Chair of Waste Processing Technology and Waste Management

Doctoral Thesis

Sensor-Based Sorting and Waste Management Analysis and Treatment of Plastic Waste With Special Consideration of Multilayer Films

Dipl.-Ing. Gerald Rudolf Koinig, BSc

February 2023

MONTANUNIVERSITÄT LEOBEN
www.unileoben.ac.at

EIDESSTATTLICHE ERKLÄRUNG

Ich erkläre an Eides statt, dass ich diese Arbeit selbständig verfasst, andere als die angegebenen Quellen und Hilfsmittel nicht benutzt, und mich auch sonst keiner unerlaubten Hilfsmittel bedient habe.

Ich erkläre, dass ich die Richtlinien des Senats der Montanuniversität Leoben zu "Gute wissenschaftliche Praxis" gelesen, verstanden und befolgt habe.

Weiters erkläre ich, dass die elektronische und gedruckte Version der eingereichten wissenschaftlichen Abschlussarbeit formal und inhaltlich identisch sind.

Datum 03.02.2023

Gerald Koinig

Unterschrift Verfasser/in
Gerald Rudolf Koinig

Danksagung

Mehr sein als scheinen -

viel leisten und wenig hervortreten

Zitat von Helmuth James Graf von Moltke

Dieses Zitat sei all jenen gewidmet, dich mich in der Verfassung dieser Doktorarbeit unterstützt haben. All jenen liebsten Menschen, die unermüdlich in meiner Ecke standen und mir den Rücken gestärkt und freigehalten haben.

Es ist an der Zeit, mich herzlichst bei euch zu bedanken.

An erster Stelle sei hier meiner Frau Celestine gedankt. Du bist mit mir durch alle Höhen und Tiefen gegangen, die ein Studium auf der Leobner Alma Mater so mit sich bringt, und hast mich nach Kräften unterstützt - hast die Höhen verschönert und den Tiefen ihren Schrecken genommen, hast es mir ermöglicht, meine wildesten Ideen Wirklichkeit werden zu lassen. Während der Zeit des Verfassens dieser Arbeit ist in unserem Leben viel passiert. Du hast mein Leben unfassbar bereichert, mir deine Hand für den Bund der Ehe gereicht und mir unseren wunderschönen Sohn Matthias geschenkt. Ich liebe unsere kleine Seilschaft unendlich und kann es kaum erwarten, was unser gemeinsames Leben noch so parat hält. Eines ist gewiss, mit dir an meiner Seite kann kommen, was wolle.

Der zweite Dank gebührt meiner Mutter Ilse Koinig. Du hast während meines ersten Semesters unfassbaren Mut bewiesen, hast ein altes verkommenes Buch zugeschlagen, ein neues Kapitel begonnen und uns mit dir in eine wunderbare, verheißungsvolle Zukunft genommen. Ich kann mir keine bessere, liebevollere Mutter vorstellen. Dass dies nicht an meiner eingeschränkten Fantasie liegt, hast du immer wieder unter Beweis gestellt. Dein Enkel Matthias und deine beiden Söhne haben mit dir unglaubliches Glück und wir, allen voran dein kleiner Enkel, lieben, brauchen und schätzen dich sehr. Ich möchte mich hier in diesen Zeilen bei dir für die unaufwiegbare Unterstützung in allen Lebenslagen bedanken.

Der dritte Dank gebührt meinem Doktorvater Prof. Dr. Daniel Vollprecht für seine unermüdliche Unterstützung. Deine enorme fachliche und menschliche Kompetenz hat dazu geführt, dass du einer Berufung auf die Augsburger Universität folgen konntest, die du nun um deinen eigenen Lehrstuhl bereichern wirst. Dieser berufliche und persönliche Wandel hat jedoch deinen Einsatz und deine Unterstützung um nichts geschmälert. Ich möchte mich hier bei dir dafür bedanken, dass du mich auch von Augsburg aus weiterhin nach Kräften unterstützt und mir das Verfassen dieser Arbeit ermöglicht hast.

Der Platz in diesen Zeilen ist dürftig, um mich angemessen zu bedanken. All meinen Freunden gebührt für ihr Zuhören, Ablenken und Austarieren jedenfalls mehr Dankbarkeit, als dieses Blatt wiederzugeben im Stande ist – ***<u>Vielen Dank euch allen!</u>***

Kurzfassung

Sensorgestützte Sortierung und abfallwirtschaftliche Analyse und Behandlung von Kunststoffabfällen unter besonderer Berücksichtigung von Mehrschichtfolien

Der Verbrauch von Kunststoffverpackungen steigt seit Jahren kontinuierlich an. Die Nachfrage nach Verpackungen, die Produkte schützen, ihre Haltbarkeit erhöhen und gleichzeitig den Konsumenten durch ansprechende Haptik und Optik zum Kauf eben jener Produkte anregen, steht dem Bedarf nach möglichst geringem Materialeinsatz und einem vorteilhaften Masseverhältnis von Verpackung zu Produkt gegensätzlich gegenüber. Kunststofffolien erbringen eben diesen Spagat. Ein jährlicher Verbrauch von etwa 69.000 Tonnen, was etwa 23% des jährlichen Aufkommens an Kunststoffverpackungsabfall in Österreich darstellt, spiegelt wider, dass sowohl Konsumenten als auch Märkte die Vorteile dieser Materialien erkannt haben.

Die Materialeigenschaften, die den Einsatz von Kunststofffolien als Verpackung attraktiv machen, erschweren jedoch eine Sortierung mittels Nahinfrarotspektroskopie, welche den Stand der Technik in der Abfallwirtschaft darstellt. Dies führt dazu, dass die stofflich verwertbare Monolayerfraktion gemeinsam mit der Mehrschichtfraktion bestenfalls dem Downcycling und schlechtesten Falls einer thermischen Verwertung zugeführt werden muss, was sich negativ auf die Recyclingquote auswirkt und gleichzeitig wertvolle Ressourcen verschwendet.

Diese Doktorarbeit liefert einen Beitrag, um die Sortierung der Folienfraktion zu erleichtern. Hierzu wird in dieser Arbeit eine Bestandsaufnahme der derzeitigen Situation in Österreich anhand einer Handsortierung der Leichtverpackungsfraktion und eine Stand-der-Technik-Analyse mit Fokus auf die Nahinfrarottechnologie in der Abfallwirtschaft durchgeführt. Anschließend wird in einer umfassenden Lebenszyklusanalyse der Effekt eines verstärkten mechanischen Recyclings der Folienfraktion der thermischen Verwertung gegenübergestellt und erhoben, dass durch forciertes Recycling bis zu 63% der Treibhausgasemissionen verhindert werden könnten.

Aufbauend auf diesen Erkenntnissen werden Methoden zur Adaption von Nahinfrarotsortierern präsentiert, die durch Messung in Transflektion die für die Nahinfrarotsortierung hinderlichen Eigenschaften der Folienfraktion umschiffen. So erlauben sie eine materialbasierte Sortierung der Folienfraktion auf bestehenden Aggregaten.

Weiters werden datenanalytische Methoden auf Grundlage der Spektralzerlegung präsentiert, die es erlauben, die durch die Hardwareadaption verbesserte Spektralgüte weiter zu optimieren. Anschließend werden Machine-Learning-Algorithmen auf ihre Anwendbarkeit zur Sortierung von Mono- und Multilayerfolien hin untersucht, wobei sich die Support Vector Machine und ein Shallow Neural Network als die geeignetsten Methoden für eine materialunabhängige Klassifikation von Folienabfall in Ein- und Mehrschichtfolien herausstellten.

Abstract

Sensor-Based Sorting and Waste Management Analysis and Treatment of Plastic Waste with Special Consideration of Multilayer Films

The consumption of plastic packaging has been increasing continuously for years. The demand for packaging that protects products, increases their shelf life and at the same time encourages consumers to buy those products with an appealing feel and look conflicts with the need for the lowest possible use of materials and an advantageous mass ratio of packaging to product. Plastic foils precisely perform this balancing act.

An annual consumption of around 69,000 t, representing around 23% of the annual volume of plastic packaging waste generated in Austria, reflects that both consumers and markets have recognised the benefits of these materials.

However, the material properties that make the use of plastic films attractive as packaging make sorting using near-infrared spectroscopy, which represents the state of the art in waste management, more difficult. As a result, the materially recyclable monolayer fraction together with the multilayer fraction are sent for downcycling at best and energy recovery at worst, which negatively affects the recycling rate and at the same time wastes valuable resources.

This doctoral thesis contributes to facilitating the sorting of the film fraction. For this purpose, an inventory of the current situation in Austria is carried out in this work using a manual sorting of the light packaging fraction and a state-of-the-art analysis with a focus on near-infrared technology in waste management.

Subsequently, in a comprehensive life cycle analysis, the effect of increased mechanical recycling of the film fraction is compared with thermal recycling and it is ascertained that up to 63% of greenhouse gas emissions could be prevented through improved recycling.

Based on these findings, methods for the adaptation of near-infrared sorters are presented, which circumvent the properties of the film fraction that hinder near-infrared sorting by measuring in transflection.

These methods allow material-based sorting of the film fraction on existing units. Furthermore, data analysis methods based on spectral decomposition are presented, which allow to further optimize the spectral quality, which has been improved by the hardware adaptation. Subsequently, machine learning algorithms are examined for their applicability for sorting mono- and multilayer films, whereby the support vector machine and a shallow neural network turned out to be the most suitable methods for a material-independent classification of film waste into single- and multilayer films.

Publications

Journal Papers:

Friedrich, Karl; **Koinig, Gerald**; Fritz, Theresa; Pomberger, Roland; Vollprecht, Daniel (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.

Friedrich, Karl; **Koinig, Gerald**; Pomberger, Roland; Vollprecht, Daniel (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.

Koinig, Gerald; Rutrecht, Bettina; Friedrich, Karl; Barretta, Chiara; Vollprecht, Daniel (2022): Latent Recycling Potential of Multilayer Films in Austrian Waste Management. In *Polymers* 14 (8). DOI: 10.3390/polym14081553.

Koinig, Gerald; Grath, Elias; Barretta, Chiara; Friedrich, Karl; Vollprecht, Daniel; Oreski, Gernot (2022): Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison. In Polymers 14 (17), p. 3620. DOI: 10.3390/polym14173620.

Koinig, Gerald; Friedrich, Karl; Rutrecht, Bettina; Oreski, Gernot; Barretta, Chiara; Vollprecht, Daniel (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.

Koinig, Gerald; Kuhn, Nikolai; Barretta, Chiara; Friedrich, Karl; Vollprecht, Daniel (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), p. 3926. DOI: https://doi.org/10.3390/polym14193926.

Conference Presentations:

11. Wissenschaftskongress „Abfall- und Ressourcenwirtschaft" der DGAW e.V.
Gerald Koinig (Redner, Autor)
16 Mär 2022 → 18 Mär 2022

Neue Entwicklungen und Möglichkeiten von Sensor-based sorting and control (SBSC)
Gerald Koinig (Redner)
8 Mär 2022

16. Recy & Depotech 2022
Verbesserte Trennung von Mehr- und Einschichtfolien mittels Nahinfrarotspektroskopie
Gerald Koinig (Redner, Autor)
11 Nov 2022

Table of Contents

1 Introduction

The current recycling rates reveal that many countries in the EU struggle to reach the postulated recycling rate of 60% of all plastic packaging waste which has to be reached in 2025 (EU, 2008). The statistical evaluation of the material flow and recovery of plastic packaging waste in Austria shows that a substantial percentage of the annually generated plastic packaging waste is small films under 1,5m². More precisely, small film packaging accounts for 69,000 t of the 300,000 t of the annually generated small film packaging waste in Austria. Of this 69,000 t, only 12,000 t are mechanically recycled and used as re-granulates and re-enter the circular economy in the form of r-resources. The remaining 56,000 t of film packaging is used in industrial incineration or waste-to-energy plants (Van Eygen et al., 2018). Calculating the resulting percentages reveals that only 17.4% of small film packaging is mechanically recycled. The remaining 82.6% are either lost after thermal recovery as off-gas or landfilled (Van Eygen et al., 2018).

The use of small film packaging has steadily increased over the last decade, and this development is unlikely to recede (Briassoulis et al., 2017). The widespread application of film packaging lies in the unrivalled ability to provide a wide array of functions with minimal material use. Plastic film packaging gains this ability by combining multiple polymers, adhesive layers and even the incorporation of metallic layers (Niaounakis, 2019). This combination yields protective, decorative and functional packaging. The widespread application of these materials in the food packaging industry shows that consumers and producers have recognised such benefits.

However, the same characteristics which make the application of film packaging viable, pose issues when their purpose has been served. There are currently three different routes plastic film packaging can take after entering the waste stream. A thorough analysis of the waste flow of film packaging in Austria has been conducted by van Eygen et al., and the resulting flows are represented in Figure 1. It can be seen that films exit the waste stream through the recovery of energy in waste-to-energy plants (Kaiser et al., 2018), are downcycled to low-quality products with inferior mechanical and optical properties (Plastic Europe, 2019), or are used as residue derived fuel in industrial applications (Kaiser et al., 2018). Further, valuable monomaterial fractions are “contaminated” by multilayered film packaging due to the inadequacy of the applied sorting mechanisms, which incorrectly classify multilayer films as monomaterial (Ragaert et al., 2017).

Estimates show that approximately 17% to 20% of all plastic film packaging consists of multilayer packaging (Tartakowski, 2010; Dahlbo et al., 2018). Considering the initially stated percentages, this leaves up to 57.270 t of monolayer packaging. This monolayer packaging could be used in mechanical recycling and thus enhance the circular economy of plastic packaging.

To improve the circular economy of polymers and to raise the recycling rate, it is necessary to improve the sortability of films, and this improvement is necessary to separate multilayer materials from monolayer plastics. The first study on near-infrared-based sorting of multilayer post-consumer packaging demonstrated the feasibility of using this technology with minor adaptations on a laboratory scale using transflection measurements (Chen et al. 2021). Implementing these findings on an industrial scale would create a feedstock for chemical recycling plants currently in development for multilayer films while simultaneously recovering valuable monomaterial films for mechanical recycling.

While test plants for recycling post-industrial film packaging have been implemented and small-scale plants are under construction, the recycling of post-consumer film packaging currently lacks such developments. Technologies like physical delamination, implemented by Saperatec GmbH in Germany (Niaounakis, 2019), separating adhesive layers from materials layers via a liquid solvent (Kaiser et al., 2018), the "CreaSolv" process capable of separating the different layers of film packaging (Fraunhofer IVV, 2020) or the "Newcycling" process by APK GmbH (APK AG, 2020) are being implemented for the recycling of post-industrial films. All these technologies need a well-defined input stream and knowledge of the composition of the film packaging in common. Post-consumer lightweight packaging lacks the rigorous separated collection of post-industrial packaging waste. The inhomogeneity of post-consumer plastic waste and the lack of rigorous separated collection necessitates extensive sorting into well-defined material classes before further recycling.

Near Infrared Spectroscopy (NIRS) is the state-of-the-art technology for sorting plastic packaging (Feil and Pretz, 2020). This predominance is due to the high throughput and sorting accuracy achievable with NIRS. NIRS offers the possibility of determining the material of a given polymer through the interaction of the radiation and the polymer's molecular structure. This interaction yields a characteristic spectrum, a fingerprint, by which the material can be identified. Though applicable to a wide array of materials, NIRS reaches its limit with materials that show inadequate interaction with the NIR radiation. Amongst these materials are polymers coloured with carbon black, metals, ceramics, and two-dimensional objects with a very thin material thickness (Masoumi et al., 2012; Beel, 2017). Low material thickness decreases the specificity of the characteristic peaks of a given NIR spectrum and subsequently lowers the information content of the given spectrum (Masoumi et al., 2012).

In addition to the already low information content, films exhibit a disturbing signal component in the spectrum due to destructive interferences. This noise obscures useful information and hinders classification (Jeszenszky et al., 2004). However, Fast Fourier Transformation may remove these interferences with correctly set parameters. Nonetheless, determining these parameters proved time-consuming and laborious (Jeszenszky et al., 2004).

The plethora of film compositions in circulation poses an additional problem to existing sorting models. A sorting model capable of confidently separating mono- from multilayer materials without being overwhelmed by the sheer overabundance of possible material compositions needs to be created. The fulfilment of this task asks for a method to teach sorting models capable of detecting multilayer materials without the need to explicitly teach each possible layer combination to the sorting model. This specific use case suggests the applicability of machine learning algorithms in sorting film packaging. A systematic literature review performed in 2022 showed that machine learning is currently used to evaluate NIR spectra (Kroell et al., 2022). The use cases of machine learning in NIRS vary from the recognition of food quality such as beer or fruit (Viejo et al., 2017; Zhang et al., 2020), application in the medical sector (Shoushtarian et al., 2020), the analysis of environmental hazards such as water pollution (Chen et al., 2020) and the quality assessment of biofuels, such as pellets (Mancini et al., 2020). So far, no classification of film packaging has been conducted via machine learning methods in NIRS, although the application seems an ideal fit.

This work aims to aid in increasing the Austrian recycling rate by facilitating the mechanical recycling of film packaging and delivering additional data on the composition of Austrian lightweight packaging waste. This work addresses this issue by conducting sorting trials to evaluate the mono- and multilayer film content in the Austrian lightweight packaging waste fraction.

Based upon the existing data, supported by the results of the hand sorting trials, multiple life cycle analyses (LCA) are conducted to establish whether mechanical recycling of films is environmentally favourable to thermal recovery.

After this preliminary work to establish a current state of affairs in the Austrian waste management of film packaging and to gauge the ecological viability of film recycling, a technological review is conducted. This technological review is performed to evaluate the available sensor-based sorting techniques and to assess their potential for film sorting. This review showed NIR spectroscopy to be the most promising technology which is consequently subjected to further analysis. This evaluation of the suitability of NIR technology for film sorting revealed both the issues NIR sorters may have because of the material properties of film packaging and possible remedies to mitigate these limitations.

The initially stated material properties of film packaging like the thin material thickness that make them ideal for packaging purposes, cause a lack of interaction between the material and the NIR radiation. This lack of interaction leads to spectra that contain little to no information about the material in question and make classification difficult.

The lack of spectral information is being addressed by modifying an industrial NIR sorter. These adaptations include optimising recording parameters like illumination, measuring geometry and the effects of changing the measuring method from reflectance to transflection. These adaptations increase the information content of the film spectra and reduce the occurrence of disturbing signal components from interferences. To further decrease these obscuring interferences, Fourier Transformation is used, and the laborious setting of parameters is facilitated by automating the search for the correct parameters, such as finding the Fourier components needed to be eliminated prior to the reconstruction of the spectra using inverse Fourier transformation.

These adaptations result in NIR spectra with increased information content which is then used to train machine-learning models to classify multilayer- and monolayer film packaging. To this end, an array of machine learning models, including decision trees, support vector machines and neural networks, are compared to each other based on the prediction accuracy, calculation speed and computational requirements. This approach yields a sorting model that is not material based but instead utilises overlying differences in the spectral makeup resulting from inherent differences between mono- and multilayer materials to make a classification.

These software enhancements are built upon each other to establish a technology readiness level (TRL) of 2 and raise this TRL to 4. The hardware improvements, enhancing the spectral quality of film packaging, are based upon existing findings and a resulting TRL of 3. This thesis aimed to raise the TRL of these hardware enhancements to TRL 6 through trials on the NIR sorter.

This thesis delivers new findings regarding the composition and abundance of film packaging waste and shows the environmental benefits of mechanical recycling compared to energy recovery. The results on the composition of the film fraction itself, the lightweight packaging fraction overall and the results of the LCA, which show that considerable CO_2 emission reduction can be achieved through the material recycling of film packaging, offer a good basis for decision-making and discussion.

Simultaneously personnel dealing with the technical minutiae of film sorting may use this thesis as a steppingstone for further development in film sorting. Additionally, this thesis delivers the basis and statistical evaluation of beneficial adaptations to existing NIR sorting aggregates and displays software-based enhancements which increase the sortability of film packaging further. Thus, it may also benefit researchers focussing on waste management who wish to enhance the capabilities of sensor-based sorting systems.

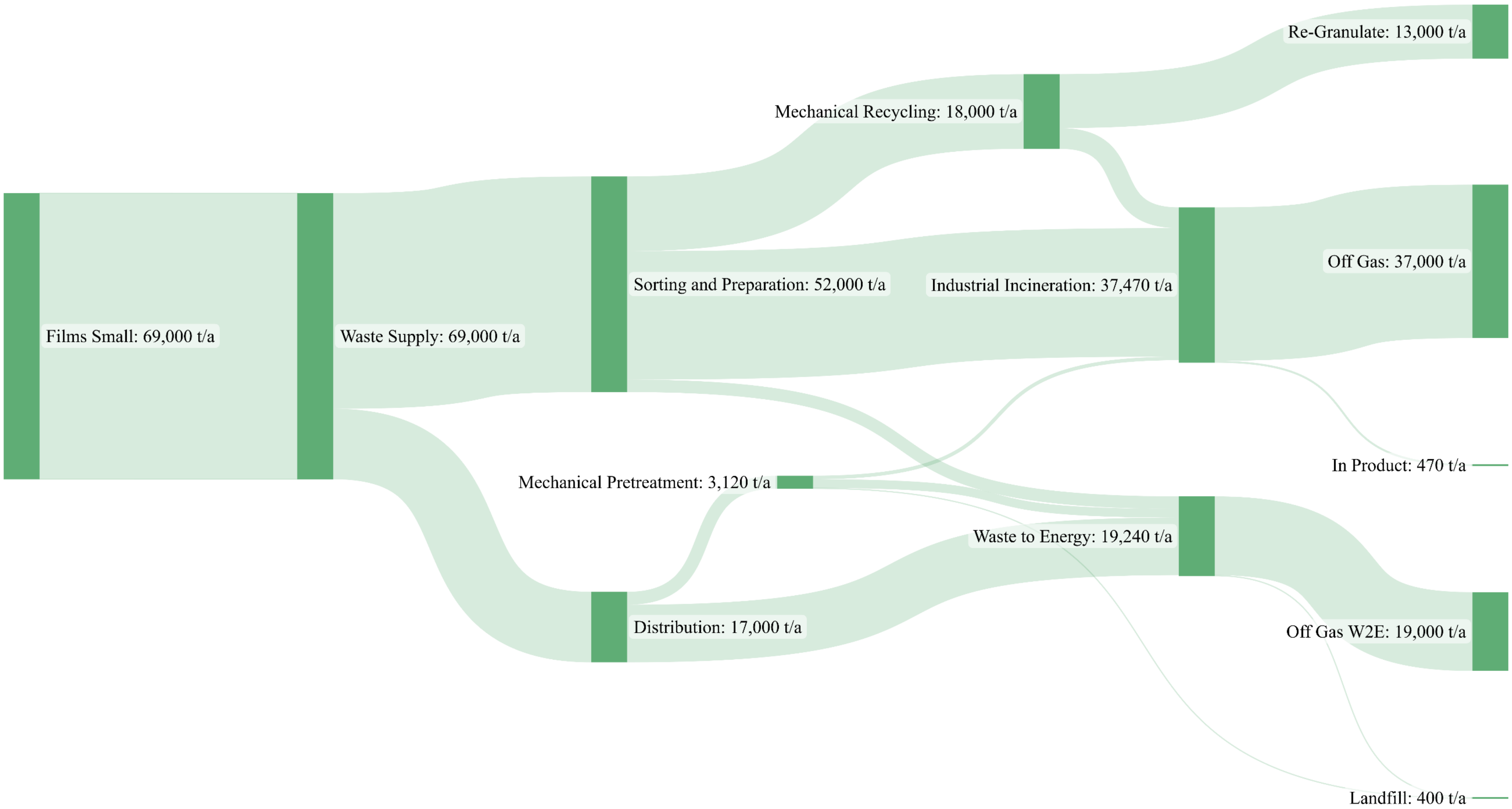

Figure 1: Mass flow of Small Film packaging in the Austrian Waste Management. Data taken from van Eygen et al. 2018, Depiction by the author, Flows consolidated.

1.1 Problem Definition

The rise in plastic packaging in recent years, and the fact that recycling rates for plastic packaging waste have stagnated during the last decade indicate the need for action and change (Eurostat, 2022). These trends are visualised in Figure 2, which shows Austria's plastic waste production and recycling rate from 2012 to 2019.

Despite the postulated goal to reach a recycling rate of 55% for all lightweight packaging by 2030, small plastic packaging films are hitherto almost ignored in recycling and waste processing (EU, 2018; Van Eygen et al., 2018). Small films, two-dimensional plastic packaging with an area smaller than 1.5 m^2, make up 69,000 t of Austria's annually produced 300,000 t waste packaging and are mainly thermally recovered (Van Eygen et al., 2016; Van Eygen et al., 2017). This valorisation method does not add to the recycling rate (EU, 2018) of lightweight packaging. Furthermore, it causes significant greenhouse gas emissions (Gradus et al., 2016; Mohn et al., 2008) and wastes valuable resources.

Due to functional requirements, plastic packaging is often produced as multilayer composites of different materials. Depending on the requirements, films with up to 12 layers can be produced in the co-extrusion process. The composition of these materials fulfils various tasks such as stability, flexibility, UV protection or gas impermeability.

In 2020, at the start of the work for this doctoral thesis, these multilayer composites pose a great challenge for material sorting. Although small-sized films are one of the most prevalent fractions of plastic packaging waste, only a few are intentionally recycled because common sorting systems have issues recognising multilayer films (Van Eygen et al., 2016; Van Eygen et al., 2017; Van Eygen et al., 2018). These multilayer composites pose a significant challenge for recycling, as the additional plastic layers can contaminate the main recyclates and reduce the material quality.

In addition, no comprehensive comparison between the environmental impact of thermal recovery and increased film recycling had been conducted based on the occurrence of mono- and multilayer packaging in the separate collection of waste in Austria.

These technological shortcomings necessitate answering the following research questions: (A) Can mechanical recycling reduce the environmental impact of film packaging? (B) How can film packaging be mechanically recycled using existing aggregates?

Without answering these questions, thermal valorisation remains the only viable destination for film packaging waste, and with that, the opportunity to recover resources in over 20% of the annually produced plastic waste in Austria remains untapped.

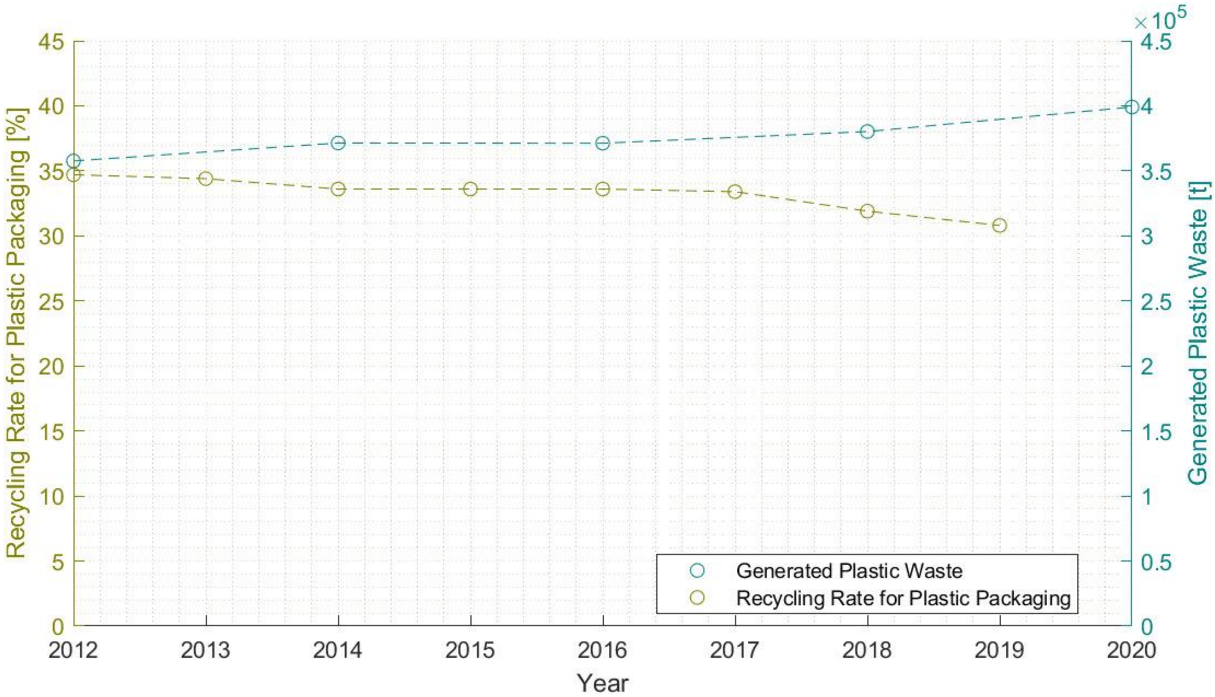

Figure 2: Available data on Plastic Waste Production from 2012 to 2020 and Recycling Rate in Austria from 2012 to 2019 Eurostat, Generation of waste by waste category, hazardousness and NACE Rev. 2 activity, Statistical office of the European Union. Eurostat, Recycling rates for packaging waste Statistical office of the European Union (2022), - Author's depiction

1.2 Framework of This Doctoral Thesis

This thesis comprises two phases to aid in finding a solution to the problems stated in Chapter 1.1. These phases are the "Waste Management Analysis Phase" and the "Process Optimisation Phase". The first phase´s goal is to prepare results on which to base phase two.

The first phase, "Waste Management Analysis Phase", aims to evaluate the current situation in the waste management of film packaging. Here, existing findings covering the occurrence of film packaging in separate collected waste will be assessed, and a hand-sorting trial will be performed to confirm the existing results. Further, the current technologies available in the waste management sector will be assessed and ranked for their applicability for sorting film packaging.

The aim of this broad-scope investigation of all available technologies is to find the sorting method with the highest potential to improve the sorting of film packaging. Additionally, the hand-sorting trials will result in a better understanding of the composition of film packaging waste.

Based on these results, the second phase, "Process Optimisation", will deal with improving existing sensor-based technologies to enhance the sortability of film packaging. The second phase will include an extensive LCA detailing the environmental effects of various levels of improved film packaging recycling. This LCA will determine the environmental consequences of improved film recycling and the resulting decrease in thermally recovered film packaging.

This assessment aims to evaluate the ecological feasibility of replacing thermal valorisation with mechanical recycling. Additionally, hard- and software improvements on a NIR sorting aggregate will be presented, and these improvements will incorporate changed measurement geometries and machine learning-based sorting models.

Figure 3 depicts the thesis structure and shows the corresponding research articles. In addition, concise research questions that need to be answered are displayed. A more comprehensive list of research questions is shown in Chapter 1.3, “Scope of Investigations”.

This thesis and the detailed findings were completed as a result of a research project funded by the Zukunftsfonds Steiermark. The research project is called “Multilayer Detection” and was conducted in cooperation with the Polymer Competence Center Leoben (PCCL).

