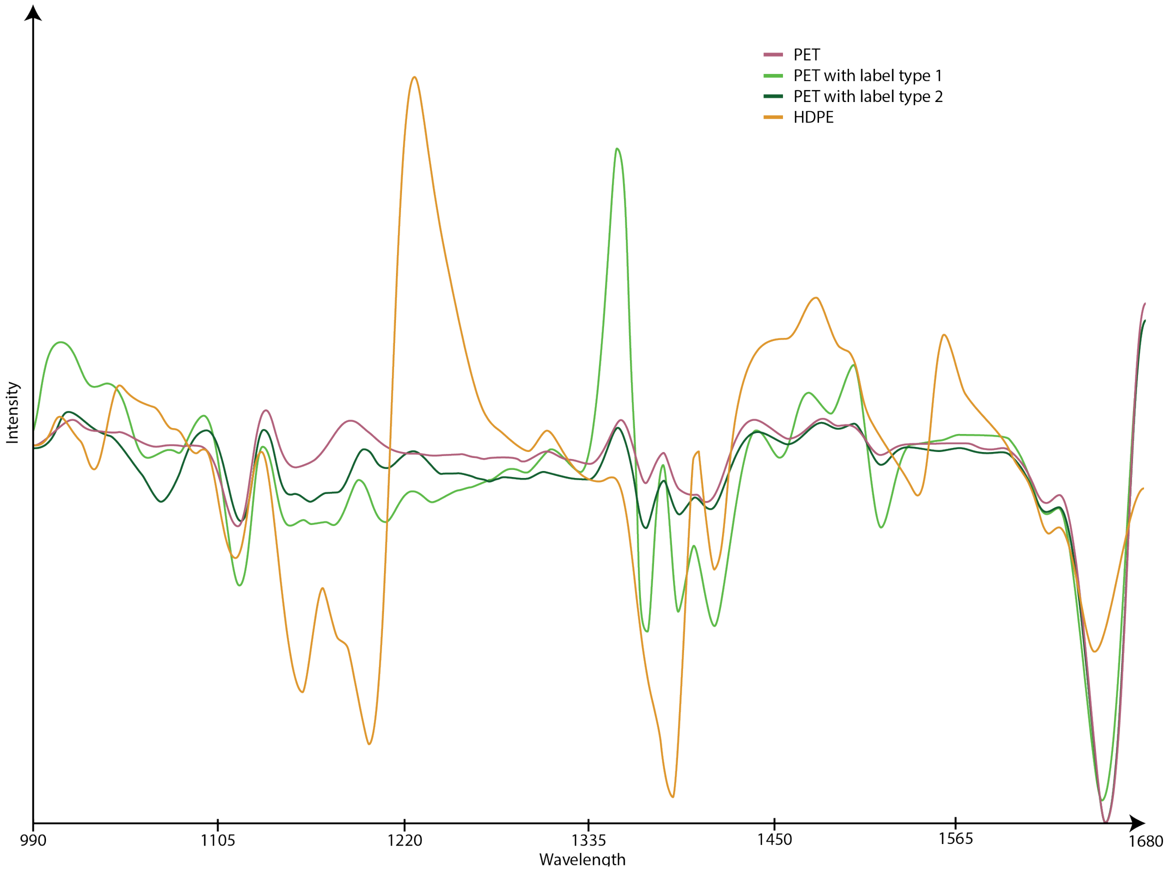

FIGURE 6: Qualitative spectral course (first derivative, normalized) of PET, PET with label type 1, PET with label type 2 and HDPE.

classificator with four different spectra was developed to distinguish between PET, PET with label and HDPE.

Examples for classified bottles are given in Figure 7. It can be seen that PET, HDPE and PETL can be distinguished from each other very well. It should be noted that even though some pixels of the fifth bottle were wrongly classified due to the influence of water, in this trial, all labelled bottles could be correctly classified as such.

To double-check the functionality of the created classificator, pictures of delabelled bottles were taken and classified as well. The result can be seen in Figure 8. All bottles are classified as not labelled PET and the caps (on bottles 1 and 4) are also correctly classified as HDPE. Only a few pixels on the edges of objects in Figure 7 and 8 are falsely classified as PETL due to edge effects. The amount of incorrectly classified pixels is insignificant and differentiation between PET bottles with and without labels can be expected.

Additionally, the extent of the PET spectrum before and after delabelling was analysed as well as the signal-to-noise ratio. In total 60,096 spectra were analysed for this purpose. The results are given in Figures 9 and 10. The spectra before and after delabelling are displayed. Apart from outliers (grey), it can be seen that 90% of the derived spectra (interquantile deviation) show significantly higher extents and marginally higher averaged standard deviations after the delabelling process than before. Prior to delabelling, the characteristic and most important absorption for classification of PET at a wavelength of about 1650 nm is barely noticeable let alone smaller peaks, e.g. between 1110 nm and 1180 nm. This complicates the classification significantly because the spectra have to be normalized for consistent sorting efficiency, which results in enhanced background noise.

Despite the fact that correct classification before and after delabelling is possible, mechanical treatment during label removal simplifies the classification and therefore enhances sorting of PET bottles. The trials showed that the differentiation between labelled and delabelled PET bottles is possible. This can be used for processes aiming for high product purities by installing a downstream sensor-based sorting unit after the delabelling step. The downstream sensor-based sorting unit separates the remaining labelled PET bottles from the delabelled bottles to recirculate them as input for the delabelling step once again.

5. CONCLUSION

For mechanical recycling of PET bottles with the aim of high-quality RPET production, the reduction of defilements is of utmost importance. An important part of this process is the separation of the labels and sleeves from the PET

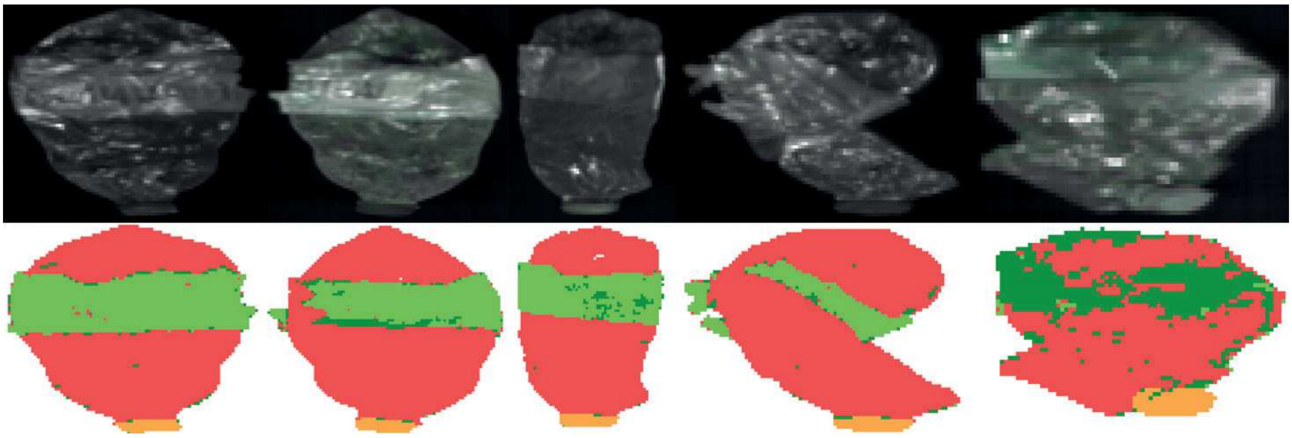

FIGURE 7: Comparison of live picture (upper row) and classified picture with false colours (lower row) of labelled PET bottles; red=PET, green=PETL, orange=HDPE.

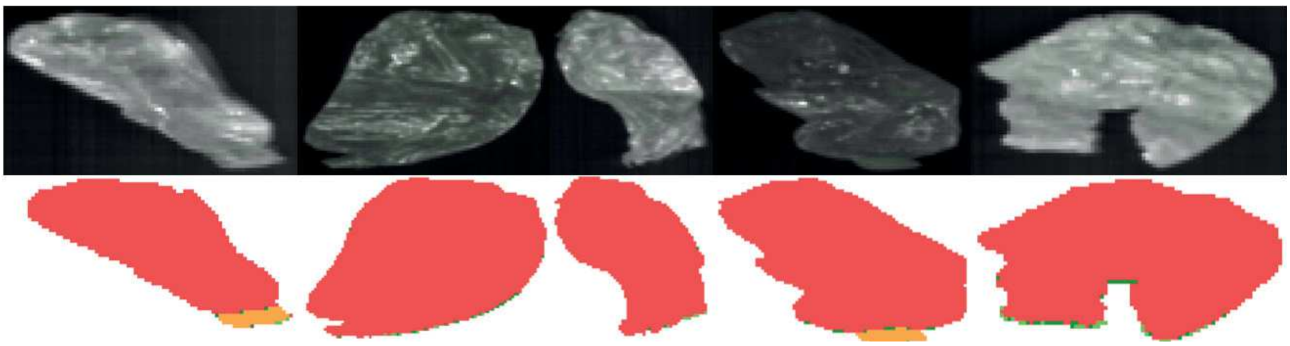

FIGURE 8: Comparison of live picture (upper row) and classified picture with false colours (lower row) of delabelled PET bottles; red=PET, green=PET with label, orange=HDPE.

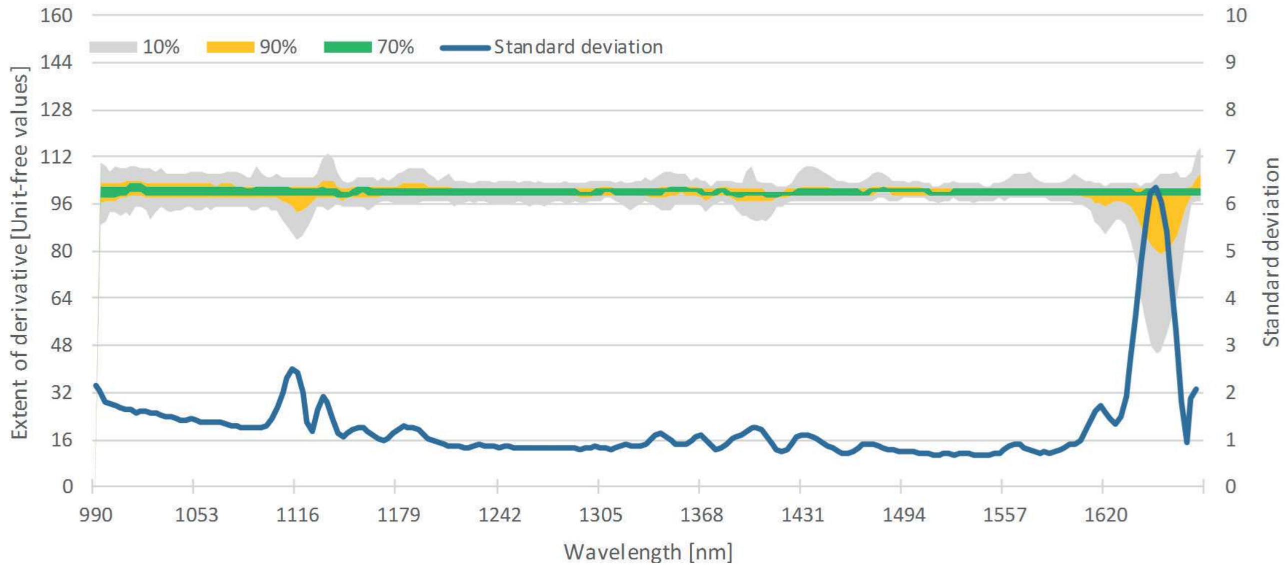

FIGURE 9: Interquantiles (90%, 70%) and outliers (10%) of derivatives basing on the raw spectra, recorded of PET pixels prior to delabelling (primary axis) and standard deviation of derivatives (secondary axis).

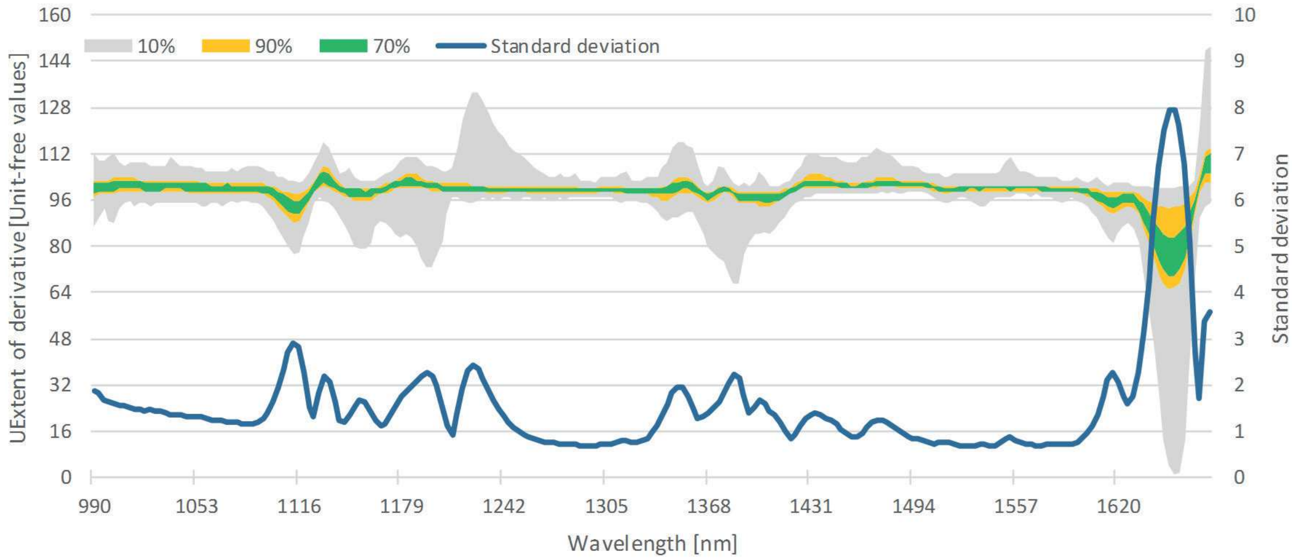

FIGURE 10: Interquantiles (90%, 70%) and outliers (10%) of derivatives basing on the raw spectra, recorded of PET pixels after delabelling (primary axis) and standard deviation of derivatives (secondary axis).

bottles. This can be achieved by the application of a mechanical delabelling step.

The studied "STADLER label remover" showed a delabelling efficiency of 90% at a throughput of about 4 t/h. It was found that the number of bottles unsuccessfully treated was strongly affected by the number of small bottles, <0.5 l filling volume. Therefore, in an industrial process, a screening step prior to delabelling would improve the efficiency of the delabeller furthermore.

Findings showed that the bottles were neither shredded nor significantly deformed during delabelling, enabling high efficiencies of downstream machinery, e.g. sensor-based sorting units. It was found that PET bottles with and without labels/sleeves could be classified and separated when applying HSI NIR technology. A sensor-based sorting unit could be installed downstream a delabeller to sort out PET bottles still containing labels, improving the purity of the PET stream. Additionally, it was found that the mechanical treatment roughens the bottle surface, resulting in an enhanced peak extension and, consequently, improved PET bottle classification.

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4.3 Publication VII, Identification, Transflection

"Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials"

Original Article
Koinig, G., **Friedrich, K.**, Rutrecht, B., Oreski, G., Barretta, C., Vollprecht, D. (2022). *Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials.* In Waste management (New York, N.Y.) 144, pp. 543–551. DOI: 10.1016/j.wasman.2021.12.019.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 4-3.

Table 4-3: Annotation on the doctoral candidate's contribution to Publication VII

Conceptualization	Koinig, G., **Friedrich, K.**, Oreski, G.
Methodology	Koinig, G., **Friedrich, K.**, Oreski, G., Barretta, C.
Software	Koinig, G.
Validation	**Friedrich, K.**
Formal Analysis	Koinig, G., Rutrecht, B., Oreski, G., Barretta, C.
Investigation	Koinig, G., **Friedrich, K.**
Resources	-
Data Curation	Koinig, G., **Friedrich, K.**
Writing: Original Draft Preparation	Koinig, G., **Friedrich, K.**
Writing: Review and Editing	Koinig, G., **Friedrich, K.,** Rutrecht, B., Oreski, G., Barretta, C., Vollprecht, D.
Visualisation	**Friedrich, K.**
Supervision	Koinig, G., Rutrecht, B., Oreski, G., Barretta, C., Vollprecht, D.
Project Administration	Koinig, G., Oreski, G., Barretta, C., Vollprecht, D.
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Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials

G. Koinig [a,*], K. Friedrich [a], B. Rutrecht [a], G. Oreski [b], C. Barretta [b], D. Vollprecht [a]

[a] Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Franz Josef Straße 18, Leoben 8700, Austria

[b] Polymer Competence Center Leoben GmbH, Roseggerstraße 12, Leoben 8700, Austria

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ABSTRACT

Most two-dimensional plastic packaging materials are thermally recovered, which does not add to the recycling quota of 50 % required by EU legislation for all lightweight packaging until 2025. Furthermore, the separation processes for 2D materials cannot reach the same level of accuracy, which is possible in the sorting of rigid plastic packaging.

This study proposes new adaptations to existing sorting aggregates to increase the near-infrared spectral quality of two-dimensional materials. It aims to improve the spectral quality, which was defined by the deviation of the spectra from a reference spectrum and the variability of the recorded spectra, which can be achieved by installing reflectors behind the material made up of copper or aluminium. This setup enables detection in transflection rather than reflection mode.

The variability could be reduced by a factor of 6 through the use of a reflective background. Meanwhile, the spectral fidelity to the reference spectrum could be enhanced, in some cases decreasing the deviation from the reference spectrum by 30 %, which means enhancing a spectrum from unrecognisable to useable. Apart from using reflective materials, the effects of emitter intensity, material and thickness were evaluated.

1. Introduction

The material recycling of plastics requires substantial innovation in the next five years to achieve the environmental policy goals set by the EU. Including a recycling quota of 50 % for all lightweight packaging and an obligation for all lightweight plastic packaging material to be recyclable in a cost-efficient manner as stated in the Waste Framework Directive (2008/98/EC). For this reason, projects aim at identifying two-dimensional (2D) films in plastic sorting to increase the material recycling of packaging film waste. However, multilayer films are challenging to be mechanically recycled according to the current state of the art and negatively affect the quality of the other recycled plastics by polluting the recyclates if they enter the material stream.

Currently, mono- and multilayer packaging is recycled into low-value products as part of the downcycling process or are used as refuse-derived fuel (RDF) (Kaiser et al., 2018). This kind of treatment of flexible packaging is especially problematic since (co–)incineration does not reduce the CO_2 footprint to a degree like recycling would do.

Mono- and Multilayer sorting techniques are necessary to prepare collected lightweight plastic packaging material for further processing in recycling plants. According to Niaounakis (2020), the different technologies to recycle flexible packaging can be subdivided: Films can be collected in groups of identical materials or geometry either by manual or automated sorting systems. Workers and robots can pick and differentiate many polymers and geometries given a sufficiently low throughput rate of the material stream. Vacuum suction systems, air sifters and different screens, such as the vibrating screen or the ballistic separator, sort particles according to their respective geometries and free the material from contaminants.

Marking systems, like identification codes or fluorescent additives, enable material identification but are currently not adequate or economically feasible for widespread industrial application. These systems may change once further research increases their deployability soon (Woidasky et al., 2018).

Several chemical and physical experimental methods have been developed to separate multilayer films. Among these is the CreaSolve process developed by Fraunhofer IVV and the Creacycle GmbH. The CreaSolve process is a solvent-based operation that is theoretically capable of sorting post-industrial and post-consumer multilayer plastic packaging (MPP) (Frauenhofer IVV, 2021). So far, it has been implanted

* Corresponding author.

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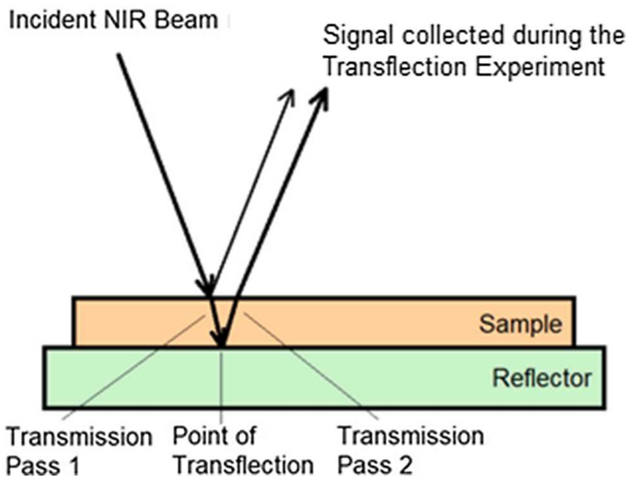

Fig. 1. Scheme of the transflection measurement principle.

in one plant, separating only post-industrial waste to recover PE (Unilever, 2020). The common denominator amongst all industrial processes currently employed to recycle MPP is the need for a feedstock with specific and known material combinations (Chen et al., 2021). Currently, there is no solution to generate this kind of feedstock from post-consumer MPP to improve these MPP recycling processes. This lack is the difficulty of recognising post-consumer MPP in the sorting process because of the vast array of materials used in MPP (Chen et al., 2020; Niaounakis, 2020).

This paper aims to improve optical separation systems' capabilities to deliver this feedstock by improving MPP detectability in optical systems.

Optical systems stand out due to their ability to detect and eject various polymers at high throughput rates compared to other sorting methods, for example, manual sorting. Optical sorters use either visible (VIS) or near-infrared (NIR) spectroscopy or a combination thereof. However, they are sensitive to interfering influences and need specific material properties and controlled operating conditions to maximise efficiency (Burns and Ciurczak, 1992).

As there is no stand-alone solution to separate plastic into different polymer fractions, plant engineering uses established sorting technologies combined with optical or electrical systems to achieve the necessary output quality. The application of sorting cascades is standard in current lightweight packaging plants (Kaiser et al., 2018).

Though widely applicable, the sensor-based sorting technology is limited by various inherent problems in its operation principle. One is the need for sufficiently reflective material to gain necessary information for separation, which is often problematic with thin 2D materials.

Studies have shown the penetration depth of NIR radiation to be highly dependent on sample material and wavelength. Evaluations on NIR analysis of fruits have shown the penetration depth to vary from 2 – 3 mm in the spectral range of 900–1900 nm to 4 mm in the range of 700–900 nm (Lammertyn et al., 2000). Other studies examining the penetration depth of NIR in bone structures and cartilage have shown the penetration depth to vary between 6.3 and 8.5 mm and 0.5–5 mm, respectively depending on wavelength and material (Faris et al., 1991; Padalkar and Pleshko, 2015). This discrepancy between penetration depth and sample thickness can lead to problems when examining samples of 30 μm thickness or less in reflectance mode due to a loss of radiation to transmission and with that a loss of spectral information.

Preliminary analysis by Masoumi et al. (2012) has shown an increase in spectral information with growing material thickness. This effect is based on a rise in reflectivity. It leads to more pronounced spectra since differences in the spectral curve can be more easily identified with high reflectivity (Masoumi et al., 2012). This effect of reflectivity depending on material thickness can have detrimental impacts when measuring the spectra of very thin 2D materials. This paper explores methods to gather valuable spectra even from very thin materials.

Though the recognition of thin plastic packaging is possible on a laboratory scale, very thin materials, especially PP with a thickness of 15–50 μm and PET with a thickness of 12–50 μm, were troublesome to identify because the materials were prone to the exhibition of sine wave spectra. These wave-like spectra complicated the identification of those materials (Chen et al., 2020).

This phenomenon of wave-like spectra in thin materials was studied by Jeszenszky et al. in 2004. It has been postulated that the wave-like spectra are caused by destructive interference due to the thin materials. This effect can lead to sine wave spectra, which are unusable for classification without further processing like fast Fourier transformation (Jeszenszky et al., 2004).

NIR sorting requires diffuse reflection for classification. If a material tends to direct reflection, the sorting becomes difficult or impossible. Rougher surfaces that tend to diffuse reflection are more accessible to separate than glossy and smooth surfaces prone to direct reflection (Küppers et al., 2019).

This paper explores possibilities to enhance the spectral information gathered from materials that tend to direct reflection, like PP foils.

Special attention in this paper is paid to the chute material and the illumination intensity. The thesis by Yu Xing Cui (2011), postulated that certain materials have particularly good NIR reflective properties. Likewise, preliminary experiments have shown the illumination intensity to have a positive influence on the sensor system. In this study, the hypothesis is tested whether and how both parameters influence the sorting result and whether one or both parameters are suitable for improving the spectra used to identify and separate packaging films.

The hypothesis tested in this study is which effect material thickness has on material identification via NIR spectroscopy. Further, this study aims to evaluate if there can be an optimum illumination setting for the identification of plastic packaging films and evaluate the influence of different reflective materials on the films' NIR spectra.

2. Materials and methods

A sensor-based sorting system serves as an experimental site to examine which adaptations can be made to the sorting set-up to facilitate the detection and separation of 2D materials. Therefore, in this paper, the technical limits of near-infrared sorting are investigated and explored. A novel measuring geometry is presented to shift these limits.

The sensor-based sorting aggregate used is an experimental NIR/VIS sorting setup provided by Binder + Co AG, representing the industrial standard. The material is manually applied over a vibrating chute with a width of 0.5 m, transporting it to the downstream sensors. The setup includes a NIR line scan sensor (EVK Helios – G2 – NIR 1), which was applied to record spectral images. NIR Sorting requires an infrared emitter.

For this purpose, an infrared lamp is utilised, which can supply 6.5 mW/mm^2 of light output in the detection area at 170 VDC, as measured with a Thorlabs S470C sensor. This sensor is sensitive to a wide range of wavelengths, making it suitable for measuring the intensity of NIR radiation.

The emitted radiation interacts with the particles and is reflected, transmitted, or absorbed depending on the material's molecular composition (Pasquini, 2003). If the measurements are taken in reflectance mode, only the dispersed reflected radiation can be detected by the NIR sensor and used for classification. The radiation is converted into a digital signal and stored in a hyperspectral imaging (HSI) cube with two spatial coordinates displaying the analysed area and a third coordinate representing the reflected intensity at each pixel (Manley, 2014; Reich, 2005).

In the utilisation of near-infrared technologies the measurement principles of transflection, reflection and transmission are distinguished. Fig. 1 shows the principle of transflection measurement schematically.

Table 1
Testing Material and the corresponding thickness.

Material	Thickness
Reference LDPE White	3 mm
Reference PP Purple	3 mm
PCW 55 – PE	20 μm
PCW 33 – PE	25 μm
PCW 56 – PE	50 μm
PCW 90 – PE	75 μm
PCW 45 – PP	30 μm
PCW 38 – PP	35 μm
PCW 41 – PP	45 μm
PCW 153 – PP	60 μm

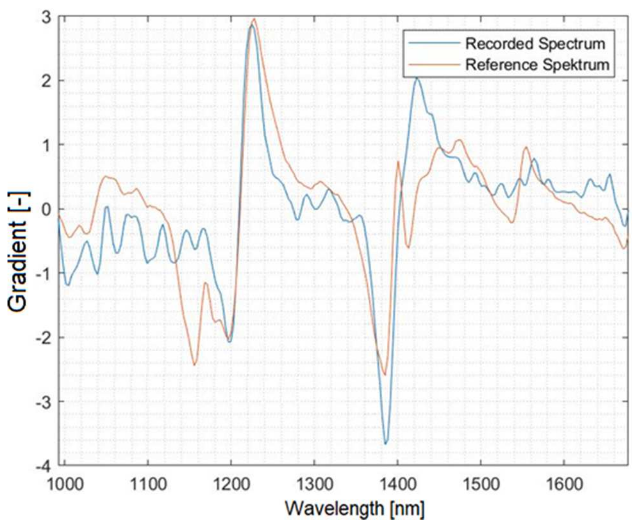

Fig. 2. Comparison between the PE reference spectrum (orange) and a PE foil spectrum (blue).

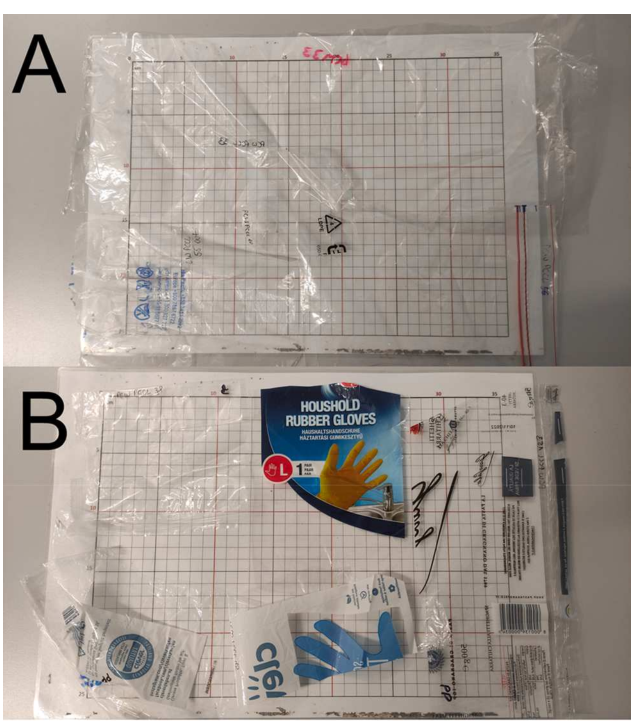

Fig. 3. Depiction of all Samples, A) PE B) PP.

First, an incident NIR beam is emitted to the sample, then the entrance angle changes and gets more acute for the transmission pass one. At the point of transflection on the reflector surface, the weakened NIR beam is reflected and passes through the sample at the transmission pass two with an acute reflection angle. Next, the reflection angle gets more obtuse at the sample surface, and this signal is sent to a computer, where the data is processed and analysed. Finally, the reflected signal and the transmitted signal at the sample surface before the transmission pass one are combined to a transflection signal. The transflection signal is analysed at the end of the experiment. The application of transflection increases the amount of information gained by the sensor since little to no radiation is lost to transmission. That is critical when applying near-infrared spectroscopy to thin materials. Measurements in transflection circumvent this problem.

The material consisted of two groups. Group A, the reference material, was specifically crafted to be used as a reference. This group consists of white LDPE and purple PP tiles, with a length of 5 cm, a width of 3 cm and a thickness of 3 mm. These materials were used to create a reference spectrum for later comparison to the 2D materials.

Group B consisted of the 2D foil materials to be evaluated. Eight samples of two different materials were selected. These samples were transparent to the human eye and showed varying thickness, as shown in Table 1.

Initial trials have shown that the spectra of group A and B are similar, barring minor differences attributable to the difference in thickness. Fig. 2 shows the comparison between the spectra of a PE reference material (orange) and the recorded spectra of a PE specimen (blue). Though the spectra show similarities in the minima and maxima at 1200 nm, 1230 nm and 1380 nm, a significant loss of information can be observed. This discrepancy between the reference spectrum is expected considering the difference in thickness.

Samples with varying thickness were chosen to evaluate the effect increasing material thickness has on the spectral images. Further, transparent samples were selected to eliminate the effect colourants have on the samplés spectra and the image quality.

Fig. 3 shows all specimens selected for the evaluation. In (A), all PE samples can be seen, while in (B) all PP samples are shown. It can be seen that some areas of the samples were printed in order to advertise the products they contained. These areas were omitted during the analysis of the spectra.

Transparent sample objects were chosen to enable the comparison of the specimen's spectra, which enabled the comparison of thinner samples to thicker samples of the same material without the spectral changes different colourants would introduce. This way, the effect increasing thickness has on the spectra could be analysed. Since the material consists of authentic household waste, coloured sections occur in the specimen. However, these were excluded in the pixel selection for analysis to prevent colourants from interfering with the spectral analysis.

2.1. FTIR spectra of materials

In addition to the recycling marks present on most post-consumer packaging waste, FTIR spectra analysis of the foils was conducted in transmittance mode to create a reliable classification of the 2D materials. Thus, a material database was created, which served as the foundation for the following analysis on the experimental sensor-based sorting setup since knowledge of the materials composition was needed to choose the correct reference spectrum for comparison with the recorded NIR spectra.

2.2. Material preparation

Preliminary tests have shown that the effect of different reflective materials is more pronounced the closer the contact of material and reflector is. Therefore, to achieve maximum contact with the

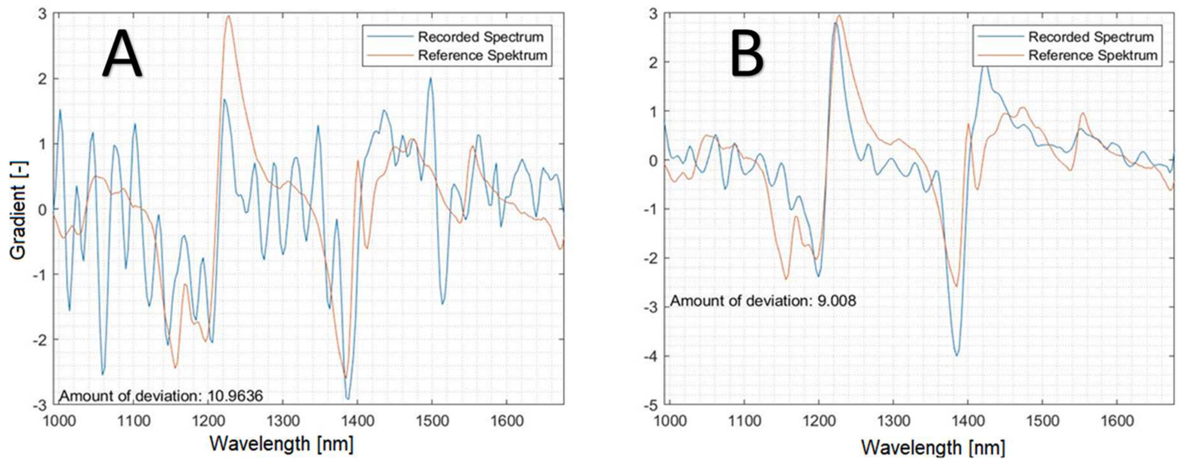

Fig. 4. Increasing fidelity to the PE reference spectrum of two spectral images taken without reflective background[A] and with a reflective copper background [B]

background and eliminate trajectory effects, each specimen was encased between two glass plates, one of which was covered with the respective background materials. This method ensured the same circumstances for every recording of spectral data. In addition, the known NIR inactivity of glass due to its high transmittance was tested during preliminary studies, which showed no substantial impact of the glass plates on the specimen's spectra.

2.3. Changes of emitter intensity

Preceding experiments have shown that increasing the emitter intensity has positive effects on spectral quality. Preliminary spectral examinations show the correlation of mean spectral quality with increasing emitter intensity. The spectral range from 1200 – 1400 nm, which contains one of the typical PP spikes explained by Küppers et al. in 2019, becomes more pronounced with increasing intensity. The spectra at low-intensity lack discernible patterns useable for classification. Taking spectral images without sufficient illumination leads to random spectral intensity values. These random spectra lack any regularity and are therefore not suitable for classification. Preliminary evaluations to find the correct intensity range have shown that decreasing the emitter intensity increases spectral variability. Therefore, low emitter intensities are included in the trials, reducing the emitter intensity to further evaluate the effect of low NIR intensity on spectral quality.