- Multilayer Detection - Identification of multilayer films in plastic sorting to increase the recycling of packaging film waste (2020 – 2022; Project Number: 1314)

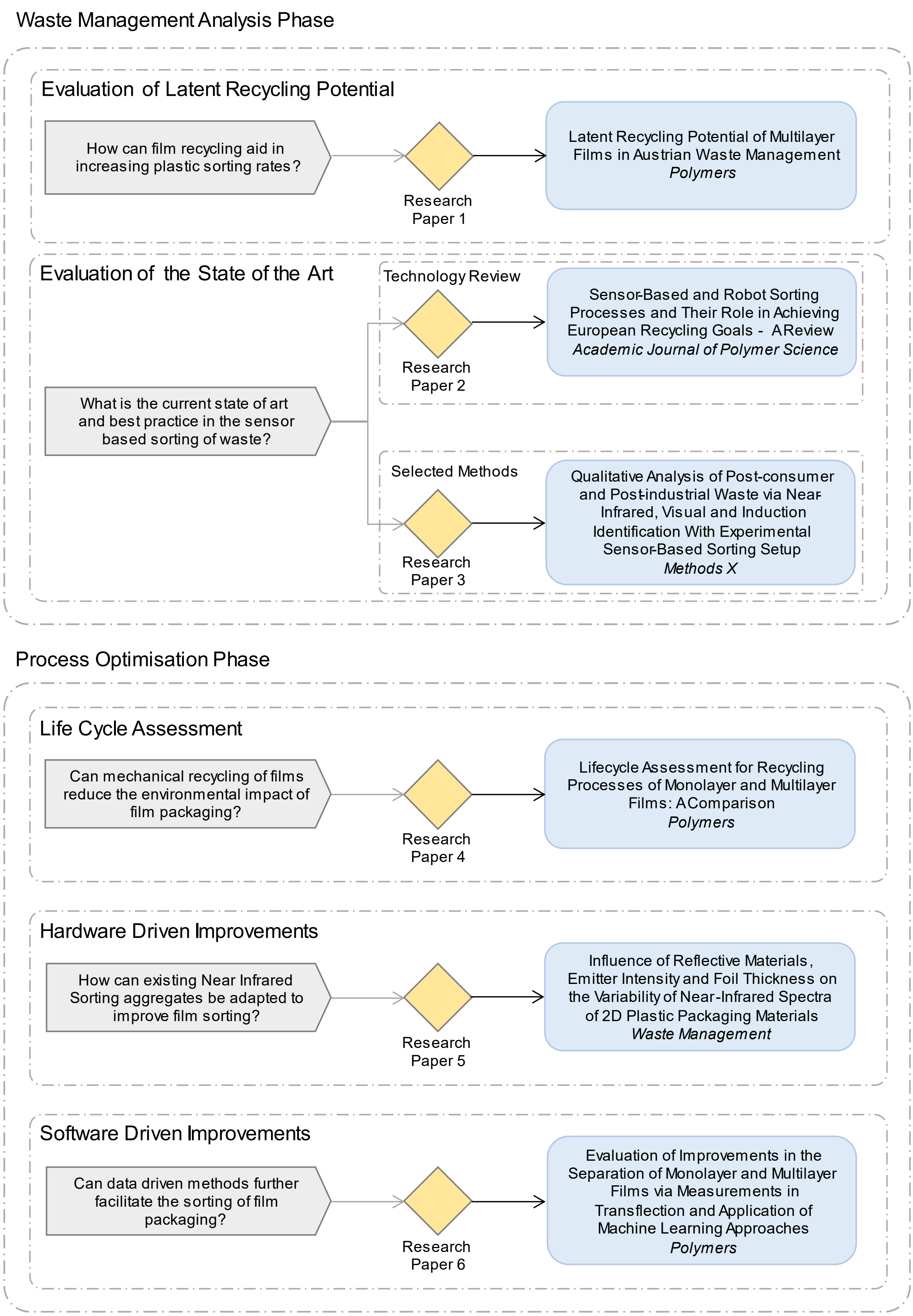

Figure 3: Structure and framework of the doctoral thesis

1.3. Scope of Investigations

This chapter describes the research publications included in this thesis and the research questions that were to be answered in the respective publications.

1.3.1 Publication 1

This publication introduces the groundwork for the following research. The current situation regarding film packaging is evaluated based on an extensive hand sorting trial of lightweight packaging waste. The current proportion of film packaging in the Austrian waste has been determined. Additionally, the composition of this film packaging waste was tested. This publication shows the relevant proportion of multilayer and monolayer packaging in the separate collection of waste and provides the foundation for calculating the latent recycling potential of film packaging.

Research questions:
(1a) How prevalent is film packaging in Austrian lightweight packaging at the start of the investigations?

(1b) What percentage of film packaging are multilayer films?

(1c) What were the most common applications of multilayer films found in the separate collection of lightweight packaging waste?

(1d) How would an increased film recycling affect the overall recycling rate?

1.3.2 Publication 2

This publication introduces the existing sensor-based sorting technologies. Here, relevant technologies prevalent in waste management are reviewed, and their application possibilities are evaluated. This work serves as an overview of the current best practices and shows relevant technology available to achieve recycling goals. Additionally, conventional sensor-based sorting processes are compared to emerging robot sorting processes regarding their suitability and potential for achieving these goals. This systematic overview aided in choosing the correct sorting method for film packaging.

Research questions:
(2a) What is the current state of the art and what is the best practice in sensor-based waste sorting?

(2b) Which currently available technique shows the highest potential for improving the sortability of film packaging waste?

1.3.3 Publication 3

This publication introduces the selected methods and presents the near-infrared sorting aggregate used in all upcoming publications. It further elaborates on the application of this sorting aggregate and details all used sensors and their specifications.

Research question:
(3a) What are the working principles behind the sorting techniques best applicable to film sorting?

1.3.4 Publication 4

This publication presents an extensive LCA of film packaging and its recycling processes. Here, the sensibility of replacing the currently employed method of thermal valorisation of film packaging waste is compared to a mechanical recycling process. The overarching question is whether thermal recovery and its subsequent provision of heat and electricity are superior regarding greenhouse gas emissions and the depletion of abiotic fossil fuels. This publication answers the question whether replacing thermal recovery of film packaging with mechanical recycling would reduce the ecological impact of film packaging or whether retaining thermal recovery is the more sensible approach at present. To this end, various scenarios, including improved collection, sorting, and a closed material cycle, have been compared and their respective ecological impact has been computed. In addition, the effect of reaching the postulated recycling goals and exhausting the current technological limits for recycling content in recycling film was calculated.

Research questions:
(4a) Can mechanical recycling of films reduce the environmental impact of film packaging?

(4b) Is mechanical recycling of films ecologically viable despite the reduction in thermally recovered energy from film waste?

(4c) How will reaching the postulated recycling goals in film recycling impact the global warming potential and depletion of abiotic fossil fuels?

1.3.5 Publication 5

The inhibiting factor when sorting thin plastic film packaging in near-infrared is the low material thickness which does not permit sufficient interaction of the near-infrared radiation with the material. This lack of interaction leads to spectra containing little to no useful information. This lack of information prevents classification based on the material´s spectra. This publication evaluates possibilities for adapting an existing near-infrared sorting aggregate to increase the spectral quality and thus enable the classification of film materials. All found possibilities to increase spectral quality were statistically evaluated and compared to each other, revealing the most effective adaption to enable thin film sorting on an existing machine.

Research questions:
(5a) What hardware adaptions mitigate the lack of spectral information when sorting with near-infrared technology?

(5b) What changes provide the most significant improvement in spectral quality?

(5c) How can existing near-infrared sorting aggregates be adapted to improve film sorting?

1.3.6 Publication 6

After implementing extensive hardware modifications to improve the spectral quality of multilayer films, attention was shifted to software adaptations. This publication details data-driven possibilities to facilitate the classification and sorting of film packaging through the use of Fast Fourier Transformation. Fast Fourier Transformation decreases spectral noise instigated by destructive interferences caused by the low material thickness of film packaging. In addition, a method to select the correct Fourier Components prior to the reconstruction of the spectrum via inverse Fast Fourier transformation without laborious manual selection of the most relevant Fourier components is presented.

Additionally, machine learning methods classify multilayer and monolayer films irrespective of their material composition to alleviate the issue posed by the plethora of existing material compositions in the multilayer fraction. This plethora of possible material compositions with their corresponding individual spectra would make creating a sorting model to recognise all multilayer materials infeasible.

This publication shows the classification of film packaging by using overlying characteristics differentiating monolayer from multilayer materials regardless of the specific material composition. This separation is conducted via support vector machines and shallow neural networks, which were shown to be the most suitable methods for this classification task regarding prediction accuracy, training time and susceptibility to overfitting.

Research question:
(6a) Can data-driven methods further facilitate the sorting of film packaging?

(6b) Can Fast Fourier Transformation automatically improve spectral quality?

(6c) Can machine learning techniques be used to separate monolayer from multilayer materials without explicitly teaching the sorting aggregate to recognise the spectra of all present multilayer compositions?

2 Waste Management Analysis Phase

The first of two subject areas of this thesis “Waste Management Analysis Phase” consists of three peer reviewed publications. These publications are presented below.

2.1 Publication 1

Research Paper 1:

“Latent Recycling Potential of Multilayer Films in Austrian Waste Management”

Koinig, Gerald; Rutrecht, Bettina; Friedrich, Karl; Barretta, Chiara; Vollprecht, Daniel (2022): Latent Recycling Potential of Multilayer Films in Austrian Waste Management. In *Polymers* 14 (8). DOI: 10.3390/polym14081553.

Annotation on the doctoral candidate’s contribution to this publication:

The general concept of the publication was designed by the doctoral candidate and discussed in contribution with the co-author Bettina Rutrecht. Afterwards, the relevant scientific literature on the subject was reviewed by the doctoral candidate and Bettina Rutrecht. The publication was then written independently by the author of the doctoral thesis based on a draft created by Bettina Rutrecht. The internal review process was done with the consultation of the co-authors Karl Friedrich, Barretta Chiara and supervisor Daniel Vollprecht.

polymers

Article

Latent Recycling Potential of Multilayer Films in Austrian Waste Management

Gerald Koinig [1,*], Bettina Rutrecht [1], Karl Friedrich [1], Chiara Barretta [2] and Daniel Vollprecht [1]

[1] Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet Leoben, Franz Josef Straße 18, 8700 Leoben, Austria; bettina.rutrecht@unileoben.ac.at (B.R.); karl.friedrich@unileoben.ac.at (K.F.); daniel.vollprecht@unileoben.ac.at (D.V.)

[2] Polymer Competence Center Leoben GmbH, Roseggerstraße 12, 8700 Leoben, Austria; chiara.barretta@pccl.at

* Correspondence: gerald.koinig@unileoben.ac.at

Abstract: This work presents a hand sorting trial of Austrian plastic packaging, which showed that according to an extrapolation of the 170,000 t separately collected waste collected in Austria, 30 wt% are flexible 2D plastic packaging. Further, the applications for these materials have been catalogued. The composition of these films was evaluated via Fourier-Transformed Infrared Spectroscopy, which showed that 31% of all films were made of polyethene, 39% of polypropylene, 11% of polyethene–polyethene terephthalate composite, and 8% of a polyethene–polypropylene composite, further resulting in the calculation that of all flexible packaging, 20 wt% are multilayer films. These findings were used to calculate the latent potential for raising the current recycling quota of 25.7% to the mandated rate of 55% in 2030. To this end, scenarios depicting different approaches to sorting and recycling small films were evaluated. It was calculated that through improving the sorting of films the recycling rate could be increased to 35.5%. This approach allows for the recycling of monolayer films by avoiding contamination with foreign materials introduced by multilayer films that impede the recyclates' mechanical properties. The evaluation showed that sorting multilayer films of this fraction could raise the recycling quota further to 38.9%.

Keywords: multilayer; monolayer; recycling rate

Citation: Koinig, G.; Rutrecht, B.; Friedrich, K.; Barretta, C.; Vollprecht, D. Latent Recycling Potential of Multilayer Films in Austrian Waste Management. *Polymers* **2022**, *14*, 1553. https://doi.org/10.3390/polym14081553

Academic Editor: Cristiano Varrone

Received: 3 March 2022
Accepted: 7 April 2022
Published: 11 April 2022

1. Introduction

The consumption of plastic packaging has been increasing continuously for years. According to Plastics Europe and Consultic Marketing and consulting carried out in 2016, 49 million tons of oil and gas were used in 2015 to produce plastic, of which around 40% were used for the production of packaging [1–3]. The demand for packing that protects products, increases their shelf life, and at the same time stimulates the consumer to buy those products through appealing haptics and optics, contrasts with the need for minimal material use and advantageous product protection while maintaining an ideal proportion of packaging to product mass [4]. Plastic films accomplish this balancing act, reducing the necessary film thickness for achieving essential characteristics such as oxygen barrier function by a factor of one to two orders of magnitude [5]. The annual consumption in Austria of around 69,000 tons of small films, with a surface area of under 1.5 m^2, per year shows that both consumers and markets have recognised the advantages of thin-film plastic packaging [6].

The consumer usually is unaware that many of these inconspicuous plastic films are high-tech products made up of a composition of different materials, so-called multilayer films [3]. This material composition and the low layer thickness make the foils more desirable than single-layer foils or other packaging materials, and this composition poses a challenge in recycling this fraction [7]. Multilayer films and single-layer films are currently not separated and are recycled together [3]. The problem here is that multilayer films with a composition that deviates from the target material can cause complications in film recycling since this requires single-layer films. Introducing multilayer films to a monolayer fraction diminishes the mechanical properties of the recyclates because of impurities introduced by the multilayer material, increasing degradation of the recyclates [8]. This deterioration reduces the possibilities of recycling for these fractions and only leaves two primary avenues for further use. One is downcycling products for mechanically untaxing applications, and the other is the use as refuse derived fuel for co-incineration. Either approach prohibits recycling into high-value products [9]. Therefore, each input stream of polymers for recycling must be monitored to ensure compatible quality marks, such as melt flow rate, degree of crystallinity, degree of degradation and level, and type of low molecular weight compounds. In particular, polymer mixes in the remelting process lead to problems and quality losses in the end products due to the different melting temperatures of the polymers. Additives used can noticeably change the separation properties of the plastics, e.g., the density, and thus impair the sorting process and the recycling process [10]. Understanding the waste stream's composition is a prerequisite for creating monitoring systems for this purpose.

The current approach of energy recovery from plastic films wastes valuable resources, and is increasingly problematic as EU guidelines dictate an increase in the recycling rate and demand that 50% of all lightweight packaging be recycled in a cost-efficient and sustainable manner [11]. Achieving the goals set by these new guidelines demand incorporating new technologies to separate monolayer and multilayer films, which could reduce CO_2 output and increase the recycling rate.

The basis for these technologies is the knowledge about the composition of two-dimensional post-consumer waste (PCW). Previous studies have decomposed the PCW according to material classes [6], evaluated the composition of waste plastics in the feed of Austrian waste-to-energy facilities [12], or provided an in-depth analysis of plastic flows and stocks in Austria [6].

These analyses of plastic flows and stock showed that the small film fraction sums up to 69,000 tons, equivalent to a share of 40 wt% 2D material in separately collected waste (SCW) and 23 wt% of the total waste packaging plastics input in Austria. Within an extended packaging market, considering the whole of Europe, flexible packaging accounts for 26.1% of all plastic packaging [9]. Given the structure of the plastic packaging films, around 17% of all produced packaging in 2010 films worldwide were multilayer material [7].

Van Eygen et al. showed in 2018 that 24 wt% of this small film fraction, consisting of mono- and multilayer materials, are subject to a mechanical recycling process, while 76 wt% of mono- and multilayer films are incinerated or co-incinerated [6].

This article aims to enhance the existing findings by evaluating the composition of two-dimensional PCW regarding the amount of multilayer and monolayer materials in the current material stream by quantitatively and qualitatively analysing samples taken from Austrian waste streams. This evaluation will determine the occurrence of multilayer films in the post-consumer waste stream, its material composition and its utilisation options. Future applications for improved recycling technologies for 2D PCW are derived based on the performed hand sorting trials. This comparison of future scenarios for small films recycling is achieved by comparing different scenarios concerning technological developments in recycling small films and their implementations in the Austrian waste management sector regarding their potential to increase the current recycling efficiency.

2. Materials and Methods

2.1. Sample Description

The samples were taken from the waste collection system "yellow bag", the collection system for lightweight plastic packaging in rural areas of Austria, during the first quarter of 2021. The waste is collected in yellow bags with a volume of 110 litres. Collection of the materials is conducted in Lower Austria. The yellow bag collection system consists of plastic packaging and metal packaging in this area. The samples were taken from the input material of a sorting plant. The samples consisted of unopened waste collection bags. The samples were taken directly after delivery to the waste sorting plant. Twelve yellow bags from separate plant deliverers were taken, and their content was the object of for the investigation in this study. All samples present a surface area of under 1.5 m² and therefore fall under the category "Films Small" as established by Van Eygen in 2018. Figure 1 gives an impression of the flexible waste plastic packaging sample. The estimated sample volume amounted to 1300 litres while the mass amounted to 39.3 kg.

Figure 1. Exemplary manually pre-sorted bulky three-dimensional plastic packaging waste. **Left**: Two-dimensional flexible plastic waste. **Right**: Three-dimensional solid plastic waste.

2.2. Hand Sorting Analysis of a 2D Fraction from a Packaging Sorting Plant

The sample was examined and sorted into flexible packaging, flat and two-dimensional packaging, and bulky three-dimensional rigid packaging. The flexible waste packing samples accounted for 10.4 kg of the overall sample mass of 39.3 kg. The three-dimensional particles were discarded, and each flexible packaging was categorised further according to its usage. The investigated sample was manually sorted into these categories, and each category was weighed using a digital scale (KERN 440-49-N, precision 0.1 g). Subsequently, the flexible waste packaging was hand sorted into its respective material classes as determined by the recycling code and categorised according to their use. Figure 1 shows an example of the separated sample. On the left, the two-dimensional plastic films are depicted with the three-dimensional portion of the sample depicted on the right.

Table 1 shows part of the sample and the different categories into which the PCW has been categorised. These categories were chosen to accurately reproduce and depict the uses in which 2D materials are currently employed. Primary packaging describes material directly in contact with the product or food item respectively while secondary food packaging does not directly contact the product or food item.

Table 1. Definition of sorting categories of application of two-dimensional plastic waste.

Category 1	Category 2	Example/Packaging of:
Primary food packaging	Bakery products	Bread, rolls, pastry
	Coffee	Coffee bags
	Dairy	Sliced cheese, yoghurt lids
	Dry food	Rice, noodles, cereal
	Fresh produce	Fruit and vegetables
	Frozen food/convenience	Frozen vegetables,
	Household packaging	Zip-bags, cling film
	Meat	Sausages, steak, cold cuts
	Snack metallised	Chocolate Bars,
	Snack uncoated	Granola Bars
Secondary food packaging	Beverage	Wrapping of six-packs

Primary product packaging	Construction/workshop Dry pet food Garden Household products Sanitary products Toys Wet pet food	Cement, Tools, oil Soil, mulch, bark chips, Clothes, toner Toilet paper, kitchen roll interlocking (plastic) brick
Secondary product packaging	Gift wrapping	Wrapping paper, ribbons,
Bags	Generic bags	Transparent single-use bags
Foils	Generic foils	Pieces of foil

2.3. FTIR-ATR Measurements of the Specimens

In order to classify the specimens into their respective material classes and to evaluate the proportion of multilayer material, a subset (n = 143) out of the complete set of samples (N = 842) was chosen for Fourier-Transform Infrared Spectroscopy (FTIR) in Attenuated Total Reflectance (ATR) mode.

The necessary sample size has been determined following Equation (1) while the tolerated error resulting from the sample size has been calculated using Equation (2). According to the calculation of the minimum sample size for a sample from a finite population (N = 843) under the premise of normal distribution (D(z) = 0,95; z = 1,96; P = 0.24) and a sample size of n = 143 randomly picked objects the tolerated error of the result equals ε = ± 6.4%, instead of ± 5% for the given confidence interval.

$$n \geq \frac{N}{1 + \frac{(N-1) * \varepsilon^2}{z^2 * P * Q}} \quad (1)$$

$$\varepsilon = \sqrt{\frac{P * Q * z^2 * (n - N)}{n(N-1)}} = 0.064 \quad (2)$$

In addition, the range R of values is taken as a measure of dispersion to check for comparability of the sample subset with the finite population. It is noted that some material happens to be underrepresented by weight, e.g., bags of construction and workshop material (R = 10%), generic bags (R = 7%), and wet pet food (R = 5%), and some tend to be overrepresented, e.g., packaging of bakery products (R = 9%), fresh produce (R = 4%), and dry food (R = 4%), in the sample.

The characterization was carried out using a Spectrum Two FTIR spectrometer (Perkin Elmer) equipped with a Zn/Se crystal with diamond tip in the range from 650 cm^{-1} to 4000 cm^{-1}, averaging four scans per measurement point and a spectral resolution of 4 cm^{-1}.

FTIR-ATR is a non-destructive method in quality assurance and inspection [13]. The subset of random objects of the total two-dimensional yellow bag sample is subjected to this further examination to identify multilayered films. The specific type of polymer can be identified by comparing the obtained infrared spectrum to literature data. Before the measurement, every sample is cleaned and cropped, and then three test points are analysed for each side of the fragment.

The materials were cleaned using a soft paper wipe and water, no solvents were used in order to not alter the samples (e.g., print removal, degradation at the surface). The samples were let dry from any water residue before performing the measurements. We ascertained that the samples were clean by visual inspection. Additionally, when performing FTIR ATR spectroscopy measurements it was possible to observe whether the materials showed additional peaks due to remaining surface contaminations or not. Preliminary trials were performed to verify that the cleaning process performed as described and to prohibit altering the samples in a way that would significantly influence the material identification.

The identified type of polymer of every specimen is noted. According to the results of these trials, the specimen with differing results for front and back are designated multilayer films. However, the FTIR-ATR characterization method allows to identify the polymeric material that is on the surface of the sample, penetrating only a few microns of the specimen's thickness. In case of uncertainty in the assignment of a sample to the mono-material or multi-material category, additional FTIR measurements were carried out in transmittance mode to investigate the material composition through the entire thickness of the specimen, so as to ensure reliable results. The measurements in transmittance mode performed removing the ATR unit and replacing it with the proper accessory.

The spectra displayed in Figure 2 are an example of the measurements performed on the collected samples. The inner (IN) and outer (OUT) side show characteristic peaks of a polyethylene (PE) and a polyamide (PA) material, respectively. This sample was assigned to the multilayer category. The characteristic bands and their assignment can be seen in Tables 2 and 3 below.

Table 2. FTIR ATR characteristic bands of PE and their assignment [13–15].

Wavenumber [cm^{-1}]	Comment
2914, 2850	Stretching vibrations of CH_2
1471	Bending vibrations of CH_2
717	Rocking vibrations of CH_2

Table 3. FTIR ATR characteristic bands of polyamide and their assignment [13–15].

Wavenumber [cm^{-1}]	Comment
3295, 3070	Stretching vibration of NH
3000–2840	Stretching vibrations of CH_2
1633	Vibration of C=O
1534	Bending vibration of NH, stretching vibration of CN
1462	Bending vibration of CH_2
1368	Deformation vibration of CH_2
1260	Bending vibration of NH, stretching vibration of CN
730	Rocking vibrations of CH_2

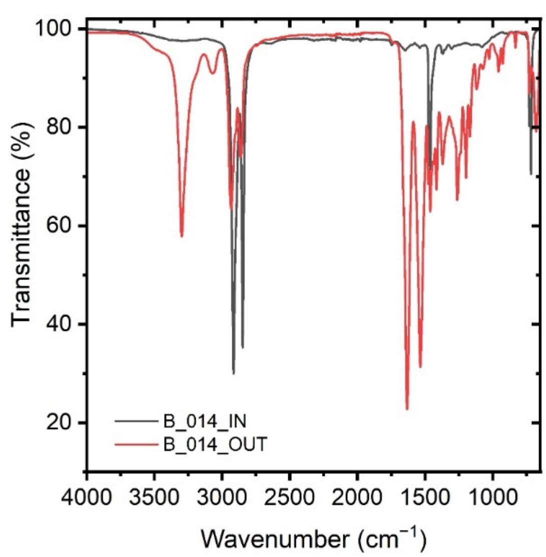

Figure 2. FTIR ATR spectra of a PE, PA multilayer specimen from the inner PE side (grey) and the outer PA side (red).

The following depiction in Figure 3 is an example of the measurements performed on a collected PP sample. The inner (IN) and outer (OUT) side show characteristic peaks of a PP. This sample was assigned to the monolayer category. The characteristic bands and their assignment can be seen in Table 4 below:

Table 4. FTIR ATR characteristic bands of polypropylene and their assignment [13–15].

Wavenumber [cm^{-1}]	Comment
2959, 2916, 2868, 2837	Stretching vibrations (symmetrical and asymmetrical) of CH_2 and CH_3
1452, 1376	Bending vibrations of CH_2 and CH_3
1167	Rocking vibrations of CH_3, bending vibrations of CH, stretching vibrations of C-C
998,	Rocking vibrations of CH_3, bending vibrations of CH_3, bending vibrations of CH
972	Stretching vibration of C-C, rocking vibrations of CH_3
841, 732	Rocking vibration of CH_2, stretching vibrations of C– CH_3
809	Rocking vibration of CH_2, stretching vibrations of C-C, stretching vibrations of C-CH

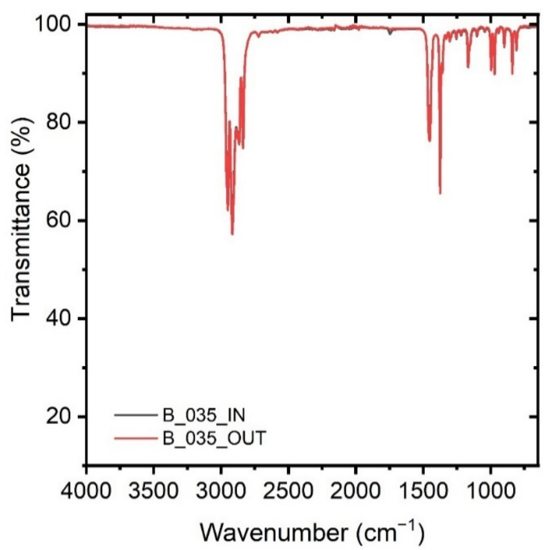

Figure 3. FTIR ATR spectra of a PP sample from the inner side (grey curve) and from the outer side (red curve).

2.4. Assessment of Recycling Potential of Mono- and Multilayer Packaging Films

This section explains how the recycling potential of multilayer films and the recycling thereof impact on the Austrian plastic packaging recycling efficiency has been estimated. The figures for the estimation are based on the material flow analysis (MFA) of the Austrian waste plastic packaging management published by Van Eygen (2018) and complemented by the hand sorting analysis findings. By supplementing the results of the hand sorting analysis with existing findings and by utilising the comparability of the two-dimensional foil fraction hand sorting analysis and the analysis carried out by Van Eygen general statements can be made for Austria [3,6,7,9,12].

The latent recycling potential of two-dimensional plastic packaging can be computed by combining the material flow of the flexible plastic packaging recycling routes with the findings of the multilayer film in the yellow bag fraction. As part of the small films, the fraction "multilayer films" takes the same recycling routes.

Three scenarios are evaluated to assess the latent recycling potential of mono- and multilayer packaging films. Each scenario assumes a different multilayer and monolayer recycling level and assesses its influence on the Austrian plastic packaging recycling efficiency. In Table 5, the three scenarios are explained in detail.

Table 5. Different scenarios for the assessment of the contribution of multilayer films to the Austrian plastic packaging recycling-quota.

	Scenario 1		Scenario 2		Scenario 3	
	Monolayer	Multilayer	Monolayer	Multilayer	Monolayer	Multilayer
Recycling	24 wt%		100 wt%		100 wt%	100 wt%
Incineration	76 wt%			100 wt%		

Scenario 1 reflects the current situation in Austria. Small films follow their respective recycling routes unchanged. Currently, 24 wt% (12,280 tons) of small films derived from SCW are mechanically recycled, and the remaining 76 wt% are co-incinerated. This scenario is used as the benchmark.

The current situation is a product of the presently available technology, its limitations and further of existing political and socioeconomical factors. Subsequently, substantial innovation is needed to improve the current recycling rate of two-dimensional plastic packaging. Recent reviews discussing the current technological environment have been published by Schlögl and Friedrich et al. in 2021 and 2022, respectively [16,17].

Scenario 2 assumes this substantial innovation. In this scenario, recycling techniques to detect, eject and recycle multilayer films and monolayer films are available and used on an industrial scale. This improvement facilitates the ejection of multilayer materials and leads to a pure monolayer film fraction without pollution by foreign materials introduced by missorted multilayer materials, ready for mechanical recycling and subsequent regranulation. This scenario assumes further that no material utilisation of multilayer materials is incorporated in the Austrian waste management on an industrial scale. In this scenario, multilayer materials continue to be used for energy recovery.

Scenario 3 reflects that no flexible packaging derived from SCW is used in energy recovery. New technologies to detect, eject, and recycle multilayer films are available and used on an industrial scale. Ideally, the co-incineration of monolayer- and multilayer films is entirely replaced by mechanical or chemical recycling. This scenario represents an ideal way to maximise the usage of latent potential for increasing the recycling rate by minimising the amount of thermal reuse of flexible plastic packaging.

3. Results and Discussion

3.1. Occurrence of Multilayer Material in the Waste Stream

The hand-sorting resulted in 30 wt% of the examined SCW as flexible 2D plastic packaging. Of this fraction, two-dimensional flexible packaging with two or more layers accounted for 20 wt%. This results in 6 wt% of the total sample being multilayer materials. Extrapolating this result leads to expect that flexible 2D plastic packaging accounts for approximately 52,000 t of the 171,000 t SCW per year. This outcome is congruent with the findings of van Eygen in 2018. Supposed, the amount of multilayer packaging is also representative of the waste composition in Austria, 10,260 t or about 6 wt% of the total SCW and approximately 20 wt% of all flexible 2D plastic packaging are multilayer films. This composition is represented in Figure 4, which shows the composition of all SCW split into the categories of flexible 2D plastic packaging and the number of multilayer films. The content of multilayer films subtracted from the total amount of flexible 2D plastic packaging would yield 41,740 t of flexible monolayer packaging useable for mechanical recycling. Figure 4 is a graphical illustration of the ideal recycling potential of multilayer films compared to the Austrian SCW and flexible waste plastic packaging.

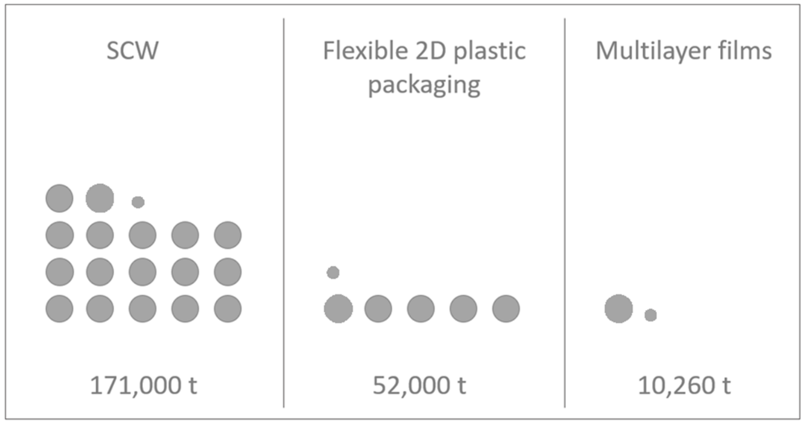

Figure 4. Graphical illustration of multilayer films compared to the Austrian separately collected waste (SCW) and flexible waste plastic packaging.

3.2. Material Composition of Monolayer and Multilayer Materials

Multilayer films tend to be numerous, lightweight, and typically accumulate in food packaging. Few but heavy specimens of multilayer films are found in product packaging. The FTIR-ATR analysis shows that multilayered material is commonly made of a combination of PE-PET, PE-PP, PE-PA, or PP-PET ranked by decreasing frequency. Other combinations, including PE-PP, PET-PP, and PET-PA, tend to be outliers. The most prevalent material found in the packaging of bakery products is PP. If the bakery packaging is multilayered, it commonly consists of PE-PA, PP-PE, or PP-PET. Meat packaging is either made of PE or a combination of PE and PET or PA. Figure 5 shows the percentage of distribution of materials in the small films fraction. The most prevalent fraction under the evaluated materials was PP with a share of 39 wt%, followed by PE monolayers with 31 wt%. Amongst the multilayer fraction, PE-PET is most abundant with 11 wt% and followed by PE-PP with 8 wt%. This composition of the small film fraction leads to the assumption that sorting processes which are able to separate monolayer from multilayer materials can both deliver a sufficient feedstock for chemical recycling to be used to recuperate functional polyolefins and PET from the waste stream and create a valuable feedstock for recycling purposes by creating clean PE and PP monolayer fractions. This approach can improve the circular economy of polymers by recuperating hitherto ignored resources for recycling by opening up a different recycling route than incineration.

	PE	PP	PET	PA
PE	31%	8%	11%	6%
PP	8%	39%	3%	1%
PET	11%	3%	0%	0%
PA	6%	1%	0%	0%

Figure 5. Composition of the small films according to the material class colour-coded to represent the highest proportion (**red**) to the lowest proportion (**green**).

3.3. Contribution of Monolayer and Multilayer Films in Waste Generation

The total share of multilayer films in the yellow bag is 6 wt%. Films account for about 29 wt% of all packaging evaluated. Main contributors to this are the categories primary food packaging (7.8 wt%), primary product packaging (7.9 wt%), and plastic bags (7.2 wt%), with primary packaging describing packaging directly in contact with the product.

The primary packaging groups in which multilayer films tend to accumulate are primary food packaging, where 49 wt% were multilayer films, followed by generic plastic bags, of which 34 wt% were multilayer films, and primary product packaging of which 19 wt% were multilayer films. Concerning primary food packaging, multilayer films accumulate primarily in the packaging of bakery products (16 wt%), meat (13 wt%), and dairy products (9 wt%), followed by frozen food and convenience (9 wt%), of which 16 wt%, 13 wt%, and 9 wt%, respectively, were multilayer films. These categories account for half the number of all multilayer films. Nevertheless, they only contribute about one third to the total weight of multilayer films.

Figure 6 shows the composition of the most common applications of 2D foils. It shows that the product groups where multilayer materials are most abundant are dairy, coffee packaging, snack packaging, and meat and frozen food packaging. Multilayer packaging accounts for more than 70 wt% of all packaging materials used in all of these categories. Simultaneously, no multilayer packaging is used in mail-order packaging, household product packaging, and gift wrapping.

Figure 7 shows the distribution of multilayer films as a Pareto diagram by weight. The most common classes in which multilayer films accumulate are plastic shopping bags which account for 29 wt%. Dry pet food Packaging accounts for 19 wt%, followed by sanitary related products with 9 wt% and then by packaging for meat and bakery products with 7 wt% and convenience food with 5 wt%. These categories account for over a fifth of all multilayer films used in packaging.

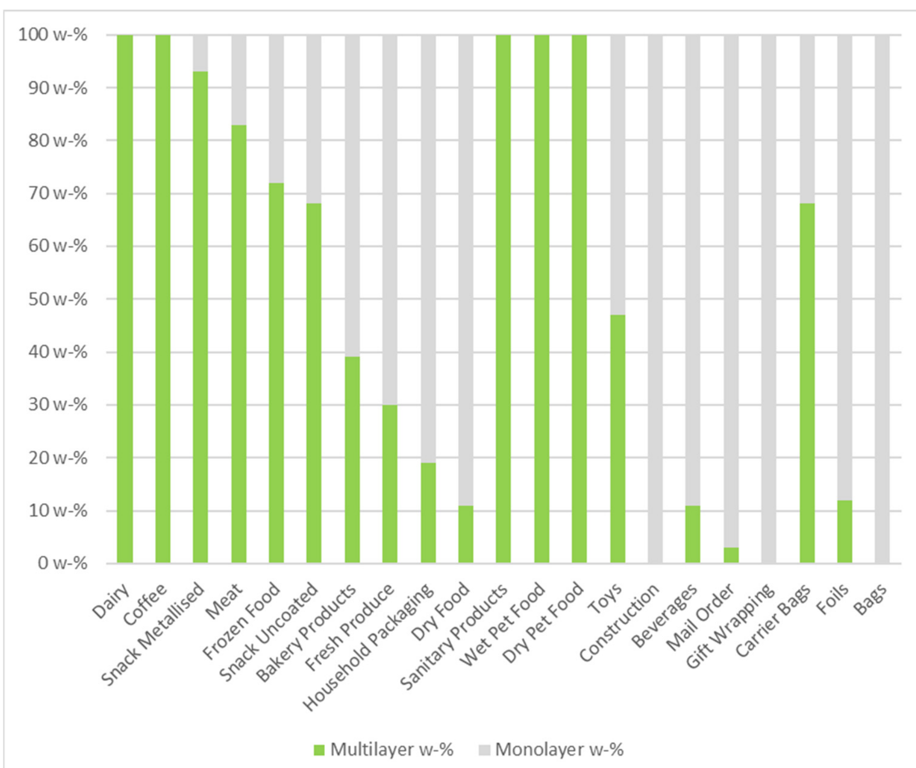

Figure 6. Percentage of monolayer- and multilayer materials in typical applications for small films.

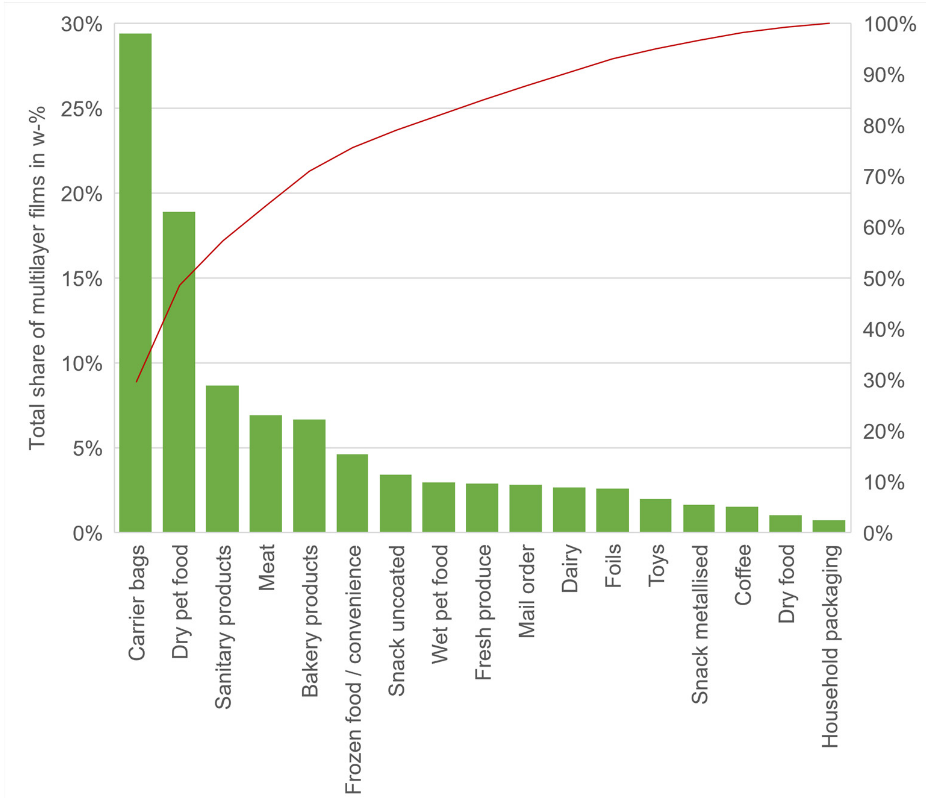

Figure 7. Pareto diagram depicting the share of each category to the total weight of the samples.

3.4. *Influence of Improved Multilayer Recycling on the Circular Economy*

Based on the hand sorting analysis, the examination of the specimens with FTIR-ATR and the MFA by Van Eygen in 2018, the ideal recycling potential of films in the Austrian SCW amounts to 52,000 t [6]. Multilayer films account for 10,270 t per year in the Austrian separately waste collection. Currently, the Austrian plastic packaging recycling efficiency is 25.7 wt%. These figures show that 77,000 t of the produced 300,000 t of waste plastic packaging are recycled. The examination of three different scenarios, current situation, new technologies, and zero incineration of flexible packaging derived from SCW, evaluate the theoretical contribution of recycling of multilayer films to the Austrian plastic packaging recycling efficiency. For better understanding, each scenario is depicted as a Sankey Diagram, illustrating the mass flow of Small Films via Municipal Solid Waste (MSW), SCW, to the respective recycling technologies.

Scenario 1: Current Situation

In scenario 1 the recycling routes of small films, including multilayer- and monolayer films, remain unchanged. The results of scenario one are displayed in Figure 8.

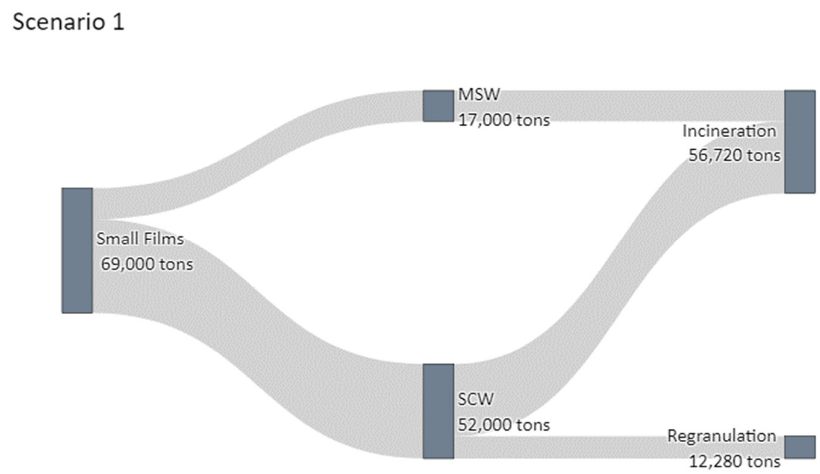

Figure 8. Sankey diagram depicting the waste flow in Scenario 1.

It can be seen that the bulk of the material continues to be industrially incinerated, and hardly any films are recycled. Until the development of new recycling techniques to an industrial scale, films remain subject to industrial incineration after being ejected from the mechanical recycling stream. Thus, the current recycling rate of small films to regranulates remains at 12,280 t per year, or 18 wt%, with the overall recycling rate remaining at 25.7% [6].

Scenario 2: New Technologies

In scenario two, the detection and ejection of multilayer films are established and complemented by a designated recycling process. Therefore, an ideal system with a successful detection and ejection rate of multilayer films of 100% can create a clean feedstock for recycling purposes. These monolayer materials have had foreign materials removed and can be incorporated into mechanical recycling processes rather than incineration. The results of scenario 2 are depicted in Figure 9.

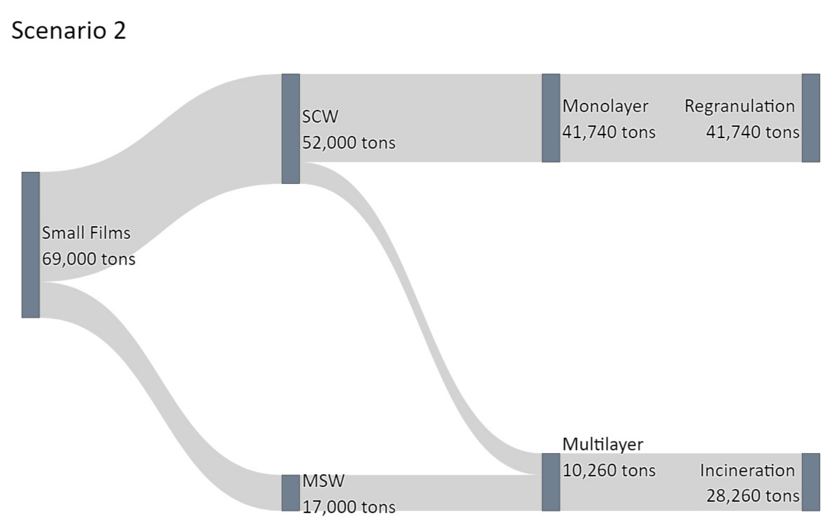

Figure 9. Sankey diagram depicting the waste flow in Scenario 2 with increased mechanical recycling of monolayer films.

It can be seen that of the 52,000 t of small films per year in the SCW 41,740 t are monolayer and 10,260 t of multilayers. These fractions need to be separated and recycled.

By cleaning the remaining plastic packaging stream from the multilayer materials, an additional 41,740 t of monolayer materials, mainly LDPE, can be added to the recycling feedstock, increasing the recycled small films fraction from 12,280 t by 29,460 t to 41,740 t annually.

This clean material stream increases the amount of totally recycled materials from 77,000 t to 106,460 t annually, increasing the Austrian recycling quota from 25.7% to 35.5%. This approach simultaneously improves the material properties of foil recyclates and enables a broader array of applications for these recyclates. Instead of manufacturing low-grade films and foils for waste bags and agriculture, they can be incorporated into higher quality products, eliminating the necessity for adding virgin material in the production. While this approach will enable the recycling of monolayer materials, multilayer films are still subjected to thermal recovery.

Scenario 3: Zero Incineration of Flexible Packaging Derived from SCW

Scenario 3 reflects a zero-waste approach. New technologies to detect, eject, and recycle multilayer films are available and applicable on an industrial scale. By those innovations, the previously latent recycling potential of small films can be realised by enhancing the sorting facilities of sorting systems, e.g., NIR sorting. Chemical recycling processes and solvent-based recycling processes, currently under development, have reached the market and are widely employed. This possible inclusion of mechanical and chemical recycling reduces co-incineration of monolayer- and multilayer films. The results of scenario 3 are depicted in Figure 10.

It can be seen that similar to "Scenario 2", 41,740 t of monolayer materials can be added to the recycling feedstock. Further, the incineration of 10,260 t of multilayer films is circumvented by intensifying the mechanical recycling of monolayer films, so these ejected multilayer films can be used as value-adding feedstock for chemical recycling processes.

This inclusion of multilayer films increases the amount of recycled small films fraction from 12,280 t to 52,000 t by 39,720 t annually. This change in recycling methods increases the amount of totally recycled materials from 77,000 t to 116,720 t annually, increasing the Austrian recycling quota from 25.7% to 38.9%. The enhanced separation of the small films fraction creates a value-adding pool of resources, improves the circular economy of plastics and at the same time creates a feedstock for future chemical recycling by providing a multilayer fraction, which would otherwise have been incinerated.

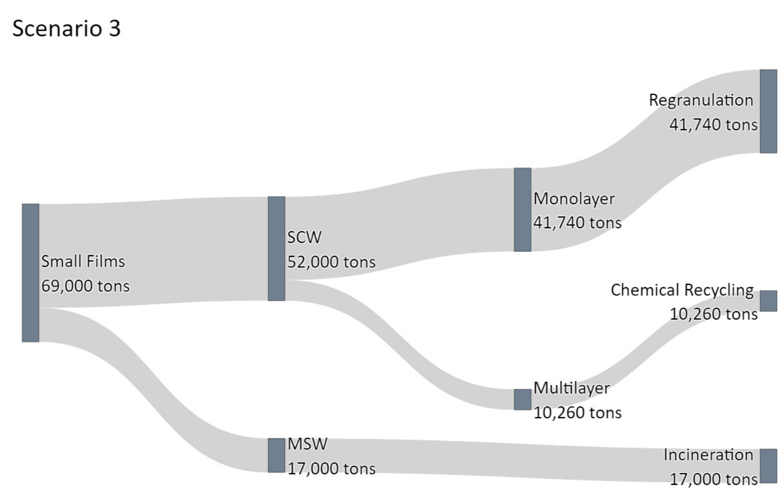

Figure 10. Sankey diagram depicting the waste flow in Scenario 3 with increased mechanical recycling of monolayer films and simultaneous increase in the chemical recycling of multilayer films.

4. Discussion

With 69,000 t annually, small films represent a sizeable portion of the total waste generation in Austria each year. Despite extensive use in packaging, these materials are not commonly mechanically recycled but primarily used in thermal energy recovery or as residue derived fuel in industrial co-incineration. This current state of affairs leads to diminished recycling rates and wasted potential for improving the circular economy of polymers and increases the number of virgin materials needed for production each year to satisfy the growing interest in packaging. As a packaging material, multilayer films are most abundant in the packaging of meat and dairy and the packaging of sanitary products and large carrier bags. Currently, the waste stream incorporates approximately 30 wt% flexible 2D plastic packaging of the 171,000 t separately collected waste (SCW) per year in Austria. The hand-sorting showed that 6 wt% of the examined materials were multilayer films. Extrapolating these results leads to expect that about 10,260 t of the total SCW are multilayer films, of which the most common types of polymers used in multilayer materials are PE and PET, which further account for 10% of all 2D plastic packaging evaluated.

Based upon these results, which were correlated with the findings in existing studies, three scenarios showing the latent potential in small film recycling were evaluated. These scenarios show the potential for increasing the recycling quota in Austria, and subsequently, the reaching of the recycling goals set by the EU was evaluated. It has been shown that the introduction of improved methods for separating multilayer- and monolayer materials leading to a clean material stream of monolayer materials uninhibited by foreign materials introduced by multilayer packaging can be used in mechanical recycling. This approach relieves the thermal recovery plants by producing a feedstock of clean monolayer materials of 41,740 t per year for mechanical recycling, yielding an increase in recycling quota to 35.5% from the current rate of 25.7%, as shown in Table 6. With the introduction of chemical recycling and solvent-based recycling to separate multilayer material compounds, polymers' recovery is likely to increase further. This fraction encompasses a reliable feedstock with an annual consumption of multilayer materials accounting for 6 wt% of the SCW collected each year. The introduction of chemical recycling processes in the Austrian waste management system to decompose multilayer materials can further increase the annual recycling quota to 38.9%, reducing the number of incinerated polymers.

Table 6. Results of the critical factors of all evaluated scenarios in tabular form.

Scenario	Scenario 1: Current Situation	Scenario 2: Mechanical Recycling of Monolayer Films Derived from SCW	Scenario 3: Zero Incineration of Flexible Packaging Derived from SCW
Total Amount of Waste	300,000 t	300,000 t	300,000 t
Sum of Small Films	69,000 t	69,000 t	69,000 t
Chemical/Solvent-Based Recycling	0 t	0 t	10,260 t
Energy Recovery	56,720 t	28,260 t	17,000 t
Mechanical Recycling	12,280 t	41,740 t	41,740 t
Sum of Recycled Small Films	12,280 t	41,740 t	52,000 t
Total Recycling	77,000 t	106,460 t	116,720 t
Recycling Quota	25.7%	35.5%	38.9%

Figure 11 shows a radar diagram comparing the three evaluated scenarios based on the characteristic metrics. These metrics are the recycling quota, the quota of recycled small films and the percentages for each recycling method. It can be seen that the ratio of thermal recycled small films progressively decreases from Scenario 1 to Scenario 3. Scenario 3 shows the least incinerated small films, which yields the highest recycling quota.

While the depicted scenario is confined to information gathered from Austrian waste processing plants, similar waste composition research has been performed in other European countries. An especially relevant and recent survey by Schmidt et al. who surveyed the recycling of two-dimensional waste reported similar composition of 2D waste in Germany [18]. This implies that the results may be applicable to the German waste management sector, but further research is needed, especially to predict the implications on the waste management in countries who deviate substantially in respect to culture and industrialisation from the current situation in Austria as these differences makes it difficult to predict the effect these changes might have on other countries around the world.

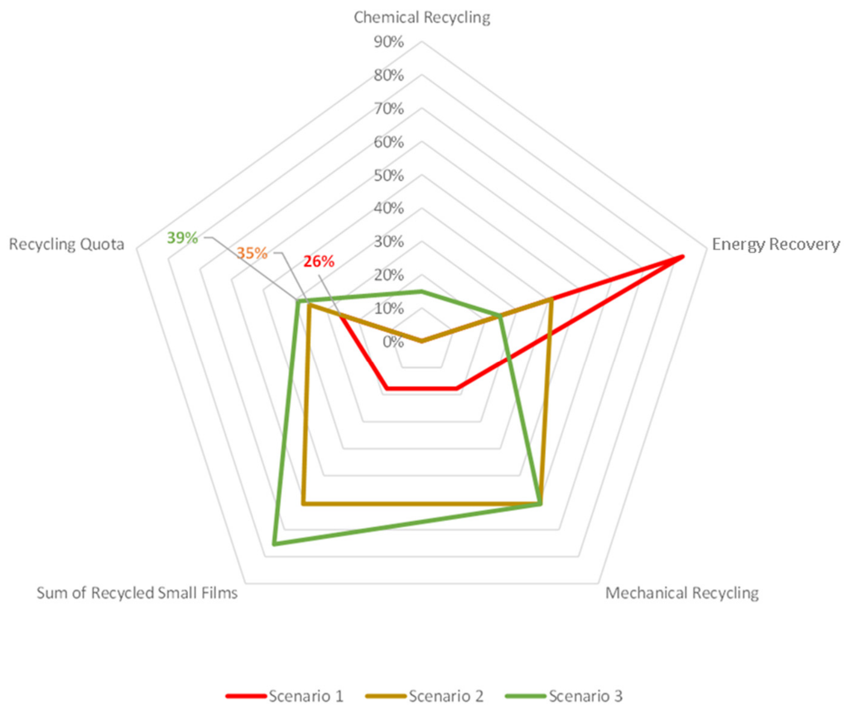

Figure 11. Radar diagram comparing the three evaluated scenarios based on the characteristic metrics: Energy recovery, Mechanical recycling, sum of recycled films, recycling quota and chemical recycling.

Author Contributions: Conceptualization, G.K., B.R., and D.V.; Data curation, G.K., B.R., and C.B.; Formal analysis, G.K., B.R., K.F., C.B., and D.V.; Funding acquisition, C.B.; Methodology, G.K., B.R., and C.B.; Project administration, G.K. and C.B.; Software, G.K.; Supervision, G.K. and D.V.; Validation, G.K., B.R., K.F., and C.B.; Visualization, G.K. and B.R.; Writing—original draft, G.K. and B.R.; Writing—review and editing, G.K., B.R., K.F., C.B., and D.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the province of Styria and Zukunftsfonds Steiermark for the project "Multilayer Detection" (project number 1314).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: In this section, you can acknowledge any support given which is not covered by the author contribution or funding sections. This may include administrative and technical support, or donations in kind (e.g., materials used for experiments).

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

References

1. PlasticsEurope. *Plastics—The Facts 2016*; PlasticsEurope—Association of Plastics Manufacturers: Brussels, Belgium, 2016; Available online: https://plasticseurope.org/wp-content/uploads/2021/10/2016-Plastic-the-facts.pdf (accessed on 15 February 2022).
2. Consultic. *Produktion, Verarbeitung und Verwertung von Kunststoffen in Deutschland 2015 (Production, Processing and Recycling of Plastics in Germany)*; Consultic Marketing & Industrieberatung GmbH: Rückersdorf, Germany, 2016; Available online: https://plasticker.de/docs/news/Consultic-Studie%202015%20Kurzfassung.pdf (accessed on 15 February 2022).
3. Kaiser, K.; Schmid, M.; Schlummer, M. Recycling of Polymer-Based Multilayer Packaging: A Review. *Recycling* **2018**, *3*, 1. https://doi.org/10.3390/recycling3010001.
4. Bilewicz, M. Analysis of structure and properties of multilayer polymer foil. In *IOP Conference Series: Materials Science and Engineering, Proceeding of the 6th International Conference on Recent Trends in Structural Materials (COMAT 2020), Pilsen, Czech Republic 30 November–4 December 2020*; IOP Publishing: Bristol, UK, 2021. https://doi.org/10.1088/1757-899X/1178/1/012007.
5. Barlow, C.Y.; Morgan, D.C. Polymer film packaging for food: An environmental assessment. *Resour. Conserv. Recycl.* **2013**, *78*, 74–80. https://doi.org/10.1016/j.resconrec.2013.07.003.
6. Van Eygen, E.; Laner, D.; Fellner, J. Circular economy of plastic packaging: Current practice and perspectives in Austria. *Waste Manag.* **2018**, *72*, 55–64. https://doi.org/10.1016/j.wasman.2017.11.040.
7. Tartakowski, Z. Recycling of packaging multilayer films: New materials for technical products. *Resour. Conserv. Recycl.* **2010**, *55*, 167–170. https://doi.org/10.1016/j.resconrec.2010.09.004.
8. Pfaendner, R.; Herbst, H.; Hoffmann, K.; Sitek, F. Recycling and restabilization of polymers for high quality applications. An Overview. *Macromol. Mater. Eng.* **1995**, *232*, 193–227. https://doi.org/10.1002/apmc.1995.052320113
9. Pilz, H.; Brandt, B.; Fehringer, R. The Impact of Plastics on Life Cycle Energy Consumption and Greenhouse Gas Emissions in Europe. Summary Report, June 2010. denkstatt GmbH. Retrieved 02.02.2022. Available online: https://plasticseurope.org/knowledge-hub/the-impact-of-plastics-on-life-cycle-energy-consumption-and-greenhouse-gas-emissions-in-europe/ (accessed on 15 February 2022).
10. Villanueva, A.; Eder, P. *End-Of-Waste Criteria for Waste Plastic for Conversion: Technical Proposals*; Final Report; Publications Office of the European Union, Luxembourg, 2014; ISBN: 978-92-79-40944-8. https://doi.org/10.2791/13033.
11. Waste Framework Directive. Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2018 on waste and repealing certain Directives. Available online: https://eur-lex.europa.eu/legal-content/EN/TXT/?uri=celex:32008L0098 (accessed on 15 February 2022).
12. Schwarzböck, T.; Van Eygen, E.; Rechberger, H.; Fellner, J. Determining the amount of waste plastics in the feed of Austrian waste-to-energy facilities. *Waste Manag. Res.* **2017**, *35*, 207–216. https://doi.org/10.1177/0734242X16660372
13. Socrates. G. *Infrared and Raman Characteristic Group Frequencies: Tables and Charts*, 3rd ed.; John Wiley & Sons, Ltd.: Chichester, UK, 2001.
14. Mecozzi, M.; Pietroletti, M.; Monakhova, Y. FTIR Spectroscopy Supported by Statistical Techniques for the Structural Characterization of Plastic Debris in the Marine Environment: Application to Monitoring Studies. *Mar. Pollut. Bull.* **2016**, *106*, 155–161. ISSN 0025-326X. https://doi.org/10.1016/j.marpolbul.2016.03.012.
15. Jung, M.R.; Horgen, F.D.; Orski, S.V.; Rodriguez, V.; Beers, K.L.; Balazs, G.H.; Jones, T.T.; Work, T.M.; Brignac, K.C.; Royer, S.-J.; et al. Lynch, Validation of ATR FT-IR to identify polymers of plastic marine debris, including those ingested by marine organisms. *Mar. Pollut. Bull.* **2018**, *127*, 704–716. ISSN 0025-326X. https://doi.org/10.1016/j.marpolbul.2017.12.061.
16. Schlögl, S. State of the Art of Plastic Packaging Sorting Plants and Potentials of Sensor-Based Material Flow Monitoring. Master's Thesis, University of Leoben, Leoben, Austria, 2021. Available online: https://pure.unileoben.ac.at/portal/files/6479484/AC16189306.pdf (accessed on 8 April 2022).
17. Friedrich, K.; Koinig, G.; Fritz, T.; Pomberger, R.; Vollprecht, D. Sensor-Based and Robot Sorting Processes and Their Role in Achieving European Recycling Goals—A Review. Correspondence: karl.friedrich@unileoben.ac.at, Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, University of Leoben, Leoben, Styria, Austria. 2022, *manuscript in preparation.*
18. Schmidt, J.; Auer, M.; Moesslein, J.; Wendler, P.; Wiethoff, S.; Lang-Koetz, C.; Woidasky, J. Challenges and Solutions for Plastic Packaging in a Circular Economy. *Chem. Ing. Tech.* **2021**, *93*, 1751–1762. https://doi.org/10.1002/cite.202100110.

2.2 Publication 2

<u>Research Paper 2:</u>

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

Friedrich, Karl; **Koinig, Gerald**; Fritz, Theresa; Pomberger, Roland; Vollprecht, Daniel (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.

Annotation on the doctoral candidate's contribution to this publication:

The general concept of the publication was designed by the doctoral candidate and Karl Friedrich and discussed in contribution with the author Karl Friedrich. Afterwards, the relevant scientific literature on the subject was reviewed by the doctoral candidate and Karl Friedrich. The publication was then written by the author of the doctoral thesis and Karl Friedrich based on a research by Theresa Fritz. The internal review process was done with the consultation of the co-authors Karl Friedrich, Gerald Koinig and supervisors Daniel Vollprecht and Roland Pomberger.

Academic Journal of Polymer Science
ISSN: 2641-8282

Juniper Publishers
key to the Researchers

Review Article
Volume 5 Issue 4 - February 2022
DOI: 10.19080/AJOP.2022.05.555668

Academ J Polym Sci

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

Submission: January 18, 2022; **Published:** February 14, 2022

***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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

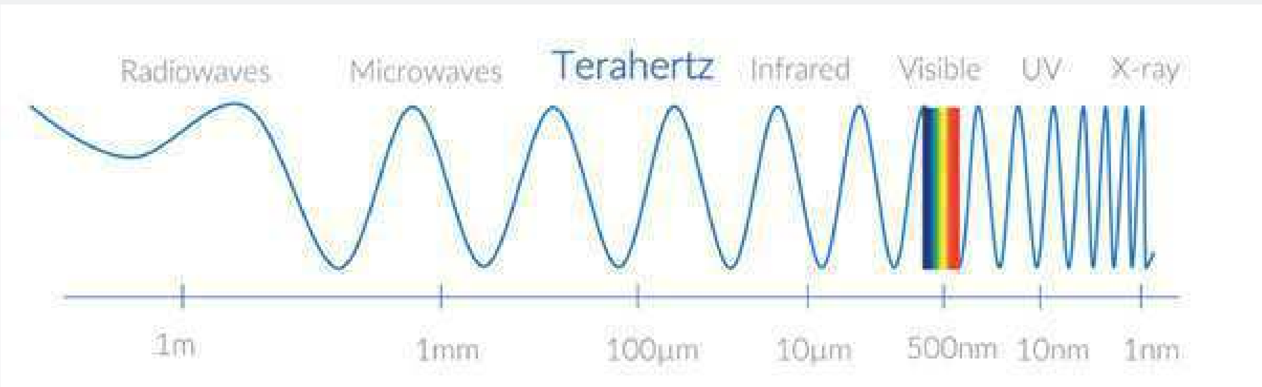

Figure 1: Embedding the terahertz range in the electromagnetic spectrum [11].

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

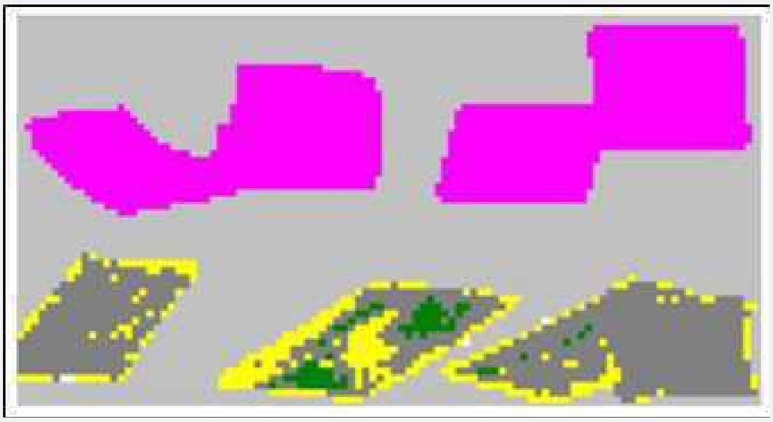

Figure 2: Polypropylene (PP) (pink) and High-Density-Polyethylene (HDPE) (grey), Non-Classified (yellow) and Polyethylene-Terephthalate (PET) (green) - Particles coloured according to their material [14].