However, it is not necessarily the case that maximum emitter intensity is always beneficial since a change in background material causes a change in reflectivity. Furthermore, because only dispersed reflections can be used for classification, increasing the emitter intensity excessively can lead to direct reflections and overexposure, which render the affected pixels and their spectra unusable. Therefore, every reflector material was evaluated using the emitter intensities 70 %, 80 %, 90 % and 100 % of the maximum intensity, or 4.55 mW/mm^2, 5.20 mW/mm^2, 5.85 mW/mm^2, 6.50 mW/mm^2 of light output in the detection area respectively, to analyse the effect changing intensity has on the spectral quality.

Background Material

Gold, copper, silver, glass, aluminium and a black polymer, coloured with carbon, were considered as background materials due to their optical properties in the relevant wavelengths. All materials, except black polymer, chosen as the negative benchmark, are promising to be usable as a reflector because of their high reflectivity in the near-infrared wavebands. The black polymer was chosen as a background to present a negative benchmark to which the metal backgrounds could be compared. Coincidentally, the black polymer reflector represents the common conveyor belts used in most sorting aggregates whose top covers are usually made of black polymers. The respective reflectance of the materials is shown in Fig. 7. These reflectance values were taken via FTIR spectroscopy.

The materials used as background were a copper plate with 99.9 % copper content, black PP polymer and rolled 100 % aluminium. The reflector materials were applied to the sample holder behind the respective sample.

2.4. Data evaluation

A Matlab R2021a script was used to extract the spectra from the Hyper Spectral Imaging Cube to gauge the quality of the spectral images taken of the materials.

This Matlab script enables the user to choose viable pixels for evaluation. It then computes the normalised first derivative of the spectra and presents a smoothed graph of the data points, using a Gaussian smoothing algorithm with a 10-datapoint interval. The image quality is defined as the variability of the spectra in its spectral range for a specific material. For this reason, the variability was computed by calculating the difference between the area integral using trapezoidal numerical integration of the spectra with the maximum intensity and the spectrum with minimum intensity.

The sensor measures the spectral intensity in Arbitrary Light Units (ALU), which is a unit used by the sensor provider EVK, and the spectral wavelength is measured in nanometres; the integration of the first derivative also yields the area in ALU. The y-axis is denominated as ALU/nm since it is the gradient of the raw spectrum.

This calculated area between the spectrum with the lowest intensity and the spectrum with the highest intensity indicates the variability, suggesting the spectral image's viability. Since the image's quality depends on the parameters under which the image was recorded, a small area between the two spectra indicates a recording of high fidelity with beneficial parameters.

Because not all wavebands are equally crucial for the classification, this computation was limited to those, which hold relevant spectral data for classification. Those wavebands were selected by evaluating the first derivative of the raw spectral intensity data. Wavelengths, in which the first derivative deviates substantially from zero, indicate the interaction of the material's molecules with the NIR radiation. This interaction results in a unique spectrum that can be used to classify the given material. This classification is the basis for separation using pressurised air.

Since a spectrum can exhibit low variability but still deviate from the benchmark spectra, rendering it unfit for classification, a second spectra quality criterion was needed. For this purpose, the deviation of the mean spectra from the benchmark was used. Initial trials showed that recorded spectra increasingly approached the reference spectrum with increasing background reflectivity. This effect is depicted in Fig. 4, which shows the

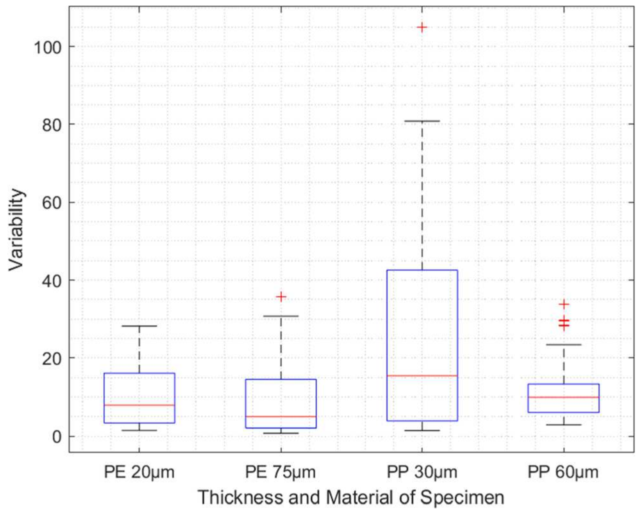

Fig. 5. Influence of spectral variability depending on thickness and material.

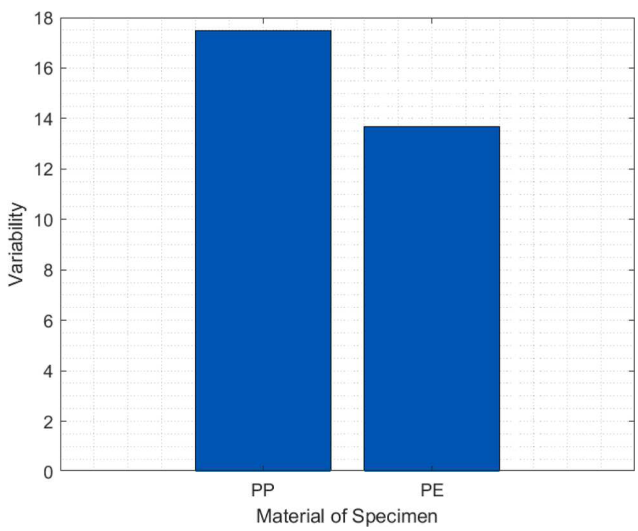

Fig. 6. Difference in average variability depending on specimen material.

increasing fidelity of the recorded PE spectrum to the PE reference spectrum. It can be seen that the spectra recorded without a reflective background (A) do not follow the reference spectrum as well as the spectra recorded with a reflective copper background (B) do. The amount of deviation shown in the figure is the sum of the differences between the recorded spectrum and the reference spectrum.

This difference, or deviation, is calculated with the Euclidian (2-norm) by subtracting the mean spectra of the selected pixels from the benchmark spectra. This calculation yields a numeric value that indicates the deviation of the HSI spectra from the benchmark spectrum, with low values indicating high fidelity to the benchmark spectrum. With that, an estimation of the usability for the classification of the material can be made.

Normalisation was applied to every spectrum using the ‘z-score’ method to enable the comparison. The ‘z-score’ method centres and scales the data to have a mean zero and standard deviation one.

$$Zscore(e_i) = e_i - \frac{\overline{E}}{std(E)}$$

$$std(E) = \sqrt[2]{\frac{1}{n-1} * \sum\nolimits_{i=1}^{n} (e_i - \overline{E})^2}$$

$$\overline{E} = \frac{1}{n} * \sum_{i=1}^{n} e_i$$

Equation 1: Calculation of Z-Score Normalization

To create spectra for evaluation each recording was repeated five times. For each of those recording, nine pixels for spectral evaluation were selected. Here, care was taken to avoid overexposed pixels and pixels on the edge of the material and coloured portions of the material. This approach yields 45 suitable pixels per setting for evaluation.

In order to evaluate whether a relevant correlation between the examined experimental variables and the spectral quality exists, regression curves were fitted to the experimental data. The goodness of fit of those regression curves was evaluated by calculating the coefficient of determination (R^2) for each fit.

3. Results and discussion

The first results are the decrease of variability and deviation with the increase in material thickness, which was further examined based on the assumption that the increase in spectral quality is different for the chosen materials. Subsequently, the effect the reflecting backgrounds and increased illumination intensity had on the variability was

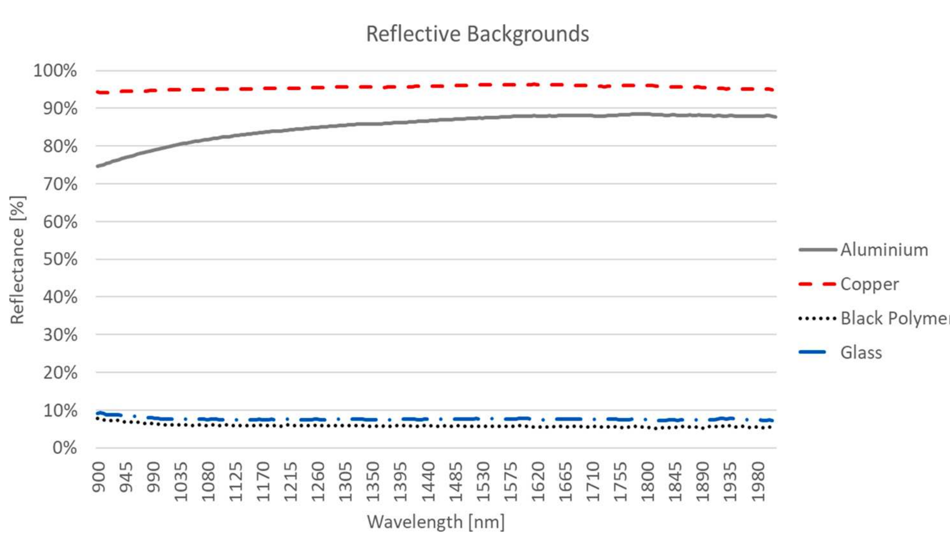

Fig. 7. Reflectance of chosen reflector materials.

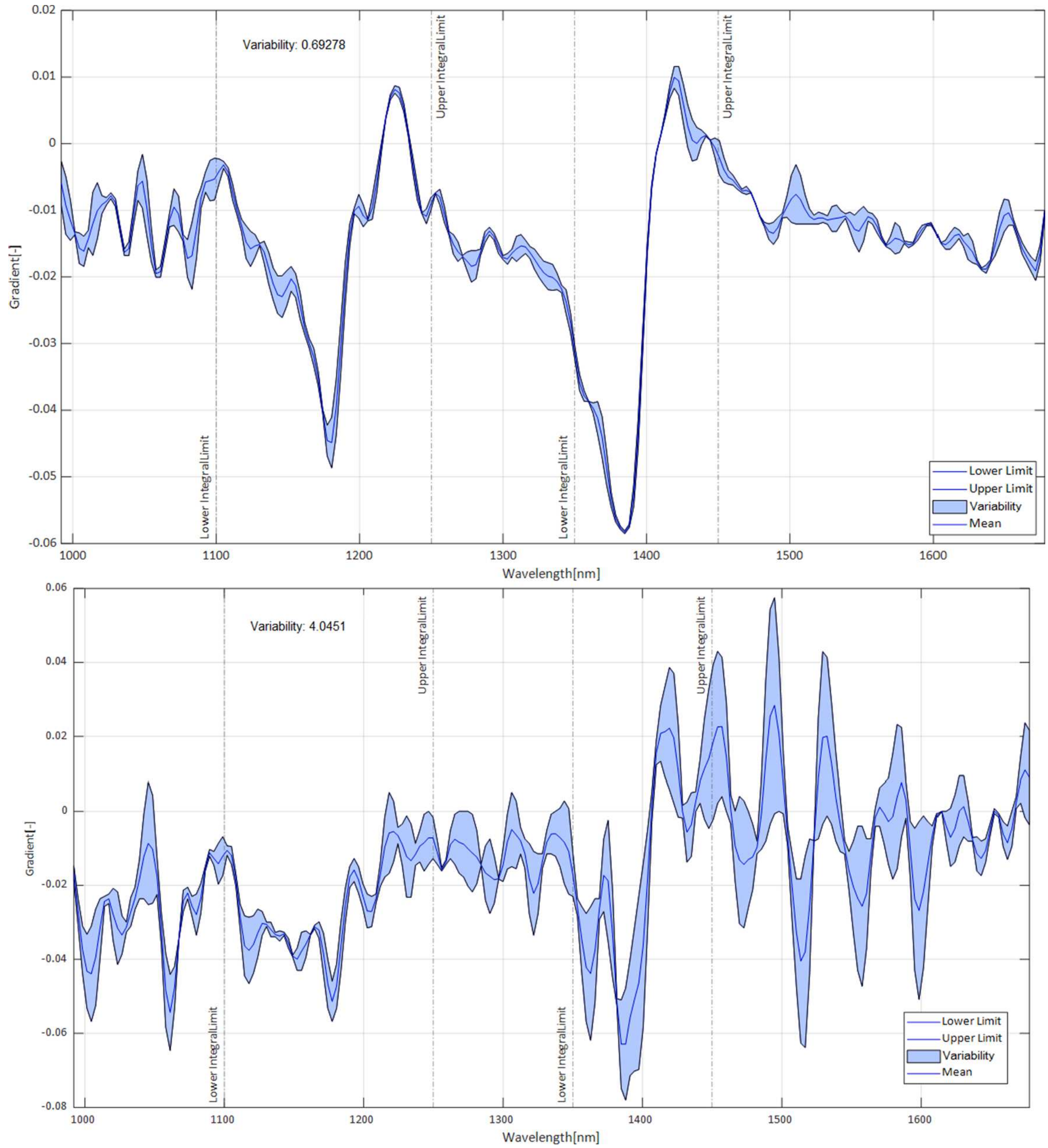

Fig. 8. Reduction in spectral variability due to increased reflectivity of background material and subsequent measurement in transflection. A) No reflector B) Copper reflector.

quantified.

3.1. Influence of thickness

With 2D materials, a rise in material thickness decreased spectral variability. The intensity of this effect is correlated to the material used. While PE spectra exhibited comparatively low variability even in specimens with low thickness and had limited room for improvement, PP spectra reacted strongly to the increased material thickness with improved spectral quality.

Fig. 5 shows a box and whisker chart displaying the comparatively high variability of PP spectra compared to PE spectra. While increasing the thickness of PE specimens lead to a small decrease in variability, increasing the thickness of PP specimens lead to a more pronounced decrease in variability.

Examination of PP materials with a thickness of under 35 μm yielded spectra in sine waveform. So far, these cannot be used for classification since the occurrence of sine wave spectra is currently not precisely attributed to a specific chemical or physical property of a specific resin. It is related to the thickness of a foil and occurs below a certain threshold thickness. This thickness is material-specific. However, it has been postulated that the sine wave effect occurs because of destructive interferences if a given correlation of the material thickness and wavelength is present. These interferences can be removed by applying fast Fourier transformation (Jeszenszky et al., 2004). It can further be confirmed that this phenomenon occurs below a certain thickness and the novel information that the threshold thickness is between 30 and 60 μm for PP can be added.

3.2. Influence of material

The PE specimen showed on average spectra with less variability, even in specimen with low thickness, while PP materials produced spectra with high variability. With PP expressing on average 28 % more

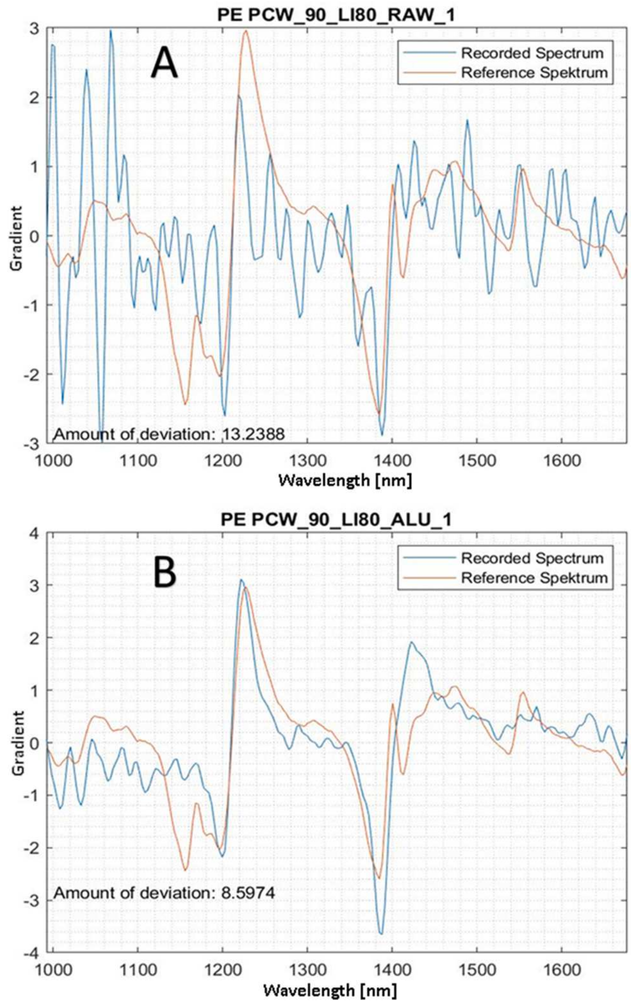

Fig. 9. Reduction in spectral deviation from the reference spectrum due to the effect of reflector material, A) No reflector B) Aluminium reflector.

variability from the mean spectrum. It can be seen in Fig. 6 that the PP specimens exhibit overall higher variability than the PE specimens.

PE yielded more useable recordings due to the higher reflectivity of the PP materials, which leads to more direct reflection instead of the useable diffuse reflection. This direct reflection yields overexposed pixels, which cannot be used for spectral analysis. Overexposed pixels cannot be used for classification due to the detectoŕs inherent limitation to processing very bright pixels. This limitation is handled by capping the maximum intensity value. If the intensity of a pixel exceeds this limit, it is simply reduced to this pre-set value. If all spectral values of this pixel are set to this value, the spectrum contains neither maxima nor minima and is a straight line instead. So, no further evaluation by derivation or other forms of processing can yield any valuable information for classification other than classifying this pixel as overexposed.

Since NIR detection uses the interaction of radiation and the material for classification, the molecular composition and material thickness heavily influence the detection outcome. This effect is especially pronounced when analysing thin materials like monolayer packaging, which routinely exhibit material thickness under 100 μm. While they yield similar spectra, due to resemblances in their chemical makeup, PE and PP, two common materials for monolayer packaging, exhibit differences in spectral quality when used for spectral analysis. These differences become increasingly pronounced with decreasing material thickness.

3.3. Influence of reflector and reflectance

Spectral images were recorded with different reflector materials behind the 2D specimen to facilitate the interaction of the 2D foils with the NIR radiation. This approach yielded improved spectral with decreased variability. This effect depended on the reflectivity of the given background material in the relevant wavebands from 900 nm to 2000 nm. Fig. 7 shows the reflectivity values of the various backgrounds as taken in FTIR spectroscopy.

Backgrounds with little to no reflectivity, e.g., black polymers or glass, had no improving effect on the recorded spectra. Increasing the reflectivity of the background material decreased their variability and enhanced the spectra's fidelity to the reference spectrum, as shown in Figs. 4 and 5, respectively. While aluminium showed promising results in preliminary examinations when virgin aluminium foils were used, the increasing formation of an aluminium oxide layer on the reflector's surface impaired its reflectivity, reducing the possible improvement of spectra recorded with this particular reflector. This reduction in reflectivity compared to virgin aluminium is shown in Fig. 7. Copper reaches approximately 10–20 % higher reflectivity than aluminium. Copper lends itself to the application as a reflector since it reaches the highest reflectivity of any material evaluated. Although not encountered during this study, the formation of copper verdigris on the reflector may become an issue.

The data analysis shows that spectral variability could be reduced by the use of copper and aluminium reflectors. This reduction renders a spectral image useable for classification since the pixel of the image deliver similar spectra. However, spectral analysis relies on creating a reference spectrum from the average of multiple pixels' spectra to determine to which material class a specific specimen belongs. Therefore, high variability of spectral information due to optical effects and imperfect reflection of near-infrared radiation in the images renders them unfit for classification.

It was shown that spectral images of 2D materials taken without a reflector exhibit a wide variation in the spectra extracted from viable pixels. Meanwhile, spectral images recorded using a reflector minimise the variability in the respective image. This reduction in variability around the mean, especially in the spectral ranges relevant for classification, is depicted in Fig. 8, showing the same material recorded under identical NIR intensity. In addition, the variability is reduced by a factor of 6 by using a reflective background.

Further, the spectral fidelity to the reference spectrum could be enhanced, in some cases decreasing the deviation from the reference spectrum from 13 to 8.5. This decrease in deviation from the reference spectrum entails that the spectrum of the specimen matches the reference spectrum more closely with increasing background reflectivity.

This increased fidelity to the reference spectrum combined with decreased variability means enhancing a spectrum from unrecognisable to useable. This reduction in deviation heeds from eliminating unwanted optical interferences and increased near-infrared intensity through transflection.

This elimination of optical interferences facilitates detecting the materials' inherent spectra, which lends itself to usage in separation processes. The comparison between the two spectra is depicted in Fig. 9, which shows the mean spectra of evaluated pixels in an image taken without a reflector compared to an image taken with an aluminium reflector of a PE film material.

3.4. Influence of emitter intensity

While increasing the emitter intensity did not change the deviation, increasing the intensity decreased spectral variability from 16.78 at 70 % emitter intensity to 13.68 at 100 % intensity. Although interesting, the effect increased intensity has is minuscule compared to the improvement obtained by increasing the reflectivity of the background. It has to be noted that an increase in intensity is comparable easy to

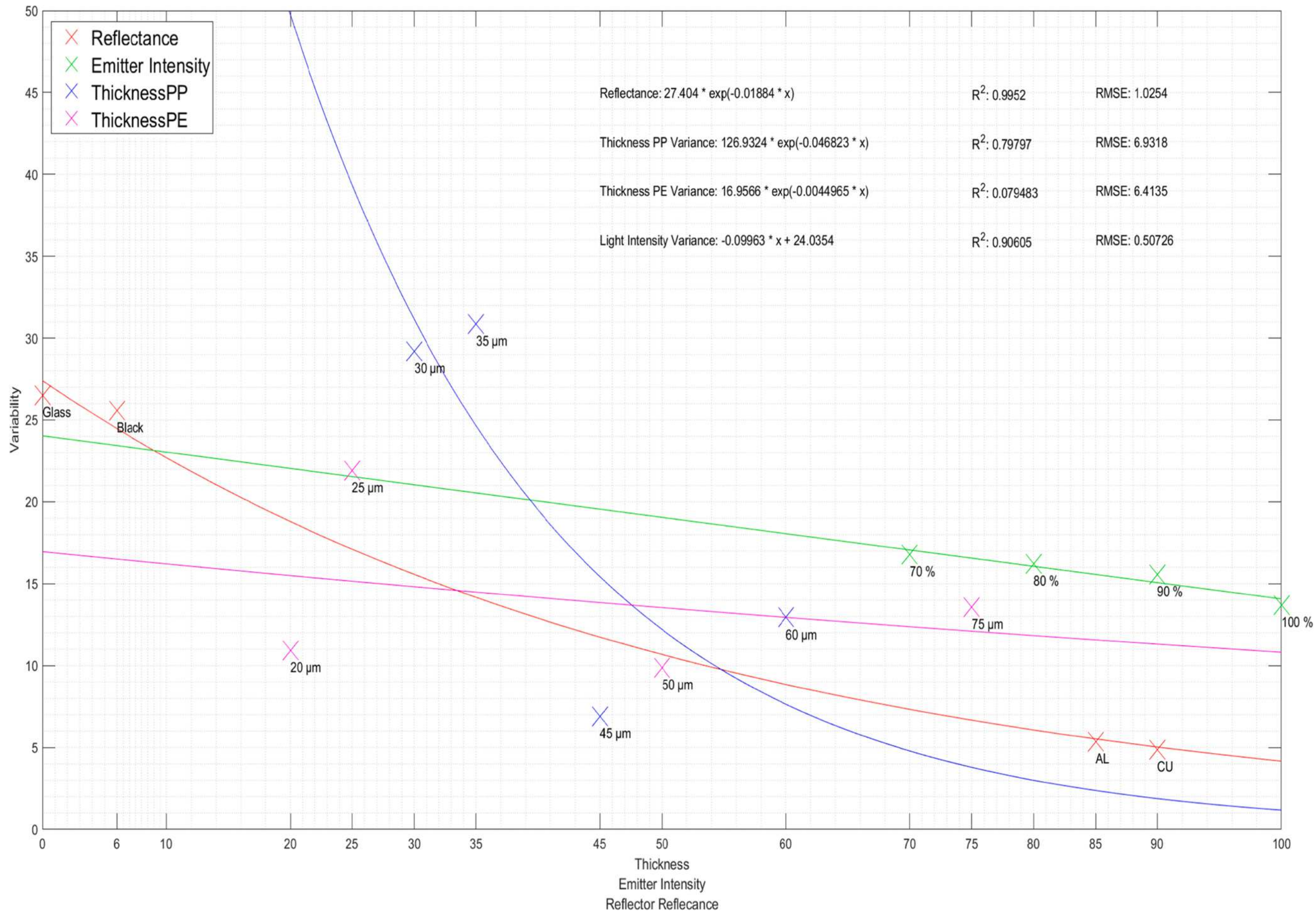

Fig. 10. Statistical evaluation of the effect changing various parameters has on the spectral variability.

achieve, needing no further adaptions to the sorting setup other than to increase the emitter intensity in the given control software. The increase in spectral quality heeds from the simple effect increasing the intensity has on the sensor-based sorting setup. With increasing intensity of the incident NIR radiation, more useful disperse reflection can occur, which is then detected by the near-infrared sensor for evaluation. This simple principle can improve the sorting result in recycling plants with relative ease if the hardware permits changing emitter intensity.

3.5. Discussion of statistical relevance of correlations

Fig. 10 shows the summary of the spectral evaluations and the effects the parameters had on the variability of spectral recordings. It shows the effects of different changes in the experimental setup on the spectral variability. Further, the regression curves for the evaluated data with their goodness of fit values R^2 and the root mean squared error (RMSE) are displayed.

The data points shown in the figure correlate to the average variability of the spectra and the given experimental settings.

It can be seen that no correlation between increasing thickness of the PE specimen and the spectral variability could be established. The PE specimen started with relatively low variability, even with a thickness of 20 μm and the variability did not decrease with increasing thickness. This lack of correlation is further supported by the R^2 value of 0.08 of the fit, which indicates that over 90 % of the variation is unexplained by the model.

Increasing thickness of the PP specimen showed a decrease in spectral variability during the study. It can further be seen in the regression curve for the PP specimen, which shows an R^2 value of 0.79. The PP specimen had an inherently higher variability and improved noticeably when material thickness increased. This effect is also caused by the decrease of sine wave spectra encountered with thicker specimens.

A rise in emitter intensity showed a slight decrease in spectral variability, improving the spectral recordings, which is supported by the regression curve. Though not as noticeable an effect as the increase in thickness, raising the emitter intensity improved all spectral recordings. The regression shows an R^2 value of 0.91, which indicates a good fit for the given data.

During the trials, increasing the background material's reflectance showed the most significant influence on spectral quality, with aluminium showing promising results and the more reflective copper reflector improving the spectral recordings further. This effect showed to improve the spectral quality of all specimens, regardless of thickness or material type. Further, this effect is supported by the regression curve for the spectral variability and the reflectivity of the respective background yielding an R2 value of 0.99.

Increasing the reflectivity of the background material to enable measurement in transflection yielded the best results for improving spectral quality.

4. Conclusions

The key findings of these trials were the effects reflective backgrounds have on the spectral quality of plastic films with a thickness of under 100 μm, which are mainly used in the packaging of goods. The spectral variability decreased substantially when using a reflector made of copper or aluminium as background. Implementing a reflective background enables the measurement to be taken in transflection rather than sole reflection, which circumvents the problematic low reflectivity of thin-film materials. While introducing a reflector decreased variability and deviation from the reference spectra in PE and PP materials, spectra of the latter showed more significant improvements as PP spectra displayed lower spectral quality without changes in the measuring geometry.

Apart from reflectors, increasing the emitter intensity in a sensor-based sorting rig increased spectral quality and fidelity to a reference spectrum. This method seems to be a convenient way of improving the sorting success of a lightweight packaging sorting operation by simply adapting the existing hardware to 2D materials by increasing the intensity setting for the near infra-red emitters. Presupposed the specific machinery design permits this technical modification and all safety concerns are addressed.

Coherent with existing findings, an increase in thickness improves the spectral quality of both PE and PP specimens, with PP showing more considerable improvements with increasing thickness, partly due to the sine wave phenomenon occurring less frequently with increasing material thickness. However, increasing the thickness of packaging is not the solution to the increasing demand for recyclable 2D packaging since the comparative lightness of these packaging materials renders them competitive.

A way to increase the recycling quota of 2D materials is to adapt existing sorting setups to use measurements in transflection, whose viability was shown in this examination, to improve the mechanical recycling of 2D materials.

Further studies are needed to examine the effect reflective backgrounds have on the sorting success of 2D materials on an existing sorting rig with the adaption of reflective backgrounds made of copper or aluminium, which have shown the most significant potential for use as reflective backgrounds.

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Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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4.4 Publication VIII, Identification, Machine Learning

"Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches"

<u>Original Article</u>

Koinig, G., Kuhn, N., Barretta, C., **Friedrich, K.**, Vollprecht, D. (2022). *Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches.* In Polymers 2022, 14(19), 3926. DOI: 10.3390/polym14193926.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 4-4.

Table 4-4: Annotation on the doctoral candidate's contribution to Publication VIII

Conceptualization	Koinig, G., Kuhn, N., Vollprecht, D.
Methodology	Koinig, G., Barretta, C., **Friedrich, K.**
Software	Koinig, G.
Validation	Koinig, G. Barretta, C., Vollprecht, D.
Formal Analysis	Koinig, G. Barretta, C., Vollprecht, D.
Investigation	Koinig, G.
Resources	Barretta, C.
Data Curation	Koinig, G.
Writing: Original Draft Preparation	Koinig, G.
Writing: Review and Editing	Koinig, G., Kuhn, N. Barretta, C., **Friedrich, K.,** Vollprecht, D.
Visualization	Koinig, G.
Supervision	Koinig, G., Vollprecht, D.
Project Administration	Koinig, G., Barretta, C.
Funding Acquisition	Barretta, C., Vollprecht, D.

polymers

Article

Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches

Gerald Koinig [1,*], Nikolai Kuhn [1], Chiara Barretta [2], Karl Friedrich [1] and Daniel Vollprecht [1,3]

1 Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanunigersitaet Leoben, Franz Josef Straße 18, 8700 Leoben, Austria
2 Polymer Competence Center Leoben GmbH, Roseggerstraße 12, 8700 Leoben, Austria
3 Chair of Resource and Chemical Engineering, Augsburg University, Am Technologiezentrum 8, 86159 Augsburg, Germany
* Correspondence: gerald.koinig@unileoben.ac.at

Abstract: Small plastic packaging films make up a quarter of all packaging waste generated annually in Austria. As many plastic packaging films are multilayered to give barrier properties and strength, this fraction is considered hardly recyclable and recovered thermally. Besides, they can not be separated from recyclable monolayer films using near-infrared spectroscopy in material recovery facilities. In this paper, an experimental sensor-based sorting setup is used to demonstrate the effect of adapting a near-infrared sorting rig to enable measurement in transflection. This adaptation effectively circumvents problems caused by low material thickness and improves the sorting success when separating monolayer and multilayer film materials. Additionally, machine learning approaches are discussed to separate monolayer and multilayer materials without requiring the near-infrared sorter to explicitly learn the material fingerprint of each possible combination of layered materials. Last, a fast Fourier transform is shown to reduce destructive interference overlaying the spectral information. Through this, it is possible to automatically find the Fourier component at which to place the filter to regain the most spectral information possible.

Keywords: 2D plastic packaging; near-infrared spectroscopy; sensor-based sorting; transflection; monolayer; multilayer films; machine learning; small film recycling

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1. Introduction

Currently, around 300,000 t of plastic waste are annually produced in Austria, of which 32% are recycled mechanically [1]. Small films with an area below 1.5 m^2 account for 69,000 t, of which 10,260 t, or 14%, are multilayer films with at least two polymers [2]. These films are separated during the beneficiation of the waste and are almost exclusively used as alternative fuel sources, incinerated or downcycled into low-value products [3]. The substantial potential is latent in the recycling of packaging films since neither co-incineration nor other thermal recovery adds to the recycling quota [2]. According to the amended EU Waste Framework Directive, municipal solid waste recycling must reach 60% by 2030 [4]. Additionally, the new EU guidelines require a recycling rate of packaging waste of 50% in 2025, with a further increase to 55% in 2030 [4]. This quota can only be reached through a mix of measures such as higher collection rates, design for recycling, and improving existing and new sorting techniques. Besides, a recycling system capable of economically handling a feedstock which accounts for 17 wt.% of all plastic packaging materials produced, requires additional research. [3].

The reason for the widespread use of multilayer packaging lies in its convenience for producers, retailers and consumers: The plethora of functions such as UV protection, handleability, printability, limited gas permeability, and attractive haptics require only a minimum of packaging material.

In turn, these inherent properties, the thin layer thickness and the combination of different polymers impede the separation process. In most sorting plants, near-infrared (NIR) sorters are used for plastics separation. This technology is based on the interaction of NIR radiation with the molecular structure of solid materials resulting in distinctive spectral fingerprints for each polymer type [5]. Thin-film packaging inhibits the separation by NIR sorting because only a limited amount of radiation is reflected [6]. This lack of spectral information limits the sorter's ability to generate a useable spectrum because the low thickness of the material allows a large amount of radiation to be transmitted [7]. Additionally, the thin layered construction of these packaging films introduces disturbances in the spectral fingerprint. Due to destructive interferences, sine wave pattern noise may overlay the spectra, masking its information and thus disfiguring an otherwise applicable spectrum [8]. Fast Fourier transformation (FFT), which is also used in laboratory-based infrared spectroscopy, can reduce these overlaying interferences. Though finding the correct cut-off point has proven to be both time-consuming and tedious if carried out manually [8].

The resulting lack of spectral information can lead to misclassified particles, which in turn could contaminate an otherwise clean feedstock. This contamination impedes the recyclability of the recyclate by altering its mechanical properties. This alteration may result in the need for additional compatibilisers and other additives for the intended recycling process. [9].

As NIR-based sorters are most widely used in sorting plants, but their potential has not yet been fully exploited, the aim of this research was to improve their material detection. Additionally, the decoupling of the material properties from the mechanical separation enables not only a change of the hardware configuration, in this case the measurement in reflectance mode, but also the software of the evaluation unit.

Given that a simple adaptation of existing sorter may improve their capability to separate thin, flexible packaging material, substantial increases in recycling quota with a limited investment are feasible. Preliminary studies have shown the possibility of separating monolayer from multilayer materials on a laboratory scale using a NIR-active background in an experimental setup [7]. Further examinations of these findings on an industrial scale NIR Sorter have proven to increase the spectral quality of flexible packaging films by implementing a metal reflector to the sorting geometry [2]. Implementing a NIR inactive metal sheet as a reflector enabled the sorter to measure in transflectance rather than the usual reflectance mode [2].

Apart from the low material thickness, another prevalent advantage of multilayer films has proven problematic during separation and recycling: the continuously changing types of polymer types, thickness and sequence to ensure the best product protection. Hence, the resulting combination possibilities further complicate the creation of separation models.

Whenever completing a complex task without explicitly programming every conceivable variation of this task, machine learning becomes the tool of choice. The application of machine learning methods in NIR spectroscopy has been successfully implemented in various fields. It has been used to assess the quality of beer from given features [10], the rapid assessment of water pollution [7] or the prediction of soil total nitrogen, organic carbon and moisture [11].