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

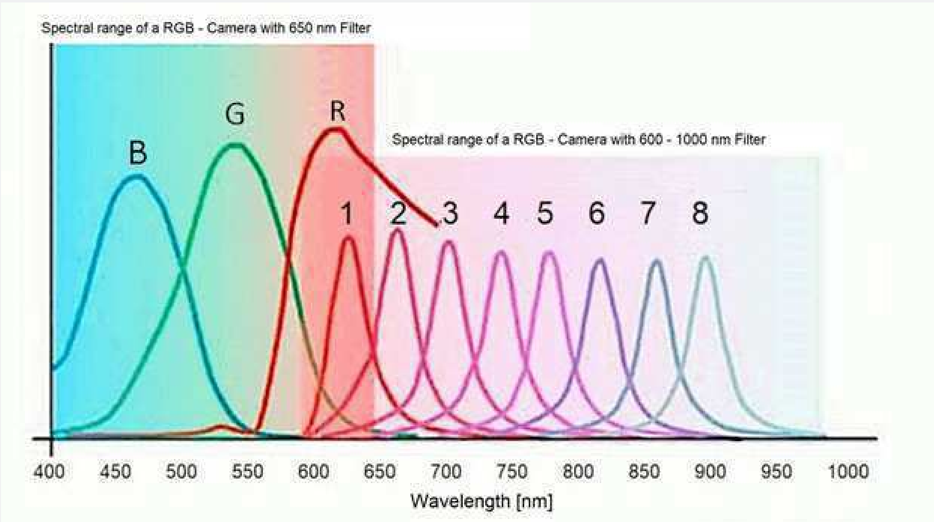

Figure 3: Transmittance curves of an RGB colour camera as well as a 9-band HSI camera for the range of 630 to 920nm [15].

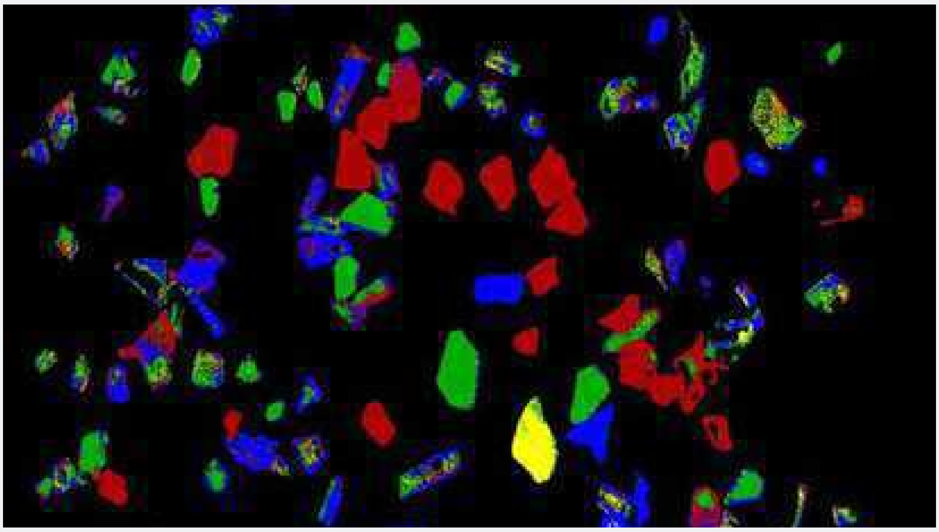

Figure 4: HSI detection on a conveyor belt in waste management and recycling [16].

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

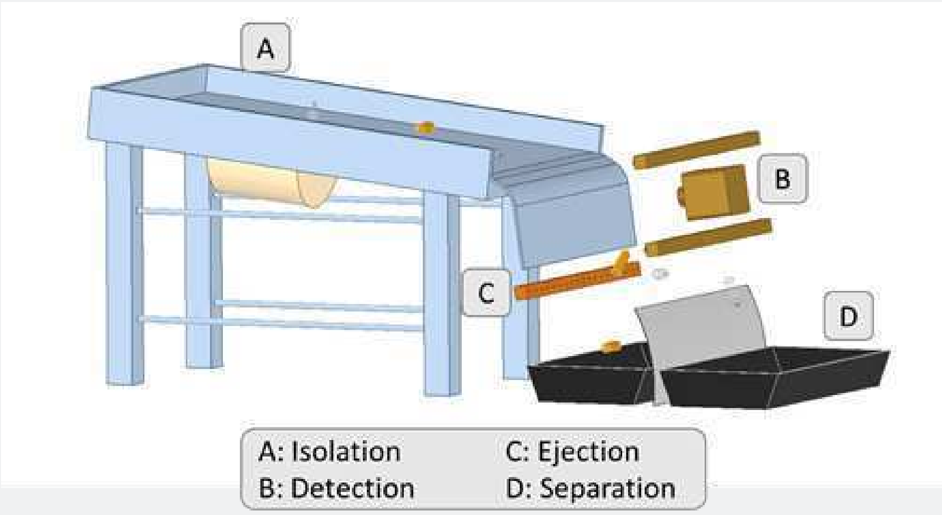

Figure 5: Principle sketch of chute sorters (authors' depiction).

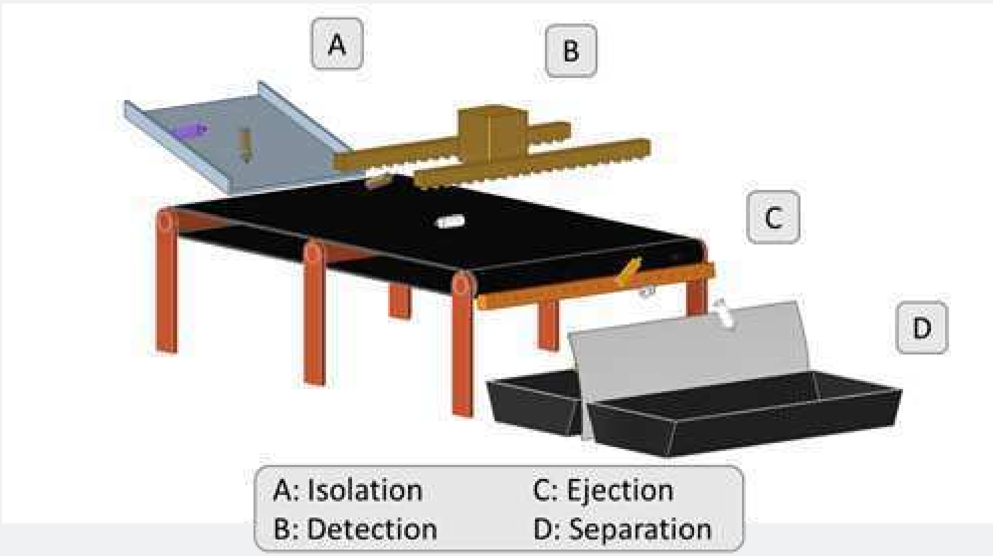

Figure 6: Principle sketch of belt sorters (authors' depiction).

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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 Nanorobots	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 communicate 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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

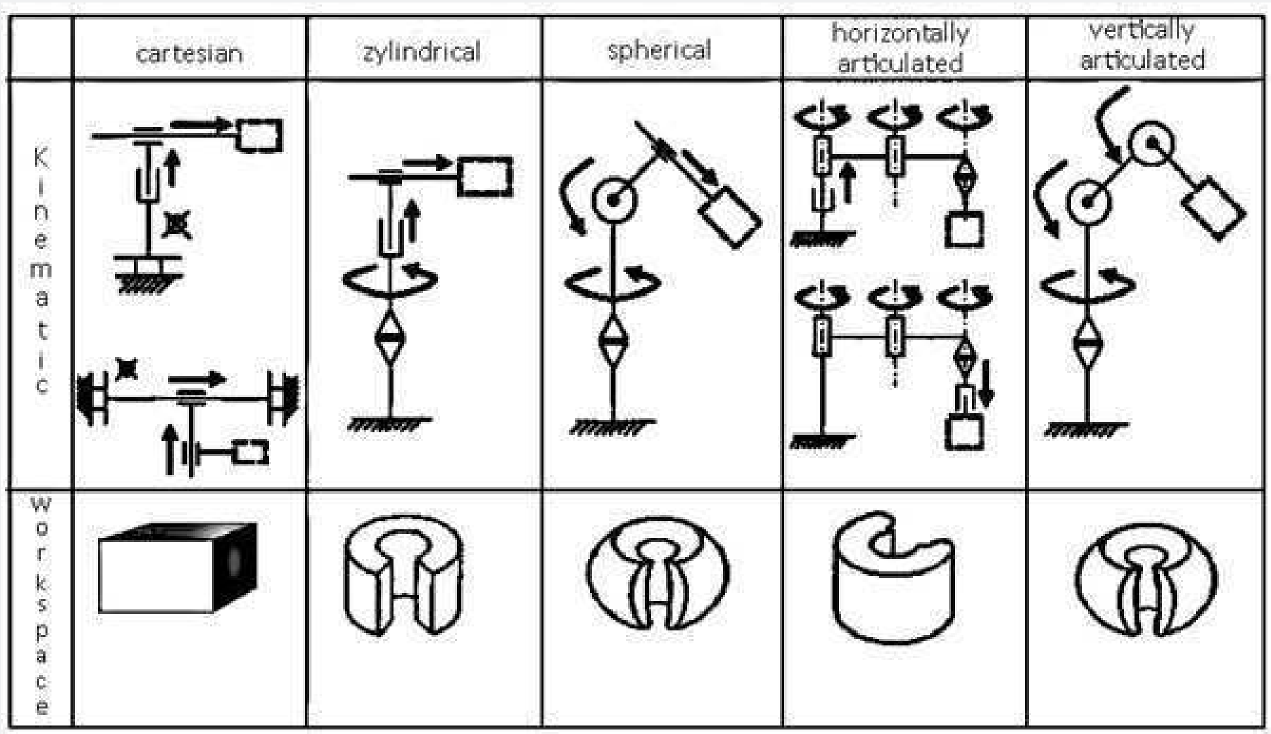

Figure 7: Positioning axes of robot systems in the industry including working range [23].

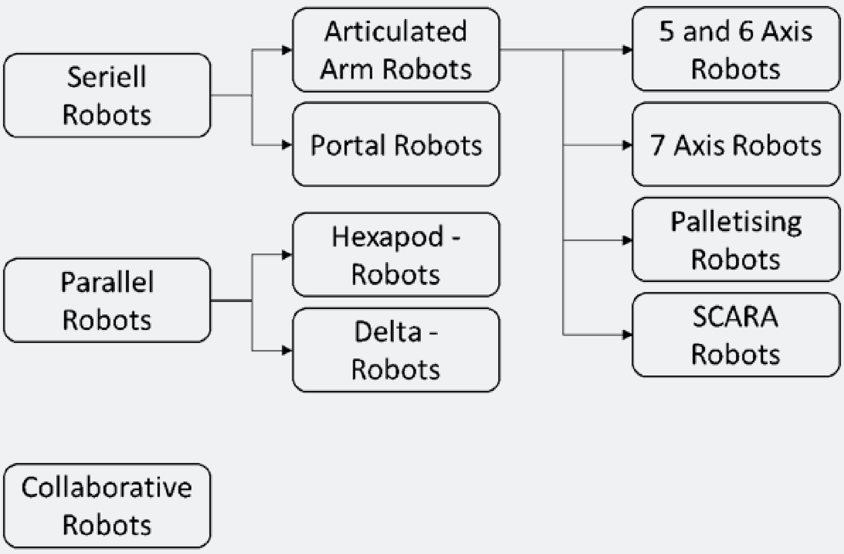

Figure 8: Classification of robots according to kinematics (authors depiction according to Induux 2021 [24]).

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

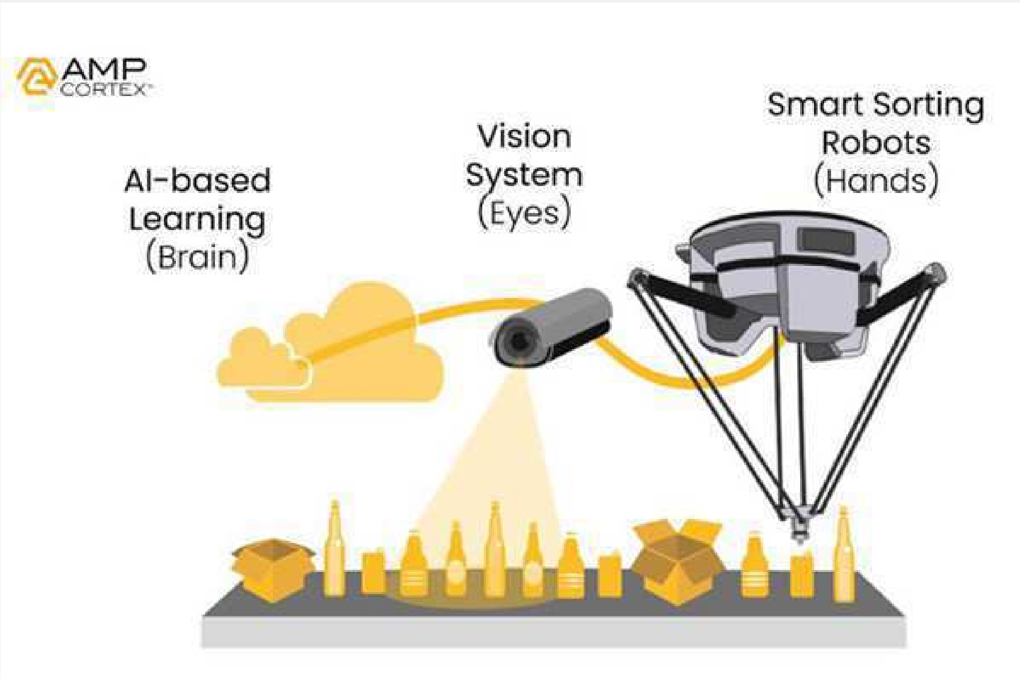

Figure 9: AMP Cortex [41].

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].

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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].

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

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.

References

1. European Commission (2019) Implementation of the Circular Economy Action Plan; Report: COM(2019) 190 final.
2. Friedrich K, Koinig G, Tschiggerl K, Pomberger R, Vollprecht D (2021a) Challenges to Increase Plastic Sorting Efficiency. International Journal on Engineering Technologies and Informatics 2(4): 114-118.
3. European Commission (2018) A European Strategy for Plastics in a Circular Economy; Report: COM(2018) 28 final.
4. European Parliament and Council (2019) Directive (EU) 2019/904 on the reduction of the impact of certain plastic products on the environment, L 155/1.
5. Global 2000 (2019) Single-Use Plastics Directive - die Einwegplastik-Richtlinie der EU (Single-Use Plastics Directive - the Single-Use Plastics Directive in the EU). (last access: 11 November 2021).
6. Beel H (2017) Sortierung von schwarzen Kunststoffen nach ihrer Polymerklasse mit Hyperspectral-Imaging-Technologie (Sorting of black plastics to their polymer types with hyper-spectral-imaging-technology), Berliner Recycling und Rohstoffkonferenz 2017 (Berlin Recycling and Resources Conference 2017), In: Recycling und Rohstoffe Band 10, Berlin, Germany, pp. 175-191.
7. Pomberger R, Küppers B (2017) Entwicklungen in der sensorgestützten Sortiertechnik (Developments in sensor-based sorting), Österreichische Abfallwirtschaftstagung 2017 - Die Digitalisierung der Abfallwirtschaft (Austrian Waste Management Congress 2017 – Digitalisation of Waste Management), In Proceedings of the Austrian Waste Management Congress 2017, ÖWAV: Vienna, Austria, Module 9.
8. Uepping R (2013) Sensorgestützte Sortiertechnik (Sensor-based Sorting Technology), Berliner Recycling und Rohstoffkonferenz 2013 (Berlin Recycling and Resources Conference 2013), In Recycling und Rohstoffe Band 6, Berlin, TK Verlag: Neuruppin, Germany, pp. 371-383.
9. Pretz T, Julius J (2008) Stand der Technik und Entwicklung bei der berührungslosen Sortierung von Abfällen (State-of-the-Art and development in contactless sorting of waste). Österr Wasser- und Abfallwirtschaft 60, ÖWAV: Vienna, Austria, pp 105-112.
10. Wotruba H (2008) Stand der Technik der sensorgestützten Sortierung (State-of-the-Art in sensor-based sorting). Berg- und Hüttenmännische Monatshefte, Volume 153, Heft 6, Springer-Verlag: Heidelberg, Germany, pp. 221-224.
11. Lydit (2021) Terahertz, the last frontier of photonics. (last access: 11 November 2021).
12. König, M (2019) Innovative Detektionstechnik und gezielte Kommunikationsstrategie zur Beeinflussung des Wegwerfverhaltens in der österreichischen Abfall- und Ressourcenwirtschaft (Innovative detection technology and targeted communication strategy to influence the throw-away behavior in the Austrian waste and resource management), Master's Thesis, FH Wien der WKW, Vienna, Austria.

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

13. Flamme S, Hams S, Zorn M (2018) Sensortechnologien in der Kreislaufwirtschaft (Sensor technologies in Circular Economy), Recy- & Depotech 2018, In Proceedings of the 14th Recy- & DepoTech Conference, 07 November - 09 November 2018, Leoben, AVAW Eigenverlag: Leoben, Austria, pp. 787-792.

14. Küppers B, Möllnitz S (2018) Versuchsstand für sensorgestützte Erkennung und Sortierung (Experimental sensor-based sorting setup). DGAW-Wissenschaftskongress„ Abfall- und Ressourcenwirtschaft" (8th DGAW Science Congress „Waste and resource economy"), In Proceedings of the 8th DGAW Science Congress „Waste and resource economy",Vienna, innsbruck university press: Innsbruck, Austria, pp. 211-215.

15. Aderhold J, Brüning R, Dittrich PG, Grählert W, Hubold M, et al. (2019) Grundlagen und Methoden des HSI (Basics and methods of HSI), Chapter 2 in Leitfaden zur hyperspektralen Bildverarbeitung (Hyperspectral Imaging Guide), Volume 19, Fraunhofer-Verlag: Stuttgart, Germany, 2019, pp. 15-34,

16. Luxflux (2018) Die nächste Stufe der industriellen Bildverarbeitung (The next step in industrial image processing). (last access: 11 November 2021).

17. Binder+Co (2021a) Sensorbasierte Sortiertechnologie mit höchster Präzision (Sensor-based sorting technology with highest precision). (last access: 11 November 2021).

18. Inc (2020) Robotics. (last access: 11 November 2021).

19. Sarc R, Curtis A, Kandlbauer L, Khodier K, Lorber KE, et al. (2019) Digitalisation and intelligent robotics in value chain of circular economy-oriented waste management - A review. Waste Management 95: pp. 476-492.

20. TÜV AUSTRIA Group, Fraunhofer Austria Research GmbH (2016) Sicherheit in der Mensch-Roboter Kollaboration: Grundlagen, Herausforderungen, Ausblick (Safety in human-robot collaboration: basics, challenges, outlook), White Paper. (last access: 11 November 2021).

21. Stark G (2009) Robotik mit MATLAB (Robotics with MATLAB). Carl-Hanser-Verlag: München, Germany, pp. 16-17.

22. Dokulil E (2001) Industrieroboter. PC News 72, April 2001, PC-NEWS-Eigenverlag: Vienna, Austria, pp. 58-64.

23. Gerke W (2015) Technische Assistenzsysteme: Vom Industrieroboter zum Roboterassistenten, De Gruyter Oldenbourg: Berlin, Germany, pp. 147-148.

24. Induux (2021) Industrieroboter - Typen Aufbau Anwendungen Auswahl (Industrial robots – Types, design, applications, selection). (last access: 11 November 2021).

25. IFR - International Federation of Robotics (2018) Welcome to the IFR Press Conference. World Robot Summit, Presentation of the IFR Press Conference, Tokyo, Japan. (last access: 18 January 2022).

26. Green Tech Cluster (2018) Digitale Abfallwirtschaft: Mehrwert entlang der gesamten Wertschöpfungskette (Digital Waste Management: Added value along the whole value chain), Green Tech Radar. (last access: 18 January 2022).

27. EVK (2021) Products. (last access: 18 January 2022).

28. SLOC (2021) SLOC Product Portfolio. (last access: 18 January 2022).

29. Binder+Co (2021b) Products - Sensor-based Sorting.

30. Pellenc (2021) Products. (last access: 18 January 2022).

31. REDWAVE (2021) REDWAVE solutions. (last access: 18 January 2022).

32. Sesotec (2021) Sorting systems. (last access: 18 January 2022).

33. Steinert (2021a) Steinert - Our locations. (last access: 18 January 2022).

34. Steinert (2021b) Steinert - Sensor Sorting. (last access: 18 January 2022).

35. TOMRA (2021) TOMRA – Recycling. (last access: 18 January 2022).

36. Apple (2018) Apple adds Earth Day donations to trade-in and recycling program, Press Release. (last access: 18 January 2022).

37. EU Recycling (2018) Abfallsortierung der Zukunft: durch Mensch oder Roboter? (Waste sorting in the future: By hand or by robot?), EU-Recycling, p. 10. (last access: 18 January 2022).

38. Heaven D (2019) Recycling-Roboter sortiert durch Tasten (Recycling robots sorts by touch), MIT Technology Review. (last access: 18 January 2022).

39. OP Teknik (2021) SELMA robot sorting. (last access: 18 January 2022).

40. ZenRobotics (2021) Robotic Waste Recycling Solutions. (last access: 18 January 2022).

41. AMP Robotics (2021a) AMP Cortex – Intelligent Robots for Recycling. (last access: 18 January 2022)

42. BHS (2021) MAX AI. (last access: 18 January 2022).

43. Bollegraaf (2021) Robotic Sorting. (last access: 18 January 2022).

44. Machinex (2018) SamurAI. (last access: 18 January 2022).

45. Erhart W (2017) Digitale Geschäftsmodelle und schnelle Innovationszyklen in der traditionellen Industrie; Am Beispiel: Konzeptionierung und Implementierung eines digitalen, mehrseitigen Geschäftsmodells in der Verwertungs- und Entsorgungsbranche (Digital business models and fast innovation cycles in traditional industries; Example: Conception and implementation of a digital, versatile business model in the recycling and disposal industry). Master's Thesis, Campus 02 - University of Applied Sciences for Economy, Graz, Austria.

46. Sarc R, Hermann R (2018) Unternehmensbefragung zum Thema Abfallwirtschaft 4.0 (Company survey on waste management 4.0), Recy- & Depotech 2018, In Proceedings of the 14th Recy- & DepoTech Conference, 07 November - 09 November 2018, Leoben, AVAW Eigenverlag: Leoben, Austria, pp. 805-812.

46. Friedrich K, Fritz T, Koinig G, Pomberger R, Vollprecht D (2021b) 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 13(16): 9472.

47. Berger R (2016) Die Digitalisierung in der GreenTech-Branche; Handlungsbedarf für Unternehmen der Umwelttechnik und Ressourceneffizienz in Deutschland (Digitalisation in the Green Tech Branche; Need for action for companies in environmental technology and resource efficiency in Germany), Bundesministerium für Umwelt, Naturschutz, Bau und Reaktorsicherheit.

48. Saubermacher (2019) Daheim App. (last access: 18 January 2022).

49. Klemmer O (2019) Digitalisation potential analysis for sustainable waste management, Master's Thesis, TU Vienna and Diplomatic Academy of Vienna, Vienna, Austria.

50. Continuous Improvement Fund (2021) Robot combines Hyperspectral vision with Artificial Intelligence for residential recycling. (last access: 18 January 2022).

51. Verbraucherzentrale Bundesverband (2015) Ergebnisse der bevölkerungsrepräsentativen Umfrage zum Thema "Wertstofftonne" (Results of the population representative survey on the subject of "valuable material bin"), forsa., Berlin, Germany. (last access: 18 January 2022).

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

52. Mittermayr R, Klünser S (2019) Smart Waste - Wie Digitalisierung und IoT die Welt des Abfalls verändern können (Smart Waste - How digitalisation and IoT can change the world of waste), Berliner Recycling- und Rohstoffkonferenz 2019 (Berlin Recycling and Resources Conference 2019), In Recycling und Rohstoffe Band, Berlin, TK-Verlag: Neuruppin, Germany, pp. 15-24.

53. Green Tech Cluster (2019) Erfolgreiche Smart-Waste Projekte (Successful smart-waste projects). (last access: 18 January 2022)

54. FG Entsorgungs- und Ressourcenmanagement, WKO Steiermark (2019) Rohstoff, Smart Waste: Erfolgreiche Mülltrennung mit Künstlicher Intelligenz (Raw material, Smart waste: Successful waste separation with artificial intelligence), p. 27. (last access: 18 January 2022).

55. ORF Steiermark (2018) Gemeinden starten Pilotprojekt "Smart Village" (Municipalities start pilot project "Smart Village").(last access: 18 January 2022).

56. Piron R (2019) Erste Smart Village - Projekte zeigen Erfolge (The first Smart Village projects are showing success), KOMMUNAL. (last access: 18 January 2022).

57. Saubermacher Dienstleistungs AG – Ecoport (2018) Der Wertstoffscanner von Saubermacher (The recyclable material scanner from Saubermacher), Video: Der Wertstoffscanner von Saubermacher. (last access: 18 January 2022).

How to cite this article: Friedrich K, Koinig G, Fritz T, Pomberger R, Vollprecht D. Sensor-based and Robot Sorting Processes and their Role in Achieving European Recycling Goals - A Review. Academ J Polym Sci. 2022; 5(4): 555668. DOI: 10.19080/AJOP.2022.05.555668

2.3 Publication 3

Research Paper 3:

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

Friedrich, Karl; **Koinig, Gerald**; Pomberger, Roland; Vollprecht, Daniel (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.

Annotation on the doctoral candidate’s contribution to this publication:

The general concept of the publication was designed by the doctoral candidate and Karl Friedrich and discussed in contribution with the author Karl Friedrich. Afterwards, the relevant scientific literature on the subject was reviewed by the doctoral candidate and Karl Friedrich. The publication was then written by the author of the doctoral thesis and Karl Friedrich. The internal review process was done with the consultation of the co-authors Karl Friedrich, Gerald Koinig and supervisors Daniel Vollprecht and Roland Pomberger.

MethodsX 9 (2022) 101686

Contents lists available at ScienceDirect

MethodsX

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

ABSTRACT

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.

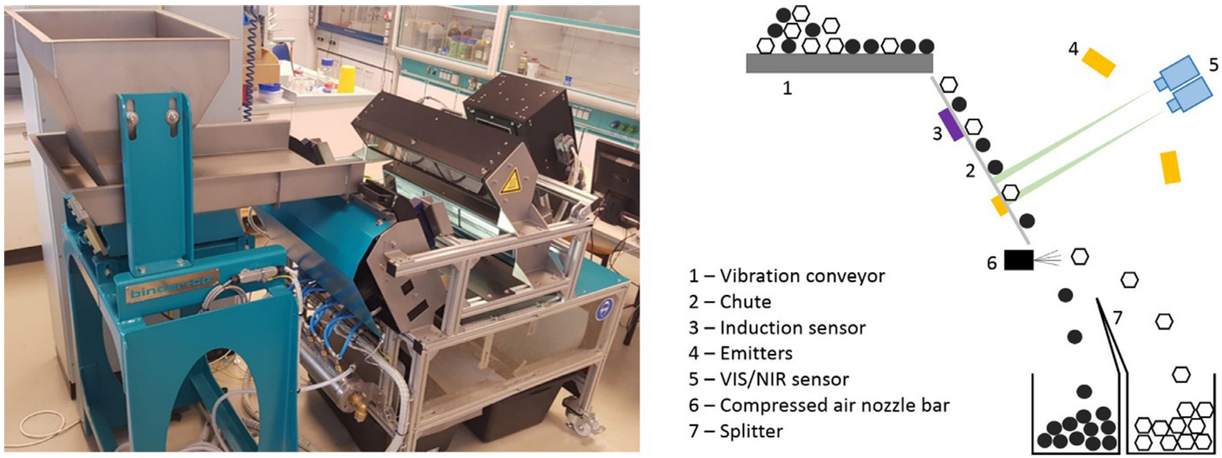

Fig. 1. Functional schematic of the experimental sensor-based sorting setup at AVAW [3].

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

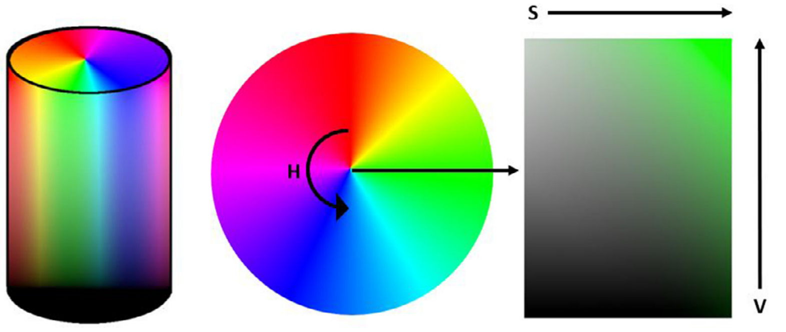

Fig. 2. Colour cylinder for creating the VIS sorting model according to the colour sector (Hue, H), the brightness level (Value, V) and the saturation circle (Saturation, S) (authors depiction).

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.

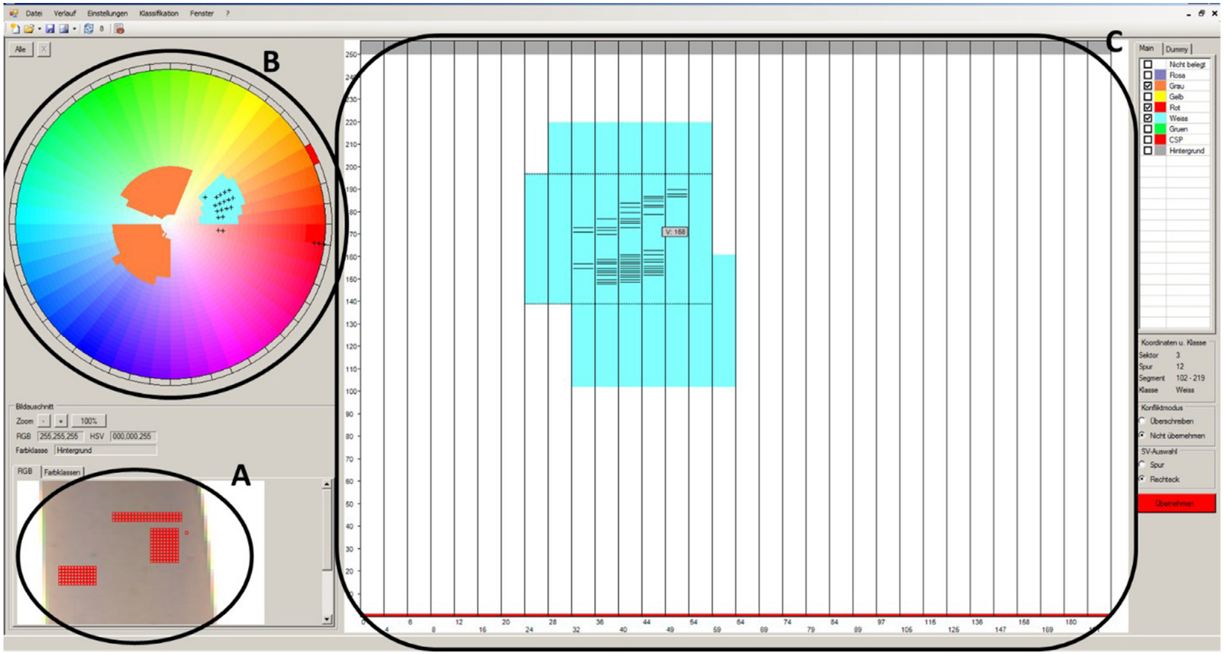

Fig. 3. Creating the classification program in Teachin ICC by configuring the colour parameters according to the HSV system, here exemplary for the white LDPE material (authors depiction).

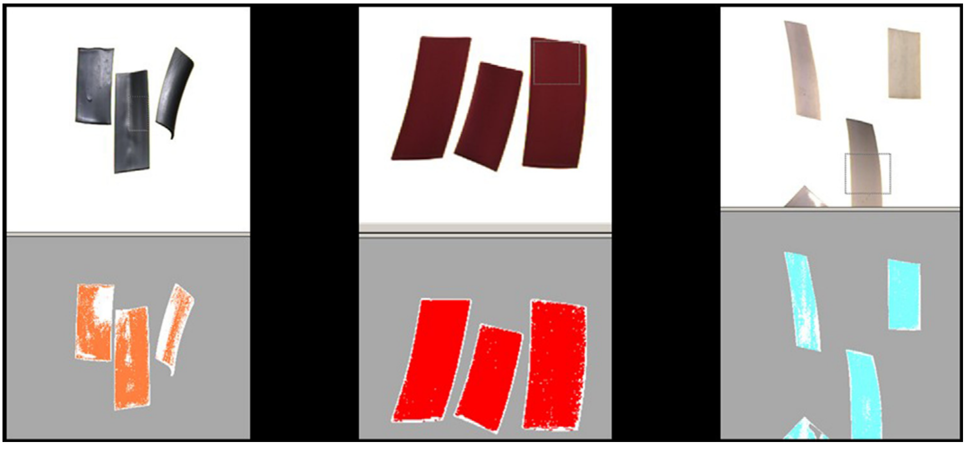

Fig. 4. Verification of the coverage ratio for three different materials in Teachin ICC (left picture colour "grey" marked in orange, centred picture colour "red" marked in red, right picture colour "white" marked in turquoise) (authors depiction).

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.

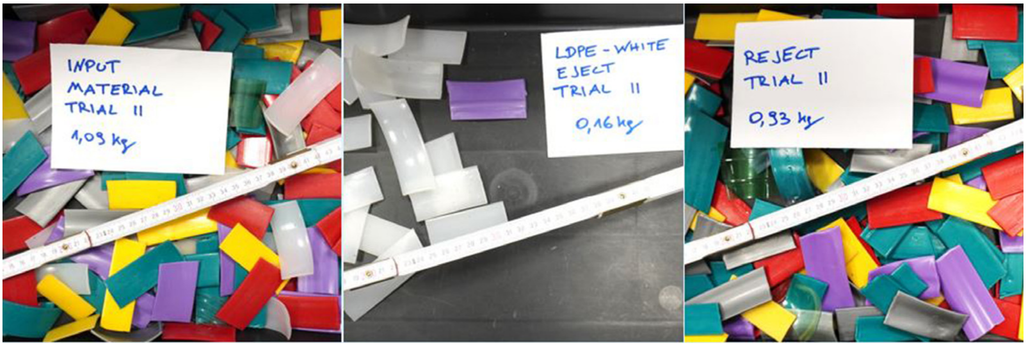

Fig. 5. Feed material (left), separated white LDPE – Eject (centre) and coloured plastic – Reject (right) (Trial 2 in Table 5) (authors depiction).

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,

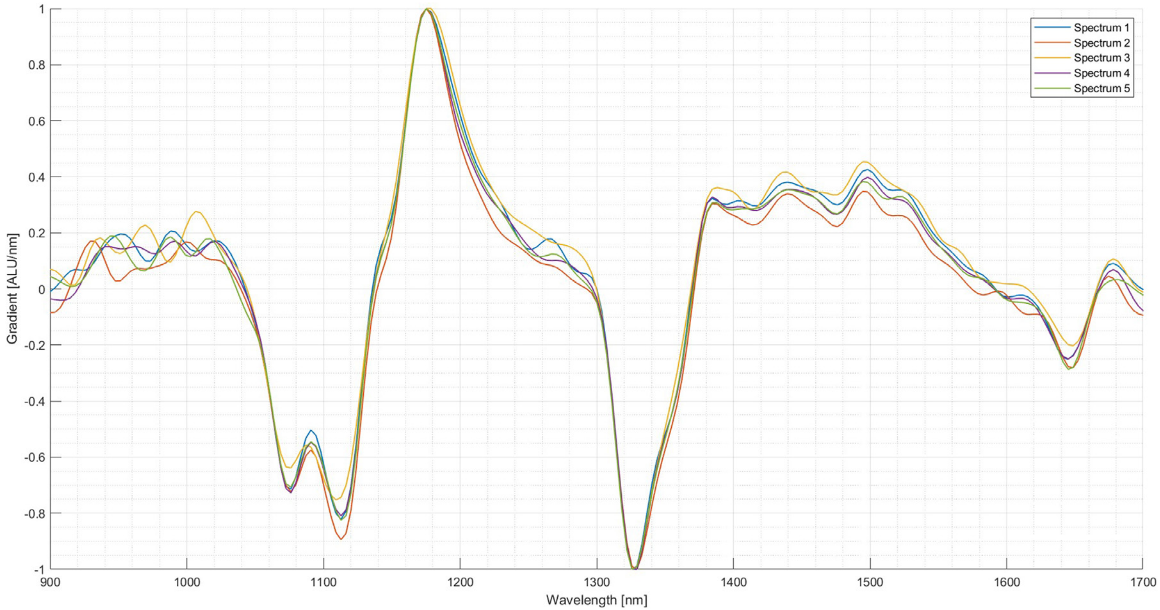

Fig. 6. Scattering of the first derivative of the NIR-spectrum of PP amongst different Pixels (evaluation performed in MATLAB, authors depiction).

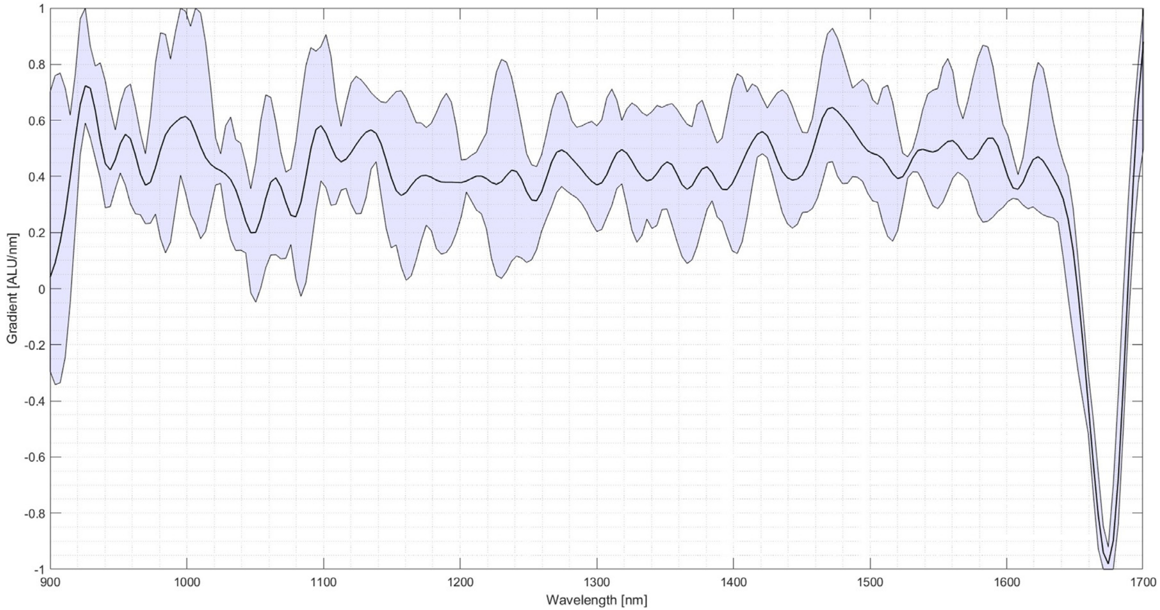

Fig. 7. Scattering of the first derivative of the NIR-spectrum of PET (blue) (evaluation performed in MATLAB, authors depiction).

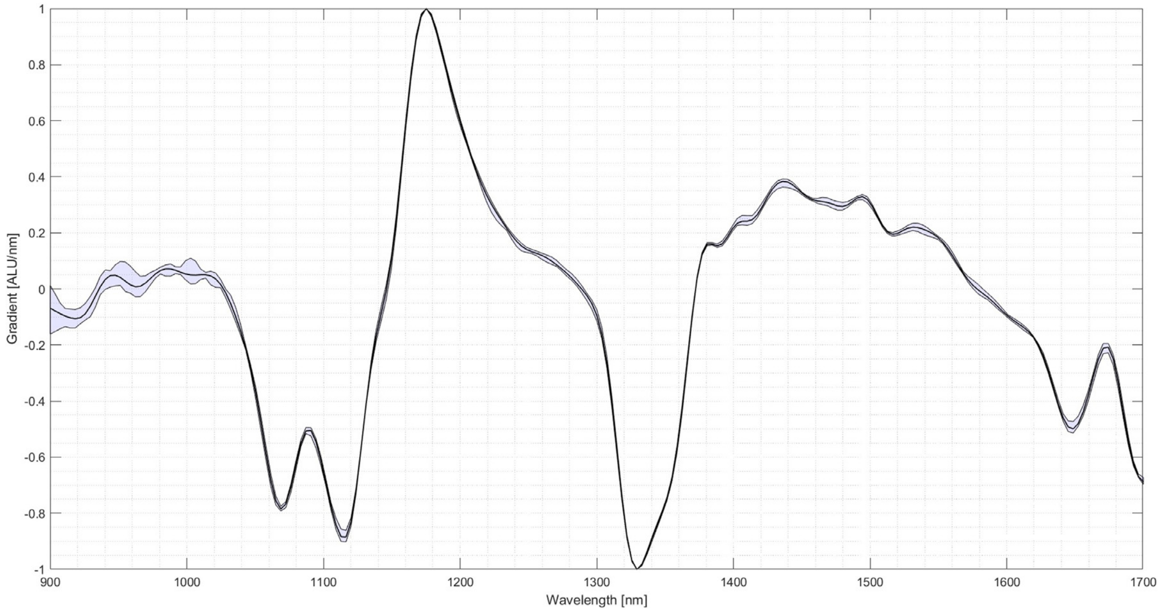

Fig. 8. Scattering of the first derivative of the NIR-spectrum of yellow TPU (evaluation performed in MATLAB, authors depiction).

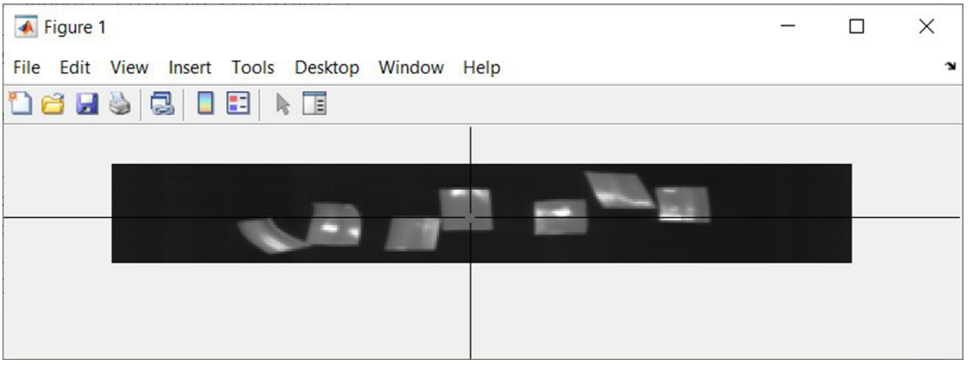

Fig. 9. Selection of pixels for evaluation from the visualised HSI Cube in SQALAR (authors depiction).

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).

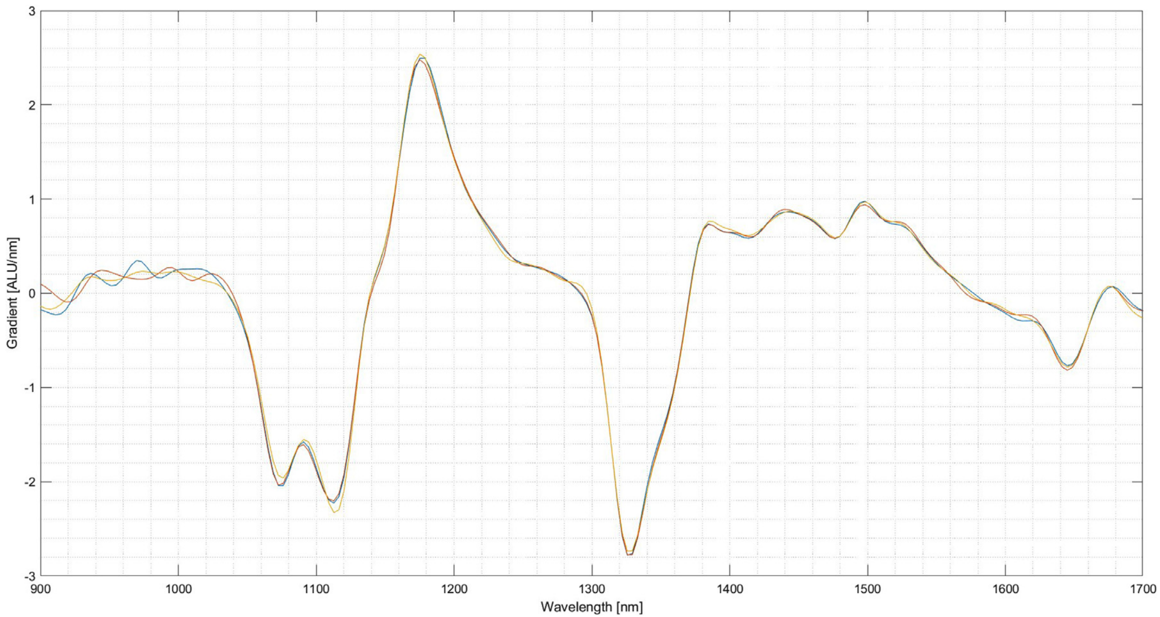

Fig. 10. Spectral evaluation of PP pixels after processing (evaluation performed in MATLAB, authors depiction).

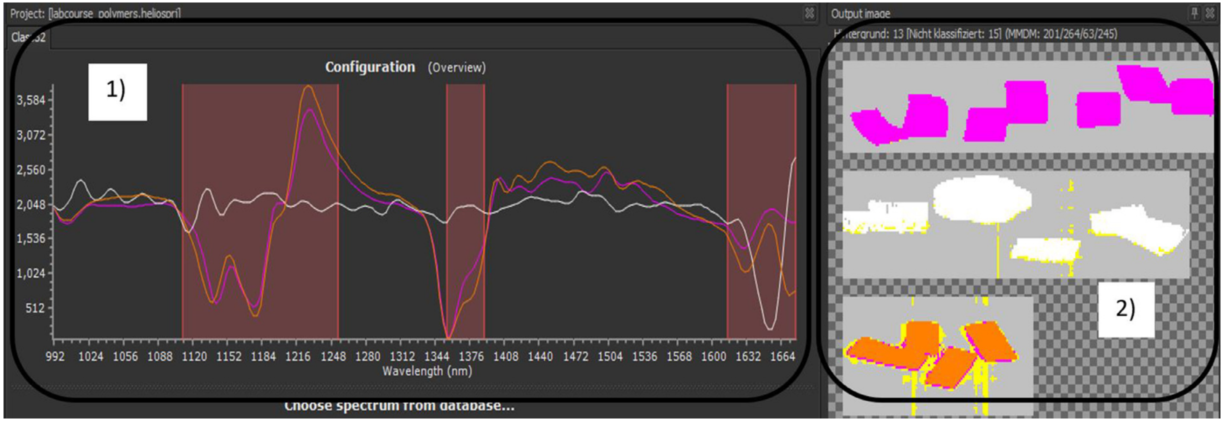

Fig. 11. Creating the classification program in SQALAR for the NIR experiment: 1) selecting three wavelength sections visualised by the red areas, 2) coverage ratios of the used pieces (PP purple, PET white, TPU orange) (authors depiction).

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.

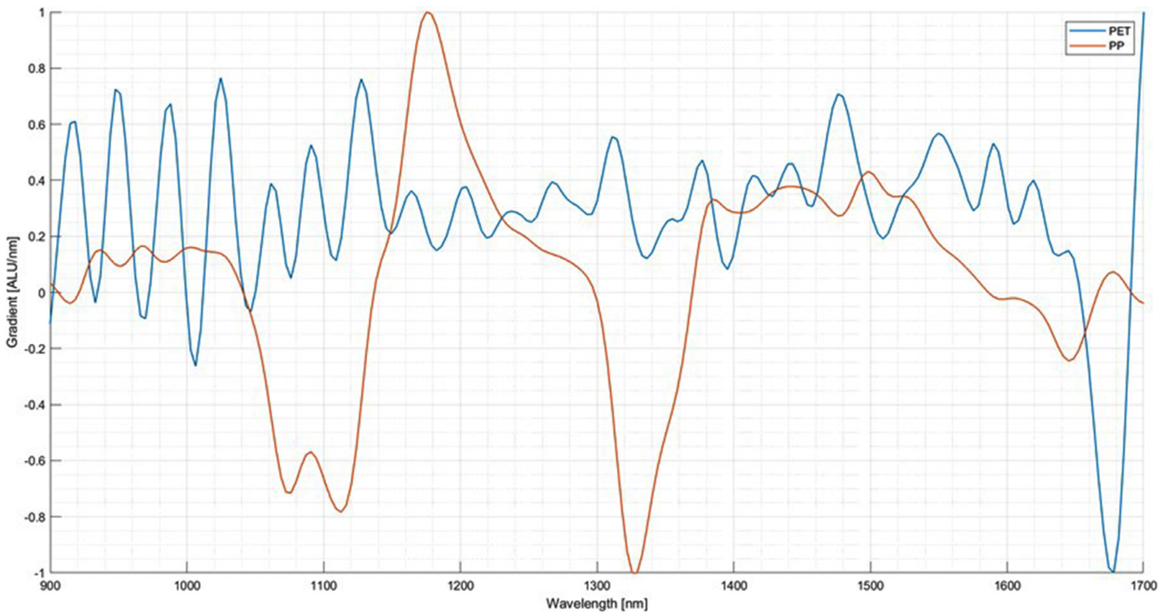

Fig. 12. Recorded spectra using NIR technology on the experimental sensor-based sorting setup and further evaluated in MATLAB: The blue line represents the characteristic PET spectrum while red represents the characteristic PP spectrum (authors depiction).

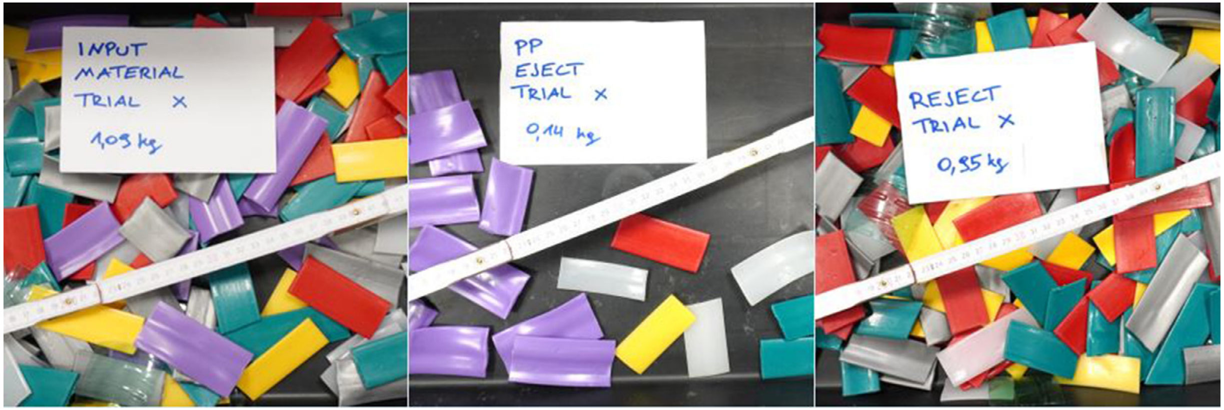

Fig. 13. Feed material (left), separated PP – Eject (centre) and coloured plastic – Reject (right) (Trial 10 of Table 7) (authors depiction).

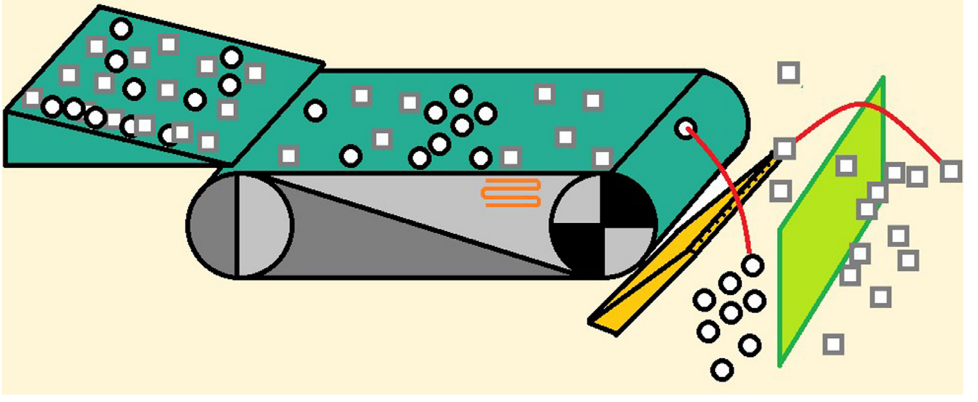

Fig. 14. Typical working schemata of induction sorting with compressed air bar and sorting screen (authors depiction).

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).

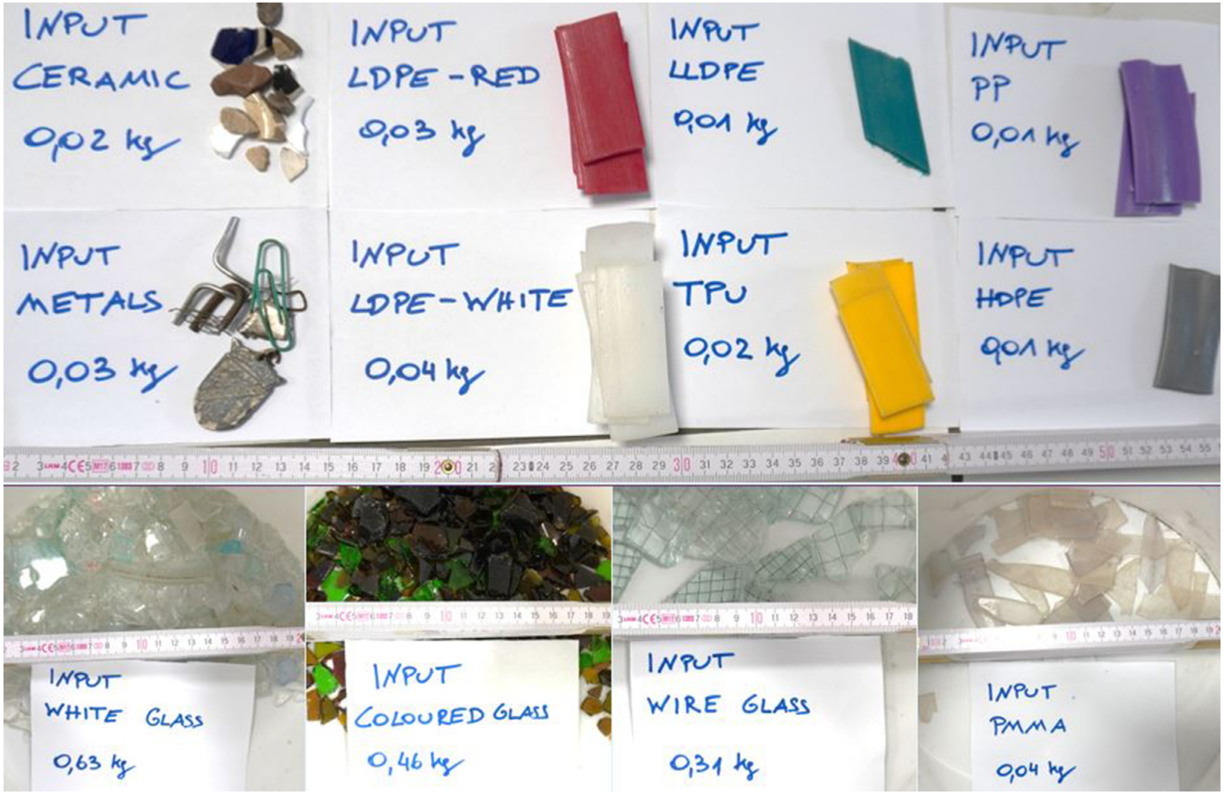

Fig. 16. Input composition of sensor fusion trial (authors depiction).

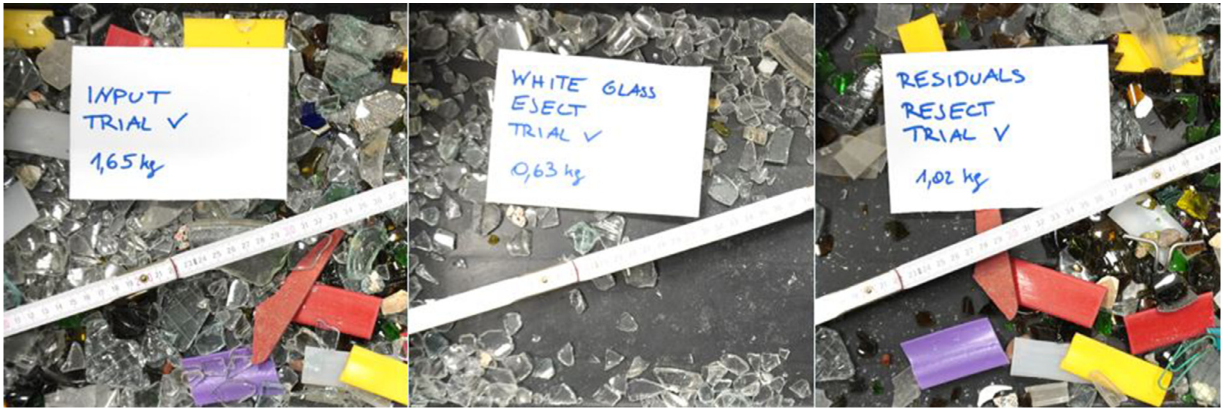

Fig. 17. Feed material (left), separated white glass – Eject (centre) and residuals – Reject (right) (Trial 5 of Table 12) (authors depiction).

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.

References

[1] ASTM D 1925: Standard Test Method for Determination Yellowness Index, 70th Edition, May 1977.
[2] ASTM D 1003: Standard Test Method for Haze and Luminous Transmittance of Transparent Plastics, Edition 2021.
[3] B. Küppers, S. Schlögl, K. Friedrich, L. Lederle, C. Pichler, J. Freil, R. Pomberger, D. Vollprecht, Influence of material alterations machine impairment on throughput related sensor-based sorting performance, Waste Manag. Res. (2020) DOI: 527 10.1177/0734242X20936745.
[4] B. Küppers, S. Schloegl, G. Oreski, R. Pomberger, D. Vollprecht, Influence of surface roughness and surface moisture of plastics on sensor-based sorting in the near infrared range, Waste Manag. Res. 37 (2019) 843–850, doi:10.1177/0734242X19855433.
[5] H.-H. Perkampus, UV-VIS Spectroscopy and Its Applications, 1st Edition, Springer, Berlin, Heidelberg, 1992 ISBN: 978-3-642-77477-5.
[6] P.A. Tipler, Physik: für Wissenschaftler und Ingenieure (Physics: For scientists and engineers), 7th Edition, Springer, Heidelberg, 2019 ISBN 978-3-642-54166-7.
[7] S.P. Gundupalli, S. Hait, A. Thakur, A review on automated sorting of source-separated municipal solid waste for recycling, Waste Manag. 60 (2017) 56–74, doi:10.1016/j.wasman.2016.09.015.
[8] Kennedy, E.D. The HSB Colour System: A Practitioner's Primer. Learn UI Design Blog, 2021, updated 01 May 2020. https://learnui.design/blog/the-hsb-colour-system-practicioners-primer.html#hsb-in-practice (accessed 28 October 2021).
[9] H. Wotruba, Stand der Technik der sensorgestützten Sortierung (State-of-the-Art in sensor-based sorting), Berg Huettenmaenn Monatsh 153 (2008) 221–224, doi:10.1007/s00501-008-0379-0.
[10] H. Martens, D. Goldmann, Recyclingtechnik: Fachbuch für Lehre und Praxis (Recycling: Reference book for education and practice), 2nd Edition, Springer Fachmedien Wiesbaden, Wiesbaden, 2016 ISBN: 978-3-658-02786-5.
[11] F. Corradini, H. Bartholomeus, E. Huerta Lwanga, H. Gertsen, V. Geissen, Predicting soil microplastic concentration using vis-NIR spectroscopy, Sci. Total Environ. 650 (2019) 922–932, doi:10.1016/j.scitotenv.2018.09.101.
[12] Y. Ozaki, C. Huck, S. Tsuchikawa, S.B. Engelsen, Near-Infrared Spectroscopy: Theory, Spectral Analysis, Instrumentation and Applications, 1st Edition, Springer, Singapore, 2021 ISBN: 978-981-15-8648-4.

[13] H. Günzler, H.-U. Gremlich, IR-Spektroskopie: Eine Einführung (IR spectroscopy: An introduction), 4th Ed., Wiley-VCH, Hoboken, NJ, Weinheim, 2003, doi:10.1002/9783527662852.
[14] C. Pasquini, Near Infrared Spectroscopy: fundamentals, practical aspects and analytical applications, J. Braz. Chem. Soc. 14 (2003) 198–219, doi:10.1590/S0103-50532003000200006.
[15] A. Kulcke, C. Gurschler, G. Spöck, R. Leitner, M. Kraft, On-line classification of synthetic polymers using near infrared spectral imaging, J. Near Infrared Spectrosc. 11 (2003) 71–81, doi:10.1255/jnirs.355.
[16] A. Feil, E. Coskun, M. Bosling, S. Kaufeld, T. Pretz, Improvement of the recycling of plastics in lightweight packaging treatment plants by a process control concept, Waste Manag. Res. 37 (2019) 120–126, doi:10.1177/0734242X19826372.
[17] H. Beel, Sortierung von schwarzen Kunststoffen nach ihrer Polymerklasse mit Hyperspectral-Imaging-Technologie (Sorting of black plastics to their polymer types with hyper-spectral-imaging-technology), in: K.J. Thomé-Kozmiensky, D. Goldmann (Eds.), Recycling und Rohstoffe Band 10, Proceedings of Recycling und Rohstoffe, Neuruppin, Germany, TK-Verlag, 2017, pp. 175–191. ISBN 978-3-944310-34-3.
[18] N.M. Morris, Electrical Principles II, 1st Ed., Palgrave, London, 1977 ISBN: 978-0-333-22062-7.
[19] T. Pretz, J. Julius, Stand der Technik und Entwicklung bei der berührungslosen Sortierung von Abfällen (State-of-the-Art and development in contactless sorting of waste). Österr Wasser- und Abfallwirtschaft 60, ÖWAV: Vienna, Austria, pp 105-112.

3 Process Optimisation Phase

The second of two subject areas of this thesis "Process Optimisation Phase" consists of three peer reviewed publications. These publications are presented below.

3.1 Publication 4

Research Paper 4:

"Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison"

Koinig, Gerald; Grath, Elias; Barretta, Chiara; Friedrich, Karl; Vollprecht, Daniel; Oreski, Gernot (2022): Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison. In Polymers 14 (17), p. 3620. DOI: 10.3390/polym14173620.

Annotation on the doctoral candidate's contribution to this publication:

The general concept of the publication was designed by the doctoral candidate and discussed in contribution with the co-authors Elias Grath and Karl Friedrich. Afterwards, the relevant scientific literature on the subject was reviewed by the doctoral candidate and Elias Grath. The computations were done by co-author Elias Grath. The publication was then written independently by the author of the doctoral thesis based on a draft created by Elias Grath. The internal review process was done with the consultation of the co-authors Karl Friedrich, Elias Grath, Barretta Chiara and supervisors Gernot Oreski and Daniel Vollprecht.

polymers

Article

Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison

Gerald Koinig [1,*], Elias Grath [1], Chiara Barretta [2], Karl Friedrich [1], Daniel Vollprecht [1,3] and Gernot Oreski [2]

[1] Chair of Waste Processing Technology and Waste Management, Department of Environmental and Energy Process Engineering, Montanuniversitaet 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: This work covers a lifecycle assessment of monolayer and multilayer films to quantify the environmental impacts of changing the management of plastic film waste. This lifecycle assessment offers the possibility of quantifying the environmental impacts of processes along the lifecycle of monolayer and multilayer films and mapping deviating impacts due to changed process parameters. Based on the status quo, the changes in global warming potential and abiotic fossil resource depletion were calculated in different scenarios. The changes included collecting, sorting, and recycling mono- and multilayer films. The "Functional Unit" under consideration comprised 1000 kg of plastic film waste, generated as post-consumer waste in Austria and captured in the lightweight packaging collection system. The results showed the reduction of environmental impacts over product lifecycles by improving waste management and creating a circular economy. Recycling all plastic film reduced global warming potential by 90% and abiotic fossil resource consumption by 93%. The necessary optimisation steps to meet the politically required recycling rates by 2025 and 2030 could be estimated, and the caused environmental impacts are presented. This work shows the need for increased collection, recycling, and significant improvement in the sorting of films to minimise global warming potential and resource consumption.