This paper investigates the effects of adding a reflective chute material to a state-of-the-art near-infrared sorting unit. This modification allows 2D plastic packaging material consisting of single and multi-layer films to be more effectively detected via transflection and subsequently separated. In addition, an automatic method for applying the FFT to spectra obtained in this transflection configuration and affected by interference is examined. This method is an alternative to manually determining the correct cut-off point in the Fourier deconstruction of the spectra. Based on these improved spectra, a principal component analysis is performed to evaluate whether there are predominant spectral differences between spectra of mono- and multilayer materials. This characteristic difference can be used to train machine learning algorithms to separate the two fractions.

Machine learning algorithms are then evaluated based on their prediction performance and calculation speed. These metrics result in a hierarchy gauging their capability to produce correct predictions in a reasonable time. This examination is necessary to gauge whether this approach is feasible for inline applications, categorising spectra generated in an industrial environment. Finally, an integrated method is discussed, using improved spectral recognition with mechanically adapted NIR sorter, improved spectra rid of sine wave interferences and separated into mono- and multilayer materials via supervised machine learning classification algorithms.

The presented information creates a stepping stone for integrating recyclable resources to increase the effectiveness of mechanical recycling. This increase in effectiveness further creates a value-adding raw material source for multilayer recycling processes currently in development, thus improving the circular economy of polymers [12,13].

2. Materials

All experiments were executed with material obtained directly from the input of an Austrian material recovery facility. This waste was collected under the Austrian lightweight packaging collection scheme. Under this scheme, lightweight packaging made of polymers, aluminium or beverage carton is collected. For plastic packaging, the collection includes both 3D and 2D material. From this material, the film specimen for this research paper were sampled.

2.1. Film Specimens

A total of 103 specimens of post-consumer waste were taken directly from a sorting plant's input fraction in Austria. The input fraction is delivered in yellow bags, and these bags were collected and the lightweight packaging therein was used for further evaluations. The samples were neither cleaned, smoothed or otherwise exposed to preparatory conditioning before the sorting trials were conducted. The samples' dimensions ranged from 10 mm × 10 mm to 210 mm × 297 mm and included printed and transparent samples. Figure 1 shows the small film fraction for reference.

Figure 1. Fraction of small films waste.

An examination with Fourier transform infrared (FTIR) spectroscopy yielded the material composition of the experimental samples. The spectrometer used was a Spectrum Two FTIR spectrometer (Perkin Elmer, Waltham, MA, USA) equipped with a Zn/Se crystal with a diamond tip. The spectrometer measures in the range of 650 cm^{-1} to 4000 cm^{-1} and has a spectral resolution of 4 cm^{-1}.

2.1.1. Classification with FTIR Spectroscopy

The exact measurement method is explained in greater detail in a paper published by Koinig et al. in 2022, which examined the composition of Austrian lightweight packaging waste using FTIR measurements. The method is therefore described in short in the following.

Fourier-transform infrared spectroscopy (FTIR) in attenuated reflectance (ATR) mode was used to classify the film specimen into their respective material classes.

Samples on which the results differ for the front and back are defined as multilayer films, while samples with identical results for the front and the back are defined as monolayer films. However, the FTIR-ATR characterisation method is limited to identifying the polymeric material on the sample's surface and penetrates only a few micrometres of the sample thickness. In case of uncertainties in assigning a sample to the mono- or multilayer category, additional FTIR measurements were performed in transmission mode to investigate the material composition over the entire sample thickness to ensure reliable results.

According to the FTIR spectral analysis, the specimens were categorised into different groups of mono- and multilayer materials. The materials represented by the selection of samples are represented in Table 1.

Table 1. List of mono- and multilayer materials used in the sorting trials.

Materials	Recycling Label	Share
Polyethene	PE	9 wt.%
Polypropylene	PP	31 wt.%
Polyethene + polyethylene terephthalate	PE/PET	28 wt.%
Polyethylene + polyamide	PE/PA	6 wt.%
Polyethylene + polypropylene	PE/PP	16 wt.%
Polypropylene + polyethylene terephthalate	PP/PET	9 wt.%
Polypropylene + polyamide	PP/PA	1 wt.%

2.1.2. Experimental Sensor-Based Sorting Setup

The trials were conducted with an experimental sensor-based sorting (SBS) setup. The NIR sensor, an EVK-Helios-G2-NIR1, was used for the trials. This sensor detects the reflected NIR radiation emitted by a halogen lamp on a sample. The emitted radiation is reflected, absorbed, or transmitted depending on the specimen and interacts with near-surface molecules [14]. The spectral resolution of the sensor is 3.18 nm with a frame rate of 476 Hz and an exposure time of 1800 µs. Each spatial pixel is 1.60 mm wide, owing to the geometrical setup of the testing rig. The waveband evaluated during the trials was 991 nm to 1677 nm, split into 220 discrete measuring points. After detection, the radiation is analysed with EVK SQALAR to classify the respective spectra.

The function principle of the sorting rig is depicted in Figure 2.

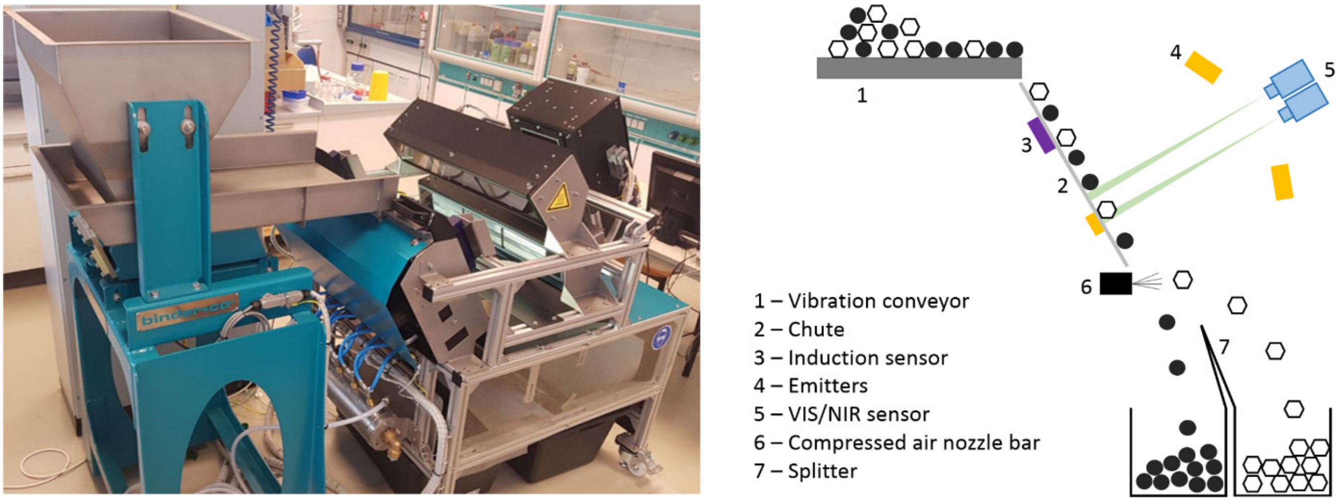

Figure 2. Experimental sensor-based sorting setup with the use of near-infrared spectroscopy.

2.1.3. Reflectors

The sorting experiments, which were the basis for the data evaluated in this paper, were conducted with two reflective chutes made of aluminium and copper. These adaptations had to be made to the existing sorting setup to allow for measurement in transflection. Two variants of the reflective chute were manufactured by laser cutting the metal plates. The specific shape of the reflector was chosen so as not to cover the illumination of the sorter, which is necessary to detect objects for ejection. Copper and aluminium were used as reflective materials because they are highly promising due to their high reflectivity of NIR radiation [15].

3. Methods

The described experimental sensor-based sorting setup was used to classify the 2D materials during the trials. This chapter explains the preparations to complete the sorting model generation and separation of materials. Further, the measurements in transflection mode are explained. Finally, the methods used in creating the machine learning approaches and the spectra improvement methods are explained.

3.1. Measurements in Transflection Mode

One of the defining characteristics of NIR sorting is the interaction of material and NIR radiation. During this interaction, the incident radiation energy is partially converted into kinetic energy of molecular vibrations, while other parts of the radiation's intensity are transmitted and reflected [16]. Only sufficient interaction between the molecules of the specimen and the incident NIR radiation creates useable NIR spectra for classification. Material with insufficient thickness causes most of the incident radiation to be lost to transmission. Additionally, the minuscule amount of reflected radiation has not interacted sufficiently with the material to cause alterations in the spectra. Preliminary studies have shown that the minor signal alterations caused by the low material thickness in reflectance mode can be alleviated by adapting the experimental sensor-based sorting setup for measurements in transflectance mode [7,17].

Placing a reflective background plate onto the chute allows measurements to be taken in transflection mode. This way of measuring thin films alleviates the problem caused by the low thickness of the material. The radiation is reflected after its first pass through the specimen. This approach enhances the interaction of radiation and material because of the lengthened path the radiation takes through the material: First, the incident NIR beam enters the sample and a small proportion of its intensity is immediately reflected. However, a significant proportion is transmitted through the specimen and consequently reflected by the reflective material placed behind the sample. Hence, it passes again through the material and can be detected through the NIR sensor. This additional pass through the material increases the spectral quality and enables the creation of a sorting model to classify film materials.

Through this process, the variability of the spectra is decreased. This variability is defined as the absolute difference between pixels of the same specimen [2].

Only if the pixels of a given specimen exhibit similar spectra, a specimen be classified correctly. Figure 3 compares the spectra of a PE film measured in transflectance mode (left) and the standard reflectance mode (right). The depiction shows the mean spectra of ten pixels, normalised via the “zScore” method and smoothed by Gaussian smoothing with a 10-point floating smoothing window. It can be seen that the characteristic PE peak at 1150 nm becomes more pronounced when measured in transflection.

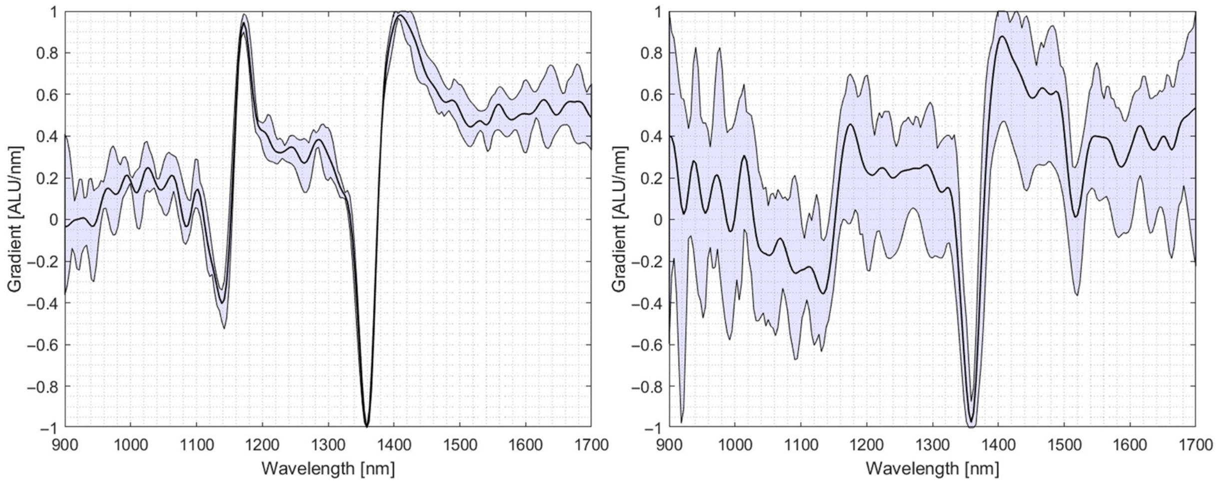

Figure 3. Comparison of spectral variability and characteristic peaks of a PE film when measured in transflection (**left**) and measured in reflectance (**right**).

3.2. Preparations for Sorting Trials

The trials were conducted with teaching and testing fractions. The specimens were separated into a teaching set to create the model containing 80% of the materials and a separate testing set to check the model prior to the sorting trials containing 20% of the specimen. A train test split of 80:20 is one of the most effective ways to train models [18]. The train set consisting of known composition mono- and multilayer materials was used to create a sorting model. The second class was the test set consisting of monolayer and multilayer materials not used for teaching the sorting model. With the teaching and test sets created, the reflective background was installed, and the sorting model, which is necessary to classify and eject the multilayer materials, was created.

Model Creation Using EVK SQALAR

The sorting model for separating the individual materials was created using EVK SQALAR.

A sorting model for NIR sorting defines the criteria for which the experimental sensor-based sorting setup sorts fractions based on reference spectra. These spectra are taken from known composition materials, and these benchmark spectra are compared to the unknown materials’ spectral information during the sorting trials. If an unknown pixel’s spectrum shows sufficient similarities to a reference, it is classified as this material class.

Apart from the reference spectra, the sorting model defines the pre-processing and spectral processing methods applied to the spectral information. Here, the upper and lower limits of spectral intensity in which viable pixels for evaluation lie, are considered. Concessions were made to create a sorting model that can use reflective backgrounds. Firstly, the white calibration with the reflective background was completed, allowing the existing white calibration algorithm to adapt to the increased intensity of reflected radiation due to the adapted chute material. Secondly, the illumination intensity had to be lowered to prevent overexposed pixels. This was performed despite the results of previous research stating that increased illumination intensity improves the spectral quality [17].

Table 2 shows the pre-processing and spectral processing methods used in preparing the spectral information for classification. These methods were described in the literature as ideal for separating post-consumer waste as they enhance the subtle differences in each spectrum, facilitating the differentiation between similar spectra, for example, between PE or PP monolayer and PE–PP multilayer [19,20].

Table 2. List of pre-processing and spatial-processing.

Pre-Processing	Spectral-Processing
Bad pixel replacement	Calculation of the first derivative
Intensity calibration	Smoothing
Noise suppression	Normalisation
Spatial correction	

This procedure for creating a sorting model was undertaken with the standard configuration for measurements in reflectance while the aluminium and the copper reflectors were used for measurements in transflectance. This approach yielded an individual sorting model for reflective surfaces and the non-reflective original chute.

3.3. Sorting Trials

The sorting trials were performed with every specimen in the test set. Each attempt was repeated five times to eliminate random factors, such as the trajectory of the film specimen. The sorter was set to eject multilayer materials.

A particle was considered to be classified correctly when the high-pressure nozzles were activated and the particle was ejected. Through this approach the number of correctly separated specimens for the respective configuration.

3.4. Principal Component Analysis to Determine the Possibility of the Application of Machine Learning Approaches

Even with increased fidelity to the material's spectral fingerprint in the available spectra, the overabundance of available multilayer material combinations poses a problem in creating a sorting model. It is infeasible to implement a sorting routine with spectral information to correctly recognise all available multilayer material to differentiate it from monolayer material, and neither is it feasible to include all existing monolayer materials in the sorting model. Therefore, it is necessary to adopt a sorting mechanism that achieves the task of detecting multilayer materials without explicitly implementing a vast number of multilayer spectra. For this, a supervised learning approach was chosen. In order to achieve this, common identifying characteristics of multilayer materials must be present. If they influence the spectra enough to enable classification, the existence of these characteristics would enable the separation of multilayer materials without the need to gather the spectra of each material. A principal component analysis (PCA) was applied to the 17,569 spectra recorded from the multilayer and monolayer specimens. The PCA was used to reduce the 220-dimensional spectral information into principal components to analyse if sufficient differences are present in the data to explain the variance of the data set with principal components.

Since the PCA indicated differences between multilayer and monolayer spectra, a comparison of the average of the multilayer material and monolayer material spectra was conducted. This comparison was used to evaluate the spectral range in which the two classes differ most. This comparison was made by taking the mean of all multilayer and monolayer spectra used in this trial. The two resulting spectra were compared by taking the two-norm of the distance of each spectral point of the monolayer spectra from its corresponding spectral point of the multilayer spectra. This yielded in the wavelengths at which monolayer spectra and multilayer spectra differ substantially from each other.

3.5. Evaluation of Machine Learning Approaches to Classify Spectral Data

With the information gathered via the PCA, an array of machine learning approaches was applied to the spectral information gathered from the thin film specimen. First, the 17,569 spectra gathered from the specimen were randomly separated into a training and a test set. This is required to enable holdout validation to train the machine learning approaches. The test set contained 20% (3513) of the spectra, while the training set consisted of the remaining 80% (14,056) of spectra, again utilising the recommended 80/20 split.

Cross-validation allows training and testing on a given number of data splits and thus permits an estimate of how well a given model will perform on unseen data. Holdout validation depends on splitting the data set according to the given ratio between the training and test set. Even with cross-fold validation potentially increasing the prediction success by 0.1–3%, the time trade-off on large data sets is substantial [21]. The machine learning approach was repeated using cross-fold validation with five cross-validation folds. One of the selected groups is used as a test set, while the other is used as a training set. After grouping, the model is trained on the training set and tested and scored using the test set. This process is repeated until all sets have been used as the test set. The holdout validation was chosen after preliminary tests resulted in a high prediction success when using holdout validation while requiring less training time.

Each NIR spectrum consists of 220 spectral data points. Every spectral point contains the radiation intensity detected by the NIR sensor and is a feature used for predicting the material class in this context. The first derivative of every spectrum was taken to enhance differences inherent in the spectral data, and no further feature engineering, e.g., feature selection, was performed. Thus, the machine learning approach initially used all 220 spectral points equally spaced over the NIR spectral region of 930–1700 nm. After these preliminary trials, a PCA was conducted, reducing the number of features from 220 to 3. These three features explained ~80% of the variance in the model. This approach tripled the number of observations per second the models were capable of and increased the prediction accuracy in one case.

All necessary computations were conducted running MATLAB by The MathWorks (Natick, MA, USA) Version 9.10.0.1710957 (R2021a) Update 4 on a Windows 10 computer equipped with an Intel® UHD Graphics 630 and an Intel ® Core ™ i5-9400H CPU clocked at 2.50 GHz.

3.5.1. Used Machine Learning Algorithms

Supervised learning approaches were used to differentiate between mono- and multilayer materials. The selection process for the correct algorithm yielded several different machine learning approaches to be tested. Since the problem at hand is a clustering problem with three possible clusters, the following algorithms were chosen and evaluated for their performance.

Decision Tree

Decision Trees are known as Classification and Regression Algorithms since they can perform classification and regression. Decision trees follow along their edges or branches and decide at the nodes which branch to follow to label a new input. A condition is queried at every node to decide which branch to follow [22]. When categorising whether a given material is a multilayer film or not, the prime features to be evaluated are the intensity of the given pixel at a specific wavelength. Figure 4 shows an example of a simple decision tree.

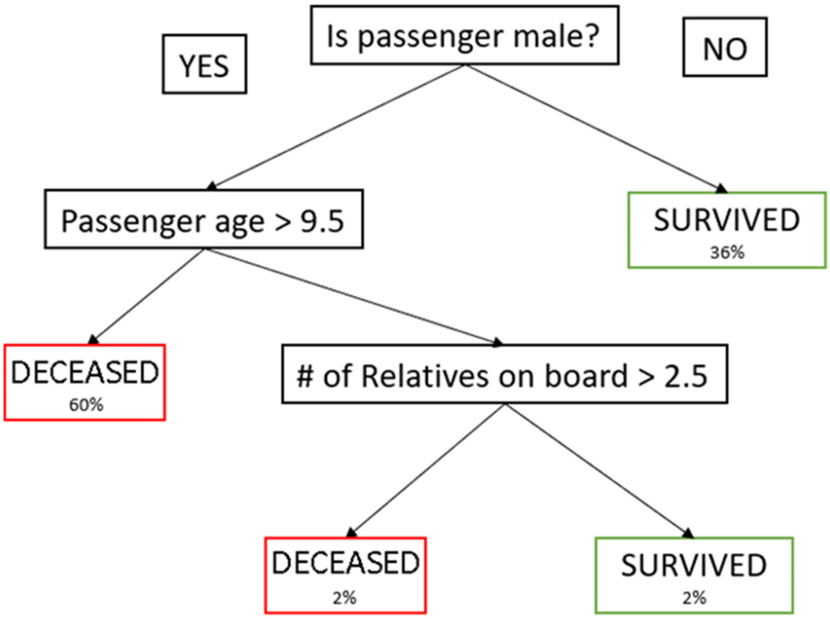

Figure 4. Example of a decision tree.

k-Nearest Neighbour

The k-nearest neighbour (kNN) algorithm works by analysing the distance between a new data point and its k-nearest neighbours. The user determines the number of neighbours evaluated, k, influencing the algorithm's outcome. The new data point is then assigned the label of the majority of its neighbours. The Euclidian distance between neighbouring data points is used as a decision criterion. [23].

Figure 5 shows an example; if k = 5 and 3 neighboring points are classified as multilayer while two are classified as a monolayer, the new data point will be labeled multilayer. In this example, the dimensionality has been reduced from 220 to 2 by a prior PCA. This reduction in dimensions is usually made in preparation of a kNN approach to avoid the effects of the curse of dimensionality, which plagues many machine learning algorithms [24]. In kNN, the Euclidian distance becomes useless as a metric in higher dimensions since all vectors are equidistant to the search query vector.

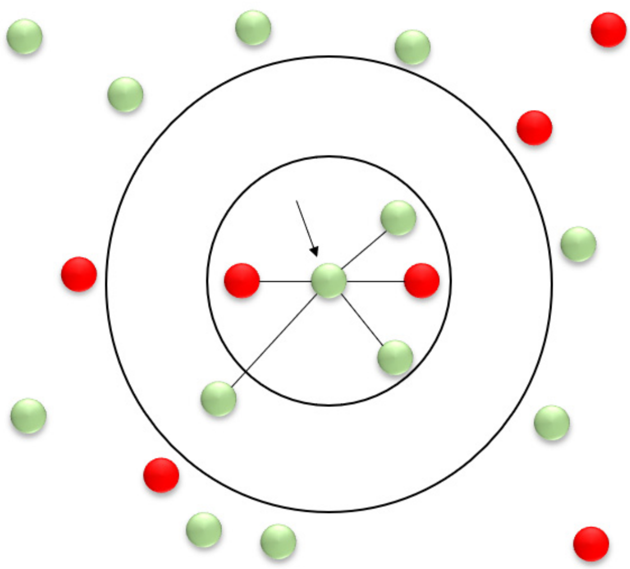

Figure 5. Example for k-nearest neighbour classification using k = 5 neighbours.

k-Means

The k-means algorithm is well suited to classification problems. It works by defining a number, k, of clusters. Then a set of centres for those clusters is randomly selected. All data points are then labeled according to their distance to these clusters. After this clustering, the new centres of those clusters are calculated, and the algorithm begins anew, again clustering the data around the new cluster centres. With every iteration of the algorithm, the change of the centres becomes smaller. The procedure is repeated until a threshold number of iterations is reached. The classification is then complete, and the model can be used to classify new data according to the k-clusters. The success of this approach dramatically depends on the selection of the initial centres. It is therefore advisable to create various k-means models with different starting parameters. Apart from relying on the starting conditions, the k-means approach's low computational and memory requirements are its advantages. Figure 6 shows a completed clustering using the k-clusters approach.

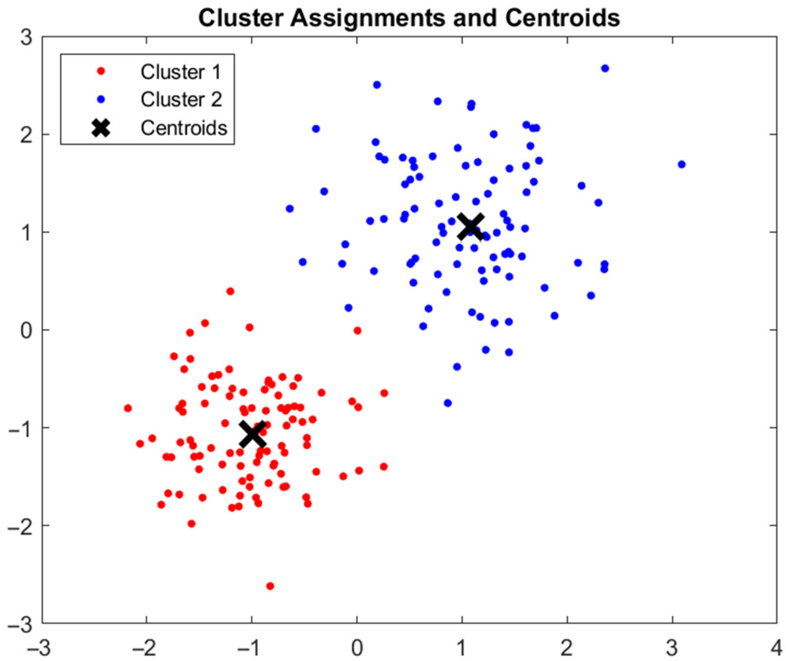

Figure 6. Example of a k-clusters clustering problem.

Support Vector Machine

Support vector machines (SVM) separate the given data set by a hyperplane that maximises the empty area between different data sets. This area is called the margin. The solution offering the maximum margin separating the given data sets is considered the optimum and chosen to classify new data. These separating lines, or hyperplanes, are generated by support vectors, thus the name. A sample showing the classification process of an SVM is shown in Figure 7. These hyperplanes can be linear and not linear, rendering the SVM able to classify most data sets of natural features where a linear separation is impossible [25].

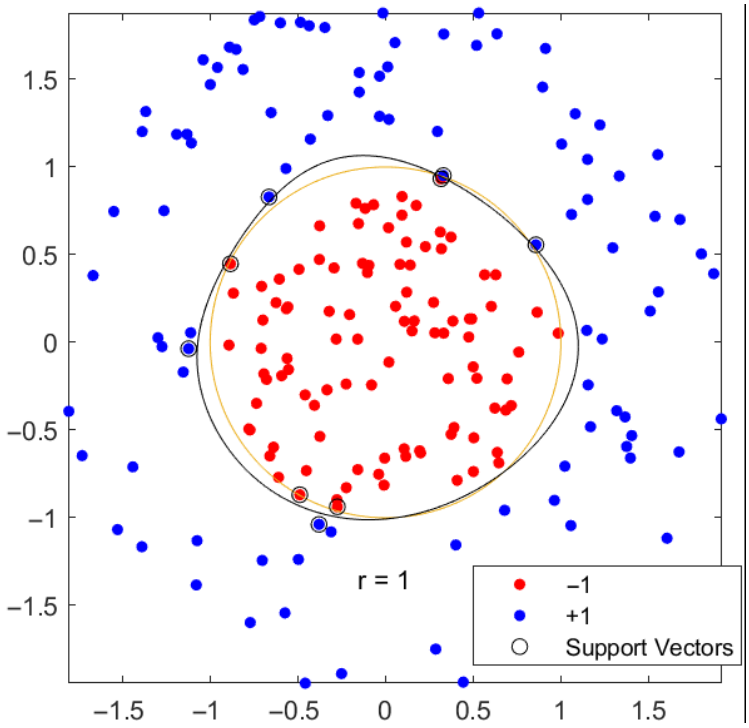

Figure 7. SVM classification using a nonlinear hyperplane and the classification result and the used support vectors to create the hyperplane.

Neural Net

The application of neural networks for classification differs from traditional machine learning algorithms. A classification task requires the input of labeled data, and this supervised learning approach can be used to classify all data that humans can label. Neural networks are commonly applied to text classification, fraud detection, voice identification, or video analysis. A shallow neural network (SNN) with one connected layer has been applied to the input. The input consisted of the first derivative of the spectra contained in the spectral image. The classification yielded three classes for the evaluated pixels: multilayer, monolayer and background.

3.5.2. Feature Engineering

Before classification, the raw spectral data was normalised using the "zScore" method, which ensures a mean value of zero and a standard deviation of one. The spectra were smoothed using a Gaussian smoothing algorithm with a ten-element sliding mean window. Additionally, the first derivative of the spectral data has been taken to make the differences inherent in the spectral data more prominent.

3.6. Use of Fast Fourier Transformation to Improve Spectra

Fast Fourier transformation (FFT) was applied to improve spectral quality. This approach enabled overlying sine wave-like spectral abnormalities to be reduced. This reduction in overlying sine wave-like spectral abnormalities made the analysis of previously obscured spectral information possible.

The fast Fourier transformation algorithm of MATLAB is used to achieve the original spectrum's discrete Fourier transformation (DFT). The DFT of a signal decomposes the original spectrum into a series of harmonic sinewave parts and represents a frequency spectrum. Figure 8 shows a representation of a generic noisy signal. Here it can be seen that any signal composes itself of a series of overlying frequencies. The underlying signal is overlaid with noise, making it difficult to determine the original signal. The noise could be eliminated by manipulating the signal in this representation, making the signal clearer.

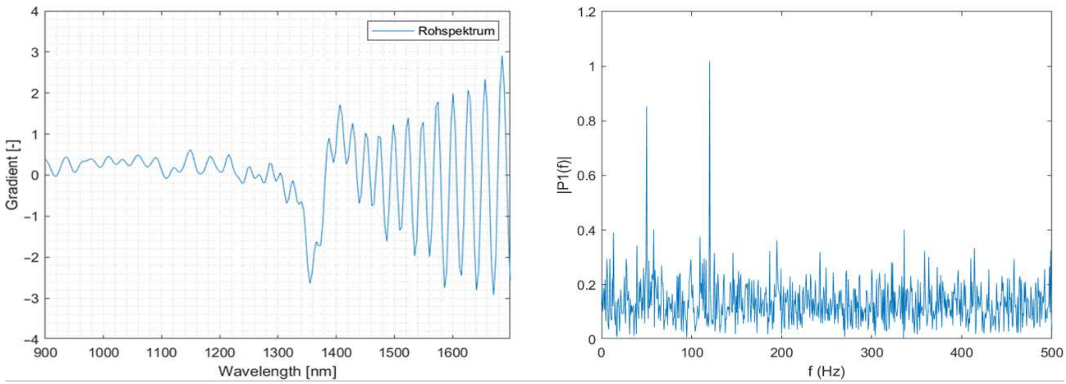

Figure 8. Spectral and Fourier depiction of a noisy signal.

By manipulating the representation of the original spectrum, unwanted noise, for example, the aforementioned sine wave abnormalities, can be omitted in the inverse Discrete Fourier transformation (iDFT). The iDFT is used to recreate the signal. To generate a usable spectrum, the placement of this filter has to be evaluated, and the resulting spectrum has to be compared to a suitable reference spectrum. This computation takes the two-norm of the difference between the new spectrum and the reference spectrum. An algorithm evaluates the resulting spectrum concerning the reference spectrum and places the filter in the position that yields the optimum spectrum, which facilitates this evaluation. This way, manual experimentation of filter placement, which previously took considerable time, can be automated [8]. The deviation from the reference spectrum is plotted over the corresponding filter position for visual inspection to evaluate the correct positioning. The result of this process is shown in Figure 9, which depicts the evaluated placement point for the low pass filter and the resulting deviation. The point in the search with the lowest deviation is marked. This placement point was then used for further processing.

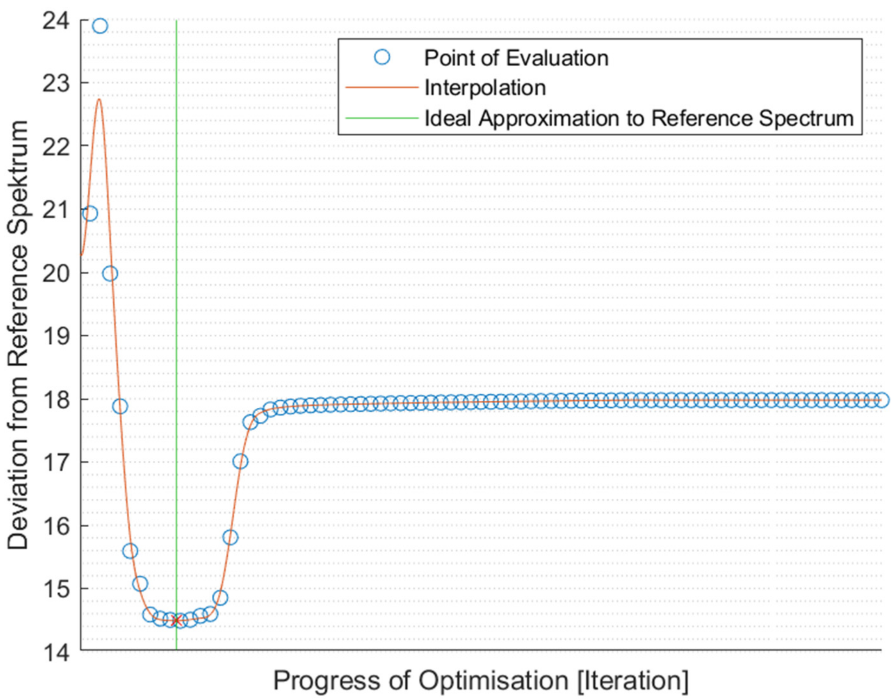

Figure 9. Progress of the optimisation over the deviation of the resulting spectrum from the reference spectrum.

The original spectrum is represented in 220 Fourier coefficients. These coefficients correspond with the camera's spectral resolution with which the spectrum was recorded. Figure 10 shows the representation of the spectrum after the FFT was applied. Further, the location of the deep pass filter is visualised.

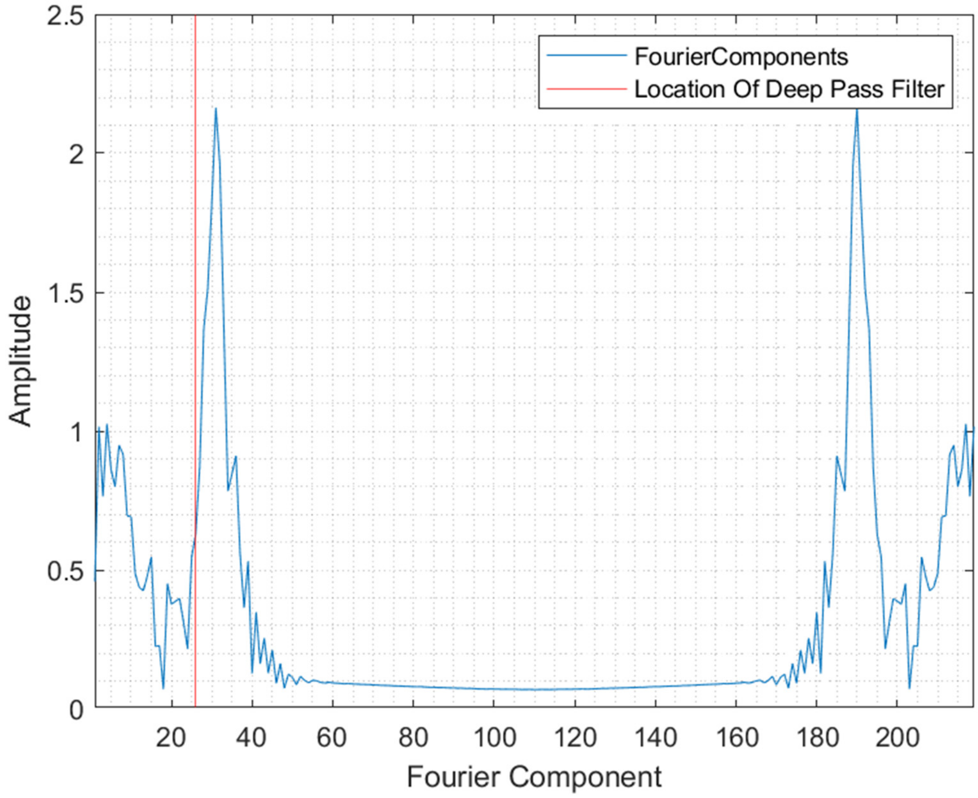

Figure 10. Fourier representation of the original spectrum.