Keywords: 2D plastic packaging; near-infrared spectroscopy; sensor-based sorting; life cycle assessment; small film packaging

Citation: Koinig, G.; Grath, E.; Barretta, C.; Friedrich, K.; Vollprecht, D.; Oreski, G. Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison. *Polymers* **2022**, *14*, 3620. https://doi.org/10.3390/polym14173620

Academic Editors: Paul Joseph and Leon Chernin

Received: 20 July 2022
Accepted: 23 August 2022
Published: 1 September 2022

1. Introduction

Plastics are omnipresent in everyday life, and their primary areas of application can be found in the packaging industry, the construction industry and the automotive industry [1]. Plastics as packaging material reduces packaging mass, energy consumption and greenhouse gas emissions [2]. In the packaging industry, in particular, plastic products are required, which, in addition to the requirements for the protection of the packaged products and industrial processability, must also meet the optics, haptics and consumer information.

The legal framework in the European Union and Austria creates the basis for an increased focus on the recycling of plastic packaging. The legal framework for plastics and packaging in the European Union and Austria, defined by laws, regulations, directives, strategies and action plans, sees regulations such as the EU circular economy package, the EU plastics strategy, the EU single-use plastics directive, the EU packaging directive 94/62/E.G. and the Austrian Waste Management Act 2002 propose increases concerning plastics recycling.

Along with the increasing annual volume of plastic waste of around 19% in the period from 2006 to 2018 [1] and the policy instrument to realise the potential of waste for the provision of secondary raw materials through mandatory recycling quotas [3], optimisations in sorting and recycling processes are necessary.

Increasing these recycling quotas is an ecologically viable way to fulfil ecological requirements by increasing the recycling of currently ignored materials streams such as multilayer films, which make up a substantial portion of lightweight packaging in Austria and are currently being incinerated, which adds to the carbon footprint and squanders valuable resources. Considering that of 300,000 t of plastic packaging waste generated per year in Austria small films account for 69,000 t, the potential for improvement in this area is substantial [4,5]. These films are commonly made from polyolefins, like polyethylene (PE), polypropylene (PP), or other polymers such as polyethylene terephthalate (PET). Further in the multilayer materials, various combinations of polymers, such as polyamide and PE or PE and PP are common.

Despite the current difficulty in recycling mono- and multilayer packaging, techno-economic analysis of processes to separate multilayer materials and use the separated polymers for recycling show promise. Considering that recycled polymers must be produced at a price similar or lower than virgin materials to be economically viable and simultaneously have to require less resources such as energy in their production to be considered ecologically sensible, the creation of processes that satisfy all these requirements is currently undergoing. Amongst these are APK's Newcycling [6], Unilever's CreaSolv [7] and the STRAP [8] process. The STRAP process showed a 37% reduction in energy requirement for separating the layers of a multilayer, recovering the PET contained therein, compared to the energy required in the production of virgin PET [8].

Recycling monolayer films is equally difficult because foreign materials may be introduced to an otherwise-clean mono-material waste stream. This contamination can occur by introducing multilayer films into the feedstock, which contain foreign materials and thus can have a detrimental effect on recyclability [9]. To remove these contaminants or subsequently receive them as a separate recyclable fraction, optimisations in the waste management processes of plastic films are necessary.

Instruments for quantifying the changes in environmental impact are required to justify necessary optimisations and gauge their possible impact. In particular, the lifecycle assessment (LCA) is applicable. An LCA quantifies and represents the lifecycle or changes in processes throughout the product's lifecycle [10].

Existing LCAs include a study conducted by Choi et al. from 2018, who investigated the carbon footprint of packaging films made from low-density polyethylene (LDPE), polylactic acid (PLA), and PLA/polybutylene adipate terephthalate blends (PLA/PBAT) in South Korea. The results of this LCA show that incineration, as the waste treatment measure with the highest global warming potential (GWP), has the worst balance sheet for each plastic fraction considered [11].

Volk et al. carried out an additional LCA in 2021, representing a techno-economic assessment and comparison of different plastic recycling pathways. The study done by Volk et al. (2021) evaluates the effects of different recycling routes of separately collected lightweight packaging in Germany. The GWP, the cumulative energy requirement (CED), the carbon efficiency and the product costs were considered by Volk et al. The recycling routes included mechanical recycling, chemical recycling, and a combination of both methods. The study shows that incineration accounts for 95% of the GWP impact of the recovery route. By combining mechanical and chemical recycling, around 0.48 kg CO_2-eq per kg input of waste can be saved concerning the current situation of the recycling route in Germany [12].

It remains to determine whether replacing the incineration and thus the generation of energy by recycling processes and subsequent reduction of virgin materials benefits the environment. An increase in transportation and collection efforts to manage the increase in separately collected lightweight film packaging and the increased effort to recycle these materials may offset the potential benefits of reduced thermal recovery.

Further, technological limitations may hinder the implementation of a circular economy of films packaging, as the amount of recyclate which can be introduced to new products is limited.

The LCA conducted in the here-presented work considers the effect improved collection, sorting and recycling of lightweight two-dimensional packaging can have on the GWP and abiotic resource depletion fossil (ADPF) in the Austrian waste management sector. To this end, scenarios reflecting different collection and recycling models of monolayer and multilayer materials are depicted and compared to the status quo. These scenarios entail separating monolayer materials and using them as a value-adding feedstock for mechanical recycling, thus reducing the need for thermal recovery and virgin material.

These scenarios show latent potential for saving resources and greenhouse gas emissions through improved sorting and increased recycling of mono- and multilayer films. The ADPF has been calculated for each scenario. The ADPF mirrors the consumption of fossil fuels such as oil or gas and subsequent depletion of non-renewable abiotic resources. The consumption of these resources represents the environmental impact of the production of virgin packaging materials.

To conclude, it may be stated that the sensibility of replacing thermal recovery with other means of use depends on the comparison of the environmental impact of each after-use recovery method. This article aims at aiding in the building of a fundamental basis for discussion for the implementation of future policies and the prioritisation in the development of recovery techniques by showing whether a reduction of GWP and ADPF is indeed feasible with the recycling of packaging film and by providing an estimate as to the possible reduction in these metrics with different measures taken.

2. Materials and Methods

In the following, the used materials for conducting the LCA and the used software are explained.

2.1. Current Status Survey of the Situation Regarding the Occurrence and Treatment of Plastic Waste in Austria

Prior to the LCA, comprehensive research of the current situation regarding the generation and treatment of plastic waste in Austria was conducted. The collected data form the basis for the LCA. Further, the collected data enable a comparison between the current status with the alternative scenarios, namely the GWP and the depletion and use of non-renewable and renewable abiotic resources or fossil abiotic resource depletion, in short ADPF. Both gauges were calculated in the course of the LCA. Data from Statistics Austria, Eurostat and existing literature representing the current status were collected during this preliminary work.

2.2. Software Used

2.2.1. subSTance flow Analysis

The freeware subSTance flow Analysis (STAN), Version 2.6.801 by the Research Unit of Waste and Resource Management at TU Wien (Vienna, Austria) was used for the computation of the LCA. STAN offers the user a platform for presenting material flow analyses according to ÖNORM S2096. STAN allows the user, after complete modelling of the material flows, to automatically calculate unknown variables.

2.2.2. GaBi (Holistic Accounting) (Education Licence)–Version 9.2.1.68

The LCA software GaBi was used for the LCA presented in this manuscript. The software enables the modelling of complex processes with automatic tracking of material and energy and emission flows, and its implemented databases allow access to data for modelling. The used databases are mentioned throughout the manuscript. GaBi allows for assessment methods for quantifying environmental impacts. The software also supports the user in displaying results. It has been used to create flow diagrams for each scenario.

2.3. Conduction of the Lifecycle Assessment

The presented LCA examines the environmental impact caused by plastic films throughout their lifecycle. The focus of this study was the analysis of the environmental impact the improved separation and subsequent recycling of mono- and multilayer films has. This improved separation is enabled by adapting current sorting methods to enable classification of polymer films and allows for a material utilisation of foil materials which are currently primarily recovered thermally.

2.3.1. Functional Unit

The considered "functional unit" comprised 1000 kg of plastic film waste generated as post-consumer waste in Austria, recorded in the collection and recycling system of the light packaging collection.

2.3.2. Calculations and Definitions

The LCA in this work will look at the performance of sorting plants and recycling plants and their impact on the overall metrics gauging the depletion of fossil fuels and emission of greenhouse gases. The output of these plants will be depicted by the relative mass yield of the sorting and recycling plants.

The mass yield of the sorting plant is depicted as the sorting depth, and it is calculated using the input mass and the mass of the valuable output. The respective mass yield of the beneficiation plant is calculated as the mass yield of the beneficiation plant, in short, the recycling yield.

The process of recycling the functional unit is represented using the collection rate, the sorting depth, the recycling yield and the overall recycling rate. The collection rate represents the proportion of packaging put into circulation and collected after use. This collected fraction is then transported to the sorting plant.

The success of this sorting plant is depicted in the mass yield of the sorting plant, or sorting depth in short. After sorting, the waste fractions are processed in a recycling plant. The amount of waste successfully recycled in this step is depicted as the mass yield of the beneficiation or recycling plant, in short, the recycling yield. The overall success of the packaging recycling is calculated and depicted in the recycling rate.

The following paragraphs explain these gauges and their calculation in greater detail.

<u>Definition of Collection Rate:</u>

The collection rate has been calculated using the quotient of thin-layered plastic packaging produced and collected as shown in Formula (1). The collection rate represents the effectiveness of the waste collection scheme and its effectiveness in collecting thin-layered plastic film packaging. Improving the sorting discipline of the consumer and reducing sinks such as littering raises the collection rate and facilitates subsequent processes such as sorting and recycling.

In accordance with the Austrian packaging ordinance 2014, packaging put into circulation refers to the amount of packaging handed over to the end consumer (Packaging sold by the final distributor).

$$Collection\ Rate\ [\%] = \frac{Collected\ Post\ Consumer\ Packaging\ \left[\frac{t}{a}\right]}{Packaging\ put\ into\ circulation\ \left[\frac{t}{a}\right]} \times 100 \quad (1)$$

<u>Definition of Sorting Depth:</u>

The mass yield of the sorting plant, henceforth referred to as sorting depth in this work, represents the success rate when sorting the functional unit of thin-layered plastic films into the categories monolayer (S-MO) and multilayer (S-MU). This mass yield of the sorting plant is calculated for each of the two fractions generated at the sorting plant [13]. The sorting depth has been calculated as shown in Formula (2).

$$Mass\ yield\ of\ sorting\ plant\ [\%] = \frac{Sorted\ fraction\ [t] - Output\ of\ sorting\ plant\ [t]}{Input\ of\ sorting\ plant\ [t]} \times 100 \quad (2)$$

Definition of Recycling Yield:

The recycling yield is the quantitative proportion of a target product obtained concerning the total input flow of a recycling plant. This yield is the mass yield of valuables from the recycling plant. Improving the recycling process increases the number of valuable resources recovered from the input stream and facilitates the substitution of virgin materials with recycled polymers. The calculation is shown in Formula (3).

$$Recycling\ Yield\ [\%] = \frac{Recycled\ Fraction\ [t] - Output\ of\ recycling\ plant\ [t]}{Input\ of\ recycling\ plant\ [t]} \times 100 \quad (3)$$

Definition of Recycling Rate:

According to Article 11a of directive (EU) 2018/851 of the European Parliament, which defines the new calculation method for the recycling rate, the recycling rate is calculated from the quotient of generated and recycled packaging waste weights, as shown in Formula (4). The amount of packaging waste produced is equated with the amount of packaging placed on the market in the same year. Packaging waste that underwent the necessary screening, sorting and conditioning processes to remove non-recyclable waste materials and was then sent to a recycling plant to be processed is represented in the formula as recycled post-consumer packaging.

$$Recycling\ Rate\ [\%] = \frac{Recycelt\ Post\ Consumer\ Packaging\ \left[\frac{t}{a}\right]}{Packaging\ put\ into\ circulation\ \left[\frac{t}{a}\right]} \times 100 \quad (4)$$

Figure 1 lays out the inputs and outputs of the different stages evaluated. Here, the flow of packaging waste is depicted to enhance the formulae stated above.

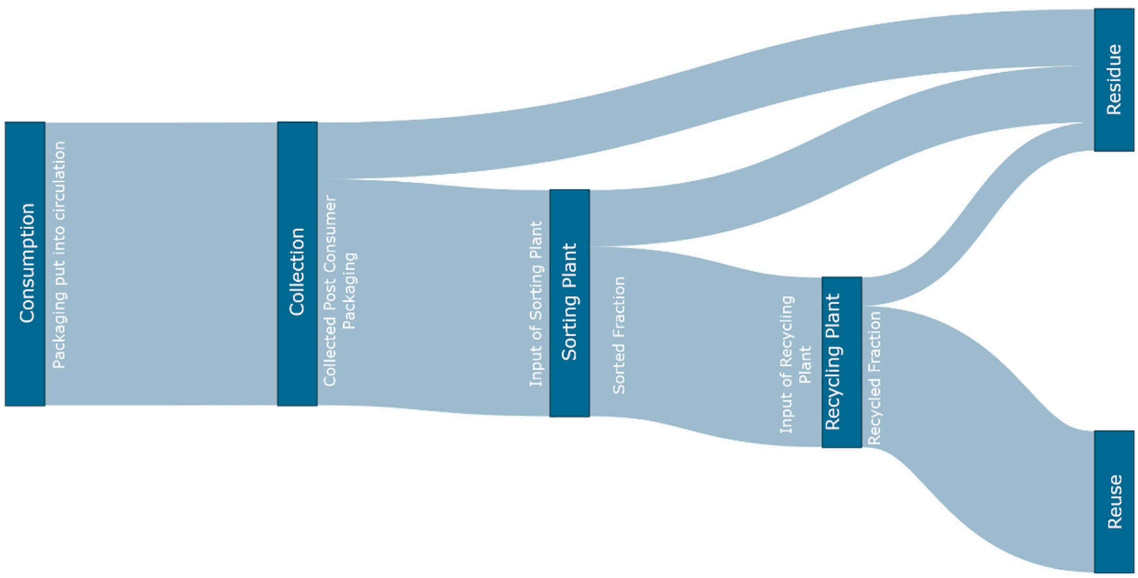

Figure 1. Sankey diagram laying out the different inputs and outputs of the recycling system.

2.3.3. The Geographical Scope of the Investigation

The geographical scope of the investigation included the cycle of plastic products in Austria, which were manufactured, processed, disposed of and returned to the cycle in Austria.

Figure 2 shows the balance area of the product lifecycle of plastic films and delimited by the system boundary. The energy supply, supply of operating resources and the transport processes involved, which were included in the balance, were omitted for clarity. The technical standard of the processes is assumed to be an average technology mix. The product lifecycle balanced using **GaBi** is shown in Appendix A.

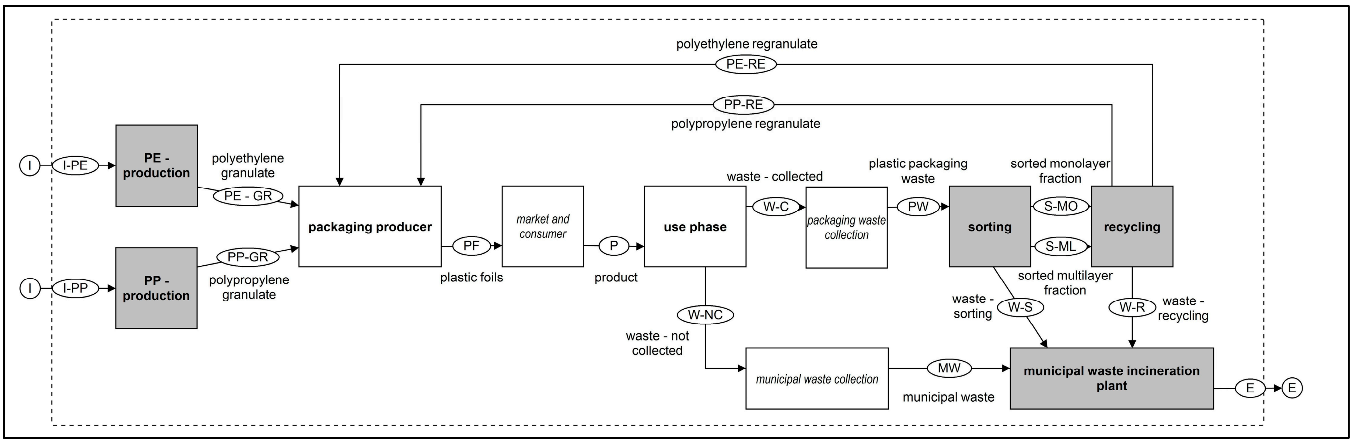

Figure 2. Product lifecycle of plastic films.

2.3.4. Scenarios

The evaluated scenarios include the status quo, improved collection, improved separation and improved recycling. In addition, scenarios depicting the stipulated recycling quotas were calculated. Further, one scenario shows the reduction in GWP and ADPF if the currently possible maximum amount of recycled granulates were used in the production of new films, reducing the need for virgin granulates as far as possible with the current state of the art. The respective representations show the changes in the material flows due to the adjustment of the collection rate, sorting depth and recycling yield. For better illustration, only the changed material flows and waste management processes are shown. The complete material flows of the scenarios can be seen in Appendix B.

Scenario 1: Status Quo (SQ)

In Scenario 1, the current status of the recycling of plastic films was considered. In this scenario, the goal was to separate monolayer films from multilayer films. Therefore, the monolayer fraction was considered the target fraction for the calculation while the multilayer materials were considered contaminants. Figure 3 shows the mass flow of these plastic films concerning the respective recycling processes. The composition of the functional unit and its utilisation follow the findings from van Eygen et al. in 2018 [5].

Scenario 2: Improved Collection (IC)

This scenario considered the complete collection of plastic film waste. Scenario 2 was compared to the status quo. As shown in Figure 4, all plastic film waste was brought into the sorting process. The sorting depth and the recycling yield were taken from the status quo (SQ) scenario. As a result, the amounts of waste from the output flows of the sorting and recycling processes to waste incineration were increased. The increase in the amount of waste collected also increased the amount of polyethene regranulate from the recycling process, which could be brought back into production, reducing the need for virgin granulates.

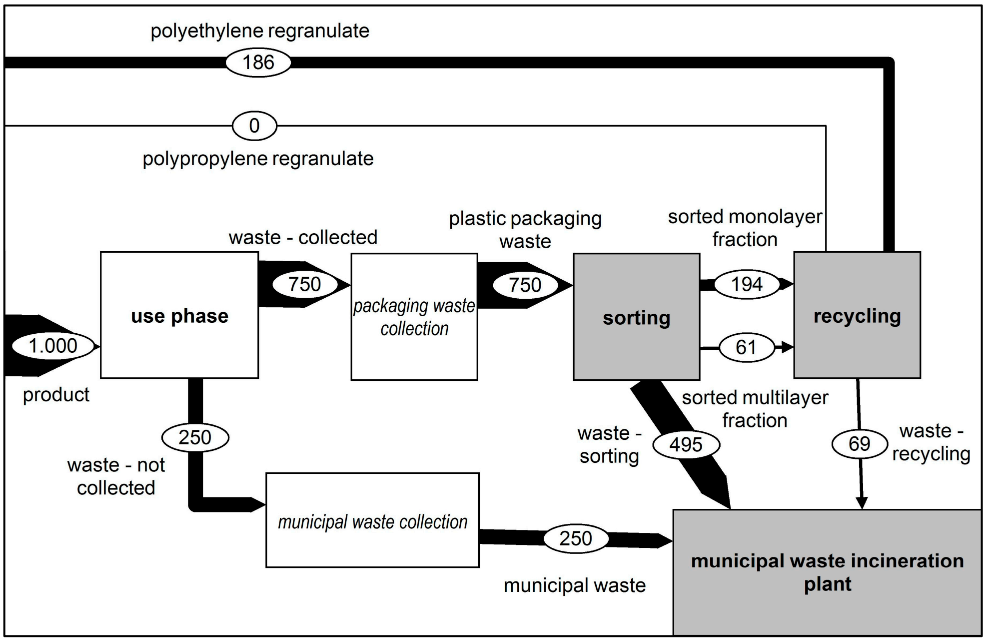

Figure 3. Representation of material flows—Status Quo Scenario. Composition of the functional unit and the utilisation from van Eygen et al., 2018 [5].

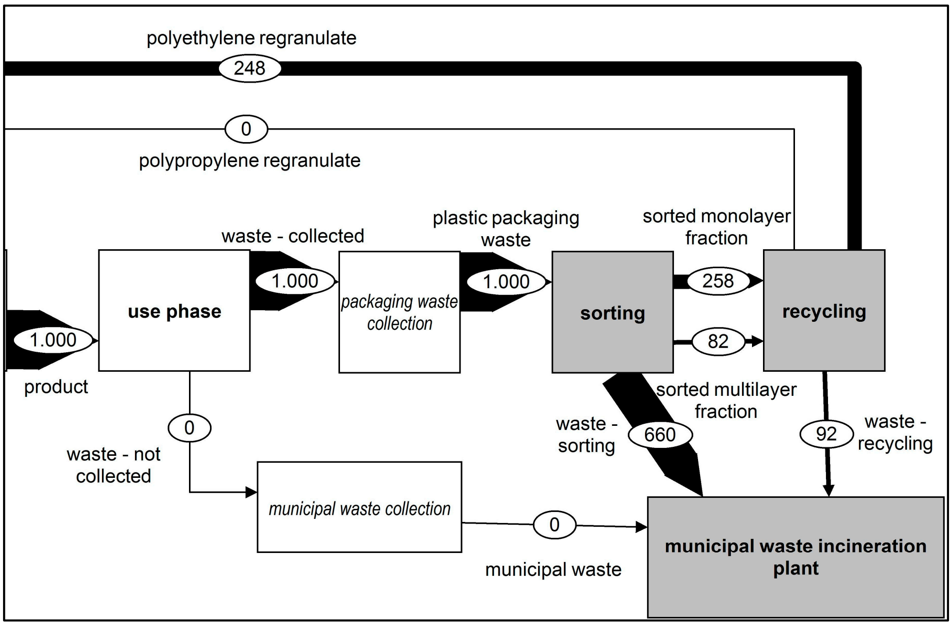

Figure 4. Representation of the changed material flows—Scenario 2.

Scenario 3: Improved Sorting (IS)

This scenario presents the changed environmental impact caused by the collection of all plastic films and a maximally optimised sorting of the monolayer films. In this scenario, multilayer films were separated from the film stream and subjected to thermal recovery while the monolayer films were sorted, recycled and subsequently used as substitute for virgin material in the production of new foils. Figure 5 shows the mass flows of Scenario 3.

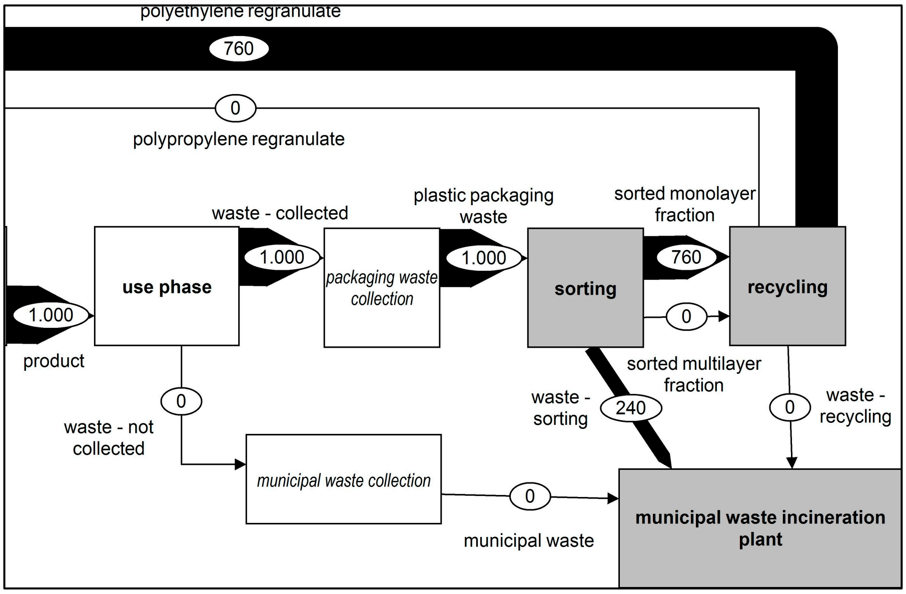

Figure 5. Representation of the changed material flows—Scenario 3.

Scenario 4: Closed Material Cycle (CMC)

This scenario expanded Scenario 3 by including the multilayer film fraction as a targeted recyclable material in the sorting and recycling processes. This scenario presumes leaps in the available technology in all areas of the recycling chain. Here, the optimum of collection, separation, recycling and substitution of virgin material has been implemented. Thus, the thermal recovery has be replaced by recycling, as shown in Figure 6. The collection rate, sorting depth, and recycling yield selected in Scenario 4 represent the optimum theoretical improvement possibilities of the waste recycling processes.

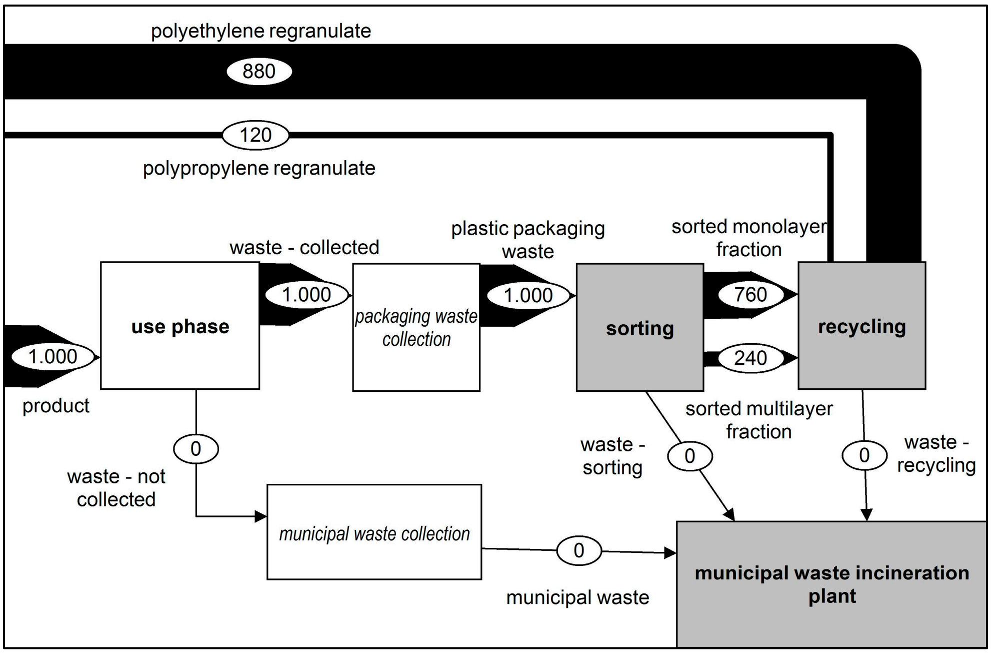

Figure 6. Representation of the optimised material flows—Scenario 4.

Scenario 5: Recycling Goals 2025—Optimisation of Collection, Sorting and Mechanical Recycling (2025)

In the 2025 scenario, the necessary optimisation steps to meet the recycling rate of 50% stipulated by the EU packaging directive through the recycling of films were examined, and the resulting environmental impact was considered [3]. To reach these recycling goals, an improvement in collection, sorting and recycling was deemed necessary. These improvements formed the basis for the calculation of this scenario. The respective percentages of the recycling chain have been improved to reach the recycling goal. Furthermore, the multilayer film fraction was considered a targeted recyclable material fraction in the recycling processes. The output flow of the recycling process thus corresponded to a total quantity of regranulate of 500 kg. Figure 7 shows the changed mass flows of the 2025 scenario.

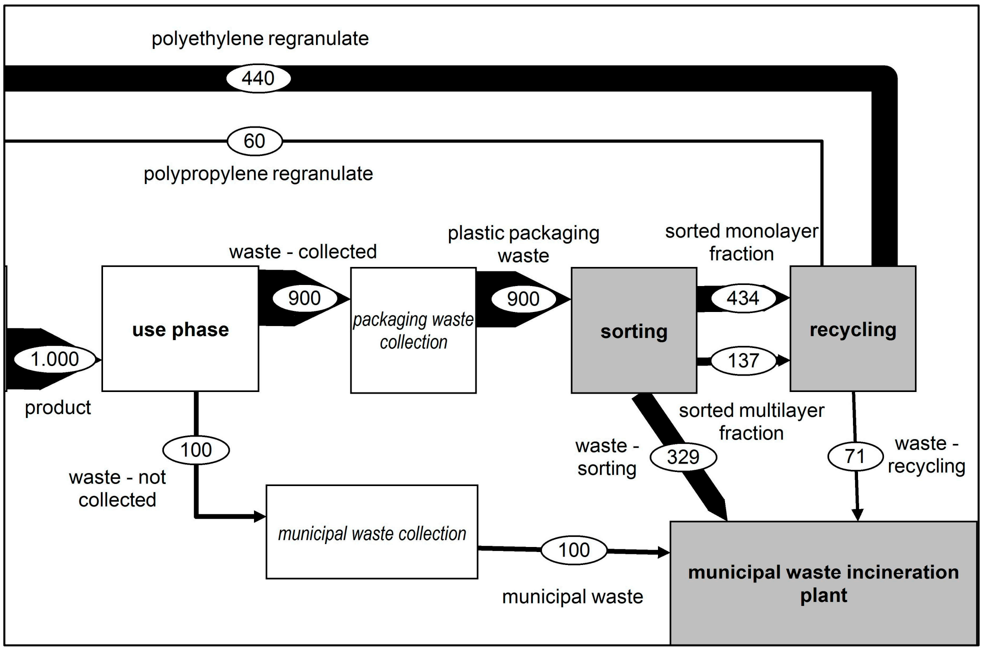

Figure 7. Representation of the material flows—2025 scenario.

Scenario 6: Recycling Goals 2030—Optimisation of Collection, Sorting and Mechanical Recycling (2030)

The 2030 scenario included determining the changing environmental impact based on the necessary optimisation steps to meet the recycling rate of 55% set by the EU packaging directive. The optimisation steps included increases in the collection rate, sorting depth and recycling yield. As a result, the amount of regranulate, consisting of polyethylene (PE) and polypropylene (PP), from the recycling process could be increased to 550 kg. This result is shown in Figure 8.

Scenario 7: Currently Possible Maximum Recycling Quantities with the Current State of the Art—State of the Art (SOA)

Jönkkäri et al. have shown in laboratory studies conducted in 2019 that the recyclates created from an input of 100% used films can exhibit mechanical properties congruent with the requirements for production [14]. These trials were conducted in a controlled environment and faced significant challenges during pretreatment and compounding [14]. Current recycling processes on an industrial scale require virgin material input alongside recycled polymers. This virgin input is used to ensure the mechanical properties of the final product and processability. These required mechanical properties vary depending on the production method and the desired use of the manufactured polymer.