Summary of Applied Methods

In summary, three methods were used to solve problems in sorting films. Firstly, the spectra quality was insufficient for separating the material. This issue was remedied by applying measurement in transflection. The second problem was that after the inclusion of reflective backgrounds for measurement in transflection, sine wave-like disturbances were still occurring in the spectra. These in turn were reduced with FFT. Because finding the correct cut-off point for the low pass filter by hand is time-consuming, an algorithm is used which finds the cut-off point that results in the best spectra after reconstruction.

The third problem was the abundance of material compositions in multilayer films, which impeded the creation of a sorting model that recognises multilayer materials. PCA and the comparison of multilayer film and monolayer film spectra evaluated the viability of applying machine learning methods to solving this problem. With these methods, characteristic differences in the spectra were found, which promised a successful application of machine learning methods. These methods were used to classify film spectra into two groups and were compared to each other's prediction accuracy and computation speed to find the best machine learning method suited for the task. Figure 11 shwos a summary of encountered problems when sorting films and the applied solutions.

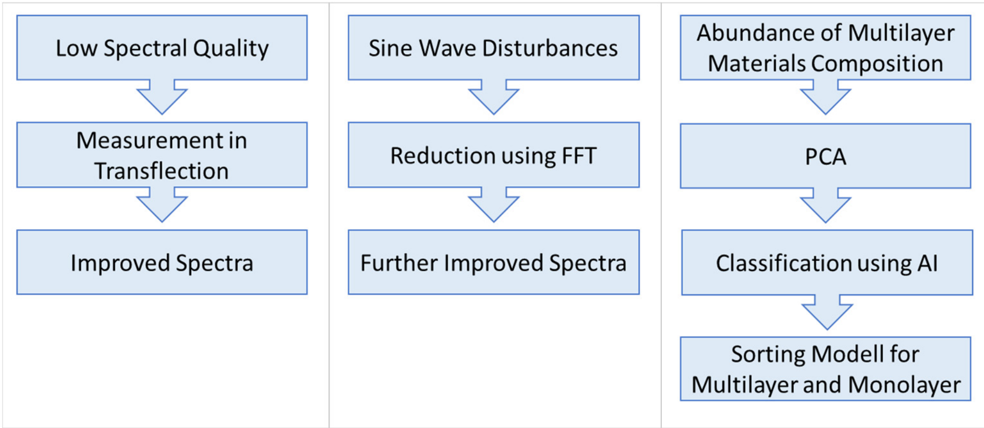

Figure 11. Summary of encountered problems when sorting films and the applied solutions.

4. Results

All results are assessed based on the number of correct ejections. The first sorting trials were conducted without adaptations to the sorting rig. These results are used as reference values to compare the effect of introducing a reflective background on sorting multilayer and monolayer films.

4.1. Detection Rate without Reflector (Glass Chute)

In summary, 46% of all materials were correctly sorted using no reflective surface as a background for classification. The lack of useable spectral information explains this low sorting success. Given the lack of spectral information to base the classification, creating the sorting model proved difficult.

Figure 12 depicts the detection rate for all materials using no reflective background.

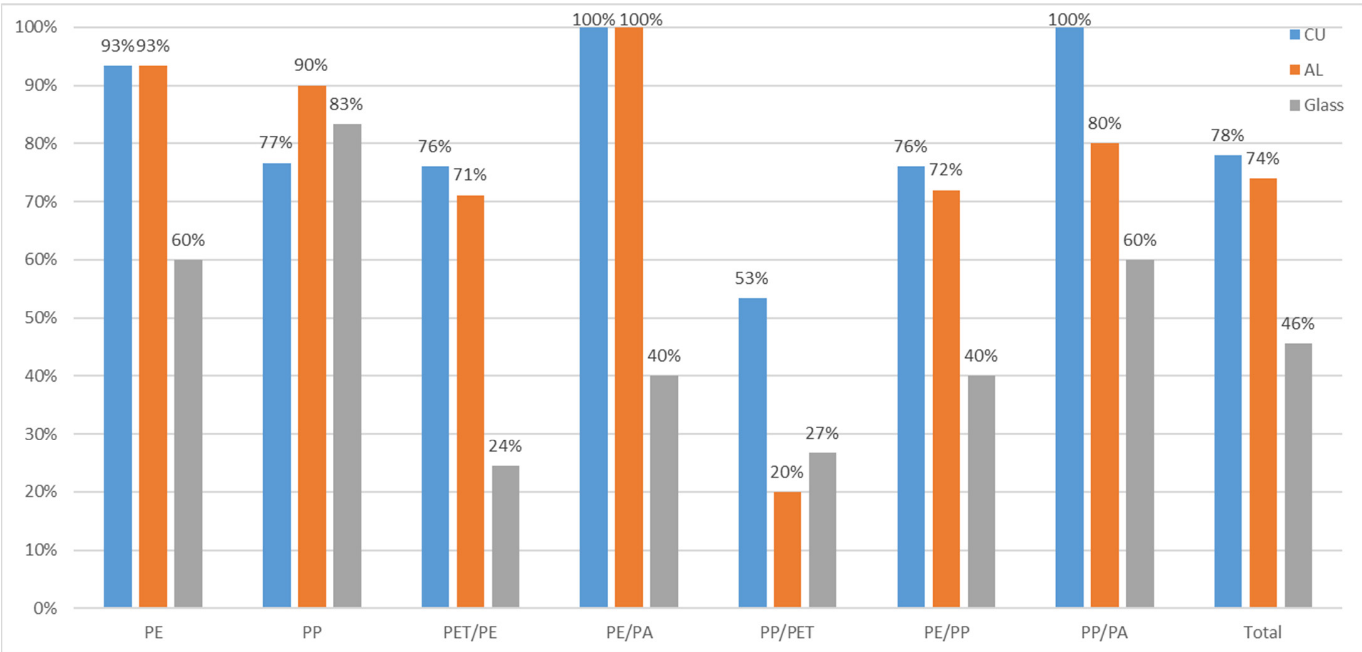

Figure 12. Detection rate with different reflectors concerning different materials.

4.2. Detection Success with Aluminium Reflector

The second trial was conducted with the use of an aluminium reflector.

Due to the optical properties of aluminium, it reflects near-infrared radiation and permits measurements in transflection mode. Since less radiation is lost to transmission, more pixels contain useable spectral information for classification. This effect permits the detection of the 2D materials, independent of their thickness and coloring. Optically transparent materials are detectable and, therefore, sortable with a reflective surface. This improved sortability is shown in Figure 12, which depicts the detection rate for all materials using an aluminium reflector and compares it to the initial results without a reflector. After the trial, 74% of all multilayer materials were ejected correctly, which is 61% more compared to the measurement in reflection.

The aluminium reflector showed great promise as a reflective surface, although its tendency to accrue an oxide layer that diminishes its reflective capabilities needs to be considered.

4.3. Detection Success with Copper Reflector

The third trial was conducted using a copper plate as a reflective surface. The high reflectivity of copper facilitated the model creation. Due to the high reflectivity, the number of useable spectra for model creation was increased. The copper's reflectivity enabled a sorting model that successfully distinguished the majority of mono and multilayer materials used in the trials. Figure 12 shows a comparison between all three setups.

4.4. Comparison of the Detection Experiments

In addition to its inherent higher reflectivity in the NIR spectrum compared to aluminium, copper does not tend to create an oxide layer, and this property may make it more viable as a reflector despite its higher cost relative to aluminium. Figure 12 shows the overall detection rate for all materials on all reflectors as a comparison and the total percentage of detected objects. The formation of verdigris was not encountered during the trials but will most likely pose an issue when using the reflective surface in an industrial setting and must be included in planning.

4.5. Evaluation of Differences in Ejection Rate between Polymer Types

This chapter explains the differences in detection and subsequent ejection between the polymer types. The spectral differences causing this lack of uniformity in ejection are explored. For this purpose, spectra were taken in each measurement mode (RAW), standard measurement without reflector, transflectance with aluminium reflector (AL-TR), and transflectance with copper reflector (CU-TR), are shown and compared with each other. In addition to the mean spectrum of the specimen, the variability of the spectrum is shown. The lower this spectra variability is, the easier the specimen can be assigned to one material group. In Table 3, the results of the trials are presented in tabular form for ease of reference in the comparison.

Table 3. Ejection rates with different reflectors.

Film Material	Ejection Rate Copper Reflector [%]	Ejection Rate Aluminium [%]	Ejection Rate No Reflector [%]	Average Ejection Rate [%]
PE	93	93	60	82
PP	77	90	83	83
PET/PE	76	71	24	57
PE/PA	100	100	40	80
PP/PET	53	20	27	33
PE/PP	76	72	40	63
PP/PA	100	80	60	80
Total	78	74	46	66

4.5.1. PE

It can be seen that 40% of PE films were falsely classified as multilayer materials and ejected when using no reflector. Figure 13 shows the spectra of a PE specimen used in the trials and shows that the variability of the spectrum taken without a reflector is comparably high. Especially in the area of 1200 nm, the second characteristic PE section is absent and diffuse. The spectra recorded using the copper reflector show very sharp characteristic sections at 1200 nm and 1400 nm with little variability. The spectra are shown in Figure 13.

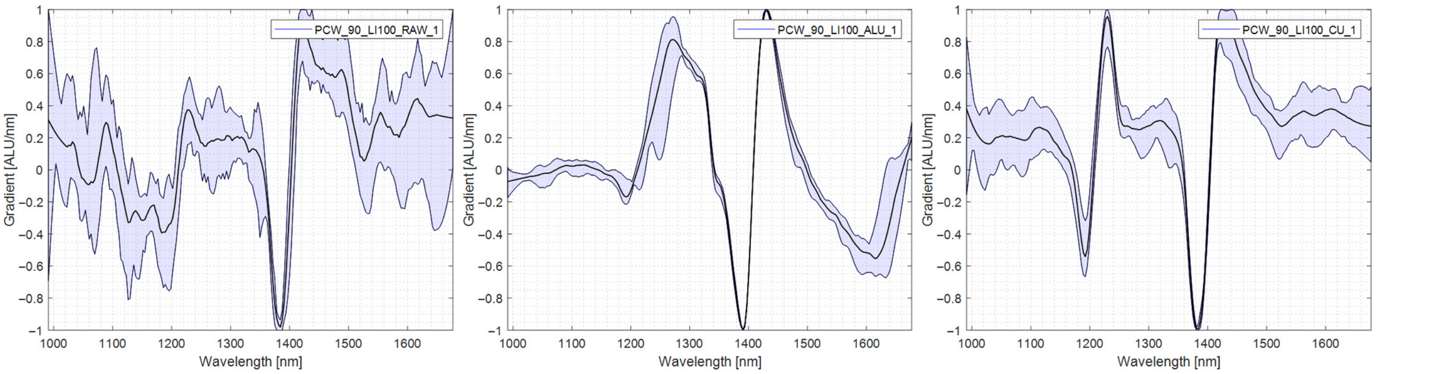

Figure 13. Comparison PE spectra, **left**: no reflector, middle: aluminium reflector, **right**: copper reflector.

4.5.2. PP

PP was recognised much better than other plastics in the trials. Without a reflector, 83% of the specimen were correctly sorted. Implementing an aluminium reflector raised this to 90% while implementing a copper reflector reduced the result to 77%. The answer to this abnormal behavior can be found in the spectral analysis. Examining the spectra taken in AL-TR, it can be seen that three characteristic peaks are present, namely at 1300 nm, 1400 nm and 1550 nm. In RAW, only one of those characteristics is present. In CU-TR, two of these three sections are present and can be used for classification, with the dip at 1550 nm absent. Irrespective of the used reflector, the quality of the PP spectra is more susceptible to the thickness of the specimen. PP specimens exhibit sine wave-like noise disturbances of the spectra at a higher thickness than other polyolefins such as PE [8,17]. The spectra are shown in Figure 14.

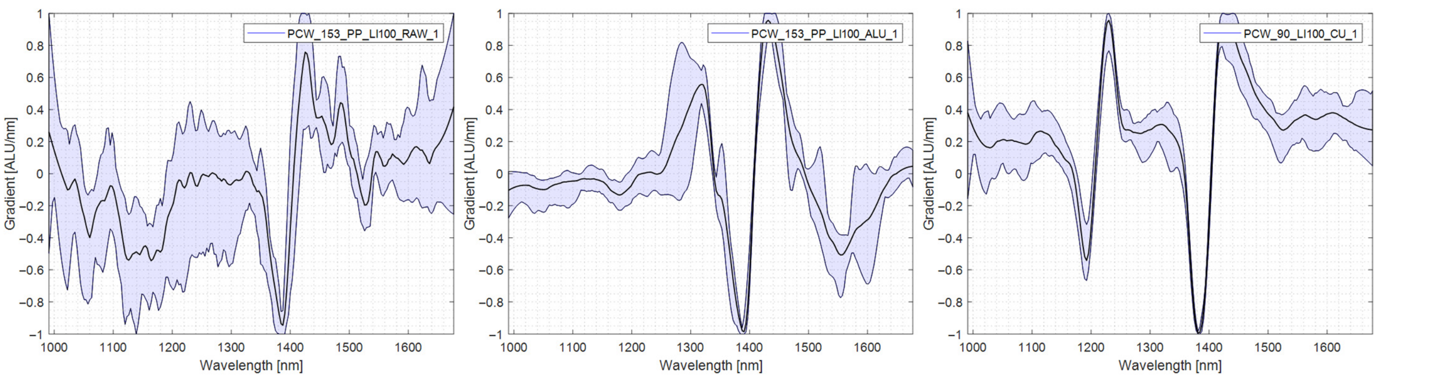

Figure 14. Comparison of PP spectra, **left**: no reflector, middle: aluminium reflector, **right**: copper reflector.

4.5.3. PE/PA

PE/PA showed a slight improvement in spectral quality. The characteristic regions at 1200 nm and 1400 nm are present without or with the reflector. The dismal ejection rate without the reflector was due to misclassification as a monolayer since the PE is dominant in the PE/PA spectrum. It can be seen that an aluminium reflector alters the spectrum in the region of 1200 nm by extending the peak in comparison to measurements without a reflector or with a copper reflector. The spectra are shown in Figure 15.

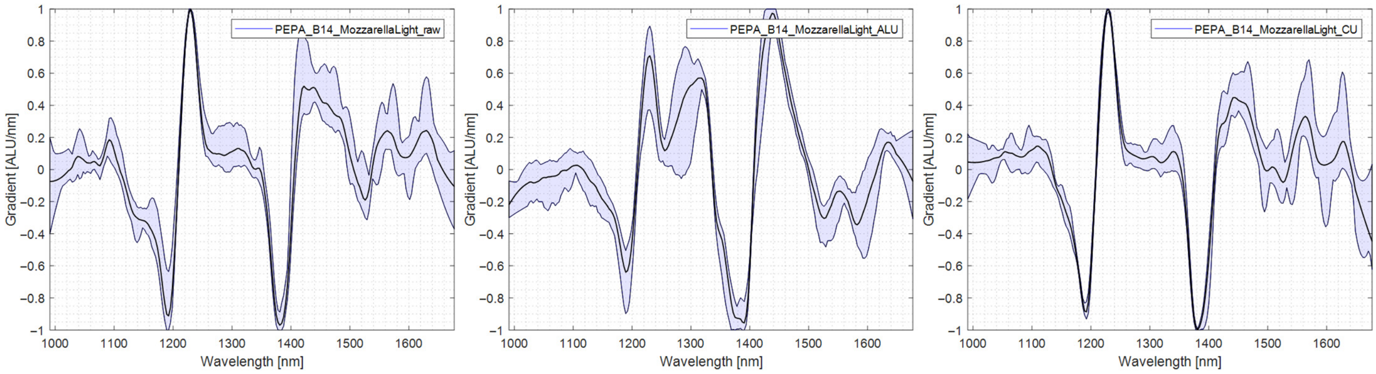

Figure 15. Comparison of PE/PA spectra, **left**: no reflector, middle: aluminium reflector, **right**: copper reflector.

4.5.4. PE/PET

PE/PET had the worst detection rate, with an average of 33% of all specimens correctly ejected in all trials. The cause is that PE makes up the central part of PE/PET composites. Since the intensity of any spectral component is proportional to the material's thickness, what little spectral information is detected resembles PE [26]. This dominance of the PE spectrum leads to the misclassification of the multilayer material as PE monolayer and, subsequently, the low sorting accuracy. These spectra can be seen in Figure 16. In the spectra recorded in RAW, the characteristic PET dip at 1500 nm is blurred by the variance. Measured with AL-TR, the characteristic PE peak is blurred, and the PET dip is diminished while the dip at 1400 is present. In CU-TR, all characteristic features of the PE PET multilayer are sharp and easily distinguishable, leading to the correct results.

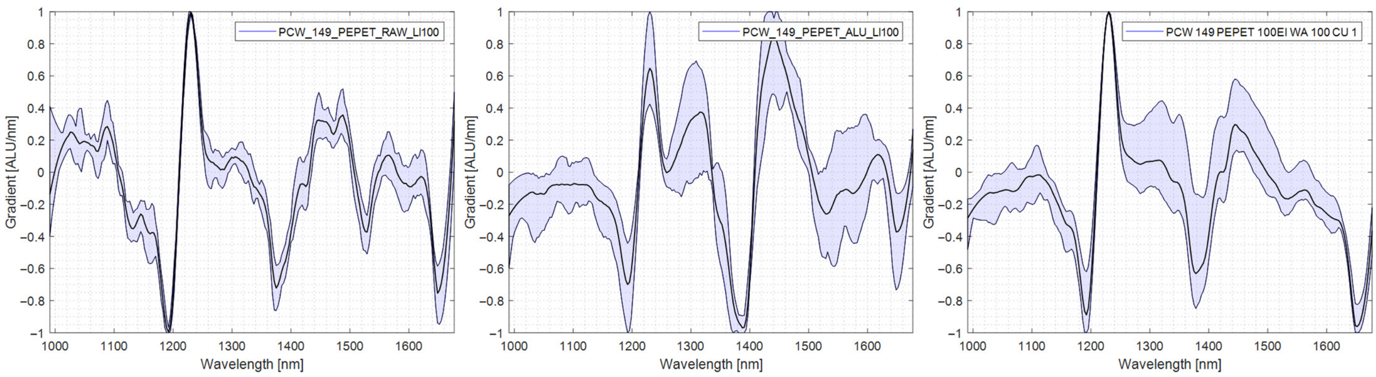

Figure 16. Comparison PE/PET spectra, left: no reflector, middle: aluminium reflector, right: copper reflector.

4.5.5. PP/PET

PP/PET was one of the films with the lowest ejection rate. It can be seen in Figure 17 that the characteristic PET peak at 1650 nm only starts to appear when a copper reflector is used. The spectra recorded without a reflector exhibit no spectral information and are unsuitable for classification. The inclusion of an aluminium reflector improves the spectra to a limited extent. More pronounced improvements are reached after a copper reflector was installed. After this installation, the characteristic peaks of PP and PET become apparent, reducing the risk of misclassifying the films as PP. The spectra are shown in Figure 17.

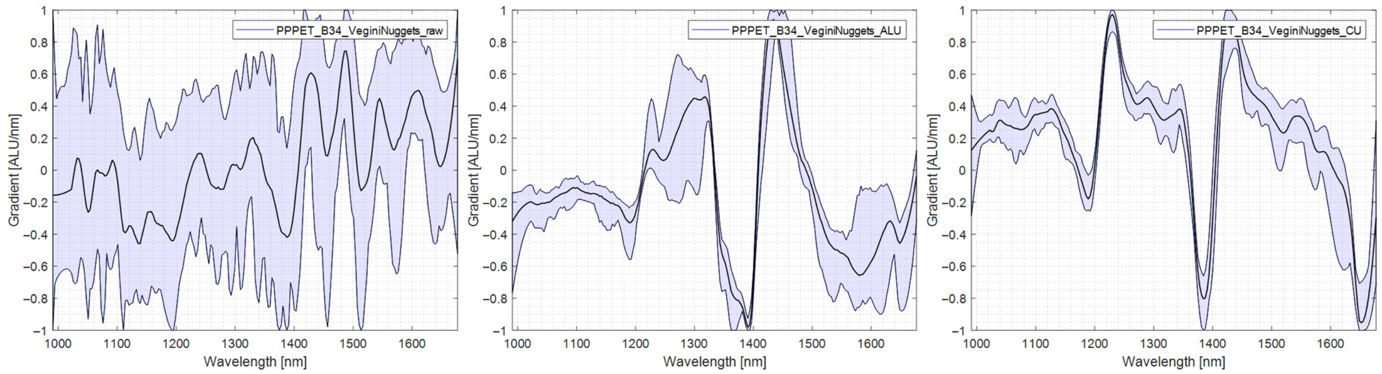

Figure 17. Comparison PP/PET spectra, left: no reflector, middle: aluminium reflector, right: copper reflector.

4.5.6. PE/PP

PE/PP multilayer specimens were sorted out without a reflector 40% for the time, and the introduction of AL-TR raised this to 72%, and CU-TR further increased this result to 76%. PE PP multilayer is especially susceptible to high variability in the spectrum since it is a composition of two materials exhibiting similar NIR spectra. All peaks overlap the PE and PP spectra and are present in CU-TR; thus, the material can correctly be classified as a multilayer film. The spectra are shown in Figure 18.

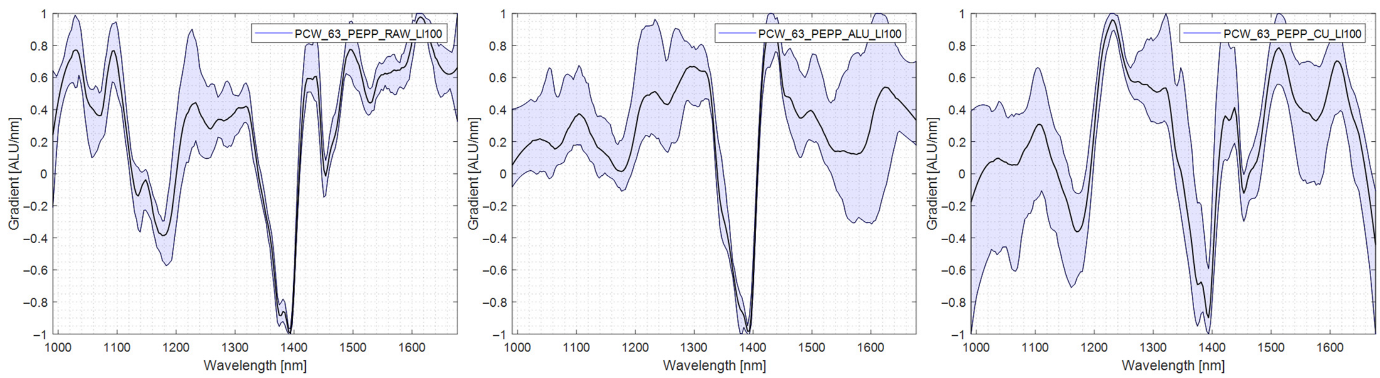

Figure 18. Comparison PE/PP spectra, left: no reflector, middle: aluminium reflector, right: copper Reflector.

4.5.7. PP/PA

PP/PA was comparatively well separable without a reflector. The spectra taken in RAW exhibit the material's characteristic peaks and minimal variability. The sharpness of the characteristic peaks and the variability of the spectra were further improved when measuring in AL-TR or CU-TR, mirrored by the improved results in the sorting trials. The spectra are shown in Figure 19.

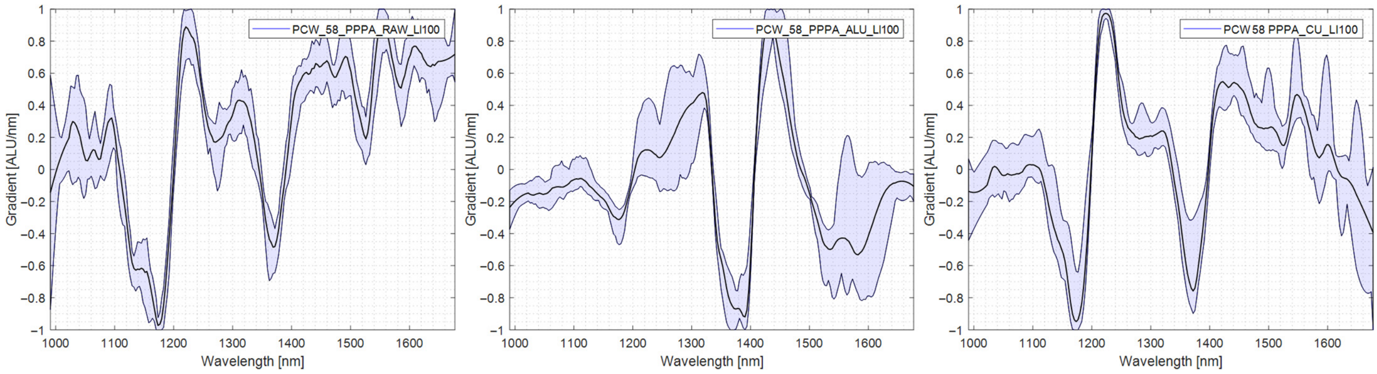

Figure 19. Comparison PP/PA spectra, left: no reflector, middle: aluminium reflector, right: copper reflector.

4.6. Application of Machine Learning Algorithms to Classify Film Spectra into Multilayer and Monolayer Categories Results

As a precursor to the classification via machine learning algorithms, a PCA and a comparison between the mean spectra of monolayer and multilayer materials were conducted to determine whether discernible differences between the two material groups exist, which can be exploited for their differentiation into the classes monolayer and multilayer material.

The application of PCA onto the spectral information yielded three clear clusters. The evaluation of the PCA showed that the first principal components could explain approximately 80% of the variance. This result successfully classified multilayer, monolayer, and the sorter's background into the three categories by machine learning algorithms. Figure 20 shows the result of this PCA. Here the three clusters can be seen. Green represents monolayer spectra, red represents multilayer spectra, and black represents the background material used in the trials. The monolayer and multilayer materials variance is described in dominant parts by the first principal component, further shown in the Pareto distribution diagram in the lower right corner. The first three principal components correspond with the spectral wavelengths of the separately examined spectra of 1038 nm, 1187 nm and 1309 nm that correspond to the second overtone of CH vibrations typical of CH_2, CH_3 and C=C chemical structures [27].

The evaluation of the spectral differences in the mean spectra taken from the monolayer and multilayer fraction yielded three spectral regions in which the mean spectra of monolayer and multilayer materials differ significantly. The comparison is visualised in Figure 21, which shows the mean multilayer spectrum in yellow, the mean monolayer spectrum in red and the three most pronounced differences. The first region where significant spectral differences can be seen is 1230 nm, corresponding to the second overtone of the CH bond [27]. Here the multilayer spectrum exhibits a more prominent peak than the monolayer fraction, possibly because of a different CH content within the two fractions. A similar difference can be observed at 1380–1410 nm, where the monolayer spectrum experiences a more pronounced dip than the multilayer fraction. This spectral region corresponds to the stretching and deformation vibrations of the CH bond of CH_2 structures [27]. While these two differences expressed a similar characteristic, namely a dip or a peak, the third difference sees the two spectra deviating strongly from each other [27]. Between 1410 nm and 1440 nm, the multilayer spectrum exhibits a wave-like pattern while the monolayer spectrum rises until a peak is reached. This spectral region can be associated with vibrations of several chemical bonds as the first overtone of OH stretching vibrations, stretching and deformation vibrations of CH in CH_2 and aromatic structures and the first overtone of NH vibrations. In particular, the shape of the spectra for the multilayer material would suggest that multiple peaks are present, and they might correspond to vibrations of aromatic or NH bonds typical of PET and PA, respectively. The spectra of the monolayer material would suggest possible vibration of one chemical bond type.

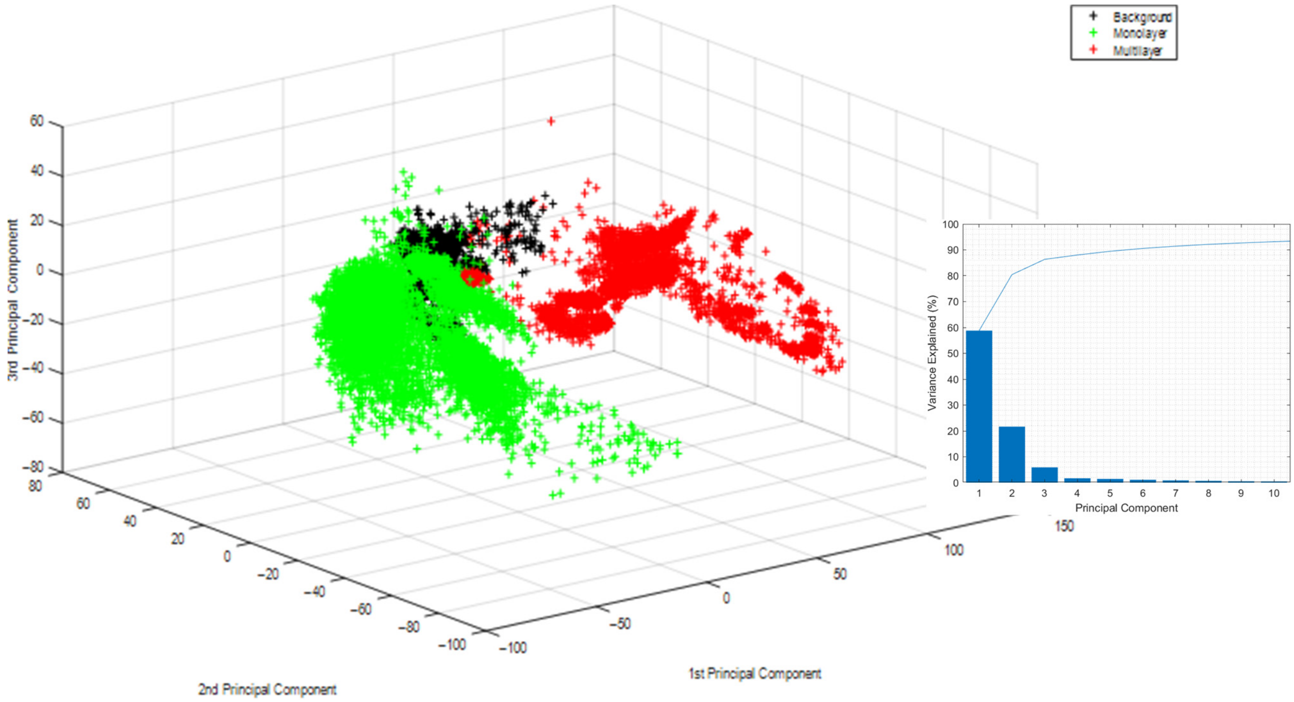

Figure 20. Result of the principal component analysis of approximately 17,000 spectra of monolayer, multilayer and background material to discern their sortability.

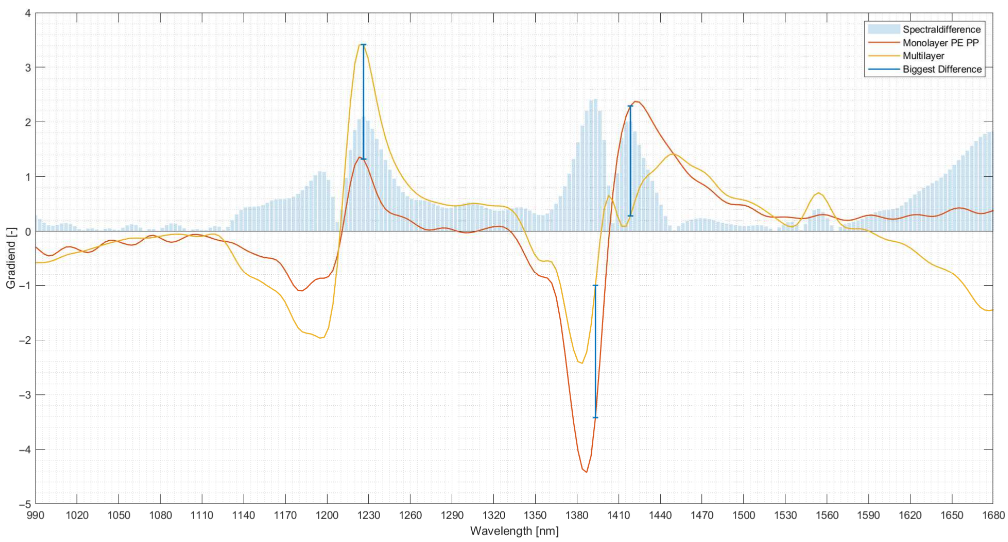

Figure 21. Differences in the mean spectra of multilayer and monolayer materials.

While the comparison of mean spectra of different materials cannot determine whether the differentiation of individual materials into the categories monolayer and multilayer is possible, it shows that differences between the two materials exist, which may be used to classify them accordingly.

After these preliminary examinations, the respective machine learning algorithms were used to classify the spectral data. Table 3 shows the success rate of each respective algorithm in correctly classifying the material into the classes multilayer, monolayer and background. All used algorithms show promising results apart from the k-means algorithm. This algorithm could not correctly identify the material, reaching an accuracy of only 60%. Amongst the others, the SVM and the SNN reached the highest accuracy.

Prediction Speed

The NIR sorter can achieve a refresh rate of approximately 500 Hz, which can effectively be halved without substantial loss of information while recording 320 spatial pixels with a spectral resolution of 220 points. This recording speed means that approximately 80,000 spectra must be evaluated every second. A machine learning algorithm's prediction speed is given as the number of observations processed per second, and its inverse would be the time taken for one prediction in seconds. The fastest examined machine learning algorithms were capable of prediction speeds of 83,000 observations per second, which would be fast enough to classify every pixel the spectral imaging camera recorded. It has to be noted that no pre-processing steps and additional computing time were considered for this calculation, reducing the number of spectra processable per second.

After evaluating the prediction speed and accuracy, a hierarchy of machine learning algorithms was established. Table 4 shows the percentage of correctly identified pixels and respective machine learning algorithm. With a PCA leaving three principal components for classification, the SVM outperformed the other algorithms regarding prediction speed and accuracy. This comparison is shown in Figure 22, which compares the examined algorithms and their success in classifying the test set. On the left, the prediction accuracy is presented. Here it can be seen that while all algorithms were able to label the spectra correctly in at least 80% of cases, the SVM, after PCA using the one versus one approach, could predict the material in 93% of cases correctly. Because these examinations aim to evaluate the algorithms for their applicability in a sorting operation, accuracy without prediction speed is irrelevant. Figure 22 shows on its right the comparison of the machine learning approaches concerning their time requirements per correct prediction. It can be seen that the introduction of a PCA prior to model generation decreased the time necessary to predict the label of a spectrum. Further, the PCA did not decrease accuracy. Therefore, the fastest algorithm was the SVM and the SNN with prior PCA using three principal components for prediction.

Table 4. Correctly identified pixels and respective machine learning algorithm.

Algorithm	Correctly Identified Pixels
Decision tree	98.15%
k-nearest neighbour	98.17%
Neural net	99.47%
Support vector machine	99.63%
Shallow neural network	**99.90%**
k-means	~60%

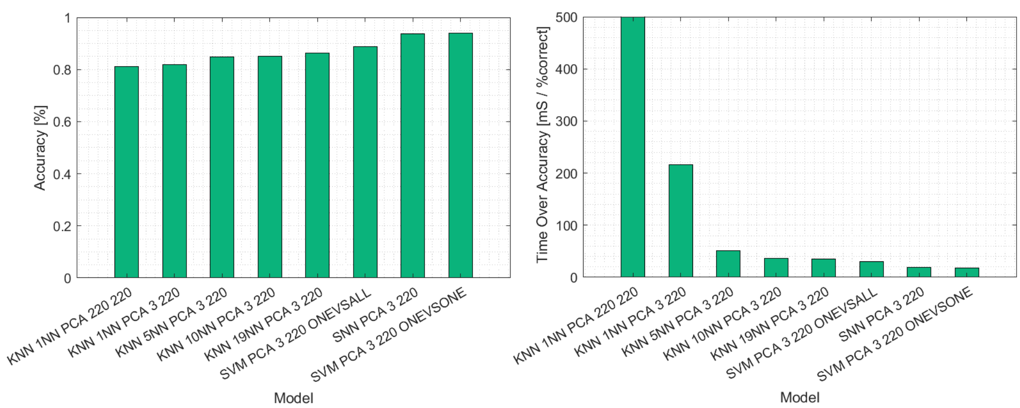

Figure 22. Comparison of the different machine learning algorithms used for classifying monolayer and multilayer materials in the test set.

4.7. Visualisation of the Classification Results of the Shallow Neural Network

The comparison of the applied machine learning tools yielded two methods especially well suited to the classification of films. The SVM and the SNN were almost identical in prediction accuracy and speed when presented with unknown data. Though both methods are on equal footing on these metrics, the SNN is superior in terms of training time. The SVM took 260 s to train, while the SNN only took 16 s. While these specific times are highly dependent on the hardware used for training, the ratio between the training times is independent of the hardware used for training. It took almost 18 times longer to train the SVM. Due to this advantage of the SNN, it was used to classify film specimens. In the following, the classification results of the SNN are shown.

The following figures show the classification results of the films. Each pixel identified in the evaluated rectangle as monolayer is displayed in green, multilayer pixels are shown in red and pixels identified as background are black.

Figure 23 shows the classification of a PE monolayer film. The SNN correctly identified most of the material. Areas with low spectral intensity were classified as background and are shown in black. A small number of pixels was wrongly classified as multilayer material. This issue is caused by the close resemblance of PE monolayer material´s spectra with PE/PP multilayer films, which can lead to misclassification.

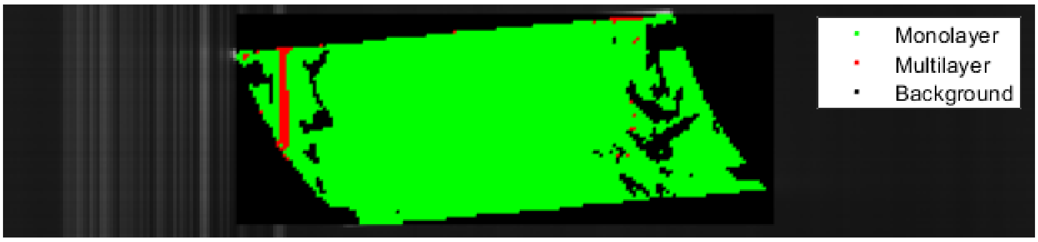

Figure 23. Classification of a PE monolayer film with the SNN.

Figure 24 illustrates the classification result of a PE/PET multilayer film. The specimen in question had an elongated form and some overexposure occurred, as shown by the bright sections in the image. The model had issues classifying the overexposed pixels, which can be seen by the red and green pixels, misclassified as mono- and multilayer film. Concerning classifying the specimen itself, the model was successful, shown by the resulting classification in red and the small number of misclassified pixels in green.

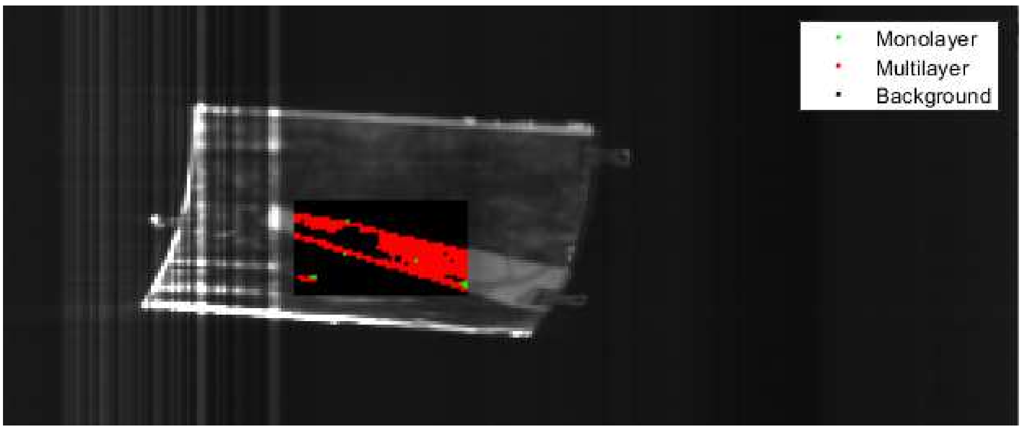

Figure 24. Classification of PE/PET multilayer film with the SNN.

Figure 25 shows the classification result of a PE/PP multilayer packaging film. PE/PP multilayer materials challenge the classification model due to the close resemblance of the PE/PP multilayer spectrum and the corresponding monolayer spectra of PE and PP monolayer materials. The result is a rather large proportion of misclassified pixels, as shown in the figure. Despite these unfavourable circumstances, the model managed to classify most of the specimens correctly as multilayer material.

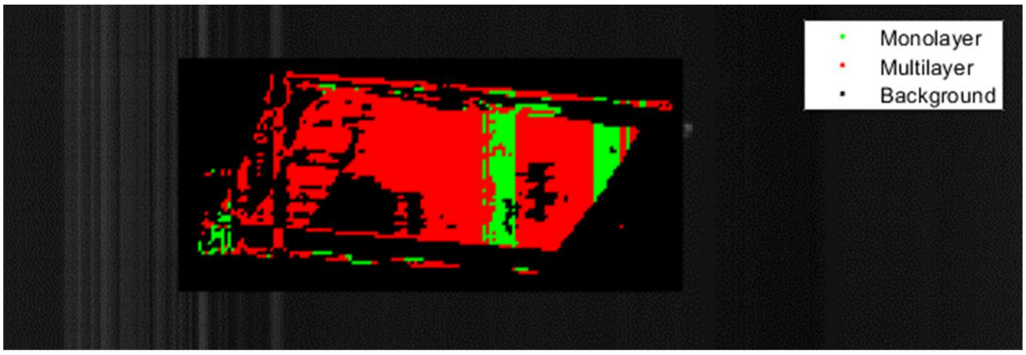

Figure 25. Classification of PE/PP multilayer film with the SNN.

Figure 26 shows the unclassified specimen and the classification result of the multilayer cheese packaging. The neural network had issues with the low intensity of the recording in some areas, shown by the large proportion of pixels classified as background in black. The neural network correctly classified most of the specimen´s pixels where the intensity was sufficient for classification. Only a minuscule number of pixels were wrongly classified as monolayer pixels, shown by the green pixels in the classified image.

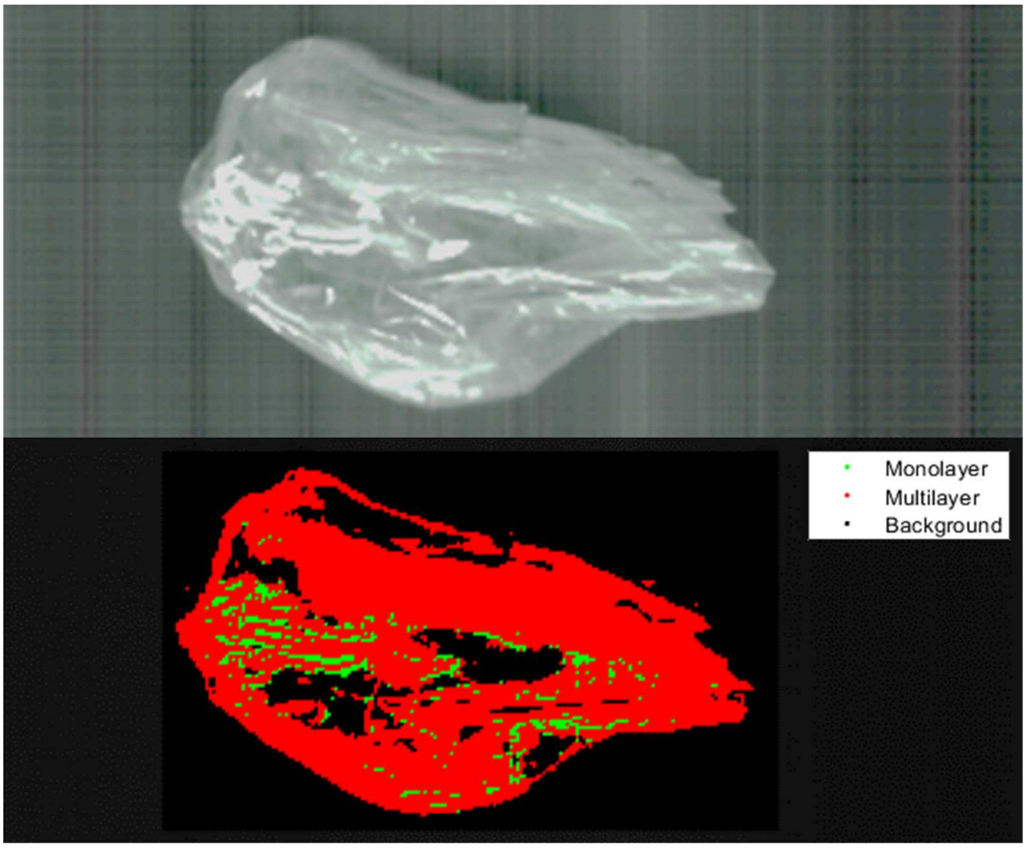

Figure 26. Classification of a cheese packaging film not used in training and testing with the SNN.

4.8. Application of FFT and Elimination of Frequencies

The application of FFT and subsequent elimination of interfering spectral abnormalities yielded improved spectra. These spectra regained their specific form used to categorise the respective materials. Figure 27 visualises the original spectrum before applying FFT and the following elimination of overlaying wave patterns. It can be seen that the spectrum exhibits almost no discernible patterns which could be used for classification. The characteristic peak at 1350 nm is insinuated but not pronounced. Contrarily, the characteristic peaks at 1150 nm and 1410 nm, expressed by the reference spectrum, are absent. After eliminating the overlying sine wave-like patterns, the fidelity of the spectrum to the reference spectrum improves. Although the peak expressed by the reference spectrum at 1150 nm could not be reproduced, the peak at 1350 nm becomes more pronounced and a second peak at 1410 nm becomes apparent. Further, the sine wave begins to form in the original spectrum at around 1390 nm and becomes less pronounced.

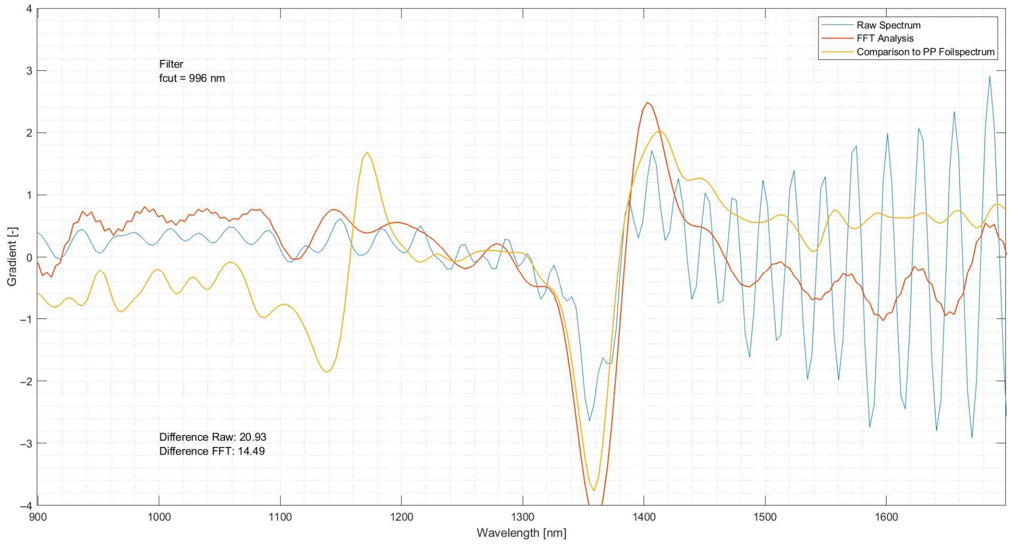

Figure 27. Difference between the raw spectrum (blue) and an improved spectrum (red) and their comparison to a reference spectrum (yellow).

The deviation from the reference spectrum could be reduced by up to 30%. This way, the information contained in PP spectra which were unuseable for the classification and generation of a separation model, could be extracted.

Finding the correct place for the filter has been automated, significantly reducing the workload for finding the correct filter placement.

4.9. Spectral Library of Film Materials

During the creation of the machine learning tests and the sorting trials, an abundance of spectral information of film materials has been recorded. This spectral information has been stored in MAT-files. MAT-files are binary files that store workspace variables. This spectral library contains the spectral data of over 130 film specimens. These spectra and the necessary MATLAB code library to visualise the spectral images and to extract spectra from these files have been organised into a repository. This repository and the data therein may be used to create proprietary film sorting models for further trials. This spectral library expands the existing TrashNet-NIR library by adding film spectra. For access to the repository, the corresponding author may be contacted.

5. Discussion

The sorting trials, the application of FFT and the machine learning approaches are discussed in the following. Further, the limitations of using a chute sorter to separate film specimens are evaluated and the possibility of incorporating the shown procedure in an integrated film separation process is elaborated upon.

5.1. Discussion of Sorting Trials

The sorting results indicate that the success rate of film sorting increases when reflecting backgrounds are used. The detection rate with a traditional non-reflecting glass chute did not reach 50%. With the introduction of a reflective chute, the detection rate reached over 70%, with better sorting results in every material category. This result supports the findings of previous experiments, which showed the improvement of film spectra using measurements in transflectance [2].

The increase in the detection rate is due to better useable spectra when the measurements are taken in transflectance mode. Furthermore, adding a reflective surface decreases the amount of radiation lost to transmission and enhances the spectral data quality available for classification and model creation.

The transflection mode was only evaluated with a chute sorter. However, in material recovery facilities, belt sorters are usually used for their higher throughput and the continuous speed of the particles. The specimen´s speed depends on its density and shape on a chute sorter. While in this case the input material is film, it is not so much the particle density as the particle shape that is a problem. Films, in particular, are difficult to sort, as their low weight and large surface area make them prone to gliding, making their ballistics hard to predict and their ejection difficult. Though the improvement in spectral quality and sorting of films using the transflection mode could be shown, further evaluation of transflectance measurements with a belt sorter would be advisable.

In addition, some material classes have been underrepresented due to a lack of available specimens owing to low occurrence in the waste stream.

Finally, the created monolayer fraction could be further sorted into the respective monolayer materials, PE and PP. Out of this monomaterial feedstock, recyclate and subsequently test pieces for mechanical examinations could be produced. These tests, for example, tensile tests or Charpy tests, could then be used to assess the mechanical properties of the recyclate.

5.2. Discussion of the Application of Machine Learning Approaches

Implementing machine learning algorithms such as an SVM or a deep neural network showed great promise in classifying monolayer and multilayer materials. The prediction speed without a preliminary dimension reduction was insufficient to even theorise about their feasibility in an industrial setting. After implementing a dimension reduction using principal component analysis, the prediction speed increased substantially. In addition to an increase in prediction speed, prediction accuracy also saw an incremental increase.

The correct classification of multilayer material without creating a specific model for each material class can be achieved by using common patterns among multilayer material. This is because machine learning methods can use these shared properties to detect multilayered particles which can subsequently be ejected. Hence, machine learning is suited to be used for this purpose.

5.3. Discussion of the Application of FFT to Improve Spectra Overlain by Sine Wave Abnormalities

Because the implementation of reflective background materials only reduced the occurrence of sine wave noise, this issue still needed attention. The tedious search for the ideal cut-off point was replaced by a simple algorithm that finds the optimal position where the reconstructed spectrum comes closest to a reference spectrum.

The main problem with this approach is that it depends on knowledge of the polymer type of the material. Its purpose was to elaborate on the possibilities of using FFT to improve film spectra. Further research is needed to ensure that the system can improve a spectrum without prior knowledge of its polymer type by having generic reference spectra of polymers to compare the improved spectra against. It is not necessarily the case that the recreated spectrum needs to adhere to a spectrum of the same material class. Instead, the goal of the FFT process is to reduce or eliminate overlaying sine wave spectral noise. So, comparing the spectra with an adroitly chosen generic reference spectrum exhibiting no sine wave disturbances could be sufficient. The improved spectrum could then be used for the actual classifying process. Further, only the application of a low pass filter has been described in this article as it extraordinarily improved the spectral quality. Additional trials may show that a supplementary implementation of a high pass filter may improve the spectral quality further though this has not been evaluated.

5.4. Discussion of an Integrated Process

Combining all processes shown in this work may be used to classify film spectra. First, the spectral image is taken in transflection and evaluated. The spectra used for classification are then classified either as suitable or unsuitable. If a spectrum is unsuitable for further classification due to sine wave noise caused by destructive interferences, the spectrum is improved via the shown FFT. Based on the spectra, the material is then classified by an SVM or neural net. Depending on the classification result, monolayer or multilayer film, the material is subsequently handled accordingly. In the case of monolayer material, further classification into the respective material groups via NIR is undertaken to create a monomaterial input stream for supplementary recycling processes. Two options are available for discussion if the material is classified as a multilayer. The material can either be thermally utilised or used as a feedstock for chemical recycling. Figure 28 shows a flowchart for this method.

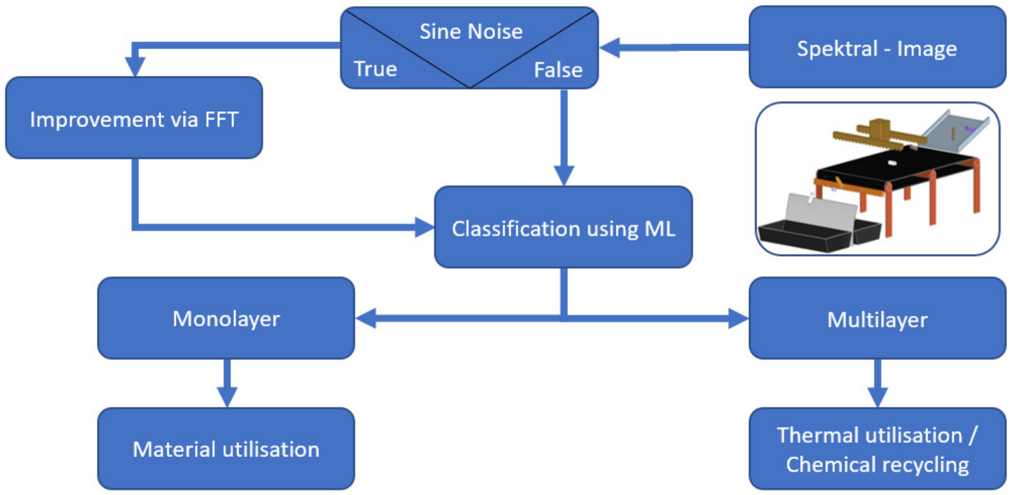

Figure 28. Integrated film recycling process.

6. Conclusions

NIR sorting success depends on the availability of high-quality spectral information. Traditional approaches struggle to provide spectra with high fidelity, as shown in the sorting trials lacking reflective backgrounds. Introducing reflecting backgrounds enables measurements in transflection, permitting the separation of monolayer and multilayer materials. This approach yielded an increase in detection rate from 46% to 74% with an aluminium reflector. Implementation of a copper reflector improved the detection rate further to 78%. Apart from an increase in the average detection rate, the recognition of every individual material increased with the introduction of reflective backgrounds. These findings support existing results that by increasing the reflectivity of the background material and the coinciding measurements in transflection, the sorting success of 2D materials can be increased.

Existing findings regarding the application of FFT to improve the spectral quality further were deepened. We proposed a method to apply FFT to spectra in order to eliminate destructive interference which in turn reduces the (manual) time demand. The improved spectra can then be used in machine learning methods to separate monolayer from multilayer materials. This adoption of machine learning methods was performed after the applied PCA showed characteristic differences between the spectra of mono- and multilayer films, regardless of their material composition. These overarching differences were used to train machine learning models. The trained machine learning models could correctly categorise mono and multilayer materials without the need to include every combination of multilayer materials in the training set. The computation times were low enough to consider the applicability of these methods for inline classification. Here, additional research is needed with more potent hardware.

Author Contributions: Conceptualisation, G.K., N.K. and D.V.; data curation, G.K.; formal analysis, G.K., C.B. and D.V.; investigation, G.K.; methodology, G.K., C.B. and K.F.; project administration, G.K. and C.B.; resources, C.B.; software, G.K.; supervision, G.K. and D.V.; validation, G.K., C.B. and D.V.; visualization, G.K.; writing—original draft, G.K.; writing—review and editing, G.K., N.K., C.B., K.F. and D.V. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Conflicts of Interest: The authors declare no conflict of interest.

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4.5 Publication IX, Mechanical discharge, Parameter dependency

"Influence of material alterations and machine impairment on throughput related sensor-based sorting performance."

Original Article

Küppers, B., Schlögl, S., **Friedrich, K.**, Lederle, L., Pichler, C., Freil, J., Pomberger, R., Vollprecht, D. (2021). *Influence of material alterations and machine impairment on throughput related sensor-based sorting performance.* Waste Management & Research. 2021;39(1):122-129. DOI: 10.1177/0734242X20936745.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 4-5.

Table 4-5: Annotation on the doctoral candidate's contribution to Publication IX

Conceptualization	Küppers, B., Schlögl, S., **Friedrich, K.**
Methodology	Küppers, B., Schlögl, S., **Friedrich, K.**
Software	-
Validation	Koinig, G. Barretta, C., Vollprecht, D.
Formal Analysis	Küppers, B., Schlögl, S., **Friedrich, K.**, Vollprecht, D.
Investigation	Küppers, B., Schlögl, S., **Friedrich, K.**, Lederle, L., Pichler, C., Freil, J.
Resources	-
Data Curation	Küppers, B., Schlögl, S., **Friedrich, K.**, Lederle, L., Pichler, C., Freil, J.
Writing: Original Draft Preparation	Küppers, B., Schlögl, S., **Friedrich, K.**
Writing: Review and Editing	Küppers, B., Schlögl, S., **Friedrich, K.**, Lederle, L., Pichler, C., Freil, J., Vollprecht, D., Pomberger, R.
Visualization	Küppers, B., Schlögl, S., **Friedrich, K.**
Supervision	Vollprecht, D., Pomberger, R.
Project Administration	Küppers, B., Vollprecht, D.
Funding Acquisition	Küppers, B., Vollprecht, D.

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Influence of material alterations and machine impairment on throughput related sensor-based sorting performance

Bastian Küppers , Sabine Schlögl, Karl Friedrich, Laura Lederle, Celestine Pichler, Julia Freil, Roland Pomberger and Daniel Vollprecht

Abstract

Experiments with sensor-based sorting (SBS) machinery provide insight into the effect of throughput rate and input composition on the sorting performance. For this purpose, material mixtures with certain compositions and particle size distributions were created from waste fractions and sorted at various throughput rates. To evaluate the sorting performance of the SBS unit (using near infrared technology) in dependence of the applied load, four assessment factors concerning the output fractions were studied: yield, product purity, recovery/product quantity and incorrectly discharged share of reject particles. The influences on the assessment parameters of light twodimensional (2D) particles in the input of a sorting stage and failing air valves in an SBS unit were evaluated for various input compositions at different throughput rates. It was found that a share of approximately 5 wt% 2D particles in the input had a similar negative effect on the yield as the malfunction of 20% of all air valves in an SBS machine at high throughput rates. Additionally, the failure of the air valves reduced the product purity of the sorting stage at increased throughput rates. Furthermore, qualitative observations concerning systematic effects of prior studies could be confirmed. Resulting graphs for a specific input composition of an SBS unit at varying throughput rates could be used to adjust the throughput rate to meet the exact demands for a sorting stage.

Keywords

Sensor-based sorting, sorting performance, purity, yield, recovery, throughput rate, input composition, NIR

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Introduction

The amended EU Waste Framework Directive sets new requirements for waste management to improve sustainability and resource efficiency. To target the implementation of an enhanced circular economy specific recycling rates for municipal waste were announced. By 2030 the recycling of municipal waste must be increased to a minimum of 60 wt% (Directive (EU) 2018/851, The European Parliament and the Council of the European Union (2018b)). Additionally, the required recycling rate for plastic packaging waste (PPW) by 2030 will be 55 wt% (Directive (EU) 2018/852, The European Parliament and the Council of the European Union (2018a)). In 2016 an average of just 42 wt% of 16.3 million tonnes of European PPW was recycled. Germany reached 48 wt% and Austria 34 wt% (Eurostat, 2019). Besides these conditions, the DKR (Deutsche Gesellschaft für Kreislaufwirtschaft und Rohstoffe mbH) sets further quantitative and qualitative specifications in some countries, such as Germany and Austria. Amongst others this concerns minimum amounts of recyclables, as well as the nature and limit for impurities (Feil et al., 2017).

To attain these required recycling goals significant improvements, not merely concerning the collection but rather the treatment of waste, are necessary. The modern recycling of post-consumer PPW is carried out in automatic sorting facilities. The use of sensor-based sorting (SBS) machines for this material is state of the art and enables the separation of various types of plastic. Normally a cascade of near-infrared (NIR) units follows pretreatment steps such as bag opening and metal and film removal to guarantee the demanded quality of products (Jansen et al., 2015). The separation of different types of plastics is crucial for a successful circular economy. If certain impurities remain in the sorting product special treatment (e.g. the forming of polymer blends using compatibilizers) is necessary for the regeneration of plastic. Otherwise the recycling products will be of lower quality ('downcycling') (Ragaert et al., 2017). As a consequence, not only the quantity but also the quality assurance of PPW recycling products is important.

According to technical literature and manufacturer specifications for SBS machinery the performance of such technologies is

Montanuniversität Leoben, Chair of Waste Processing Technology and Waste Management, Austria

Corresponding author:
Bastian Küppers, Montanuniversität Leoben, Chair of Waste Processing Technology and Waste Management, Franz-Josef-Straße 18, Leoben 8700, Austria.
Email: bastian.kueppers@unileoben.ac.at

subject to the load put on a respective unit. This load can be defined by the throughput rate (either volumetric or mass specific), material properties (e.g. particle size distribution) and the composition of the input material for a sorting unit (e.g. share of material that is supposed to be ejected via air shocks) (Cord-Landwehr, 2010; Redwave, 2019; Steinert, 2019).

To increase the performance of a sorting plant, not only the used technology in an SBS unit is relevant. The operation mode of the machine (e.g. the classification algorithm) as well as the functioning of prior processing and sorting units can have a severe influence on the sorting performance (Feil et al., 2016).

Generally speaking, there are two main external factors which determine the performance of an SBS machine: the throughput rate and the input composition (Feil et al., 2019). These factors are influenced by various aspects of a sorting plant. Besides others, the following are crucial:

1. Fluctuations of input quantity and quality (Feil et al., 2019; Martens and Goldmann, 2016)
   - Waste heterogeneity and seasonal or regional fluctuations
   - Batch-feeding of the continuously working sorting plant evokes mass flow peaks, for example through use of mobile loading technology (wheel loaders)
   - Inconsistent material discharge of processing machinery can result in under- or overfilling of aggregates (fluctuations throughout the week or day)
2. Screening efficiency (e.g. drum screen) (Feil et al., 2019)
   - Varying particle size distribution of heterogeneous waste
   - Low bulk density of plastics
   - Screen mesh size
   - Inclination and rotational speed (calibrated to achieve the residence time for a certain material flow rate)
   - Degree of filling (under- or overfilling)
3. Operation mode of other aggregates (Feil et al., 2016, 2017; Jansen et al., 2015)
   - Air classifier: air velocity defines which materials (films, beverage cartons, etc.) are separated
   - Feeding hopper: mechanical stress performed on the material might change the bulk density and therefore the throughput.

The aforementioned factors determine the mass flow (short and long term) and composition of the input into downstream SBS stages. In addition to the sensor performance, which can depend on the surface conditions of particles (e.g. moisture and roughness influence the classification) (Küppers et al., 2019), there are other influences which determine the efficiency of SBS:

- Number of sorting stages: rougher, scavenger and cleaner units. One step can either focus on yield or product quality (Feil et al., 2019).
- Singling of particles versus monolayer for spatial delimitation: basis for particle identification and selective separation (Feil et al., 2019).

A precise knowledge of possibilities and limits of the different units in a recycling plant is fundamental for operating ecologically and economically (Feil et al., 2017). The current research at the Chair of Waste Processing Technology and Waste Management of the Montanuniversität Leoben aims to quantify the impact of input composition and throughput rate (occupation density) on SBS. Küppers et al. (2020) found the following systematic effects from prior SBS trials:

- With increasing throughput rate the yield, recovery and product purity decrease while the product quantity increases.
- With increasing eject share in the input the yield, recovery and product purity increase as well as the product quantity.

This study focuses on input specific effects of varying particle sizes and two-dimensional (2D) disturbing material (e.g. from poorly functioning air classification) in the input and the influence of failing air valves on the sorting performance of an SBS machine.

Materials and methods

In the conducted series of tests, the separation of post-consumer polyethylene terephthalate (PET) from polyolefin (PO) was studied. In all experiments PET was intended to be discharged via air shocks while PO was intended to be rejected (no ejection through air shock).

Materials

The examined material originates from a shredded (<30 mm) air classifier heavy fraction of separately collected PPW material. Films, metal particles and other impurities were removed to generate a defined initial state, ensuring correct classification of all particles in the test material. This way the uncertainty factor 'sensor' was excluded from the study, which meant that all observed variations were due to sorting and not to sensing errors. Both the PET and the PO fractions were sorted and analysed multiple times with the SBS test stand in advance to ensure that both materials had 100% purity before the start of the experiments.

To generate a 2D fraction with assured correct recognition as reject material, standard paper (80 g m^{-2}) was cut into pieces of approximately identical size. The side length of the squares was about 5.2 cm (in the range of 4.5–5.5 cm).

Equipment

The experimental SBS setup, engineered by Binder+Co AG, is used to separate material according to different sorting criteria via a compressed air nozzle bar. As shown in Figure 1 a colour line scan sensor (VIS), an induction sensor and the employed NIR line scan sensor (EVK Helios-G2-NIR1) are part of the test stand but only the NIR line scan sensor was used for the experiments. An upstream vibrating conveyor with an optional feeding hopper was

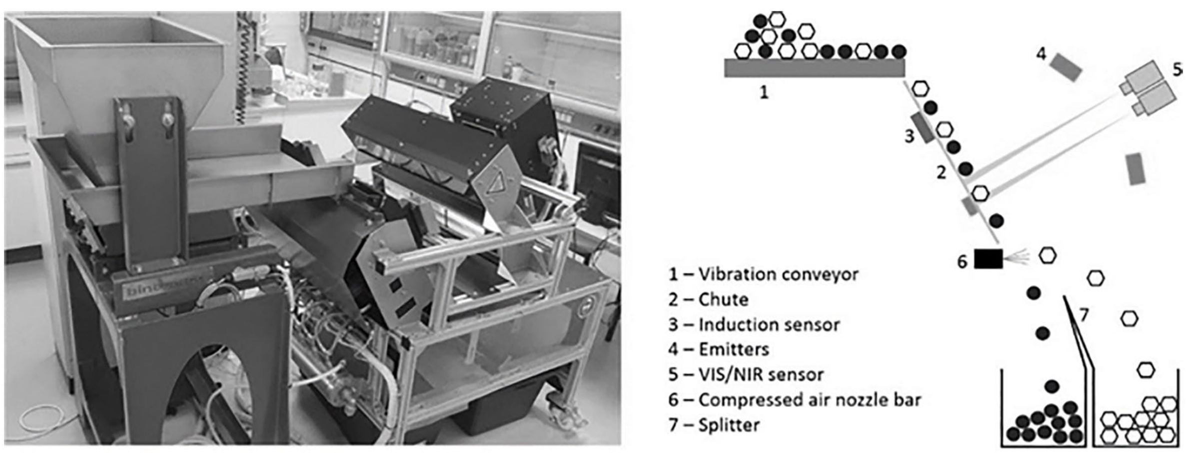

Figure 1. Experimental setup for sensor-based sorting trials.

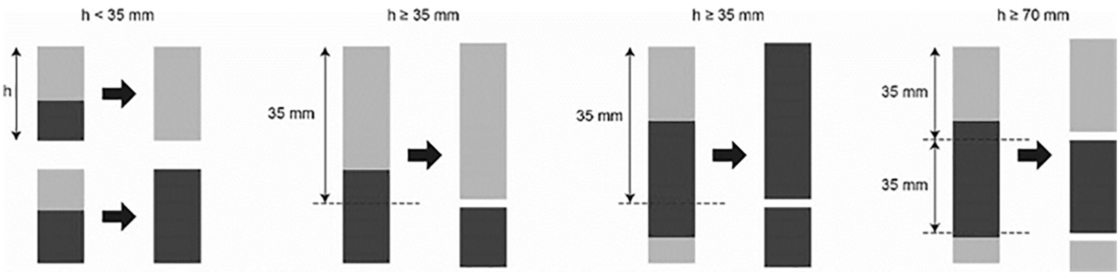

Figure 2. Classification mechanism depending on particle height (h).

used to feed the sample material to the chute sorter. The working width and length are 500 mm and 455 mm, respectively.

An infrared lamp is utilized as the emitter for the setup. The emitted radiation interacts with the near-surface molecules of the particles and is reflected, absorbed and/or transmitted depending on the chemical composition of these particles. The dispersed reflected radiation strikes the NIR sensor and is detected. Subsequently, this radiation (wavelength range: 1000–1700 nm) is converted into an electrical signal. A spatial pixel is 1.60 mm wide due to the geometry of the experimental setup. Depending on the sliding speed of the particle on the chute, the length of the pixel may vary but is always smaller than 1.60 mm. The frame rate of the line scan sensor is always 476 Hz with an exposure time of 1800 µs.

The sorting algorithm of the test stand digitally segments objects >35 mm in conveying direction. Every object is then classified individually as the material whose false colour pixels dominate the object. This is especially relevant for overlapping particles of different material. Figure 2 shows different scenarios depending on the particle height and the composition of a detected and segmented object.