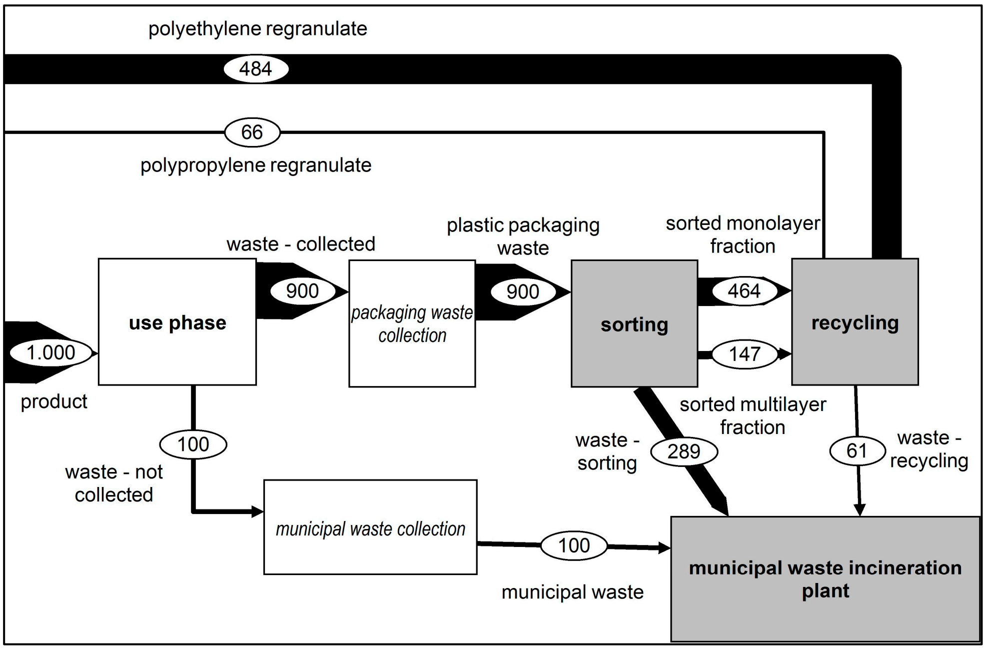

Figure 8. Representation of the material flows—2030 scenario.

To examine a scenario that represents the maximum amount of recycled material currently used in production without jeopardising the mechanical properties of the manufactured product, existing polymer films using recycled raw materials have been evaluated. This evaluation showed recycling contents ranging from 30% to 50% in recycled products. LDPE foils used in mechanically demanding applications, such as packaging film or stretch films, commonly comprise 30% recycled material. As stretch film made from LDPE represents the most common type of polymer packaging, this percentage has been chosen for this scenario [15]. Figure 9 shows the material flows between the collection, sorting and recycling stages.

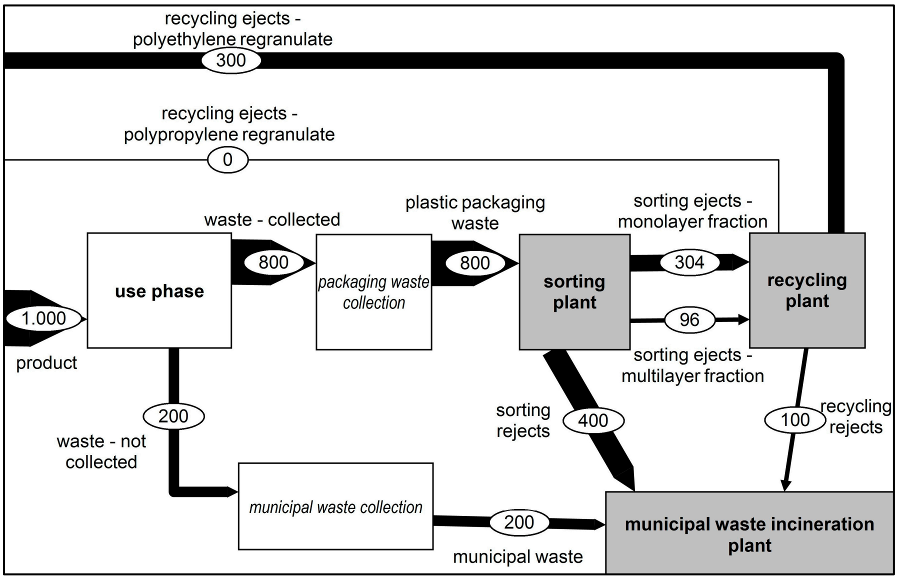

Figure 9. Representation of the material flows in Scenario 7.

2.3.5. Comparative Overview of All Scenarios

In Table 1, an overview of the calculated scenarios is given. The collection rate, sorting depth and recycling yield of the respective scenario served as the basis for the changing process flows, shown in Figures 2–9.

Table 1. Overview of the collection rates, sorting depths and recycling yield in the evaluated Scenarios.

Scenario	Collection Rate	Sorting Depth		Recycling Yield	
		Monolayer Films	Multilayer Films	Monolayer Films	Multilayer Films
1 SQ	75%	34%	34%	73%	0%
2 IC	100%	34%	34%	73%	0%
3 IS	100%	100%	0%	100%	0%
4 CMC	100%	100%	100%	100%	100%
5 2025	90%	63%	63%	88%	88%
6 2030	90%	68%	68%	90%	90%
7 SOA	80%	50%	50%	75%	0%

2.4. Lifecycle Inventory

In the following section, concrete data and assumptions for the LCA selected, based on the target and investigation framework conditions, are shown. Furthermore, the processes presented in the balance area are explained, and the lifecycle data assigned. Existing data concerning the lifecycle of the lightweight packaging fraction was used for the calculations and assumptions [5]. For non-existent data regarding the material linear low-density polyethene (LLDPE), data for the material LDPE were used.

2.4.1. Raw Material Production

The processes of the primary material production of fossil PE and PP granules were modelled from the datasets "EU-28: Polyethylene Linear Low-Density Granulate (LLDPE/PE-LLD)" and "DE: Polypropylene granulate (PP) mix" of the balancing software GaBi. The transfer of the output flows of the processes to packaging production were modelled via a transport step. It was assumed that the entire amount of recyclate is used in the production in each scenario, and any gap between the provided amount of recyclate and the demand for input material in the production of new polymer films is filled with virgin material.

Scenario 4 considers a closed material loop. It has to be mentioned that this approach is currently unfeasible. As stated, current recycling processes need the implementation of virgin material to ensure the product's mechanical properties. The assumption of a closed material loop was taken to show the latent potential in the recycling of films regarding the reduction of GWP and ADPF and to emphasise the need for technological innovation.

In scenario 7, the current limits in producing polymer films from a feedstock partly consisting of recyclates are addressed. In this scenario, the current limitations of state-of-the-art production of polymer films govern the proportion of recyclates in the input and thus the percentage of waste which can enter the recycling process chain.

2.4.2. Packaging Producer

The packaging production was created as a unit process, including the data related to a specific process and lifecycle inventory (LCI) data. The fossil granulate flows from the production of raw materials, and the regranulate flows from the recycling process were recorded as input flows. The output flow included the produced plastic film fraction. Austrian waste flow consists of monolayer films mainly made of low-density PE or PP and multilayer films mainly made of combinations of PE/PP, PA/PP, PET/PA and polydimethylsiloxane (PDMS) [4]. The assumption of the material composition of mono- and multilayer films followed these findings, supported by the current materials used in the packaging sector. The composition of the material flow is shown in Table 2.

Table 2. Material composition of the plastic films under consideration and their share in the material flow [4].

	Material Composition		Share in the Material Flow
Monolayer Film	LDPE 100% by weight	/	76% by weight
Multilayer Film	LDPE 50% by weight	PP 50% by weight	24% by weight

The calculations determined the energy requirement for producing plastic films from granules. For this purpose, the data of the plant Walter Kunststoffe GmbH–Gunskirchen were used. The input consumption was calculated concerning the output as shown in Appendix C. The plant produces plastic films on large rolls from PE granules (regranulates), and 353 kWh/t OUTPUT electricity consumption was determined.

The 353 kWh were determined from the output masses and the resource consumption of a comparable, state-of-the-art plant.

The substitution of primary raw materials with recyclates can only be realised to a limited extent due to the material requirements for the manufactured products and the quality of the recyclates [13]. In the LCA, the possibility of a complete substitution of the fossil granules with sufficient regranulate input was assumed to represent the optimum, and any production waste was not considered. Additionally, the currently possible highest recycling quota has been researched and implemented in an additional scenario to assess the possible savings in GWP and ADPF attainable with current technology.

2.4.3. Trade and Consumer

The "Trade and consumer" process was added to complete the product life cycle of plastic films. It caused no substantial environmental impact or energy consumption.

2.4.4. Usage Phase

The use phase's modelling marked the product's transition to the packaging waste and caused no substantial environmental impact and energy consumption. The collection rate described the proportion of separately collected waste concerning the total waste collected. Around 69,000 t of plastic film waste with a surface area of under 1.5 m^2 (i.e., "small films") are collected in Austria per year [5]. Of this 69,000 t, around 52,000 t were collected separately. The ratio of these waste quantities was assumed as the collection rate in the SQ scenario. The coverage rates of scenarios 2, 3 and 4 were chosen to consider maximum coverage optimisation. In the 2025 or 2030 scenario, the necessary increase in the collection rate to achieve the recycling rates required by the EU packaging directive of 50% and 55%, respectively, was calculated and set accordingly. In Table 3, the modelled collection rates of the respective scenarios are listed.

Table 3. Collection rates of the LVP collection.

	Collection Rate [$t_{\text{waste collected separately}}/t_{\text{waste disposed of}}$]						
	Scenario 1 SQ	Scenario 2 IC	Scenario 3 IS	Scenario 4 CMC	Scenario 5 2025	Scenario 6 2030	Scenario 7 SOA
Plastic Films	75%	100%	100%	100%	90%	90%	80%

2.4.5. Collection/Shipment–Lightweight Packaging and Municipal Waste

The collection processes were modelled as unit processes to link the use phase, sorting, and incineration. The processes did not cause a difference in environmental pollution or energy consumption between the different scenarios evaluated.

2.4.6. Sorting

The sorting process separated the incoming waste stream into the desired target fractions, namely mono- and multilayer films. The sorting depth of scenario SQ was determined using system data from sorting systems from the report by Neubauer et al.

(2020). The residual fraction output masses were divided by the input masses of the sorting plants and converted into the sorting depth of the target fraction, see Appendix D. This calculation has been performed for both target fractions, namely the monolayer films and the multilayer films.

From data collected by van Eygen in 2018, as shown in Appendix E. This parameter could be included in the calculation by dividing the sorting output (17,391 t) and the sorting input (51,964 t) [5]. Data for the energy consumption of the film sorting have been taken from existing plants using standard technology such as NIR sorting to attain the target fraction. These plants can be adapted to sort films by implementing measurements in transflection to improve the spectral quality of films [4]. The sorting depth of scenario SQ was adopted unchanged in Scenario 1. In Scenario 2, the effects of a supposed 100% successful sorting of the monolayer films and simultaneous rejection of the multilayer films as a sorting residue for energy recovery were considered. An ideal sorting process was assumed for Scenario 4 to ensure the maximum impact of this ideal scenario to show the latent potential in the recycling of plastic films. The 2025 and 2030 scenarios included the necessary optimisation of the sorting depth, considering improvements in the collection rate and recycling yield. The modelled sorting depths of the target fractions are listed in Table 4.

Table 4. Modelled sorting depths of the target fractions for every scenario.

	$[t_{output\ target\ fraction}/t_{input}]$						
	Scenario 1 SQ	**Scenario 2 IC**	**Scenario 3 IS**	**Scenario 4 CMC**	**Scenario 5 2025**	**Scenario 6 2030**	**Scenario 7 SOA**
Monolayer Films	34%	34%	100%	100%	63.4%	67.9%	50%
Multilayer Films	34%	34%	0%	100%	63.4%	67.9%	50%

Annotation. The SQ's sorting depth calculation can be seen in Appendix D.

The increased mass of 2D waste processed is associated with additional emissions. These figures were determined by examining existing plants to determine their emission of CO_2 and their electricity consumption when processing a functional unit of lightweight packaging. These numbers were then included in the LCA and shown in Appendix D.

The necessary equipment for sorting the 2D fraction in the relevant plants would be similar to the existing aggregates. The necessary implementation of additional reflectors to enable measurement in transflection to improve the spectral quality of thin polymer films to a point where sorting with existing NIR sensors is possible, as stated by Koinig et al. in 2022, was not included in the calculation because they were deemed negligible to the overall consumption [4].

The necessary sorting resources can be determined based on the report from Neubauer et al. (2020), which mentions the operational data concerning consumption and input masses of sorting plants [16]. In addition, data from the literature were considered in calculating electricity and gas consumption. The results of the calculation from Appendix D are listed in Table 5.

Table 5. Resource consumption of the sorting.

Operating Resources	Consumption	Unit
Electricity	63.97	kWh/t_{INPUT}
Gas	1.49	kWh/t_{INPUT}

Annotation. The calculation of the resource consumption for the sorting can be seen in Appendix D. Note on the resource calculation of the "Saubermacher Dienstleistungs AG" sorting system in Appendix D.

The resource consumption of the "Saubermacher Dienstleistungs AG" sorting system showed a value of around 46,981 kWh/t_{INPUT} after calculating the input-related electricity consumption. This power consumption represented a 697-fold increase in consumption compared to the resource consumption of the other sorting systems. A comparison of the literature values of the report from Neubauer et al. (2020) revealed a dot-comma error as the source of the error. After considering this source of error, the power consumption could be determined with a value of 46.98 kWh/t_{INPUT}. This value was integrated into calculating the average power consumption.

2.4.7. Recycling

The recycling process uses the pre-sorted film fractions of the desired PE and PP regranulates. Scenarios SQ and Scenario 1 viewed the pre-sorted waste flow as a monolayer film fraction contaminated by multilayer films, and subsequently the multilayer films were separated in the separation process to create a clean monolayer fraction for the recycling process. The recycling yield of the total fraction (monolayer films including multilayer films) in scenario SQ was calculated from the data in the report from Neubauer et al. (2020) calculated in Appendix F and adopted for Scenario 1 [16]. In total a recycling yield of 73% was achieved for the complete film fraction with a recycling yield of 96% for the monolayer fraction.

For Scenario 2, a recycling yield of 100% for monolayer films in the recycling plants following the ejection of the multilayer fraction in the sorting process was presumed. No material utilisation of the multilayer fraction has been implemented in this scenario. A recycling yield of 100% for mono- and multilayer films was selected for Scenario 3 to depict the closed cycle of plastic films.

In the 2025 scenario, the recycling yield was raised by 20% from SQ. This raise is necessary to achieve the recycling rate of 50% stipulated by the EU packaging directive. The 2030 scenario expanded the recycling yield by 3% relative to 2025 to meet the 55% recycling rate target. The recycling yields, which were the basis for the scenarios, are shown in Table 6.

Table 6. Recycling yield of the target fraction depending on the scenarios.

	Recycling Yield [$t_{REGRANULATE}$/t_{INPUT}]						
	Scenario 1 SQ	**Scenario 2 IC**	**Scenario 3 IS**	**Scenario 4 CMC**	**Scenario 5 2025**	**Scenario 6 2030**	**Scenario 7 SOA**
Monolayer Films	73% (96%)	73% (96%)	100%	100%	87.6%	90%	75%
Multilayer Films	0%	0%	0%	100%	87.6%	90%	0%

Annotation. The SQ's recycling yield calculation can be found in Appendix F.

Based on findings by Neubauer et al. (2020), the necessary resources for the recycling processes regarding consumption and input masses of recycling plants were calculated [16]. In addition, data from the literature were considered in the calculation (see Appendix F) regarding electricity, diesel and water consumption. The necessary resources for recycling multilayer films were assumed to be equal to those of existing recycling plants for film. This was done because reliable data for specialised recycling operations for multilayer polymer packaging films have been unobtainable because no method to fully deconstruct multilayer film into pure recyclable polymers is currently employed in recycling schemes [8,17,18]. Based on the input mass, the determined consumption of resources is listed in Table 7.

Table 7. Resource consumption of the recycling process.

Operating Resources	Consumption	Unit
Electricity	629.83	kWh/t_{INPUT}
Diesel	12.41	kWh/t_{INPUT}
Water	2.25	m^3/t_{INPUT}

Annotation. The calculation of the resource consumption for recycling can be seen in Appendix F.

2.4.8. Energy Recovery: Waste Incineration Plant

Any leftovers from sorting and recycling were used for energy recovery via transport processes. The "EU-28: Plastic packaging in municipal waste incineration plant" (GaBi) dataset was used to model the energy recovery process. The energy recovered from the incineration process was used to substitute the necessary primary energy supply, and the resulting steam was not used (steam sink).

The dataset used represents treatment in a waste-to-energy plant with dry flue gas scrubbing and Selective Catalytic Reduction as NOx removal techniques. The energy balance of the combustion model reflects the average situation in the European Union and takes the heat input of the specific waste into account. Emissions are calculated based on transmission coefficients and initial waste compositions are representative of European plant data. The dataset includes all relevant process steps for thermal treatment and corresponding processes, such as the disposal of waste air treatment residues or metal recycling. The inventory is essentially based on industrial data and is supplemented by secondary data where necessary. The system is partially closed (open outlets of electricity and steam). The electricity and steam flows need to be connected and adjusted to local conditions in order for these credits to be considered. Credits for recovered metals are already included.

2.4.9. Energy Supply

Electrical Power: The power required in the individual process steps was mainly provided by primary energy sources (renewable/non-renewable). The composition of the energy sources in Austria and the environmental impact of electricity production was quantified by the “AT: Electricity grid mix” dataset and modelled as a process.

Natural Gas: The provision of the required amount of natural gas in the sorting process was represented by Thinkstep’s “Austria (AT): Natural gas mix” dataset and modelled as a process.

Diesel: The amount of fuel for transport and recycling processes was mapped by Thinkstep’s dataset “EU-28: Diesel mix at refinery” and modelled as a process.

2.4.10. Transport

Transport processes were integrated into the accounting information to show the flow of goods in the processes. A transport model was created to map the recycling of a product in Austria and determine the average transport distances (cf. Appendix G). For this purpose, the shortest distances between selected locations of the individual processes were determined and averaged using Google Maps, considering the motorway connection for trucks. The utilisation rates of the transport vehicles were taken from the data from Öko-Institut e.V. et al. (2016), adopted for known transport routes. Unknown degrees of utilisation were estimated by assuming an optimised transport of products, considering the given literature values for similar transport processes [19]. The assignment of the transport vehicles or the data records to the transport routes was made at our discretion. The determined transport data are listed in Table 8.

Table 8. Specific transport distances, utilisation rates and vehicles.

Fraction	Route	Vehicle	Workload [%]	Distance [km]
PE-GR/PP-GR	Basic material manufacturer → packaging producer	X [a]	90	293
W-C	Use phase → packaging waste collection	0 [b]	50	10
PW	Packaging waste collection → sorting	X	75	100
S-MO/S-ML	Sorting → recycling	X	83	156
W-S	Sorting → municipal waste incineration plant	X	90	87
W-R	Recycling → municipal waste incineration plant	X	75	95
W-NC	Use phase → municipal waste collection	0	50	10
MW	Municipal waste collection → municipal waste incineration plant	X	75	100
PE-RE/PP-RE	Recycling → packaging producer	X	90	104

[a] GLO: Truck trailer, Euro 0–6 mix, 34–40 t gross weight/27 t payload capacity (GaBi). [b] GLO: Truck, Euro 5, 14–20 t gross weight/11.4 t payload capacity (GaBi). Annotation. The determination of the transport model data can be seen in Appendix G.

2.5. Impact Assessment

The impact assessment was carried out using GaBi software, version 9.2.1.68 by Sphera Solutions GmbH (Leinfelden-Echerdingen, Germany). To calculate the selected environmental impacts in the target and scope of the investigation, the following assessment method and the following impact categories selected are detailed in the following.

2.6. Evaluation Method

Developed by the Centrum voor Mileukunde (CML), the CML 2001 method is an ecologically oriented information and decision-making tool for creating a life cycle assessment in accordance with DIN EN ISO 14040. CML 2001 quantifies the environmental impacts of the processes from the inventory analysis, links them to the selected impact categories and assigns them to the impact indicators, GWP and ADPF. The impact-oriented assessment method links the environmental impacts, considering the respective impact category over 100 years and includes the impact categories of climate change and resource consumption, which were chosen to compare the different scenarios.

2.6.1. Impact Category and Impact Indicators

The impact categories considered included climate change, with the impact indicator GWP, and resource consumption, with the impact indicator fossil abiotic resource depletion.

2.6.2. Impact Categories

In the following the impact categories considered in the course of the LCA are explained:

Global Warming Potential

The GWP effect parameter expresses the assessment of the intensification of the greenhouse effect. According to Frischknecht (2020), the GWP parameter considers the absorption coefficients for infrared thermal radiation, the residence time of the gases in the atmosphere and the expected emission development. The potential effects of 1 kg of greenhouse gas over 20 or 100 years compared to 1 kg of CO_2 are determined and converted into equivalent CO_2 emissions (kg CO_2-eq) and shown in Table 9 [10].

Table 9. GWP and temperature change potential (GTP) emission parameters [20] result from 1 kg CO2.

		GWP		GTP	
	Lifetime	**Cumulative Forcing over 20 Years**	**Cumulative Forcing over 100 Years**	**Temperature Change after 20 Years**	**Temperature Change after 100 Years**
CO_2		1	1	1	1
CH_4	12.4	84	28	67	4
N_2O	121	264	265	277	234
CF_4	50,000	4880	6630	5270	8040
HFC-152a	1.5	506	138	174	19

Abiotic Resource Depletion (ADP)

The ADP for fossil resources is expressed in MJ as the quantity of resources consumed relative to the resources depleted [21].

3. Results

3.1. Occurrence and Treatment of Plastic Waste in Austria

The amount of plastics produced in Europe in 2018 was around 62 million tons (t), around 17% of global plastics production [1]. The packaging industry played the leading role in the demand for plastics with 39.9%. The PP, PET and polyethene (PE), in particular, were leaders in this segment [1].

In 2018, around 29.1 million t of post-consumer plastic waste was collected in Europe, resulting in an increase in waste by 19% compared to 2006 with 24.5 million tons. In Figure 10, it can be seen that the post-consumer plastic waste generated in Europe in 2018 was 32.5% recycled, 42.6% energetically recovered and 24.9% landfilled [1].

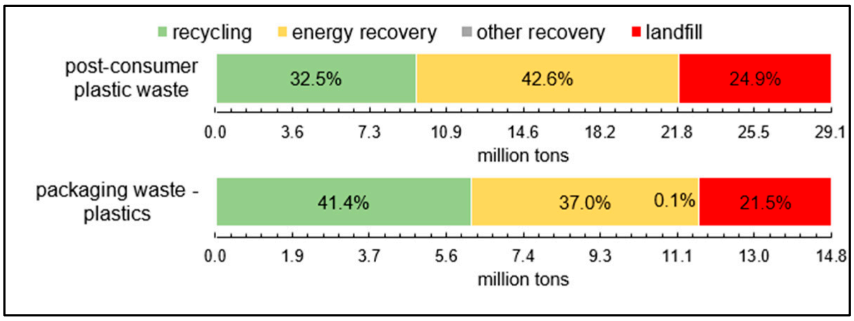

Figure 10. Treatment rates of post-consumer plastic waste and plastic packaging waste in the European Union 2018 [22].

In the EU in 2018, 41.4% of the collected plastic packaging waste was recycled, 21.5% landfilled, and 37.0% energetically recovered, as shown in Figure 8. Only 0.1% was used for other purposes. The recovery processes were depicted according to the Waste Framework Directive [22].

In 2019, 1.5 million tonnes of plastic waste were exported from the EU, and most of this plastic waste was shipped to Asia. The export volume to China was around 1.4 million tonnes of plastic waste in 2016, which fell to 14,000 tonnes in 2019 due to an import ban on certain types of waste [23].

The volume of plastic packaging waste in the European Union (EU27) grew to around 14.8 million t per year between 2009 and 2018, corresponding to a per capita volume of 33.2 kg/PE, as shown in Figure 11.

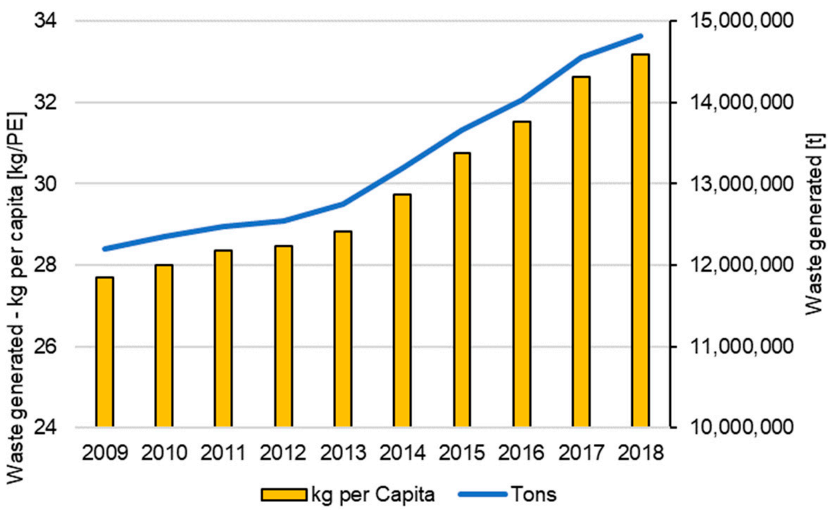

Figure 11. Plastic packaging—average waste generated in the EU from 2009 to 2018 [22].

In 2018, around 5 million tons of plastic recyclates (regenerates) were produced in Europe, and 80% of this flowed into European plastics production to create new products. With a share of 24% in recyclates, the packaging industry followed the construction industry with a share of 46% [24].

In 2018, Austria's primary plastic waste weighed around 0.95 million tonnes. Plastic waste is subdivided into sorted plastics, solid waste-containing plastic and a remainder. This remainder, which accounts for around 2% of the total waste, consists of plastics in paints and varnishes, plasticisers, and plastic sludge. About 18% was single-variety plastics, such as plastic foils, polyolefin waste and plastic containers, and around 80% was solid waste-containing plastic, such as bulky waste, old tyres, municipal waste and similar commercial waste. As can be seen in Figure 12, 26% of primary plastic waste was recycled in 2018, 72% was used to generate energy, and 2% was landfilled as part of other types of waste [25].

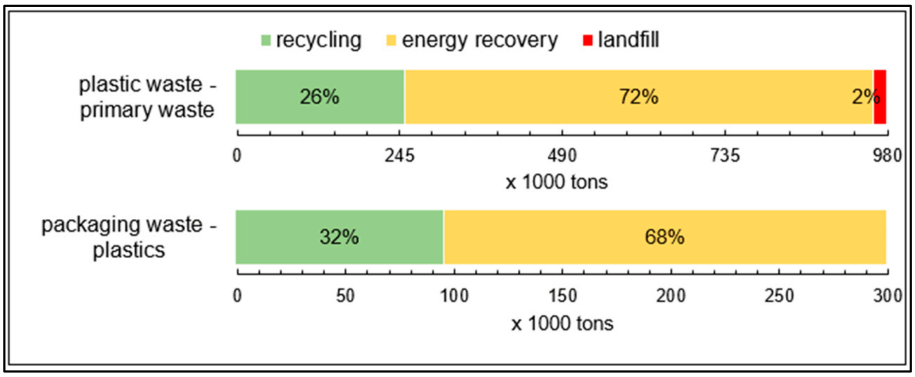

Figure 12. Treatment rates of primary plastic waste and plastic packaging waste in Austria in 2018, own illustration [22,25].

In 2018, Austria's volume of plastic packaging waste was approximately 34.2 kg per capita, totalling around 302,000 t. In 2018, 68% of the packaging waste was energetically recovered and 32% recycled, as apparent in Figure 12 [22].

According to van Eygen (2018), approximately 69,000 t of plastic foils were generated as waste in 2013. Around 52,000 t of plastic film waste were collected separately and sent to a sorting and processing process [5]. This result corresponds to a collection rate of around 75%. Roughly 17,000 t of pre-sorted plastic film waste were then sent to a recycling process, out of which roughly 12,000 t of regranulate were produced. Around 18% of all plastic film waste was mechanically recycled in 2013, and 82% was used in energy recovery [5].

3.2. Life Cycle Assessment

In Table 10, the impact assessment results using the CML 2001 assessment method are listed. The GWP and the ADPF of all evaluated scenarios are presented in Table 10. The deviations were given in the respective unit and the percentage deviation.

Table 10. Results and deviations of the impact assessment compared to the SQ.

Scenario	GWP			ADPF		
	Result	Deviation to SQ		Result	Deviation to SQ	
	[kg CO_2-eq]	[kg CO_2-eq]	[%]	[MJ]	[MJ]	[%]
Scenario 1 SQ	3237			54,769		
Scenario 2 IC	3027	−210	−6	50,978	−3790	−7
Scenario 3 IS	1191	−2046	−63	18,515	−36,253	−66
Scenario 4 CMC	335	−2902	−90	3703	−51,066	−93
Scenario 5 2025	2124	−1113	−34	35,185	−19,584	−36
Scenario 6 2030	1944	−1293	−40	32,028	−22,741	−42
Scenario 7 SOA	2840	−397	−34	35,185	−19	

As shown in Table 10, Scenario 1 causes a GWP of 3027 kg CO_2-eq and an ADPF of 50,978 MJ.

The change in collection results in a reduction of 210 kg CO_2-eq from SQ, which equals roughly 6%. Simultaneously the ADPF was reduced by 3790 MJ, or 7%.

The graphical representations of the results, including the individual process effects, are shown in Figure 13. In addition to the overall impact, six individual process impacts were plotted. The individual process effects were chosen following their most considerable contribution to the overall effect of the SQ scenario. The group "rest" of the GWP, in Figure 13, includes the total effects of the individual processes, such as transport processes and primary energy sources, which are not shown due to their low GWP. The group "rest" of the ADPF, in Figure 14, includes the total effects of the individual processes not shown due to their low ADPF, such as transport processes and individual waste incineration processes.

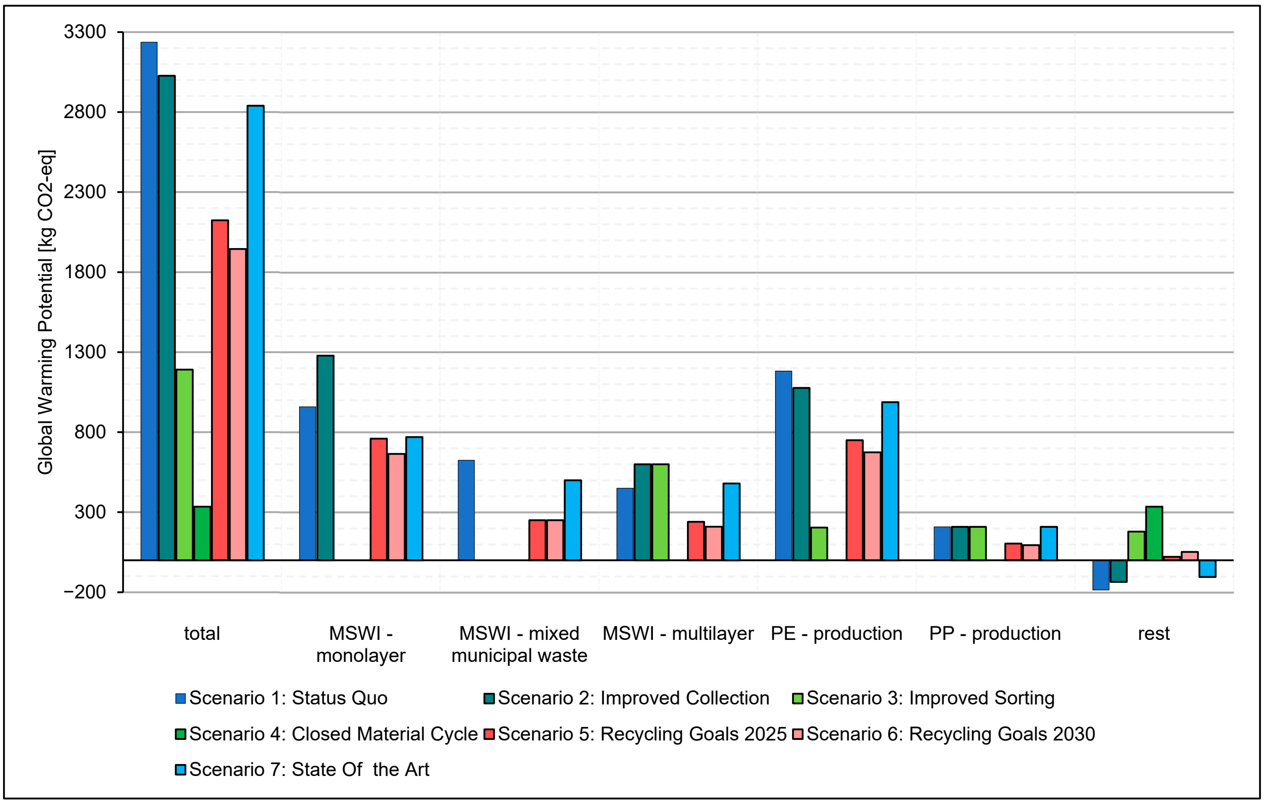

Figure 13. GWP of the individual processes over the product lifecycle. Mixed Solid Waste Incineration.