A built-in data acquisition software from Binder+Co AG recorded the material specific number of detected objects after digital processing and classification.

Methods

In the course of the investigations, 204 experiments were carried out in total. These were organized in three phases, which in turn consisted of several test series for each generated input composition (Table 1):

Phase 1: reference trials
Phase 2: simulation of a failing block of air valves (on 20% of the working width)
Phase 3: simulation of poorly functioning upstream air classification (added paper)

The results from phase 1 constituted the baseline for the maximum machine efficiency depending on the respective throughput rate and input composition. The scenario of a failing block of air valves (phase 2) represented a tangible reference value to assess the effect of other factors on the sorting performance. In phase 3 the influence of 2D material, classified as reject (PO), was investigated. The number of experiments for the three phases and respective test series can be seen in Table 1. Trials for each test series (different mixing ratios) were conducted at varying throughput rates in the range of 5–350 kg h^{-1}. The exact rerun of a certain throughput rate was not possible, as the focus was to ensure a steady material feed. Accordingly, all trials in each test series were conducted with different throughput rates. Specific mixing ratios of PO and PET, e.g. 95/5 = 95 wt% PO and 5 wt% PET, were created as input materials. The mixing ratio 95/5 represented the base mix. Further PET particles were added to create the other mixing ratios. Depending on the mixing ratio, approximately 18,500–34,500 PET and PO particles were used for each experiment, according to the data acquisition software. For the

Table 1. Number of experiments for the different trial phases.

Mixing ratio (PO/PET)	Phase 1: reference trials	Phase 2: failing block of air valves	Phase 3: failing air classifier
95/5	10	21	6
90/10	11	23	-
80/20	11	20	6
70/30	10	19	6
60/40	12	17	6
50/50	10	17	5
Total	64	117	23

PET: polyethylene terephthalate; PO: polyolefin.

Table 2. Assessment factors for trial assessment (Feil et al., 2016).

Assessment factor	Abbreviation	Equation	
Recovery	R	$R=\frac{\dot{m}_{Eject}\left[\frac{t}{h}\right]}{\dot{m}_{Input}\left[\frac{t}{h}\right]}*100\ \%$	(1)
Yield	R_w	$R_W=\frac{\dot{m}_{Eject}\left[\frac{t}{h}\right]*c_{PET\ in\ Eject}[\%]}{\dot{m}_{Input}\left[\frac{t}{h}\right]*c_{PET\ in\ Input}[\%]}*100\ \%$	(2)
Purity	P_m	$P_m=\frac{\dot{m}_{PET\ in\ Eject}\left[\frac{t}{h}\right]}{\dot{m}_{PO\ in\ Eject}\left[\frac{t}{h}\right]+\dot{m}_{PET\ in\ Eject}\left[\frac{t}{h}\right]}*100\ \%$	(3)
Incorrect PO discharges	PO_{Eject}	$PO_{Eject}=\frac{\dot{m}_{Eject}\left[\frac{t}{h}\right]*c_{PO\ in\ Eject}[\%]}{\dot{m}_{Input}\left[\frac{t}{h}\right]*c_{PO\ in\ Input}[\%]}*100\ \%$	(4)

PO: polyolefin.

trials in phase 3 paper was added to the mixture. To each mixing ratio 5 wt% of the existing total mass were added on top.

Experimental procedure

For each test series a different mixing ratio of PET and PO was generated to investigate the influence of varying reject and eject shares in the input and interdependencies with other factors. The mass of each input mixture was recorded. Prior to every trial the mixture was thoroughly mixed ensuring even distribution of the different materials in the feed. The mixture was fed with the vibrating conveyor. For each trial, the test time was recorded resulting in the throughput rate of each experiment based on the ratio of input mass to test duration. The PET particles were classified as 'eject' material and discharged via compressed air. False classification mainly occurred due to the overlapping of reject and eject particles, potentially evoking the discharge into the wrong output. The composition of the respective eject fraction was subsequently analysed using the same SBS machine. For trials with paper in the input material all paper particles were removed prior to analysis, enabling assessment of its effect on incorrect discharge of PO and yield of PET only.

Statistical evaluation

For the online analysis of both the input material of each experiment and the eject fraction a data acquisition software was used. The number of detected objects for each material (PET, PO, paper and 'unknown') was recorded. The number of detected objects in the input material allows conclusions concerning the sorting performance. The number of detected objects during the analysis of the eject fraction provides information on recovery, yield, purity and incorrectly discharged PO particles. The analyses of the eject fractions were conducted at low throughput rates to ensure particle separation, thus reliable data.

The results were evaluated with respect to recovery (R), yield (Rw), purity (Pm) and incorrect PO discharges (PO_{Eject}). For the calculation of each assessment factor the equations in Table 2

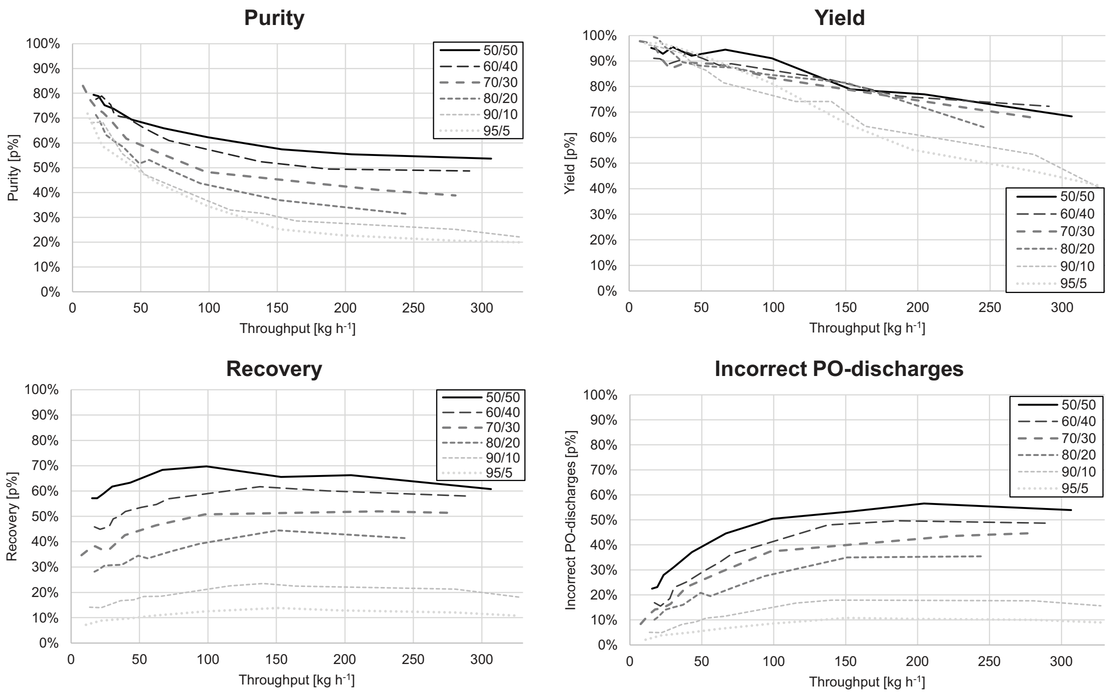

Figure 3. Effects of input composition (PO/PET) and throughput rate on yield, incorrect PO discharges, purity and recovery.
p%: particle percentage; PET: polyethylene terephthalate; PO: polyolefin.

were used. The variable ṁ describes the mass flow (input, output, recyclable material or impurities) in tonnes per hour while the concentration c in input or output is given as mass percentage.

All results presented in this study were evaluated on the basis of particle related recovery, yield, purity and incorrect PO discharges as this is most suitable for the assessment of an SBS unit. Hence, in the aforementioned calculations the mass flow complies with the number of objects in a defined time range. As a result, the assessment factors are given in particle percentage (p%) instead of mass percentage. The particle-related information can be converted into mass specific data by using material specific correction factors, taking into account the particle specific average grammages of eject and reject fractions.

Results and discussion

All experimental results are assessed on the basis of yield, purity, recovery and the share of incorrectly discharged PO particles. The first experimental results are those of the reference trials, quantifying the effects of different eject and reject shares in the input composition as well as the influence of the throughput rate on sorting efficiency. Subsequently the impact of the 2D material on the performance of an SBS stage is quantified and compared with the effect a defective block of air valves has on the sorting efficiency.

Reference trials

At throughput rates under 15 kg h^{-1}, yields >97 p% were achieved independent of the input composition. The yield was found to decrease in a linear fashion for increasing throughput rates. This decrease is caused by the overlapping or contact of PET and PO particles resulting in wrong classification of PET particles due to unfavourable digital segmentation.

For input compositions 95/5 and 90/10 the gradient is steeper than for more balanced input mixtures reaching about 50 p% yield at approximately 270 kg h^{-1}. The different gradients can be due to the fact that the experiments with PET shares >10 wt% had to be conducted by using the hopper to handle the input material, thus causing better deagglomeration, while trials with PET shares of 5 wt% and 10 wt% were conducted with the vibrating conveyor only. Additional experiments support this theory, showing that the input composition had no impact on the yield.

However, trials with coarser, rectangular particles created an exponential decrease in yield (Küppers et al., 2020). The form of the respective yield function might be dependent on the particle size distribution of the input material (Figure 3) in dependence of the sorting algorithm. This bears potential for further research, for example experiments regarding the effects of object versus pixel cluster classification on sorting performance in various particle size ranges.

The incorrect PO discharge (Figure 3) increases in the form of a saturation curve for all input compositions. As correct classification of PET and PO pixels was ensured, only two reasons for incorrect PO discharge persist:

- Overlapping or contact of PET and PO particles resulting in wrong classification of PO particles due to unfavourable digital segmentation
- Entraining of nearby PO particles via air shocks that are supposed to only eject PET particles

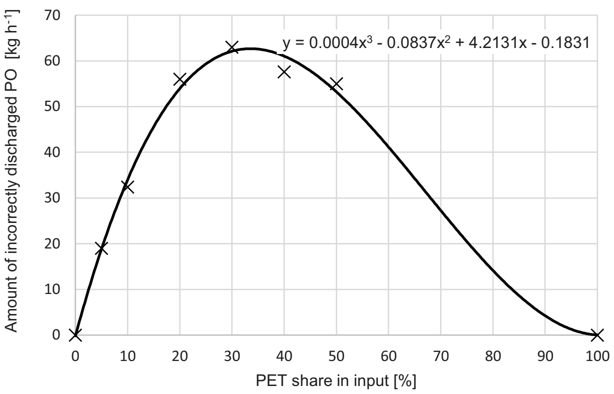

Figure 4. Quantity of entrained PO into the eject fraction per hour at throughput rate 200 kg h^{-1} and respective approximation function.
PET: polyethylene terephthalate; PO: polyolefin.

The latter reason is directly linked to the pressure that is used for the separation of eject particles with the air valves.

The forms of purity and recovery functions arise from the form of the saturation curve of the incorrectly discharged PO particles and from the linear decrease of the yield. The latter functions dictate the course of purity and recovery functions in dependence of the throughput rate.

The limit for each saturation curve of incorrectly discharged PO particles is always a multiple of the PET share in the respective input composition. This factor ranges from 2 for mixture 95/5 to 1.1 for mixture 50/50. The decreasing slope of the curve of incorrect PO discharges can be attributed to the differing numbers of PO particles that are entrained at specific throughput rates, reducing the probability that more PO particles are incorrectly discharged if the throughput rate is increased furthermore.

The share of entrained reject particles is of importance because firstly it determines the eject purity and secondly the entrained reject particles might consist of lost recyclable material that otherwise could be separated in downstream sorting stages. To know how much of this material is lost per time unit, the share of PO particles entrained into the eject fraction must be related to the total quantity (kilograms per hour) of input material for a respective sorting stage and not to the relative share of PO particles in the input material. Figure 4 shows the amount of PO particles (with regard to the total input) that is entrained into the eject fraction at a specific throughput rate, in this example 200 kg h^{-1}, for different input compositions under the assumption that PO and PET particles have the same weight. The maximum value of this function varies in dependence of the ratio of reject and eject material in the input composition.

Two variables affect the quantity of entrained PO:

The share of eject particles causing a respective number of air shocks per time unit that could potentially entrain reject particles – the higher the share of eject particles the more air shocks are triggered.

- The share of reject particles in an input mixture that could be incorrectly discharged – the higher the share of reject particles the more reject particles could be entrained.

In industrial applications usually the material fraction that dominates a mixture is rejected, while the minor fraction is ejected. Accordingly, no trials were conducted with eject shares >50 p% (Figure 4). If no PO was present in the input (100% PET content) the amount of entrained PO would be 0 kg h^{-1}. On the contrary, at 0% PET content no air shocks would be triggered resulting in 0 kg h^{-1} of incorrect PO ejection, if no false classification of PO as PET is presumed.

The right-skewed distribution function indicates that the maximum amount of losses occurs for an input mixture that comprises one-third eject and two-thirds reject material (particle and not mass related). Accordingly, neither the share of incorrectly discharged PO particles nor the eject purity are directly correlated to the entrained reject share. As a result of this observation the highest loss of reject material into the eject fraction is to be expected for mixtures with one-third eject material particle percentage and two-thirds reject material particle percentage. This maximum can be explained by the fact that one eject particle bears the chance of entraining multiple reject particles into the eject fraction and not vice versa.

Influence of increased 2D material share (paper) and a failing block of air valves

Figure 5 shows that a failing block of air valves decreases the eject yield in accordance to the working width it covers (in this case 20 p% ±5 p% as the block of valves also covers 20% of the working width) independent of the input composition or throughput rate.

The decrease of entrained PO is throughput dependent and reaches approximately 4–10 p%. The respective maximum decrease is reached at moderate throughput rates of 60 kg h^{-1} (PET-rich input mixtures) and 150 kg h^{-1} (PO-rich input mixtures).

As incorrect PO discharge is reduced to a lesser degree than PET yield the purity of the eject fraction showed a slight overall decrease of <5% due to the failure of the air valves. This can be attributed to the fact that PO particles, sliding over the area that is covered by the inactive block of air valves, can still be entrained by air shocks from working air valves nearby. Accordingly, it is presumed that the failure of multiple blocks of air valves has a bigger effect on the product purity if the blocks are not directly adjacent to one another.

The results show that the presence of 2D material in the feed of an SBS stage at low throughput rates has little to no effect on the yield but leads to a decrease of approximately 20 p% in yield for high throughput rates. A similar trend is apparent for incorrectly discharged reject material whose share decreases by approximately 10%. Accordingly, the presence of 2D material (5 wt% added) and inactive air valves (covering 20% of the working width) had a similar repercussion on the sorting process.

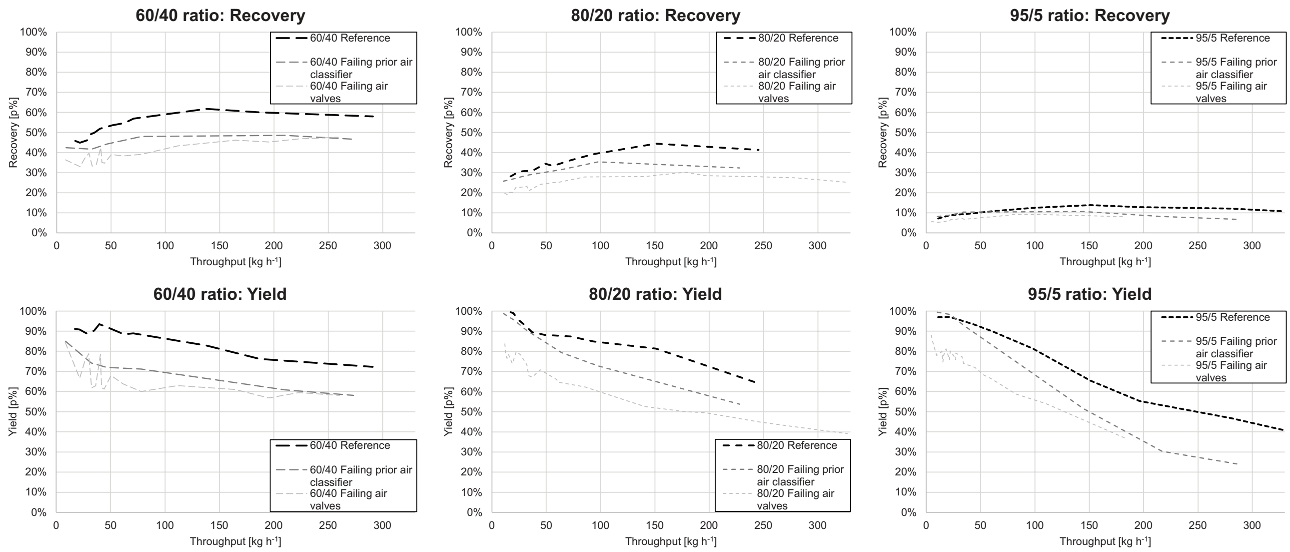

Figure 5. Influence of failing air valve blocks and 2D material on sensor-based sorting as functions of the throughput rate for various input compositions (PO/PET: 60/40, 80/20 and 95/5).
PET: polyethylene terephthalate; PO: polyolefin.

Conclusion

Quantitative investigations allow for particle specific assertions concerning the sorting performance of an SBS stage with regard to recovery, yield, purity of the eject fraction and share of incorrectly discharged reject particles. To transfer such information to mass specific statements the average grammage of eject and reject particles must be known. The given results show systematic effects of various factors that were investigated: input composition, throughput rate, presence of 2D material in the input material and malfunction of air valves on the machine performance. Further factors, either material or machine specific, are of vital relevance for the sorting performance; these are principle of the sorting algorithm (e.g. segmentation of particles), particulate weight, feeding method (e.g. type of vibration conveyor) and particle shape. Additionally, the influence of the particle surface condition (e.g. organic defilements, labels and adherent particles) on the classification must be taken into consideration to determine the overall sorting performance.

The following assertions can be made based on the conducted trials:

- Yield is not affected by the share of eject and reject particles in the input. Yield decreases with rising throughput rate.
- Incorrect discharge of PO particles increases in the form of a saturation curve with rising throughput rate. The limit for the maximum incorrect discharge is a multiple (factor 1.1–2) of the PET share, thus dependent on the input composition. The absolute quantity of entrained reject particles is highest for approximately one-third eject share although the relative loss of PO particles is highest for 50 wt% PO share in the input.
- Purity of the eject fraction decreases with increasing throughput rate. Purity of the eject fraction decreases with decreasing eject share in the input composition, whereby the influence of the eject share is enlarged with increasing throughput rate. Purity and recovery are functions of yield and incorrectly discharged reject particles.
- 2D material (classified as reject) in the input of a sorting stage proved to reduce the yield and incorrect reject discharge at increased throughput rates. For low throughput rates the influence of 2D material on sorting performance was negligible. A 5 wt% of 2D material had a similar effect on the sorting performance at high throughput rates as the failure of a block of air valves covering 20% of the working width of the SBS setup, whereas the effect of the failing air valves affected the sorting efficiency also at moderate throughput rates: incorrect PO discharge was reduced by 4–10 p%, peaking at high throughput rates for all input compositions. The yield was reduced by 20 p%, independent of the input composition.

To attain more comprehensive knowledge on interdependencies and the relevance of various machine and material specific influence factors, further trials with regard to the effects of e.g. machine design (chute versus belt sorter), air nozzle design, applied air pressure and particle properties should be conducted. Such information can enable the modelling and optimized configuration of throughput rate and machine settings to attain optimal machine and plant performances.

Declaration of conflicting interests

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ORCID iD

Bastian Küppers https://orcid.org/0000-0002-0367-4786

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4.6 Publication X, Mechanical discharge, Optimal Operation Point

"Feasibility study for finding mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste"

Original Article

Friedrich, K., Kuhn, N., Pomberger, R., Koinig, G. (2023). *Feasibility study for finding mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste.* In Polymers 2023, 15(21), 4266. DOI: 10.3390/polym15214266.

The annotation on the doctoral candidate's contribution to this publication is listed in Table 4-6.

Table 4-6: Annotation on the doctoral candidate's contribution to Publication X

Conceptualization	**Friedrich, K.**, Pomberger, R.
Methodology	**Friedrich, K.**, Pomberger, R.
Software	Koinig, G.
Validation	**Friedrich, K.**, Koinig, G.
Formal Analysis	**Friedrich, K.**, Koinig, G., Kuhn, N.
Investigation	**Friedrich, K.**, Koinig, G.
Resources	**Friedrich, K.**
Data Curation	**Friedrich, K.**
Writing: Original Draft Preparation	**Friedrich, K.**, Kuhn, N.
Writing: Review and Editing	**Friedrich, K.**, Koinig, G., Kuhn, N.
Visualization	Koinig, G.
Supervision	Pomberger, R.
Project Administration	**Friedrich, K.**
Funding Acquisition	**Friedrich, K.**, Pomberger, R.

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Article

Feasibility Study for Finding Mathematical Approaches to Describe the Optimal Operation Point of Sensor-Based Sorting Machines for Plastic Waste

Karl Friedrich [1,*], Nikolai Kuhn [2], Roland Pomberger [2] and Gerald Koinig [2]

[1] Mineral Processing, Department of Mineral Resources Engineering, Montanuniversitaet Leoben, Franz Josef-Strasse 18, 8700 Leoben, Austria
[2] Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Franz Josef-Strasse 18, 8700 Leoben, Austria; roland.pomberger@unileoben.ac.at (R.P.)
* Correspondence: karl.friedrich@unileoben.ac.at; Tel.: +43-3842-402-1812

Abstract: At present, sensor-based sorting machines are usually not operated at the optimal operation point but are either overrun or underrun depending on the availability of waste streams. Mathematical approaches for predefined ideal mixtures can be found based on the input stream composition and the throughput rate. This scientific article compares whether and under what conditions these approaches can be applied to sensor-based sorting machines. Existing data for predefined ideal mixtures are compared with newly generated data of real waste on three sensor-based sorting setups in order to make significant statements. Five samples of 3D plastics at regular intervals were taken in a processing plant for refuse-derived fuels. With the comparison of all these results, four hypotheses were validated, related to whether the same mathematical approaches can be transferred from ideal mixtures to real waste and whether they can be transferred to sensor-based sorting machines individually or depending on the construction type. The developed mathematical approaches are regression models for finding the optimal operation point to achieve a specific sensor-based sorting result in terms of purity and recovery. For a plant operator, the main benefit of the findings of this scientific article is that purity could be increased by 20% without substantially adapting the sorting plant.

Keywords: sensor-based sorting; NIR sorting; optimal operation point; throughput rate; input composition; purity; recovery; regression model

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1. Introduction

Increasingly strict governmental guidelines for the efficiency of recycling plants and growing demands for recycling rates require state-of-the-art plant management to fulfil all obligations regarding the purity of product and tonnage of waste processed while still operating profitably. The new European Waste Framework Directive [1] requires a recycling rate for all municipal solid waste of 60% by 2030. Furthermore, in 2020, 34.6 kg per capita of plastic packaging waste had been generated per capita in the European Union with as little as 13.0 kg per capita being recycled [2]. Stricter legal requirements combined with the rising consumption of plastic packaging makes new innovative technologies necessary to increase the efficiency of existing waste-sorting plants to sort plastic waste and plastic from municipal solid waste.

One of the primary concerns regarding sorting plastic waste is the dichotomy of meeting both requirements, namely output with sufficient purity while maintaining a high yield and throughput rate to process sufficient amounts of plastic waste. The dichotomy lies in the effects of increasing throughput rate on sensor-based sorting (SBS) machines commonly used to sort plastic waste [3]. It has been shown that diminishing purity is expected with the increasing throughput rate [4].

Plastic waste can be sorted using optical sensors in SBS, triboelectrostatic forces or density separation with hydrocyclones [3]. However, the most applied technology for sorting post-consumer plastic waste is near-infrared (NIR) spectroscopy applying hyperspectral imaging [5]. NIR technology is a fast non-contact and non-destructive SBS method in waste management [6,7]. The NIR region covers a wavelength range between 750 to 2500 nm [8] and allows the differentiation of various materials based on the vibration of molecules excited by radiation. The emitted light leads to vibrational and rotational movements of molecules or parts of molecules of the material. As a result, the corresponding absorption bands can be captured with an optical sensor in form of a spectrum [9]. This spectrum provides information about the chemical composition of the sorting material and enables the detection of measurable separation properties of a material stream [10].

Two NIR sorting construction types are commonly used in waste processing plants, which differ in how the waste material is moved past the sensor. The movement is based either on gravity, when the material slides down a chute, or on mechanical forces using a conveyor belt. While granular material is usually sorted using a chute, bulky materials are sorted using conveyor belt machines [11]. The latter systems are also a focus of this study.

SBS plants are susceptible to changes in input quantity and quality (composition), with surface conditions significantly affecting sorting success [12] and plants being frequently overrun or underrun, reducing sorting efficiency [4].

Finding the optimal operation point for these SBS aggregates is paramount for the success and profitability of any waste processing plant. Empirical averages can perform this optimization and provide an acceptable approximation, but it is time-consuming and assumed to be repeated for every aggregate [4].

Developing a mathematical approach to optimize the throughput rate of a specific NIR sorting setup can save valuable time and increase the profitability of existing sorting setups. Moreover, it can reduce the energy amount for the process by operating the system at the optimal operation point.

2. Degree of Novelty and Industrial Relevance

Referring to the existing findings in the correlation of input composition, the throughput rate and the SBS results (purity, yield, recovery) from Küppers [4], we know that there is a correlation within these parameters in mathematical approaches for ideal self-composed plastic fractions with a defined mixing ratio (ideal mixtures).

The research novelty of this paper is to determine whether these mathematical approaches can be extended to real plastic waste and its input compositions because this is still unknown. Furthermore, when the same mathematical approach cannot be used for real waste, it is a point of interest how similar mathematical approaches would look for real plastic waste when the same sorting task is performed.

When a mathematical approach for real plastic waste can be developed, it raises the research question of what level of precision can be reached for a mathematical approach that covers input composition, throughput rate, SBS result purity, yield and recovery and, lastly, in which ranges or threshold values for these parameters the mathematical approach can work.

If a mathematical approach like that described above can be developed for real plastic waste, the waste treatment branch can be progressively improved. Friedrich [13] investigated this in an assessment of how sophisticated the waste-sorting industry is in using data analytics to improve their sorting processes.

The goal in waste-sorting plants is to achieve a required minimum threshold value for purity and to stay below threshold values for impurities, which differ between the several types of waste streams. These threshold values are regulated by law or the recycling process after sorting, e.g., for cullets in the container glass industry, the threshold values are regulated in Austria in the "Quality requirements for cullets to be used in the container glass industry" guideline T 120 from Bundesverband Glas e.V. [14], while the threshold values for sorted plastic waste are defined in "Quality standards for sorted plastic wastes for recycling" [15].

The main interest of a sorting plant operator is to achieve these qualities so that a recycling plant buys their produced sorted waste fraction but with a throughput rate as high as possible to have the maximum possible amount of waste treated and sold per year. Considering these facts, there is an optimal operation point for achieving a specific SBS result related to the input stream composition, throughput rate, purity, yield and recovery. For a plant operator, this means that purity could be increased by 20% without substantially adapting the sorting plant with the plant at optimal operation point.

The yield was not evaluated in this study since it is only relevant for optimization when the results in purity and recovery are sufficient. For this reason, this study is focused on purity and recovery.

For the mathematical approaches to find the optimum operation point, which is the result after the evaluation and processing of the created data, there are four hypotheses to be confirmed or negated in this study:

Hypothesis 1: *It is possible to create mathematical approaches for SBS machines, which mainly depend on the input composition of waste and the throughput rate.*

Hypothesis 2: *It is possible to create a generic mathematical approach for all SBS machines related to input composition, purity, recovery and throughput rate.*

Hypothesis 3: *It is possible to create a construction-type-specific (chute or belt sorter) mathematical approach for all SBS machines related to input composition, purity, recovery and throughput rate.*

Hypothesis 4: *It is possible to create a machine-specific mathematical approach for all individual SBS machines related to input composition, purity, recovery and throughput rate.*

3. Materials and Methods

Sorting efficiency is commonly analyzed based on recovery (R), yield (R_W) and purity (P_m), three mass-specific (m%) indicators. These were previously reported by Friedrich [10], as defined in the following paragraphs.

Recovery (R) is the quotient of product mass or mass of ejected material (m_{eject}) and total mass of input (m_{input}) over a given period. Recovery indicates the product produced per unit of time or a given throughput rate.

$$R = \frac{m_{eject}\left[\frac{t}{h}\right]}{m_{input}\left[\frac{t}{h}\right]} \times 100\%$$

Yield (R_w) is defined by the quotient of the product produced in the output ($m_{eject} \times c_{eject}$) and valuable materials in the input ($m_{input} \times c_{input}$). With the mass flow of the output material (m_{eject}) and the calculated recyclable material concentration in the output fraction (c_{eject}), the quantity of valuable material generated in the output is calculated.

$$R_w = \frac{m_{eject}\left[\frac{t}{h}\right] \times c_{eject}[\%]}{m_{input}\left[\frac{t}{h}\right] \times c_{input}[\%]} \times 100\%$$

Feil proposed a further quality indicator with the calculation of purity P_m [16]. The percentage of correctly ejected input material—purity—is calculated as follows.

$$P_m = \frac{m_{recyclable\ material}\left[\frac{t}{h}\right]}{m_{impurity}\left[\frac{t}{h}\right] + m_{recyclable\ material}\left[\frac{t}{h}\right]} \times 100\%$$

3.1. Materials

Since there are many different plastic types, the first step is to define a plastic waste stream which is quite similar to the ideal materials Küppers [4] used. As these were washed and dried polyolefin plastic flakes, it was decided to use refuse-derived fuel (RDF) sampled in a waste treatment plant where an SBS machine can be installed to sort mixed plastic waste into separate plastic fractions.

The next step was to repeat the trials of Küppers [4] on the same experimental SBS setup to determine the similarity of the mathematical approaches depending on the plastic waste stream. Then, RDF trials were further performed on two SBS setups with different construction types to evaluate whether the found mathematical approaches are generally valid for SBS setups, depending on the construction type or individually on the SBS setup. In the end, the optimal operation point for achieving a specific sensor-based sorting result could be described with mathematical approaches. The material was not further processed after the sampling; it was used directly in the sampled condition for the trials.

3.2. SBS Setups

The trials to be compared were performed on three different SBS setups, the experimental SBS setup at Montanuniversitaet Leoben, the sensor-based chute sorting setup for technical facilities from an SBS machine provider and the sensor-based belt sorting setup for technical facilities from another SBS machine provider. All setups are designed as two-way systems for SBS.

The basic concept of a two-way system can be seen in Figure 1: The input fraction is passed through a vibration conveyor (1) to either a chute or a belt (2), an optional induction sensor (3) to detect metals, emitters (4) to detect the particles with signals from imaging sensors (5) and a compressed air nozzle bar (6), which separates the particles into an eject and a reject fraction. Both output boxes are separated through a splitter (7).

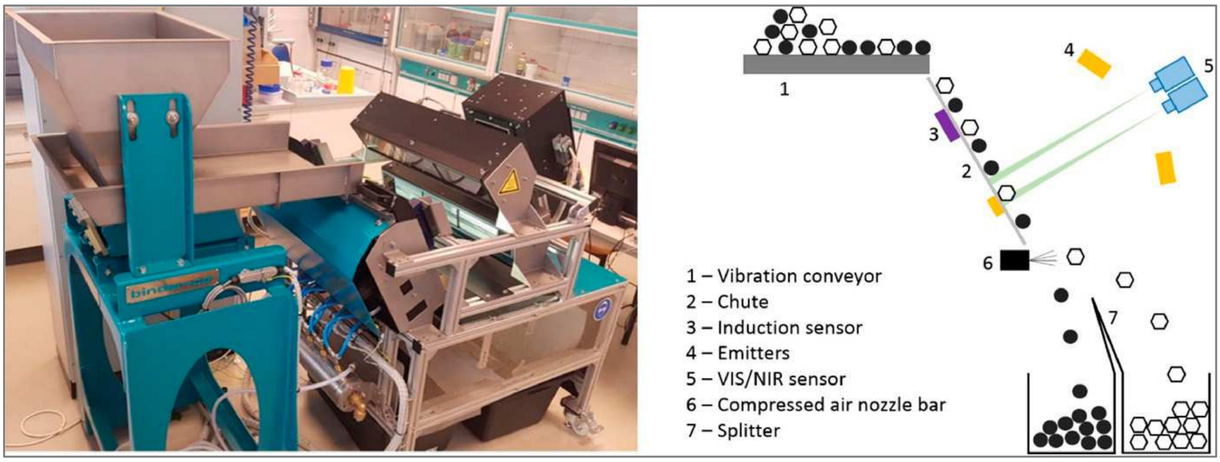

Figure 1. Experimental SBS setup at Montanuniversitaet Leoben [4].

1. Experimental SBS setup

The experimental SBS setup is located at the Chair for Waste Processing Technology and Waste Management at Montanuniversitaet Leoben. It is a chute sorter manufactured with an open design to allow simple conversions to be carried out for deriving process influences. The setup is equipped with three common sensors for waste sorting (Figure 1) [10]:

- An NIR sensor to determine the molecular composition of NIR active particles;
- A color line scan camera to determine the visible light absorbance of elementary components used for sorting by color;
- An induction sensor to identify metallic components/particles.

The present research uses the NIR sensor Helios NIR G2-320 provided by EVK DI Kerschhaggl GmbH, Raaba, Austria [17]. The chute width of the system is 0.5 m. Further details of the setup can be found in [11].

2. Sensor-based chute sorting setup for technical facilities

The provider of the used sensor-based chute sorting setup (Figure 2) has a technical facility where the trials are conducted. It is designed as a two-way system, which can be set up with different sensors like visual spectroscopy (VIS) transmission/reflection, NIR and metal detection. In the present feasibility study, the NIR sensor Photonfocus MV3-D640I-CL was used. The system is endowed with a chute width of 0.4 m.

Figure 2. Sensor-based chute sorting setup for technical facilities (own depiction).

3. Sensor-based belt sorting setup for technical facilities

The sensor-based belt sorting setup used (Figure 3) was prepared by another provider with a technical facility where the trials were conducted. The machine was built up as a two-way machine and can be set up with different sensors like an RGB line scan camera for VIS sorting, an NIR sensor and a metal detection sensor. The NIR sensor Inno-Spec RedEye 1.7 was used in the present feasibility study. The system is endowed with a belt width of 1.2 m, although the belt was split in the middle for the trials so that the working width for the trials was 0.6 m.

Table 1 overviews the different NIR sensors installed in the used SBS systems: Helios NIR G2-320 [17], Photonfocus MV3-D640I-CL [18] and Inno-Spec RedEye 1.7 [19].

The statistical evaluation software of the identification result works on each of the SBS setups in the same way. All of them prepare the pixel statistic, the material statistic and the object statistic. These values are used to calculate the purity of the sorted fractions to be compared for the SBS setups.

Figure 3. Sensor-based belt sorting setup for technical facilities (own depiction).

Table 1. NIR sensor specification overview of the different types installed in the used SBS systems [17–19].

Sensor-Based Sorting Setup	Experimental Sensor-Based Sorting Setup	Sensor-Based Chute Sorting Setup for Technical Facilities	Sensor-Based Belt Sorting Setup for Technical Facilities
NIR Sensor	Helios NIR G2-320	Photonfocus MV3-D640I-CL	Inno-Spec RedEye 1.7
Technology	n.a.	Ingas with CMOS read out circuit	InGaAs
Resolution	n.a.	649 × 512	320 × 256
Pixel size	30 µm × 30 µm	15 µm × 15 µm	30 µm × 30 µm
Spectral range	930 to 1700 nm	930 to 1700 nm	950 to 1700 nm
Line scan rate	500 Hz full frame	n.a.	n.a.
Spectral resolution	9 nm	n.a.	9 nm
Spectral sampling	3.1 nm	n.a.	n.a.
Spatial resolution	312 pixels	n.a.	rms spot radius < 35 µm
Slit width	100 µm	n.a.	80 µm
Frame rate	n.a.	300 fps	330 fps

3.3. Methods

The methodology and the experimental design to confirm or negate the four hypotheses are structured as follows:

1. Phase

The first phase was developing an NIR sorting model to compare the SBS setup performance. Sample 1 was used as a reference sample ("sorting model creation sample") to record the raw spectra to be taught and is not included in the trials. This procedure was chosen to have the material classes of the creation samples available as identical fractions for further test series on all used sensor-based sorting setups for comparability.

In order to ensure comparability, the same raw spectra from PET and PP, which were published by Küppers [4], were used in the NIR sorting model for the RDF fraction on the experimental SBS setup. Further spectra must be recorded first in order to be added to the NIR sorting model.

Using the same raw spectra files for the sensor-based chute sorting setup and the sensor-based belt sorting setup is impossible since the software does not allow the files to be imported from the experimental SBS setup. In these setups, all of the raw spectra have to be newly recorded and new NIR sorting models developed.

2. Phase

The second phase was performing trials with four RDF fractions with at least three different throughput rates to obtain mathematical approaches for each SBS setup. In sum, at least 108 trials were performed. The number of further trials depends on each setup's time availability and the recorded data's plausibility.

3. Phase

Expected results were predicted with regression algorithms in machine learning. The input parameters were used to predict the respective output parameters using regression. Regression helps define the relationship between the target variable to be predicted and created data points. It is a type of supervised learning in machine learning that helps map a predictive relationship between target values and data points. The regressions used in this study are gaussian process regression (GPR) and a regression neuronal network (RNN) for finding the best-fitting regression model in a mathematical approach. The input parameters (regressors) are the input composition and the throughput rate, the output parameters (regressands) are purity and recovery.

MATLAB code was developed to evaluate the trial results in regression models and principal component analysis for finding mathematical approaches. All computation was carried out using MATLAB by MathWorks (Natick, MA, USA) using "9.13.0.2105380 (R2022b) Update 2" on a Windows 10 computer equipped with an Intel® UHD Graphics 630 GPU and an Intel ® Core ™ i5-9400H CPU clocked at 2.50 GHz.

A ranking of features for regression using the MRMR algorithm was performed to determine which of the following parameters influence the sorting result:

- Input composition based on the purity of the input fraction: amount of target material to be ejected of the input fraction (m%);
- Throughput rate: amount of mass per hour through the sorting setup (kg/h);
- Target material: material class, which is ejected, depending on the NIR sorting model (-);
- Aggregate: type of SBS setup to be used (-).

MRMR algorithms were used to find an optimal set of features that is dissimilar and represents the response variable effectively. The parameters listed above were evaluated according to their influence in the sorting result in a predictor ranking with a predictor importance score.

Then, a statistical evaluation was carried out with RMSE and R^2; the regressions were performed with GPR and the RNN. The results are shown in 3D and 2D diagrams depending on which fits better for visualization.

The models, GPR and the RNN, were trained on a training set comprising 70% of the data. The testing set consisted of the remaining 30% of the collected data in compliance with existing findings depicting the ideal training/test split. The statistical values mentioned above were calculated from the model's performance on the test set. A short introduction to the underlying methods of GPR and the RNN is given in the following section.

The task at hand can be defined as a regression task. This initial distinction is necessary to evaluate the feasible machine learning tools. Regression is a type of supervised machine learning task where the goal is to predict a continuous numeric output (a real-valued number) based on input data. Supervised machine learning implies that the prediction algorithm is trained on labeled data consisting of input–output pairs (X, y), where X represents the input data, and y represents the corresponding output values. The model aims to learn to capture the underlying relationships.

A GPR (gaussian process regression) model is a probabilistic, non-parametric machine learning algorithm used for regression tasks. It is a powerful tool for modeling and predicting continuous data, particularly when dealing with uncertainty. GPR is based on the principles of gaussian processes, which are a method of obtaining probability distributions over functions. GPR as a non-parametric model is well suited for the underlying data as it does not make strong assumptions about the functional form of the data. This is a stark contrast to parametric models like linear regression, which assumes a fixed functional form (e.g., a linear relationship), As such, GPR can capture a wide range of functions by learning from data.

Regression neural networks (RNNs) are a type of artificial neural network (ANN) specifically designed for solving regression problems. RNNs are powerful tools for modeling complex relationships between input features and continuous target variables. RNNs consist of multiple layers of interconnected neurons, organized into an input layer, one or more hidden layers and an output layer. Each neuron is associated with a weight and a bias, which are adjusted during training to optimize the network's predictive capability.

4. Phase

The found regression models were used to test the four hypotheses of this study regarding finding an SBS machine's optimal operation point. The hypotheses were confirmed or negated. Each confirmed hypothesis can help in finding the optimal operation point and describing it depending on the result and the number of confirmed hypotheses.

4. Results and Discussion

The investigated materials were sampled in an RDF processing plant. The plant processes 16 to 17 t/a input waste streams. These waste streams consist of 70 to 80% residue from sorting processes in several waste-sorting plants for lightweight packaging waste. Of this waste, 20 to 30% comprises high caloric fractions. The waste is comes from commercial waste collection. The output fractions of the plant are 2D and 3D RDF fractions.

After PVC and metal separation of the mixed plastic fractions, the fraction was shredded to a grain size > 100 mm. Next, the material was passed through a fluted screen before a two-stage centrifugal separator was used to obtain 2D and 3D RDF fractions. The fraction relevant to this work is the 3D RDF fraction. For this reason, the material for this paper was sampled after the second centrifugal separator (Figure 4).

Figure 4. Second centrifugal separator in the RDF processing plant (own depiction).

For sampling, the flap at the side of the second centrifugal separator was opened, and the samples were taken during the fall of the conveyor belt. Since the samples must be representative to indicate the material stream, the sampling was carried out with a bucket moving slowly from left to right at the fall point of the conveyor belt. This procedure was performed five times over several days so that the five samples represented the variability of the RDF processing plants' waste streams after the second centrifugal separator.

Sample 1 from 17 August 2020 was used as the reference fraction for creating an NIR sorting model of the five samples taken. Sample 1 was chosen because it has a higher mass than the other four samples and thus represents a larger range of particles for the sorting model creation. Sample 2 is presented in Figure 5 as an example of how the sorted samples look.

Figure 5. Sample 2, sampled on 19 August 2020, mass 4.102 kg (own depiction).

In the first step, the sampled RDF fractions must be prepared before starting the trials. Metal particles were separated from all fractions with the induction sensor of the experimental SBS setup at the Chair of Waste Processing Technology and Waste Management of Montanuniversitaet Leoben. Metals have a higher density than plastics in the RDF fraction, which requires different setup parameters due to the delay time for the material discharge or the discharge pressure setting. Furthermore, Furthermore, the SBS is installed in plants after the metal separation in plants after the metal separation, which means the mathematical approaches may be used with a material flow already decontaminated from metal. Table 2 shows the sample composition of metals and metal-free fractions in their mass and percentage distribution.

Table 2. Sample composition divided into metals and metal-free fractions.

Sample **Sampling Date**	**1** **17.08.2020**		**2** **19.08.2020**		**3** **02.10.2020**		**4** **06.10.2020**		**5** **20.10.2020**	
Unit	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)
Metal-free	6.33	86.8	2.88	70.3	3.88	74.3	3.82	85.4	3.86	90.0
Metal	0.96	13.2	1.22	29.7	1.34	25.7	0.66	14.6	0.43	10.0
Sum	7.29	100.0	4.10	100.0	5.22	100.0	4.48	100.0	4.29	100.0

Next, the components of the metal-free fractions were analyzed in detail based on visual inspection followed by NIR characterization on the experimental SBS setup at Montanuniversitaet Leoben. For the characterization, the NIR sorting model used by Küppers [4] was applied for PET, PE and PP and extended with further new material classes, as shown in Table 3. Materials not listed in Table 3, such as textiles, are included in the rest "MC" (material class) category. A further breakdown of the classes is not required since individual large particles are responsible for the high mass fraction. Furthermore, particles could not be assigned to increased fine grain fraction (>2 mm), or the masses were too low to assign them to another new fraction.

Table 3. Sample composition of the metal-free fraction from selected individual fractions considered.

Sample **Sampling Date**	**1** **17.08.2020**		**2** **19.08.2020**		**3** **02.10.2020**		**4** **06.10.2020**		**5** **20.10.2020**	
Unit	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)
PP	0.94	14.9	0.38	13.3	0.46	11.8	0.46	12.1	0.44	11.5
PET	1.68	26.5	0.73	25.2	0.85	22.0	1.17	30.5	1.23	32.0
PVC	0.25	3.9	0.14	4.9	0.26	6.8	0.17	4.4	0.11	3.0
Wood/Foam	0.97	15.3	0.43	14.8	0.94	24.2	0.70	18.4	0.70	18.0
TPU	0.06	1.0	0.01	0.3	0.02	0.4	0.02	0.4	0.01	0.3
HDPE	0.18	2.8	0.06	2.0	0.05	1.2	0.04	1.0	0.11	2.9
LDPE	0.52	8.2	0.30	10.4	0.41	10.5	0.45	11.7	0.55	14.2
PS	1.00	15.8	0.72	25.0	0.64	16.4	0.54	14.3	0.57	14.8
Rest "MC"	0.74	11.6	0.12	4.1	0.26	6.7	0.28	7.2	0.13	3.2
Sum	6.33	100.0	2.88	100.0	3.88	100.0	3.82	100.0	3.86	100.0

For the trials, PET, PP and PVC were considered due to their abundance in the waste composition (Table 3). LDPE consists of many small 2D films, for which sorting is not effectively possible with the same machine settings as for 3D plastics due to their ability to fly and low density. PVC was considered because it is not desirable in RDF due to its chlorine content and must be discharged anyway. All other material classes were summed up as the Rest category. Table 4 shows the material classes considered for this study.

Table 4. Sample composition used for the trials.

Sample **Sampling Date**	**1** **17.08.2020**		**2** **19.08.2020**		**3** **02.10.2020**		**4** **06.10.2020**		**5** **20.10.2020**	
Unit	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)	(kg)	(m%)
PP	0.94	14.9	0.38	13.3	0.46	11.8	0.46	12.1	0.44	11.5
PET	1.68	26.5	0.73	25.2	0.85	22.0	1.17	30.5	1.23	32.0
PVC	0.25	3.9	0.14	4.9	0.26	6.8	0.17	4.4	0.11	3.0
Rest	3.46	54.7	1.63	56.6	2.31	59.5	2.03	53.0	2.07	53.5
Sum	6.33	100.0	2.88	100.0	3.88	100.0	3.82	100.0	3.86	100.0

After each trial, the results included the calculated purity and recovery. Next, the four hypotheses developed in this study were either confirmed or negated. In the end, the industrial outreach of the findings was predicted.

Hypothesis 1: *It is possible to create mathematical approaches for SBS machines, which mainly depend on the input composition of waste and the throughput rate.*

The input parameters of each sorting trial were the waste stream's input composition and the sorting process's throughput rate. A feature evaluation was carried out to ascertain the influence on the sorting results of the parameters input composition (based on the purity of the input fraction), throughput rate, target material to be sorted and aggregate (SBS setup).

Intuitively, one would expect the input composition and throughput rate to be the dominant input variables for predicting the output's purity and the recovery of valuable materials. This is because neither the target material nor aggregate change in response to the input material and thus only allow for a rough estimate of achievable purity and recovery.

The performed feature selection supports this intuition. The results of ranking features for regression using MRMR algorithms (Figure 6) show that two of the four evaluated parameters mainly influence the sorting result. The target material to be sorted and the selected aggregate (SBS setup) have low prediction value. This means the sorting result mainly depends on the purity of the input material and the throughput rate. The purity of the input has a predictor importance score of 0.13, while the throughput rate has a score of 0.08.

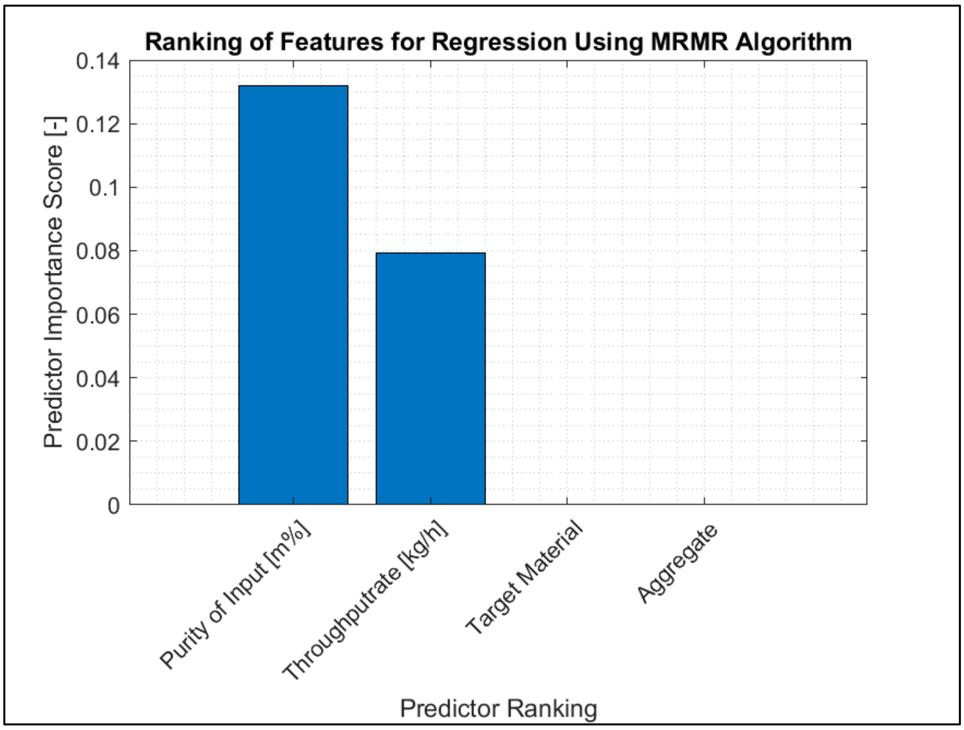

Figure 6. Ranking of features for regression using MRMR algorithm.

The performed analysis of models trained on all four input variables in comparison to models trained on input composition and throughput further supports this. Models trained on all available input variables performed as well as or worse than their counterparts that adhered to the MRMR feature selection.

Table 5 shows the results of the preliminary sensitivity analysis to gauge the model response to the inclusion of aggregate type and target material in addition to input composition and throughput. The gain is minute as the model performance on the testing set did not improve when including aggregate type and target material in the training data set.

Table 5. Results of input variable sensitivity analysis for all aggregates using two or four of the available input variables.

Model	R^2 (-)		RMSE (%)		Target
Used Parameters	2/4	4/4	2/4	4/4	
RNN for Purity	0.29	0.22	10	11	Purity
GPR for Purity	0.57	0.59	8	8	Purity
RNN for Recovery	0.48	0.5	15	15	Recovery
GPR for Recovery	0.59	0.48	14	15	Recovery

In consideration of Figure 6, **Hypothesis 1 can be confirmed.**

Hypothesis 2: *It is possible to create a generic mathematical approach for all SBS machines related to input composition, purity, recovery and throughput rate.*

In order to find a mathematical approach which describes the relation between input composition, throughput rate, purity and recovery for all trials, these data is used to create regression models.

Figure 7 shows the deviation of predicted and observed values for purity and recovery in regression models. An ideal prediction of the sorting result related to purity or recovery was considered a low deviation between prediction and observation.

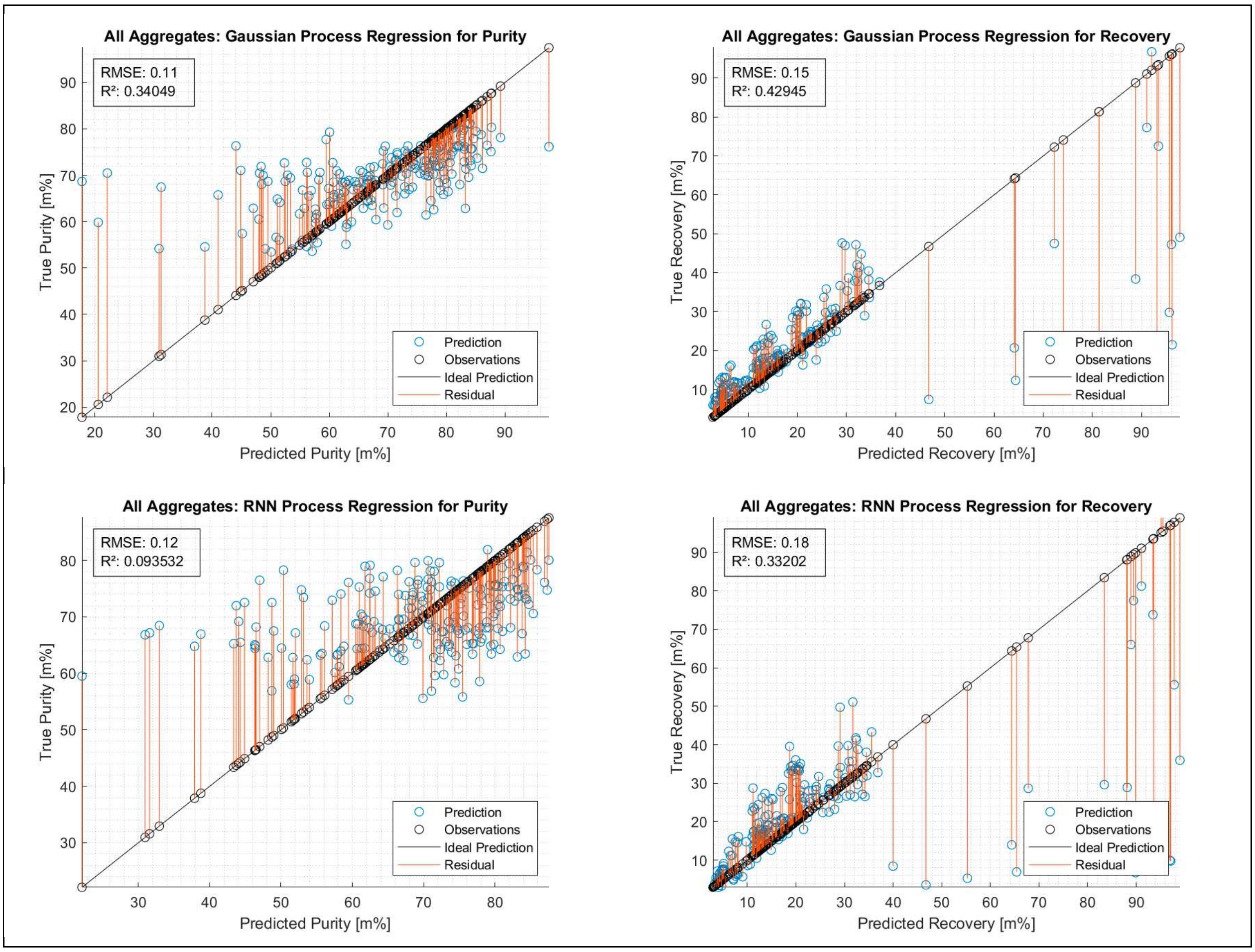

Figure 7. GPR and RNN process regressions for purity and recovery for all aggregates (SBS setups).

For purity, both of the regressions—GPR and RNN—do not allow the development of a mathematical approach that might work for a significant prediction. The RMSE with 11 and 12% and the R^2 with 0.34 and 0.094 indicate that a mathematical approach related to the input composition and the throughput rate, valid for all SBS setups, cannot be developed.

For recovery, the regression models work well up to 40 m%; from then on, only sporadic data points are available. The model works in the areas depicted by the data, as expected. The values for RMSE with 15 and 18% are far too low, as is the R^2 of 0.42945 and 0.33202, to develop the desired mathematical approach.

In consideration of Figure 7, **Hypothesis 2 can be negated.**

Hypothesis 3: *It is possible to create a construction-type-specific (chute or belt sorter) mathematical approach for all SBS machines related to input composition, purity, recovery and throughput rate.*

According to the result for all aggregates in Figure 7, it can be predicted that a mathematical approach which describes purity and recovery related to input composition and 439 throughput rate machine type-specific cannot be developed. The deviations between the 440 prediction and the observations are severe—as described in the previous hypothesis 2—441 to get suitable mathematical approaches for predicting sorting results.

In consideration of Figure 7, **Hypothesis 3 can be negated.**

Hypothesis 4: *It is possible to create a machine-specific mathematical approach for all individual SBS machines related to input composition, purity, recovery and throughput rate.*

For the data of trials with ideal mixtures on the experimental SBS setup, the RNN developed a better regression model. For the RDF trials on the experimental SBS setup, the sensor-based chute sorting setup and the sensor-based belt sorting setup for technical facilities, GPR developed the superior model.

According to the analysis of the experimental SBS setup data, the regression models differ from the type of waste to be sorted for purity and recovery. This means it is not the target material itself that influences the sorting result, as proven in hypothesis 1, but rather the condition of the waste type to be sorted. The ideal mixture was created from plastic packaging waste shredded to a grain size >30 mm, while the RDF was shredded to a grain size >100 mm. It can be stated that the pretreatment and condition of the waste influence the regression models.

The regression models on the used SBS setups for RDF differ from setup to setup, although the material is the same. This indicates that when regression models are used to describe the correlation between the input and output parameters of a sorting process, these models have to be created separately for each SBS setup.

Figure 8 visualizes an example depiction of model predictions on test sets with losses calculated on model prediction vs. true value with a 3D fitted curve. It shows the trend of the actual data related to the purity of input and throughput rate on the sensor-based belt sorting setup (A) and the sensor-based chute sorting setup (B) including R^2 and RMSE for the underlying prediction model.

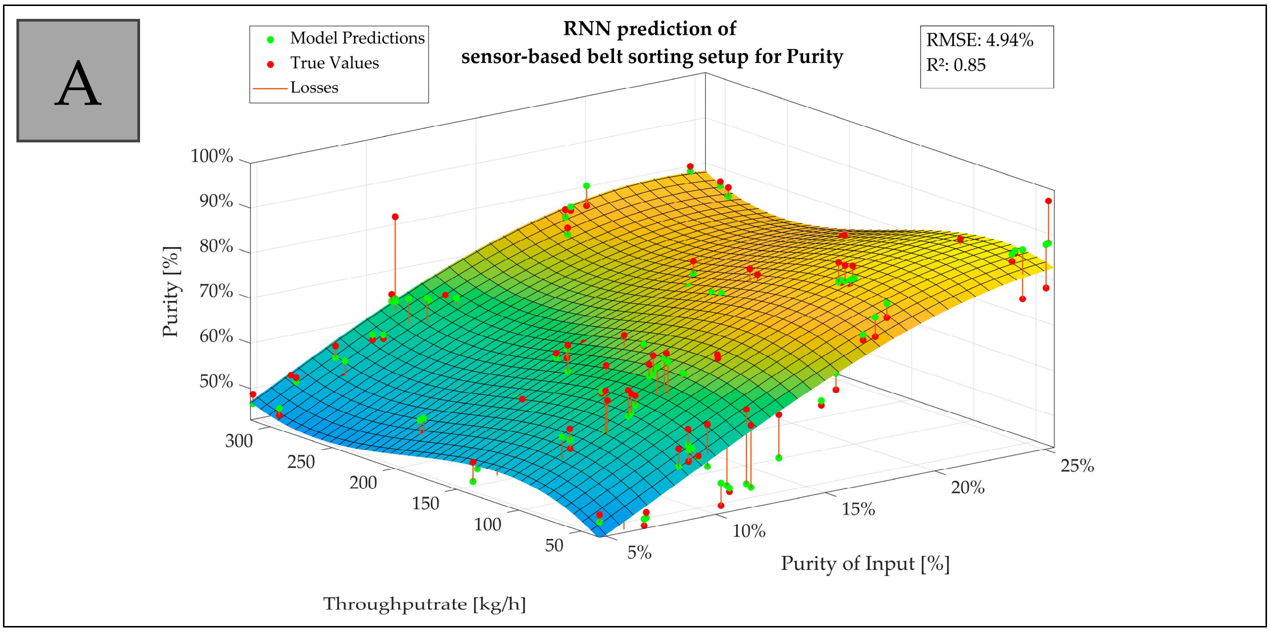

Figure 8. *Cont.*

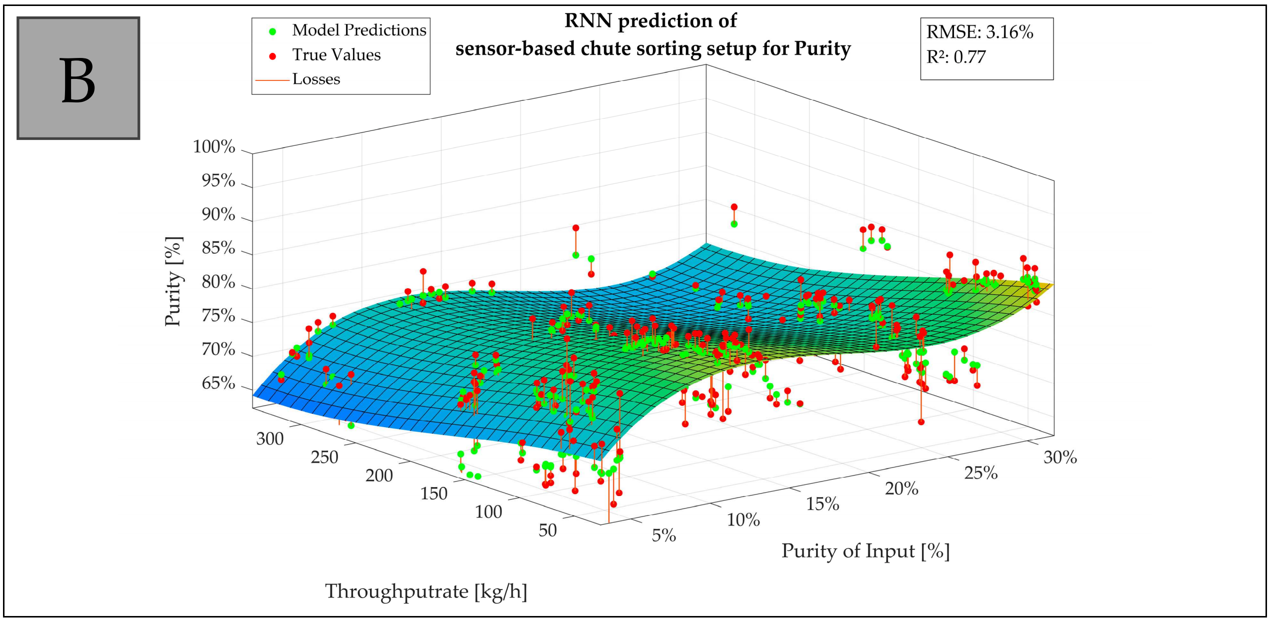

Figure 8. Example depiction of model predictions on test sets with losses calculated on model prediction vs. true value with a 3D fitted curve: trend of the actual data related to the purity of input and throughput rate on the sensor-based belt sorting setup (**A**) and the sensor-based chute sorting setup (**B**) including R^2 and RMSE for the underlying prediction model.

For interpreting the findings of each SBS setup, a statistical evaluation of the regression models was carried out with RMSE and R^2. The results are listed in Table 6.

Table 6. Statistical evaluation results of the regression models with RMSE and R^2.

SBS Setup	Sample	Regression Model	Purity		Recovery	
Statistical Value			**RMSE (%)**	**R^2 (-)**	**RMSE (%)**	**R^2 (-)**
Experimental SBS setup	Ideal mixtures	RNN	7	0.84921	3	0.95786
Experimental SBS setup	RDF	GPR	5	0.50306	2	0.96956
Sensor-based chute sorting setup	RDF	GPR	3	0.75158	2	0.92686
Sensor-based belt sorting setup	RDF	GPR	5	0.87458	1	0.95461

For purity, the values for R^2 are between 0.50306 for GPR with RDF on the experimental SBS setup and 0.87458 for GPR with RDF on the sensor-based belt sorting setup, which is a difference that does not allow a general statement. What needs to be considered is that the experimental SBS setup was designed for analyzing and sorting flakes, which led to a higher scattering of the output data and deteriorated the regression model. The RMSE was between 3% for GPR with RDF on the sensor-based chute sorting setup and 7% for the RNN with ideal mixtures on the experimental SBS setup, which is distinctly good.

The R^2 for the recovery regression models varies between 0.92686 for GPR with RDF on the sensor-based chute sorting setup and 0.96956 for GPR with RDF on the experimental SBS setup. RMSE resides between 1% for GPR with RDF on the sensor-based belt sorting setup and 3% for the RNN with ideal mixtures on the experimental SBS setup. This means that the mean variation is low, and the regression models suitably describe the recovery result.

Comparing the regression models, excluding the experimental SBS setup with RDF, the models describe the sorting result behavior regarding the input parameters (input composition, throughput rate) sufficient to regulate an SBS setup when a specific sorting result in terms of purity and recovery can be achieved.

Considering Figure 8 and Table 6, **Hypothesis 4 can be confirmed for the scope of applied data.**

Industrial Outreach

The added value for the industrial waste-sorting plants can be derived from the outcome of the four hypotheses. The optimal operation point is the maximum possible throughput rate with the expected purity of sorted waste. In short, the sorted waste mass with an expected result is maximized for a specific time frame.

The regression models for purity and recovery make it possible to predict a sorting result with the knowledge of the input composition and throughput rate with the calculated deviation range. This in turn means that the sorting result should be a specific expected purity. The regression models deliver the maximum possible throughput rate (within the model deviation range) to reach the postulated purity.

An explanation is shown in Figure 9. When a purity of 75% is required, an RNN regression model for the experimental SBS setup with RDF can reach a maximum throughput rate of 100 kg/h.

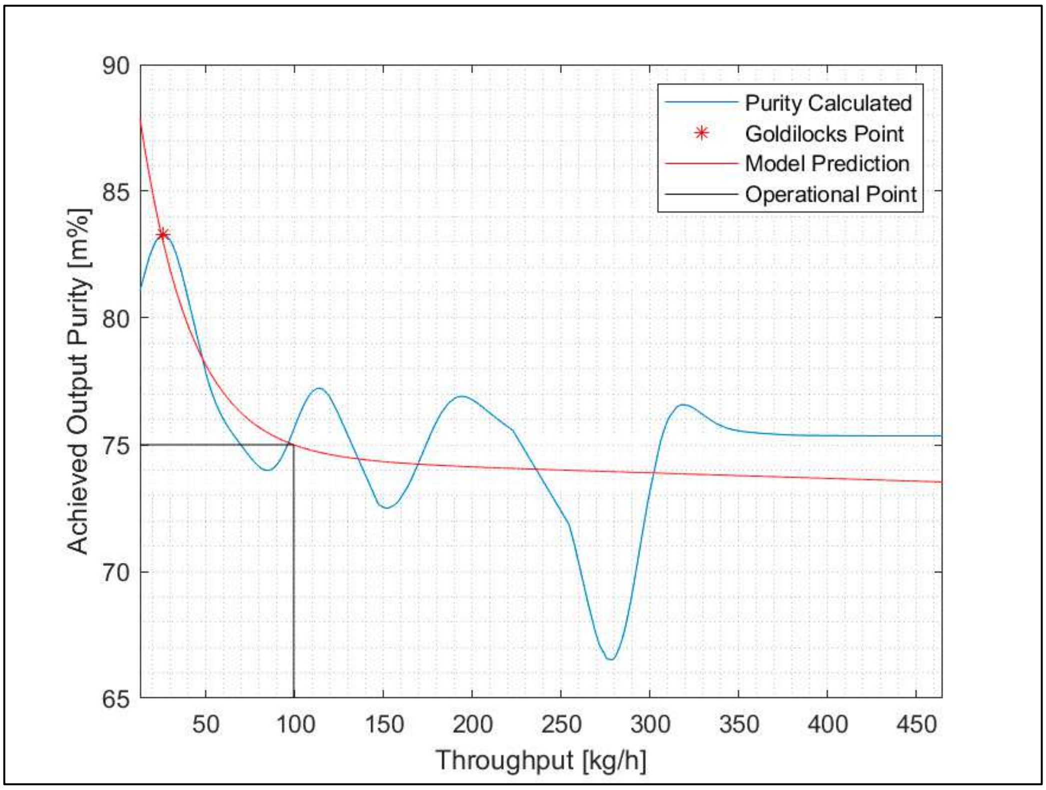

Figure 9. "Goldilocks point" and optimal operation point with RNN regression related to a purity of 75% and throughput rate of 100 kg/h of the experimental SBS setup.

Furthermore, Figure 9 shows the Goldilocks point for the regression model. This principle appears when there is a clear optimum for a value. The Goldilocks point is reached when the highest calculated purity hits the model's predicted purity for the maximum possible throughput rate. As the Goldilocks point for that model can only be reached for an unacceptably low throughput rate, the scenario in Figure 9 is not realistic for running a plant.

Another option for using the regression models is to simulate circuit operation in sorting plants or stepwise sorting with more SBS machines. The idea is to utilize a first sorting step to enrich concentrates of a specific plastic type and sort them into recyclates in a second or third sorting step. For example, in Figure 9 the first sorting step achieves a purity of 75%; with the second sorting step, the concentration of the target material starts at

75% so that a higher purity can be achieved with the same throughput rate. This principle can be used especially in small sorting plants, which can run circuit operation, or in larger sorting plants, which have either the opportunity for circuit operation or have more sorting machines that run stepwise in sequence.

Using these findings allows for a sorting plant to increase purity by running the plant on the optimal operation point without substantially adapting the plant. The only requirement is to create regression models with recorded production data to find the optimal operation point for several waste input compositions of the sorting process. Input compositions can easily be recorded by installing an NIR input characterization before the SBS machine with the same NIR sorting model selected on the SBS machine.

5. Conclusions

Sorting plant operators want to achieve specific levels of recyclate purity so that a recycling plant buys their produced sorted waste fraction, but with the maximum possible throughput to ensure the maximum possible amount of waste treated and sold within a year. This leads to an interest in finding the optimal operation point for achieving a specific SBS result related to the input stream composition, the throughput rate, the purity and the recovery.

The research task of this study was to find mathematical approaches in regression models which cover input composition, throughput rate, the SBS results in purity and recovery and, lastly, in which ranges or threshold values these parameters can be used. For the regression models, with the results of 108 trials on three sensor-based sorting setups, with ideal mixtures and five RDF samples, four hypotheses were confirmed or negated in this study.

Hypothesis 1: *It is possible to create mathematical approaches for SBS machines, which mainly depend on the input composition of waste and the throughput rate.*

This hypothesis is confirmed. The sorting result mainly depends on the purity of the input, which means the amount of target material to be sorted consists of the input fraction. Furthermore, according to the feature ranking, the type of material sorted has a weak influence on the result.

Hypothesis 2: *It is possible to create a generic mathematical approach for all SBS machines related to input composition, purity, recovery and throughput rate.*

Developing a regression model that works for a significant sorting result prediction is not feasible. The statistical results indicate that developing a mathematical approach related to the input composition and the throughput rate, valid for every SBS setup, is impossible.

Hypothesis 3: *It is possible to create a construction-type-specific (chute or belt sorter) mathematical approach for all SBS machines related to input composition, purity, recovery and throughput rate.*

This hypothesis is negated according to the results of hypothesis 2.

Hypothesis 4: *It is possible to create a machine-specific mathematical approach for all individual SBS machines related to input composition, purity, recovery and throughput rate.*

The regression models indicate that the sorting result behavior regarding the input parameters (input composition, throughput rate) is sufficient in their scope of applied data to regulate an SBS setup when a specific sorting result in terms of purity should be achieved. Furthermore, the waste pretreatment or condition before the SBS machine influences the sorting result. The findings of this scientific article demonstrate that regression models with a sufficient number trials to ensure an acceptable prediction accuracy in RMSE and

R^2 can enable a sorting plant to automatically regulate its throughput to achieve a specific purity in the sorting process.

This leads to automatic plant operation and maximizes the mass sorted in the plant with expected purity. The only requirement is the installation of an NIR input characterization device before the SBS machine to determine the input composition and to record the production data. Furthermore, the regression models can also simulate circuit operation in sorting plants or stepwise sorting with more SBS machines. After the first sorting step to enrich concentrates of a specific plastic type, the recyclates are sorted in a second or third sorting step.

In summary, the findings of this scientific article can be utilized to enable a sorting plant to increase purity by running at the optimal operation point without substantial adaptation. Superordinate considered, this helps to increase the amount of recycled plastic so that less plastic waste is thermally treated without substantial investments in adapting current plant designs.

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5 Results

This doctoral thesis consists of ten publications, which cover the introduction (Publications I and II), the environmental analysis (Publications III and IV) and the experimental design structured in methods (Publication V), identification (Publication VI, VII and VIII) and mechanical discharge (Publication IX and X). The research questions defined in Chapter 1.3, "Scope of Investigations", are answered in the corresponding publications and concluded in this chapter.

5.1 Introduction

Literature research was done in the "Introduction" of this thesis to get detailed knowledge in sensor-based sorting of plastic waste and to find research gaps to be dealt with.

Publication I, Review Article, "Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review"

This review publication lines out the State-of-the-Art in sensor-based and robot sorting processes in waste management. It gives an overview of the legal regulations in waste management on the European level for waste streams consisting of plastics: the Circular Economy Package, the Plastic Strategy and the Single-Use Plastics Directive. Next, the waste treatment process sensor-based sorting and its importance in achieving the European recycling goals is exemplified. Used sensor technologies for different types of waste streams are introduced, as well as the construction types chute sorter and belt sorter. After that, robot sorting, the types of robots, their characteristics and their field of application are elucidated. Further trend developments in waste management are derived from the literature and market research for sensor-based and robot sorting. The review is used to choose the most seminal sensor technology for sensor-based sorting of waste streams consisting of plastics.

Research question 1 (RQ 1): What is the State-of-the-Art in sensor-based sorting of waste streams consisting of plastics?

Mainly used sensor technologies for sorting waste streams consisting of plastics are near-infrared and visual spectroscopy. Visual spectroscopy is used to sort plastic particles by colour or shape according to brightness, reflection and transparency. Near-infrared spectroscopy is physically based on molecular excitation by radiation in the near-infrared range from 1.200 to 2.000 nm for sorting plastic according to the different types. Irradiated molecules vibrate by specific wavelengths to resonance frequency and reflect diffusely other wavelengths, producing characteristic near-infrared spectra of the material. Plastic waste needs to be sorted by plastic type or freed from contaminants in the first step; for this reason, near-infrared spectroscopy was selected as sensor technology to be applied in this doctoral thesis.

Publication II, Mini Review Article, "Challenges to Increase Plastic Sorting Efficiency"

This mini review article deals with current challenges in increasing and opportunities to increase plastic sorting efficiency. It handles the formation of the recycling rate consisting of collection rate, sorting rate and recycling process rate. It shows an example calculation highlighting the importance of increasing plastic sorting efficiency. The found challenges are a declined input quality of waste for sorting plants, the lack of structured knowledge for complex products and material combinations, and increasing the sorting efficiency parameters purity and yield. These research gaps help defining detailed research questions out of superordinate ones.

Research question 2 (RQ 2): What are the current research gaps for increasing the sorting efficiency of plastic waste streams?

The assumption is that the input quality for waste sorting plants gets worse. Quantitatively achieving the European recycling goals leads to an increasing volume of secondary plastic. This indicates that identifying particles in sensor-based sorting plants needs to be improved, because different qualities of secondary plastic need to be identified in the future. Some plastic particles in waste streams cannot be identified correctly or are not identifiable. Lack of structured knowledge about complex products or material combinations needs to be improved. Optimizing the identification of particles in sensor-based sorting is a main task for achieving the European recycling goals.

Moreover, increasing the sorting efficiency in the parameter purity and yield is challenging. The fluctuating input quality of waste to be sorted while increasing these parameters is a challenge in the mechanical discharge of particles. Feedback loops between the input quality and the plant operation in throughput rate are mentioned as a possible solution for running a sorting plant on the optimal operation point. Using such feedback loops is a suitable option to optimize the mechanical discharge of particles in sensor-based sorting of plastic waste.

5.2 Environmental Analysis

After the "Introduction", research gaps for increasing the sensor-based sorting efficiency for waste streams consisting of plastics were found in two sections, the identification and the mechanical discharge. Next, an "Environmental Analysis" is done to know what qualities of sorted plastic waste are expected by a sorting plant and the current state for using data analytics in sensor-based sorting.

Publication III, Original Article, "Benchmark Analysis for Plastic Recyclates in Austrian Waste Management"

This publication covers the topic of benchmark quality for plastic recyclates in Austrian Waste Management. In the plastic value chain, there are different quality requirements from the collection, to the sorting, to recycling and final plastic product manufacturing companies existing. The quality assurance for each company type focuses on different parameters and threshold values. Plastic packaging waste needs to fulfil specific requirements in sorted plastic waste for plastic waste recycling companies and in recyclates for the final plastic product manufacturing companies. Furthermore, the expected required qualities differ predominantly between the different types of plastic.

The market mechanisms of supply and demand set the pricing of recyclates. The purer the recyclates, the higher the potential price caused by the broader range of applications. Another criterium is colour purity. For colour purity, the same statement as for material purity is valid. The raw material price is mainly responsible for the recyclates total price; the recyclates price rises or falls with raw material price. At the end of the publication, the benchmark for quality requirements in the different positions in the plastic value chain are determined.

Research question 3 (RQ 3): What are the expected sorted waste qualities for different types of plastic?

For sorted plastic waste, the stakeholders of the plastic value chain consider the quality standard defined by Grüner Punkt (2023) as the benchmark. The minimum expected purities for sorted plastic waste vary from 96 to 98 %. For some impurities, further separate limits are set. This expectation in purity is too high to be currently exceeded in one single sorting step. Moreover, the stakeholders would welcome a stipulation of minimum requirements or quality standards for sorted plastic waste and recyclates on an international level by legislation.

Publication IV, Original Article, "Assessment of Technological Developments in Data Analytics for Sensor-Based and Robot Sorting Plants Based on Maturity Levels to Improve Austrian Waste Sorting Plants"

This publication aims to determine how mature Austria's sensor-based and robot sorting sector is positioned. Companies through four categories were interviewed, sorting machine manufacturers, sorting robot manufacturers, recycling plant operators, and sensor technology companies. The appliance of data analytics in sensor-based sorting is also set up in different sections like data collection, data provision and transfer, data format, data encoding and presentation, data scope, data consistency, data usage and commitment to change within the company. The maturity levels are ranked from one, the worst, to four, the highest. It is not only sufficient to be good in one section; some maturity levels are linked to other sections. Ultimately, the current technological limitations and the willingness to use data analytics in sensor-based sorting are asked. In addition, it was asked which data is recorded on the sensor-based sorting machines in production, maintenance, quality, machine, or other data. Further questions regarding possible future trends and possibilities to implement data analytics in sensor-based sorting were inquired at the end of the survey.

As a result, twelve companies out of four sectors are evaluated for their maturity levels in nine categories and the data recorded in the companies is known. At last, their suggestions on how data analytics can increase sensor-based sorting efficiency are obtained.

Research question 4 (RQ 4): Can data analytics be seen as a solution to make sensor-based sorting processes more efficient?

Ten out of twelve surveyed companies stated that they have not explored their recorded data to find mathematical relationships or models. When mathematical models can be developed, e.g. to describe the influences of process parameters on each other, the area of validity for newly found relationships in the recorded data is unknown. Finding mathematical relationships in the recorded sensor-based sorting data might be a significant step in optimizing the sorting process. Stakeholders are interested in increasing the sensor-based sorting efficiency by improving the identification to characterize more particles correctly or by improving the mechanical discharge with, e.g. mathematical models. Although the parameters of a sorting process are known, they are not examined in such a way that a sensor-based sorting machine can automatically adapt to the optimum throughput rate to achieve an expected sorting result.

5.3 Experimental Design

After the "Environmental Analysis", it is known which qualities are expected for sorted plastic waste to be treated in recycling processes and the current developments in the use of data analytics in sensor-based sorting. The chapter "Experimental Design" deals with the practical trials performed in this doctoral thesis to increase the sensor-based sorting efficiency for waste streams consisting of plastics. It is structured into three subchapters:

- Methods, which explain the used setup and the sorting technology,
- Identification, which deals with increasing the number of identified particles and
- Mechanical discharge, which deals with increasing the number of correctly ejected particles and decreasing the number of incorrect ones.

Experimental Design: Methods

The subchapter "Methods" describes the sensor-based sorting setup and the used sorting technology near-infrared spectroscopy, which was used in all experimental trials of this doctoral thesis.

Publication V, Method Article, "Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup"

This publication presents the experimental sensor-based sorting setup at the Chair of Waste Processing Technology and Waste Management at Montanuniversitaet Leoben. This equipment was used in all publications of this doctoral thesis for the experimental trials. It is designed as a two-way system with three sensors installed with different sorting technologies. Visual spectroscopy is used to sort particles by colour, near-infrared according to the characteristic spectra and the induction sensor to sort metal particles. The parameters for the sorting process to be set up and the statistical definitions pixel, object, pixel statistics, material statistics and object statistics are explained. These - in sensor-based sorting machines automated recorded - statistical data is relevant to calculate the sorting efficiency values throughput rate, purity, yield, recovery and incorrectly discharged particles. The method publication closes by explaining how the sensors must be set up for respective trials with trial examples. Ultimately, a trial example of sensor-fusion - when sensors are used in combination - is performed.

Research question 5 (RQ 5): Which parameters define the efficiency of a sensor-based sorting process?

The goal of a sorting process mainly defines the sorting efficiency of a sensor-based sorting process. If the goal is getting a pure sorted plastic fraction to be treated in a recycling plant, the parameter to be focused on is purity. Purity is the amount of correctly ejected material in the ejected fraction in percent. The parameter incorrect, which stands for incorrectly discharged particles, stands for the opposite. It describes the amount of incorrect ejected material in percent. When the goal is to get a concentrate of specific material, the yield is the most important parameter because it is the amount of material to be sorted in the output divided by the amount of material to be sorted from the input. The quotient between the ejected material's mass and the input's total mass is recovery.

In the end, for all sorting processes, the definition of efficiency is based on the sorting goal; it could be defined only by one parameter, but when another is too low, a process optimization will have to be done anyway to run a plant economically. According to the sorting goal, these parameters are decisive in finding the optimal operation point of a sensor-based sorting plant for a specific expected sensor-based sorting result in one of them.

Experimental Design: Identification

Since the used sensor-based sorting setup, the used sensor technology and the parameters, which define the efficiency of a sensor-based sorting process, are introduced, the experimental trials start. The first experiments outlined are the ones on increasing the efficiency in sensor-based sorting processes by optimizing the identification of particles.

Publication VI, Original Article, "Influences and consequences of mechanical delabelling on pet recycling"

This original article outlines and presents the influences of mechanical delabelling on the recycling of PET bottles. The labels, mostly polyethene (PE), are recognized in near-infrared light as well as the PET bottles so that specific model setup with scaling factors is required in some cases to be sorted to PET. The PE is undesirable in a PET fraction for mechanical PET recycling. The delabelling process shows a delabelling efficiency of 90 %, which means 90 % of labelled PET bottles are delabeled after one trial. The bottles delabeled inefficiently have < 0.5 litre filling volume, or a sticker is used as a label. The process might work more efficiently with a screening step before the delabeler.

Furthermore, the delabelling process does not shred or deform the PET bottles. This is welcomed for sensor-based PET bottle sorting since the grain size is not reduced and the particle amount does not increase. After delabelling, not only the PET bottles are label-free, but the surface of the PET bottles has also changed in roughness. The change in surface roughness extends peaks in the derived near-infrared spectrum of PET and improves the PET bottle classification.

Research question 6 (RQ 6): Does surface roughness influence the near-infrared identification of sensor-based sorting processes?

The roughness of the surface influences near-infrared identification significantly. 90 % of derived spectra indicate crucial higher extents and minor higher averaged standard deviations after delabelling. The characteristic PET peak in the derived spectra is at about 1.650 nm. Surface roughness influences near-infrared identification since the reflection and transmission of the light change. Especially material with such a high transmission that near-infrared light is not or marginally reflected shows better near-infrared identification results since reflection is favoured more on rougher surfaces.

Publication VII, Original Article, "Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials"

According to the finding of Publication VI, it is assumed that enhancing the reflection of near-infrared light improves the identification of particles, which are nearly or completely transmitting the light and increases the identification of thin 2D plastic packaging. Near-infrared spectroscopy often results in fluctuating spectra and some cannot be recognized by the sensor. For this reason, this publication focuses on improving the spectral quality by installing reflectors under the 2D plastic packaging material stream. Modifying the sensor-based sorting setup by installing metal plates made of copper and aluminium allow the identification in transflection mode. Transflection means the combination of reflection and transmission and increases the identification of films significantly. Since the transmitted light is going through the particle again because it is reflected at metal plates under the 2D packaging waste, the near-infrared identification improves significantly by decreasing the spectral variability. Further, the influence of the emitter intensity and foil thickness are evaluated. Enhancing the thickness improves the identification as well as enhancing the illumination intensity.

Research question 7 (RQ 7): Is the usage of transflection for near-infrared spectroscopy for 2D plastic packaging enhancing the identification in sensor-based sorting processes?

The use of transflection increases the identification of thin 2D plastic packaging significantly. Replacing the standard transparent background with a reflective one leads to spectra with low variability reduces the spectral noise and brings stable characteristic spectra. The foil thickness and the illumination intensity are relevant factors for the success in the identification. Low thickness indicates low spectral quality; the same is valid for the illumination intensity. Higher intensity leads to higher spectral qualities.

Publication VIII, Original Article, "Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches"

2D plastic packaging is either designed as monolayer or as multilayer film. The complexity in identifying multilayer films lies in their high number of material combinations and the thickness of the different material layers. Every material combination shows another characteristic spectrum, making it challenging to manually create a sorting model covering all types of multilayer films. For this reason, this publication deals with the question of whether machine learning approaches can be developed which can integrate unintegrated material combinations of multilayer films in the near-infrared sorting model automated. Frequency analysis methods are validated to increase the spectral information and eliminate the overlying noise to make this process more efficient. In the end, it is established that machine learning approaches can be used for the applied data to sort 2D plastic packaging without adding material combination spectra manually to the sorting model.

Research question 8 (RQ 8) Is the usage of machine learning algorithms suitable to enhance correct identification of particles in sensor-based sorting processes?

For the used 2D plastic packaging fraction, there is enough material-independent information in the spectral data available to implement machine learning approaches. Suitable machine learning algorithms for this approach are k-Nearest Neighbor a, Support Vector Machines and Neural Network. The derived spectra are processed with Gaussian Smoothing algorithm normalization, and preliminary tests are performed to assign the correct feature engineering. The development of the machine learning model started and the data was imported. The created algorithms were tested with spectra not used for developing the machine learning model. Neural Network derived the most accurate prediction in a short training time and performed well on the test spectra and is the most suitable one for classifying 2D plastic packaging material to monolayer or multilayer. Summing up, it can be stated that it is possible to enhance the identification of particles in sensor-based sorting processes with machine learning algorithms suitable for the available spectral data.

Experimental Design: Mechanical Discharge

Next, experiments on increasing the efficiency in sensor-based sorting processes by optimizing the mechanical discharge are performed. These experiments' results shall help to find the optimal operation point for a specific sorting result.

Publication IX, Original Article, "Influence of material alterations and machine impairment on throughput related sensor-based sorting performance"

This publication presents particle-specific assertions for sorting efficiency to the output parameters purity, yield, recovery and incorrect discharged particles. It is tested how these parameters are affected by the input parameters input composition and throughput rate. Furthermore, the influence of 2D material in the input and the malfunction of air valves for the mechanical discharge was examined. Additionally, it has to be stated that other factors like the sorting algorithm (e.g. segmentation of particles), the particulate weight, the feeding method (e.g. type of vibration conveyor), the particle shape and the particle surface condition (e.g. organic defilements, labels and adhesive particles) have influence in the sorting result and hence on the sorting efficiency. Results for the experimental trials are 2D plots, which show the influence of the input parameters to the output parameters, the influence of 2D material in the input and the malfunction of air valves.

Research question 9 (RQ 9): How do the input parameters of a sensor-base sorting process (throughput rate and input composition) depend on the sorting efficiency in the output parameters (purity, yield, recovery, incorrect discharged particles)?

Dependence on the input parameters to the output parameters is valid according to the results with assertions. Yield is not affected by the input composition; it depends on the throughput rate and decreases with increasing throughput rate. Incorrectly discharged particles show the behaviour of a saturation curve. It increases with an increasing throughput rate. Purity decreases with increasing throughput rate. Both purity and recovery are mathematically related to yield and incorrectly discharged particles.

2D material in the input reduces yield and incorrect discharged particles at increased throughput rates, while it shows only marginal influence on the sorting efficiency for lower ones. The malfunction of one air valve block, which covers 20 % of the sorting bands' width, affects the sorting efficiency at moderate and high throughput rates.

Publication X, Original Article, "Feasibility study for finding mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste"

Publication IX states in the last paragraph that more knowledge about the relation of the input to the output parameters of a sensor-based sorting process can be created by further trials concerning various machine and material-specific influence factors. This can bring up the ability to model and optimize a sensor-based sorting process with throughput rate and machine settings to achieve the optimal operation point for a specific sensor-based sorting result.

For this reason, Publication X finds mathematical approaches to describe the optimal operation point of sensor-based sorting machines for plastic waste. Mathematical approaches in regression models which underlie the input parameters input composition, throughput rate and the output parameter purity and recovery as sensor-based sorting results are developed. Yield is not considered since it depends only on the throughput rate and is not influenced by the waste input composition of a sorting process. Four respective hypotheses are proved for the regression models based on 108 trials on three sensor-based sorting setups and as materials ideal mixtures and five RDF samples. Afterwards, it is defined how a sensor-based sorting plant can run automated on the optimal operation point depending on the throughput rate and the input composition to achieve a specific sorting result.

Research question 10 (RQ 10) In what area of validity can mathematical approaches be used so that sensor-based sorting machines can run automated on the optimal operation point?

The regression models describe the sorting result behaviour regarding the input parameters (input composition, throughput rate) sufficient in their scope of applied data to regulate a sensor-based sorting setup when a specific sorting result in purity should be achieved. As the main result of this publication, regression models with enough trials to have an acceptable prediction accuracy in RSME and R^2 make it possible that a sorting plant can automated regulate its throughput to achieve a specific purity in the sorting process.

This leads to an automatic plant operation and maximizes the mass sorted in the plant with expected purity. The requirement is to record the production data before the sensor-based sorting machine. This can be done either with installing a near-infrared input characterization to know the input composition or with implementing feedback loops from the previous sorting result to the input parameter setup of the next sorting step. Furthermore, the regression models can also simulate circuit operation in sorting plants or stepwise sorting with a few sensor-based sorting machines. After the first sorting step to enrich concentrates of a specific plastic type, the recyclates are sorted in a second or third sorting step to exceed the expected result in purity. In the end, it can be stated that this outcome allows a sorting plant to increase purity by running the plant on the optimal operation point without substantially adapting it. Superordinate considered, this helps to increase the amount of recycled plastic so that less plastic waste is thermally treated without main adapting investments in current plant designs.

6 Conclusion

This doctoral thesis aims to increase the efficiency of sensor-based sorting processes for waste streams consisting of plastics. The doctoral thesis is set up so that each publication or each chapter brings results that help define necessities to be researched within the next publication or chapter.

Publication I defines the State-of-the-Art in sensor-based sorting with a literature review, while **Publication II** outlines the research gaps of the thesis topic. After knowing the State-of-Art and the research gaps and environmental analysis is performed to know which qualities of sorted plastic waste are expected by recycling processing plants (**Publication III**) and whether the usage of data analytics is a suitable solution for achieving increased efficiency in sensor-based plastic sorting (**Publication IV**). Results of these four publications in the State-of-the-Art, research gaps and environmental analysis are the base for developing the doctoral thesis's experimental design to achieve the thesis goal.

The most suitable sensor technology for sorting plastic waste is near-infrared spectroscopy, so that this sensor technology will be used in the experimental design. The research gaps are superordinately defined in increasing the identification of particles and optimizing the mechanical discharge by running the sensor-based sorting process on the optimal operation point to achieve a specific expected sensor-based sorting result. The minimum purities for sorted plastic waste, which a recycling processing plant expects, vary from 96 % to 98 %. For some impurities, further limits are set for the different types of plastic. Mathematical approaches in the recorded sensor-based sorting input and output data might be a significant step forward to optimize the sorting process in identification and mechanical discharge and get it automated.

Taking into consideration these findings, the experimental design is set up. In **Publication V,** the method of near-infrared spectroscopy as used sorting technology and the experimental sensor-based sorting setup, which is used in all publications of this thesis for trials, is introduced. Further, the experimental design is divided into two chapters for increasing the sensor-based sorting efficiency for waste streams consisting of plastics: the identification and the mechanical discharge.

Identification

First, the influence of surface roughness is examined in **Publication VI.** It focuses on the influence of mechanical delabelling in PET recycling. After delabelling, not only the PET bottles are label-free, but the surface of the PET bottles has also changed in roughness. The change in surface roughness extends peaks in the derived near-infrared spectrum of PET and improves the PET bottle classification.

Publication VII focuses on using transflection for an optimized identification of 2D films by installing a metal plate as background material in the sensor-based sorting process. This follows from **Publication VI**, which shows that the extended reflection in particles leads to an optimized particle identification in the near-infrared spectrum. Reflection and transmission combined are referred to as transflection. Transflection results in light being reflected off background materials like metal plates and with this reflection transmitting light through the particle twice. This configuration reduces the spectra fluctuation, which enhances near-infrared identification. The influence of thickness and emitter intensity are also assessed; for 2D plastic packaging particles, a thicker layer enhances the particle identification as well as the illumination intensity.

Publication VIII combines the outcomes of **Publication VII**, the use of transflection and **Publication II**, the use of data analytics. Mathematical approaches can help optimize the identification and automate this process in sensor-based sorting devices. The near-infrared sorting model is assessed if machine learning methods can be developed to incorporate new material combinations of multilayer films. For designing this development efficiently, spectral information is improved by validating frequency analysis techniques and by removing the overlying noise. Neural networks have demonstrated the best performance on test spectra and the most accurate classification of 2D plastic packaging into monolayer or multilayer in a short training time. Using available spectral data, the Neural Network machine learning approach demonstrated that improving 2D particle identification in sensor-based sorting processes can be automated for the used input data.

Mechanical discharge

Particle-specific claims for sorting efficiency to the output parameters purity, yield, recovery, and incorrect discharged particles are presented in **Publication IX**. The impact of the input parameters, input composition and throughput rate, on these parameters is evaluated. Additionally, the impact of 2D input material and the malfunction of air valves for mechanical discharge are explored.

According to the findings and assertions, dependence on the input parameters to the output parameters is valid. The input composition does not impact yield; yield is influenced by the throughput rate and declines as the throughput rate rises. Incorrectly discharged particles exhibit a saturation behaviour. It rises with the throughput rate. Purity declines as the throughput rate rises. Mathematically stated, purity and recovery are functions of yield and incorrectly discharged particles.

At higher throughput rates, 2D material in the input reduces yield and incorrectly discharged particles. At moderate and high throughput rates, the malfunction of one air valve block, which accounts for 20 % of the sorting bands' width, decreases these parameters as well.

The sorting algorithm (e.g., segmentation of particles), particulate weight, the feeding technique (e.g., type of vibratory conveyor), particle shape, and particle surface condition (e.g., organic defilements, labels, and adhesive particles) are additional factors that must be considered as they affect the sorting result and, consequently, the sorting efficiency.

Publication X, which deals with identifying mathematical approches to define the optimal operation point of sensor-based sorting machines for plastic waste, validates the major discovery of this doctoral thesis. Mathematical approaches using regression models that support the input parameters input composition, throughput rate, and output parameters purity and recovery as results of sensor-based sorting process. Since yield is only dependent on throughput rate and is unaffected by the waste input composition of a sorting process, yield is not considered. Based on 108 trials using three sensor-based sorting setups, ideal mixtures and five RDF samples, four theses are proved for the regression models.

When a specific sorting result in purity has to be achieved, the regression models define the sorting result behaviour concerning the input parameters (input composition, throughput rate) enough in their scope of applicable data to control a sensor-based sorting setup. A sorting plant can automated regulate its throughput rate to reach a specific purity in the sorting process using regression models. The development of such regression models require enough trials to have an acceptable prediction accuracy in RSME and R^2.

Mathematical approaches, which are set up to work in an acceptable prediction, can lead to a fully automated plant operation and increase the mass sorted with the desired purity. The criteria include capturing the production data and

- Either to implement feedback loops from the sorting result to the input parameter configuration of a sorting process
- Or to install a near-infrared input characterization before the sensor-based sorting machine to know the input composition.

The regression models can also indicate stepwise sorting with more sensor-based sorting machines or circuit functioning in sorting facilities. With these configurations recyclates are processed in a second or third sorting phase to achieve more purity after a first sorting stage to enrich concentrations of a particular plastic type.

Summing up, it can be stated that this result enables a sorting plant to boost purity by operating the system at its optimal operating point. This enhances the amount of recycled plastic - so that less plastic waste must be thermally processed - without significantly modifying existing plant designs.

7 Outlook and further research

Referring to the findings of the doctoral thesis in the previous chapter, "Conclusion", the opportunities for further research are predicted within this chapter.

According to chapter 1.3, "Scope of investigations", the boundaries of this doctoral thesis were set in Table 1-1 with "Sensor-based sorting" as waste processing technology, "Waste streams consisting of plastics" as waste to be processed and TRL 2 to 4. The opportunities for further research can be predicted by going beyond these boundaries in vertical or horizontal integration.

Horizontal integration beyond the boundaries

In the context of this doctoral thesis, horizontal integration beyond boundaries means getting broader with the found results. For all of the results, the set boundaries are to increase efficiency in sensor-based sorting processes for waste streams consisting of plastics. When getting broader with these results, the same efficiency-increasing opportunities can be validated for waste streams without plastics. Of course, the research questions would differ for other waste streams in detail. Still, the superordinate research questions of this doctoral thesis can be transferred, as well as the methodology and the experimental design. For the transfer of the methodology of this thesis to further research on other waste streams, the superordinate research questions are:

1. What is the State-of-the-Art for sensor-based sorting of the corresponding waste?
2. What might be suitable solutions to increase sensor-based sorting efficiency?
3. What methods can be used for sorting the corresponding waste?
4. How can the identification for sorting the corresponding waste be optimized?
5. How can the mechanical discharge for sorting the corresponding waste be optimized?

Considering these superordinate research questions, other waste streams to be sorted can be optimized with further research; examples of such waste streams would be cullets, paper or metals.

Vertical integration beyond the boundaries

Taking into consideration Figure 1-2, which describes the TRL of this doctoral thesis, vertical integration means performing further research to bring the results to higher TRL. For all the results, the set boundaries were done on TRL 2 to TRL 4 "Industrial Research". The research within this doctoral thesis is on an aggregate level, with the sensor-based sorting machine as a stand-alone equipment.

New research would be how and under what circumstances the results on aggregate level can be brought to plant level to integrate the results and validate them in industrial prototypes in the first steps with "Experimental Development" (TRL 5 to TRL 8) till they can be integrated into the operational environment of sensor-based sorting plants for "Market Launch" (TRL 9).

This vertical integration process, how to go beyond the boundaries from aggregate level to plant level, is visualized in Figure 7-1.

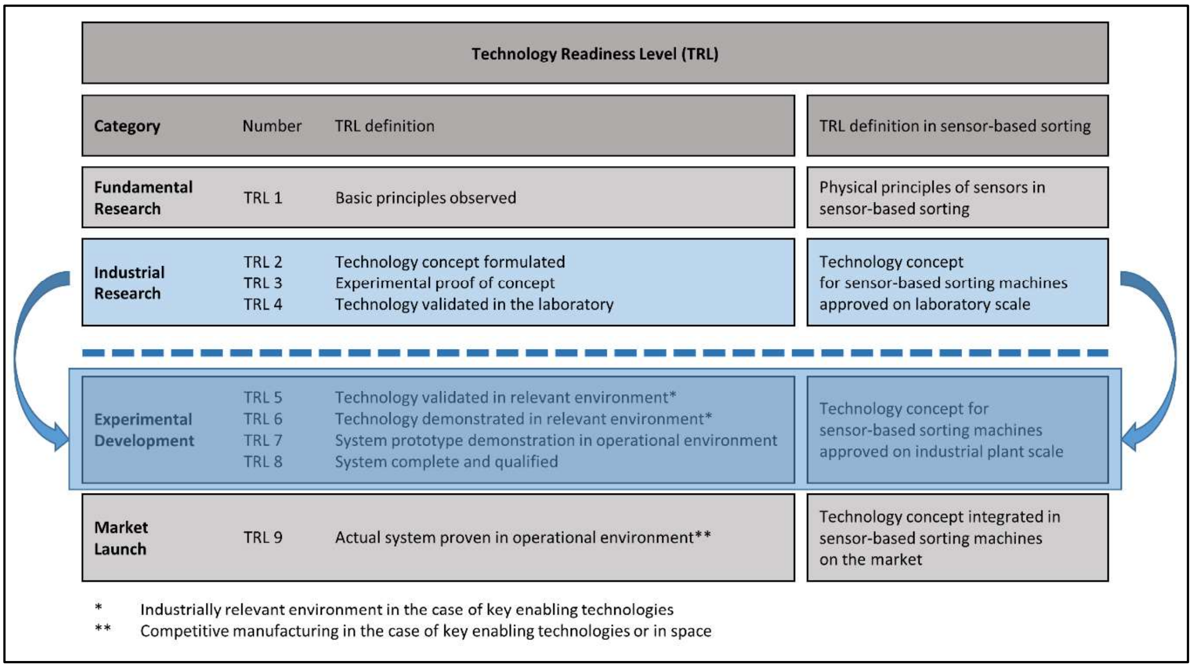

Figure 7-1: Research potential in vertical integration with extending the findings from industrial research on the aggregate level to experimental development on the plant level

Summing up, for all further research in sensor-based sorting on the plant level, which focuses on optimizing the sorting efficiency, the results of this doctoral thesis can be seen as a knowledge base (on a pre-industrial level or laboratory scale). Feedback loops of the sensor-based sorting results for regulating the input or an installation of a near-infrared sensor for getting to know the input composition before the sorting process help to build and validate this doctoral thesis's findings in industrial prototype demonstrators.

8 Bibliography

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9 List of Tables

10 List of Figures

11 List of Abbreviations

AI	Artificial Intelligence
AL-TR	Transflectance with Aluminium Reflector
ALU	Arbitrary Light Units
ANN	Artificial Neural Network
ATR	Attenuated Reflectance
AVAW	Chair of Waste Processing Technology and Waste Management
AWG	Austrian Waste Management Act
CO_2	Carbon Dioxide
COMET	Competence Centers for Excellent Technologies
CU-TR	Transflectance with Copper Reflector
DFT	Discrete Fourier Transformation
DKR	Deutsche Gesellschaft für Kreislaufwirtschaft und Rohstoffe mbH
DSC	Differential Scanning Calorimetry
EU	European Union
FFT	Fast-Fourier-Transformation
FTIR	Fourier-Transform Infrared Spectroscopy
GPR	Gaussian Process Regression
HDPE	High-Density-Polyethylene
HIS	Hyperspectral Imaging
HSV	Hue-Saturation-Value
IDFT	Inverse Discrete Fourier Transformation
IFR	International Federation of Robotics
Incorrect	Incorrect discharges
IoT	Internet of Things

IR	Infrared
kNN	k-Nearest Neighbour
LDPE	Low-Density-Polyethylene
LLDPE	Linear-Low-Density-Polyethylene
LIBS	Laser-Induced-Breakdown-Spectroscopy
MC	Material Class
MFR	Melt Mass-Flow Rate
MIT	Massachusetts Institute of Technology
MMI	Man-Machine-Interface
MPP	Multilayer Plastic Packaging
MVR	Melt Volume-Flow Rate
NIR	Near-infrared Spectroscopy
PA	Polyamide
PCA	Principal Component Analysis
PE	Polyethene
PET	Polyethylene Terephthalate
PETG	Polyethylene Terephthalate Glycol-Modified
PETL	Polyethylene Terephthalate covered with Label
P_m	Purity
PMMA	Polymethyl Methacrylate
PO	Polyolefin
PO_{eject}	Incorrect Polyolefin discharges
PP	Polypropene
PPW	Plastic Packaging Waste
PS	Polystyrene

PVC	Polyvinyl Chloride
R	Recovery
R^2	Coefficient of Determination
R_w	Yield
RAW	Standard Measurement without Reflector
RDF	Refuse-derived Fuel
RNN	Regression Neuronal Network
RPET	Recycled Polyethylene Terephthalate
RMSE	Root Mean Square Error
SBS	Sensor-Based Sorting
SNN	Shallow Neural Network
SVM	Support Vector Machines
TPU	Thermoplastic Polyurethane
RIA	Robotic Industries Association
RGB	Red-Green-Blue
SWIR	Short Wavelength Infrared
ST	Selective Technologies
TRL	Technology Readiness Level
UV	Ultraviolet Light
VIS	Visual Light
VIS	Visual Spectroscopy
WFD	Waste Framework Directive
XRF	X-ray Fluorescence Spectroscopy
XRT	X-ray Transmission