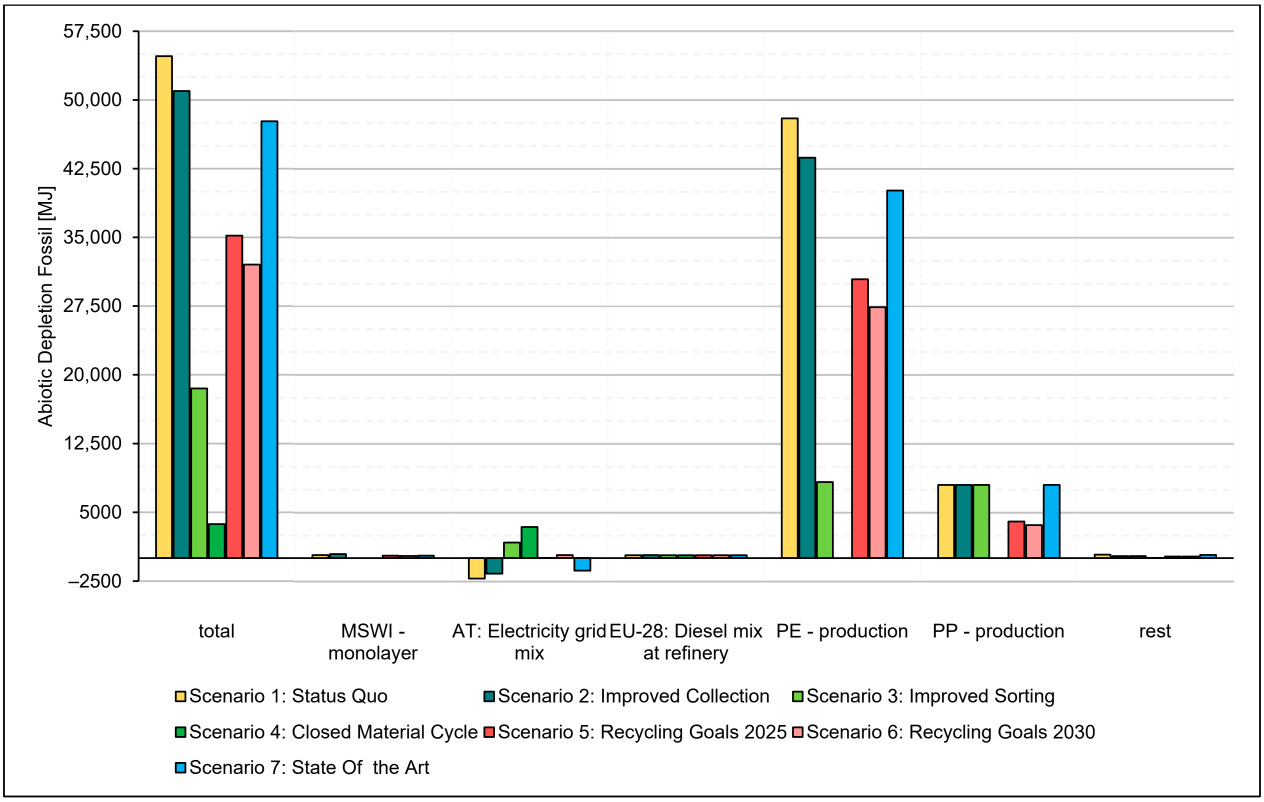

Figure 14. ADPF of the individual processes over the product lifecycle.

Note the reduction in GWP in the SQ scenario and Scenario 2 due to the "rest" group processes. This reduction mainly includes the effects of the substitute energy supply through the combustion processes concerning the primary energy supply.

The production of PE and the incineration of mixed solid waste (MSWI) and packaging films are the most significant contributors to the GWP. These are substantially reduced by implementing a recycling scheme for polymer films, as shown in Figure 13. The production of virgin PE and PP in Scenario 3 yields no emission because recycled polymers substitute virgin materials in this ideal scenario. The increased demands for fuels by sorting and transportation of the increased recycling materials yields a minuscule amount of GWP and is not shown as a unique bar in the Figure 13.

3.2.1. Global Warming Potential

Figure 15 shows the results of the GWP and the deviations from the SQ scenario and the 2025 scenario. For Scenario 2, with a GWP of 3027 kg CO_2-eq, a reduction of 6% compared to the SQ can be seen.

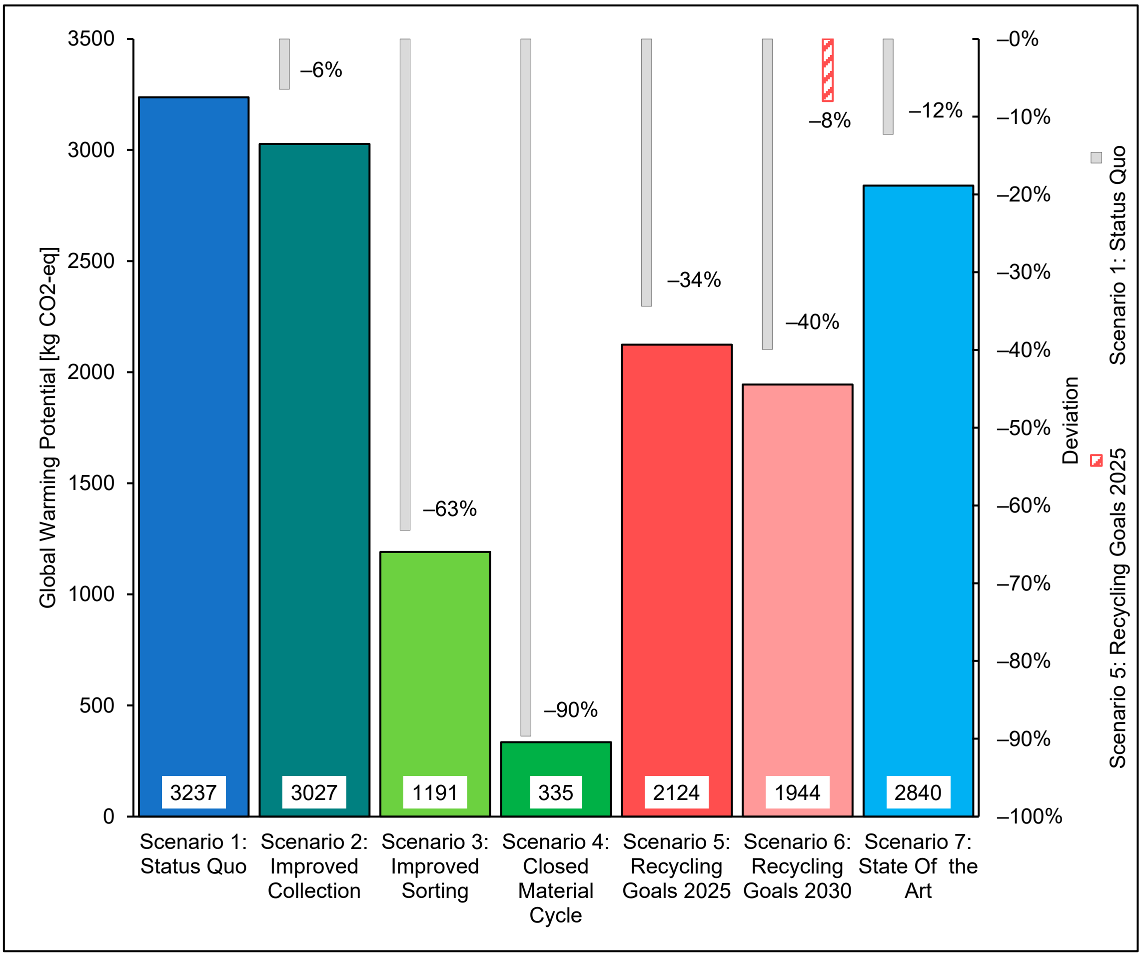

Figure 15. Global warming potential (GWP)–scenario overview.

Comparing the GWP of the scenarios shows that the SQ of plastics recycling causes the most significant environmental impact. The product lifecycle of 1000 kg of plastic films, consisting of mono- and multilayer films, causes a GWP of 3237 kg CO_2-eq in scenario SQ. The driving processes are the PE production and the waste incineration of the monolayer films, followed by the incineration of the municipal waste.

The GWP in Scenario 2 was decreased by 6% relative to the SQ. This reduction in GWP is due to an improved collection rate and amounted to an absolute reduction of 3027 kg CO_2-eq when compared to the GWP of the SQ.

The increased mass accumulation of waste to be sorted and recycled is reflected in a reduction in the impact of PE production and the increase in the contribution of monolayer film waste incineration to the GWP. The incineration of municipal waste is removed from the balance due to the separate collection of the plastic foils.

Scenario 3 shows that recycling the monolayer films reduces the GWP by 63%, from the GWP of the SQ to 1191 kg CO_2-eq This reduction is due to the exclusion of waste incineration of monolayer films and the reduced production volume of PE due to the increased amount of regranulate. The waste incineration process of the multilayer films is the primary source of emissions of greenhouse gases.

Scenario 4 has the lowest GWP and is the ecologically best scenario variant. Due to the simulated recycling of all plastic films, the GWP is 90% lower than the SQ, at 335 kg CO_2-eq per 1000 kg produced plastic foils. This reduction is achieved by substituting regranulates for all primary virgin materials used in packaging production, generating a closed material cycle. This substitution eliminates the need to produce virgin materials and, thus, reduces the production-related effects to zero. The optimisation of the collection rate, sorting depth and recycling yield eliminates the need for incineration. In Scenario 4, primary energy becomes the predominant emission source for the GWP.

The optimisations considered in Scenario 2025, the collection rate, sorting depth and recycling yield, lead to a reduction of the greenhouse potential by 34%, to the SQ, to 2124 kg CO_2-eq, as can be seen in Figure 15.

The 2030 scenario is an extension of the 2025 scenario. As a result, a prescribed recycling rate of 55% by 2030 reduces the GWP by 40% to 1944 kg CO_2-eq compared to the SQ. The prescribed increase in the recycling rate to 55% leads to a reduction of the GWP by 8%. This reduction is caused by the further reduction of process emissions by 2030.

3.2.2. Abiotic Resource Depletion Fossil

The SQ scenario maps the maximum ADPF with a value of 54,769 MJ. This value is taken as the benchmark all other scenarios will be compared against. The predominant consumption of fossil resources in the SQ occurs through the production process of PE. Compared to the SQ, Scenario 2 shows an ADPF of 50,978 MJ, which results in a 7% reduction relative to the SQ. This reduction of ADPF in Scenario 2 is due to the increased collection rate. This increased collection rate allows for increased substitution of virgin primary plastic granules with regranulates, reducing resource consumption for the production of virgin polymers.

The improved recycling of the monolayer foils considered in Scenario 3 reduces the ADPF by 66%, to the SQ, to 18,515 MJ. This recycling and the resulting increase in PE regranulate leads to a noteworthy reduction in the consumption of resources in virgin PE production. Consequently, the resource consumption of Scenario 3 is dominated by the necessary consumption for the manufacture of multilayer films. The production of multilayer films replaces the production of monolayer films as the predominant source of resource consumption because the produced regranulates reduce the necessary production volume for monolayer films.

Scenario 3 shows that the ADPF can be reduced by 93% to 3703 MJ by recycling the mono- and multilayer films. As a result of substituting virgin plastic granules from PE and PP production with regranulates from the recycling process, this consumption of resources is reduced to zero. The consumption of 3703 MJ of resources is based almost entirely on the provision of energy.

Scenario 2025 shows that optimising the waste processing procedures and the collection operation to a point where the mandated recycling quota is met leads to a reduction of the ADPF of 36% to the SQ.

Meeting the required 50% recycling rate for plastic packaging waste by 2025 in the recycling of films results in the consumption of fossil resources of 35,185 MJ. In the 2025 scenario, the PE production process causes substantial resource consumption, followed by the PP production process.

As a result of adhering to the stipulated recycling rate of 55% by 2030, the 2030 scenario shows reduced ADPF to SQ by 42%, resulting in a consumption of 32,028 MJ. Increasing the recycling rate to 55% leads to a reduction of the ADPF by around 9% from 2025 to 2030. This reduction is caused by the further reduction in the process consumption of fossil granulate production by 2030 compared to the 2025 scenario.

Figure 16 shows the abiotic resource depletion of the individual scenarios and the deviations from the SQ scenario.

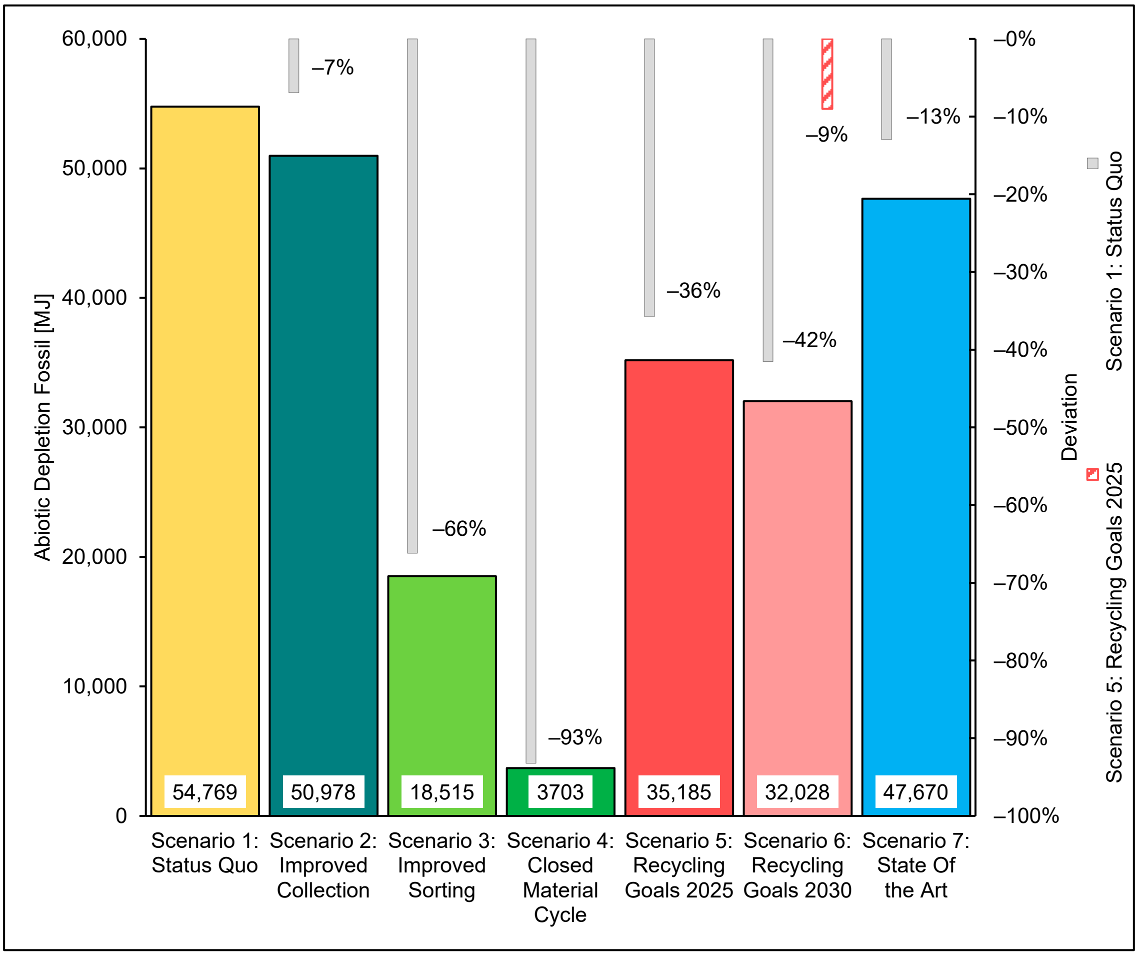

Figure 16. Abiotic Resource Depletion ADPF—Scenarios Overview.

4. Conclusions

An LCA allows for the investigation and quantification of environmental changes under changed process parameters. The LCA presented in this work determined the resulting environmental impacts of monolayer and multilayer films during their lifecycle on GWP and ADPF. For this purpose, based on the SQ, scenarios with changed parameters regarding the collection rate, sorting depth and recycling yield were created and evaluated. Finally, scenarios for evaluating the necessary improvements in the waste recycling processes to achieve the statutory recycling rate targets were examined, and the environmental impacts were considered. A "functional unit" of 1000 kg of plastic film waste, generated as post-consumer waste in Austria and recorded in the light packaging collection's collection and recycling system, was selected.

The results of the LCA showed the general trend toward reducing environmental impacts by optimising collection, sorting and recycling. The GWP of the SQ was 3237 kg CO_2-eq. This SQ was used as the basis for comparing the other scenarios. Furthermore, the ADPF in the SQ was determined to be 54,769 MJ. Increasing the collection rate for the separate collection of plastic foils in Scenario 2 reduced the GWP by 6% to 3027 kg

CO_2-eq and the ADPF by 7% to 50,978 MJ. Substantial improvements were achieved by recycling monolayer films made possible by the ejection of multilayer films from the material recycling process. Considering this, recycling in Scenario 3 led to a reduction of the GWP by 63% or 2,046 kg CO_2-eq to 1191 kg CO_2-eq and the ADPF by 66% or 36,253 MJ to 18,515 MJ. The ecologically best result was achieved by the closed cycle management of monolayer and multilayer films. Based on the SQ, the GWP could be reduced by 90% or 2902 kg CO_2-eq to 335 kg CO_2-eq. The ADPF fell by 93% or 51,066 MJ to 3703 MJ. The transition from the SQ to the circular economy caused a shift in the emission-relevant processes of the greenhouse potential from production or combustion to energy supply. Given the politically stipulated recycling rate for packaging plastics of 50% by 2025 and 55% by 2030, optimisations should be sought in all areas of waste management. The sorting depth was identified as the most influential parameter. Increasing collection rate and recycling yield by 20% demands a surge in sorting depth from 34% to 63.4%. These optimisations in the 2025 scenario reduced the GWP by 1113 kg CO_2-eq or 34% to 2124 kg CO_2-eq and the ADPF by 19,584 MJ or 36% to 35,185 MJ.

A recycling rate of 55% by 2030 requires improving the collection rate by 20% and the recycling yield by around 23% based on the SQ. This increase means doubling the sorting depth from 34% to around 68%.

Comparing the 2030 scenario to the SQ scenario showed that these improvements reduced the GWP or ADP by around 40% to 1944 kg of CO_2-eq or 42% to 32,028 MJ. The reductions in environmental impact caused by increasing the recycling rate to 55% from 2025 to 2030 could be achieved with 180 kg of CO_2-eq or 3157 MJ can be determined.

The LCA showed that improvements in improved sorting and increased recycling of mono- and multilayer films are desirable and necessary. In addition to the political and social efforts to transform waste management into a circular economy, the strive to provide renewable energy sources should be intensified. This approach would conserve primary resources and facilitate the transition to a circular economy.

Author Contributions: Conceptualization, G.K., E.G. and K.F.; Data curation, G.K. and E.G.; Formal analysis, G.K., C.B., K.F. and D.V.; Investigation, G.K. and E.G.; Methodology, G.K. and E.G.; Project administration, G.K., C.B., G.O. and D.V.; Supervision, G.K., C.B., K.F., G.O. and D.V.; Validation, E.G.; Visualization, E.G.; Writing—original draft, G.K. and E.G.; Writing—review & editing, G.K., E.G., C.B., K.F., G.O. and D.V. All authors have read and agreed to the published version of the manuscript.

Funding: This work was funded by the province of Styria and Zukunftsfonds Steiermark for the project "Multilayer Detection" (project number 1314).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

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.

Appendix A

Appendix A shows the product life cycle as balanced in GaBi. Production, transportation, packaging, usage and incineration are depicted.

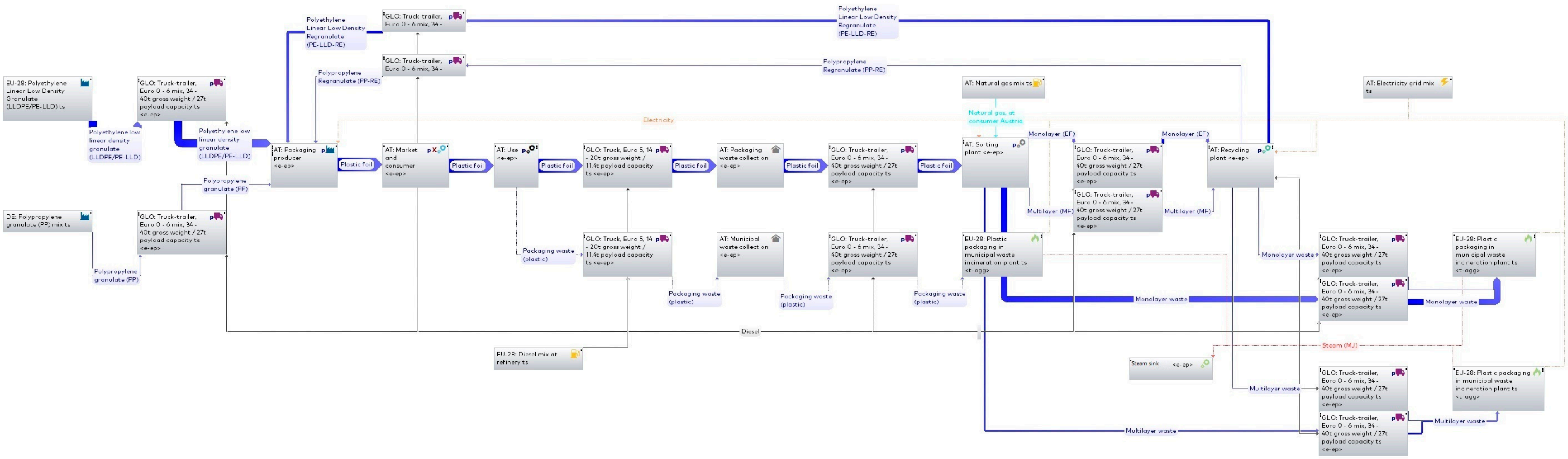

Figure A1. Balanced Life Cycle using GaBi.

Appendix B Complete Substance Flows of the Scenarios

Appendix B shows all material flows for all scnearios. In the manuscript a zoomed in version of the figures shown was depicted for a better view of the changed parts. In this appendix the complete pictures are shown.

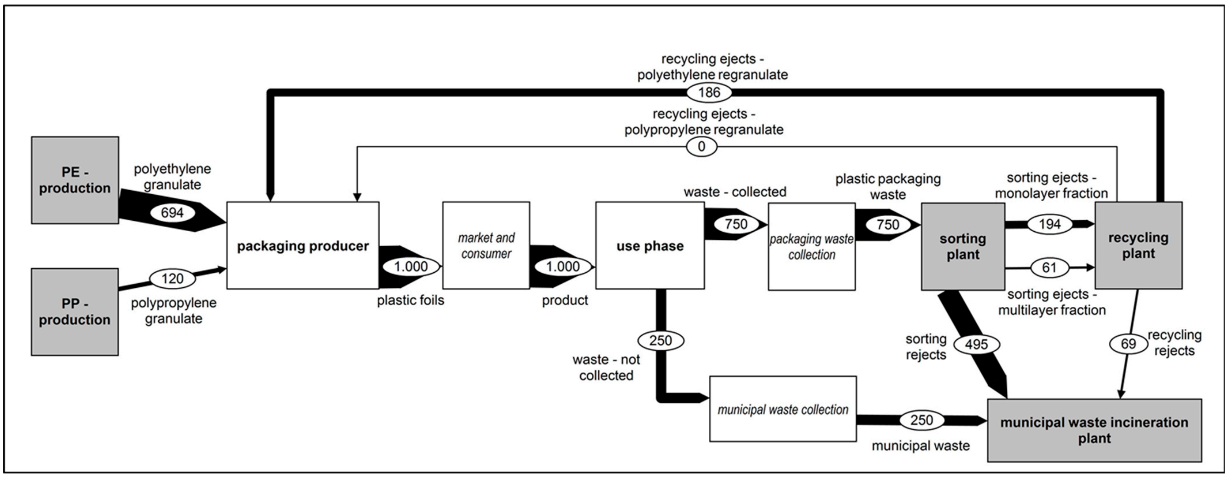

Figure A2. Material flows—Scenario 1—Status Quo.

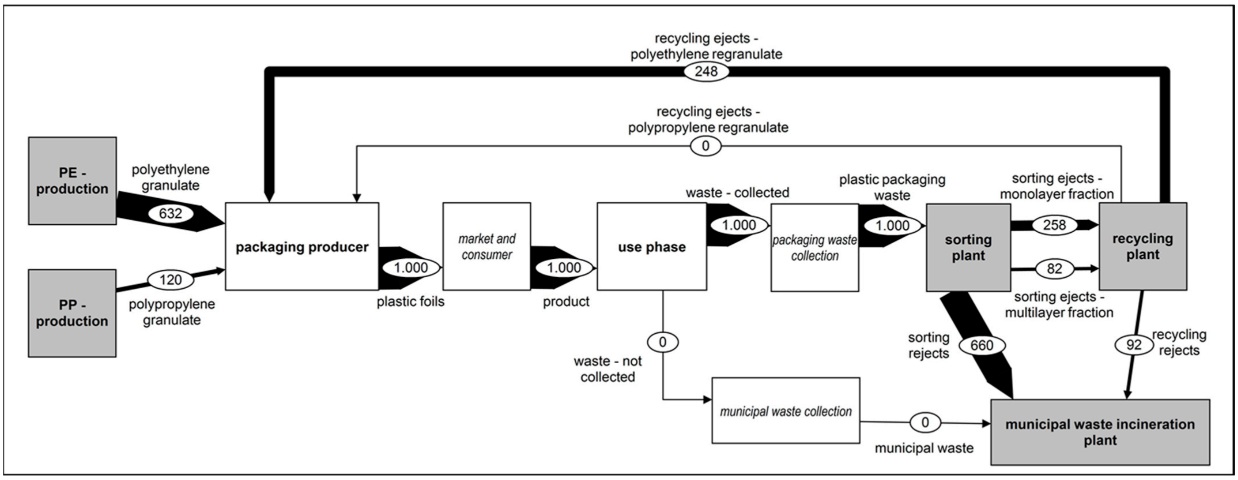

Figure A3. Material flows—Scenario 2—Improved Collection.

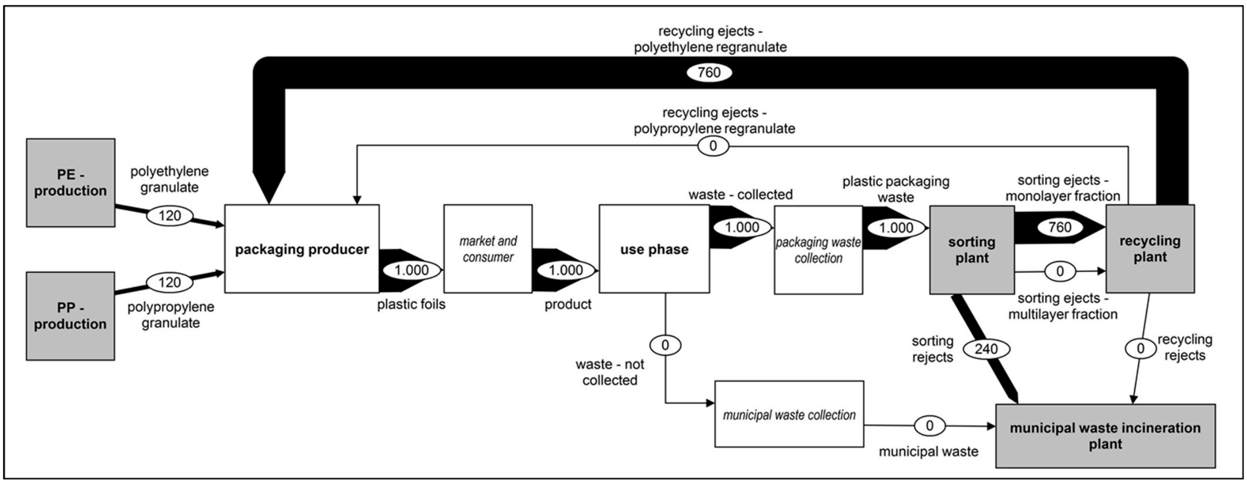

Figure A4. Material flows—Scenario 3—Improved Sorting.

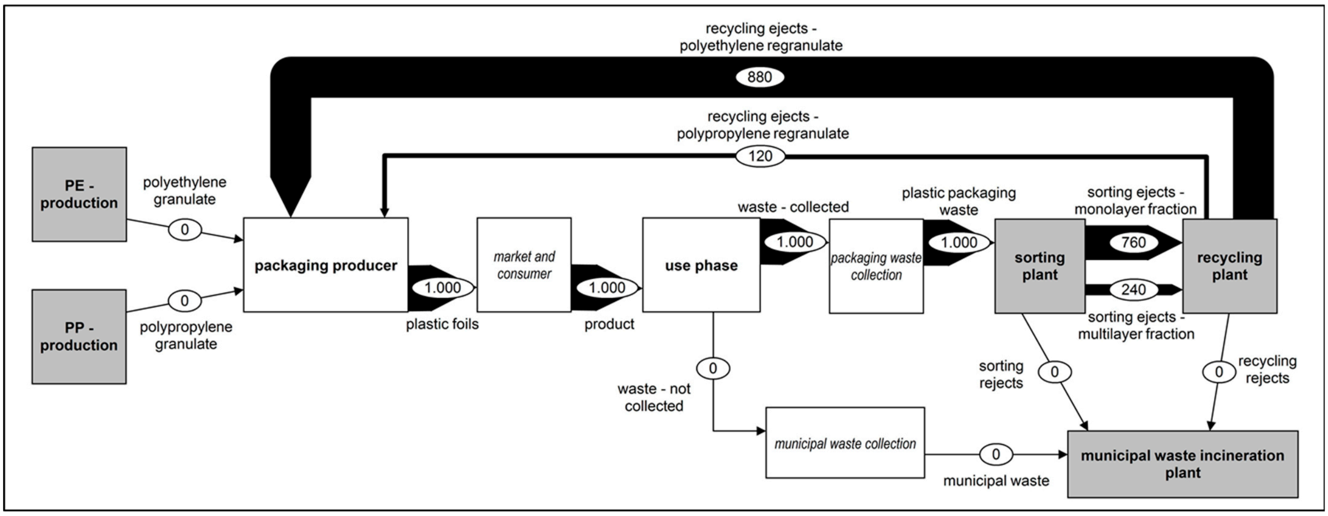

Figure A5. Material flows—Scenario 4—Closed Material Cycle.

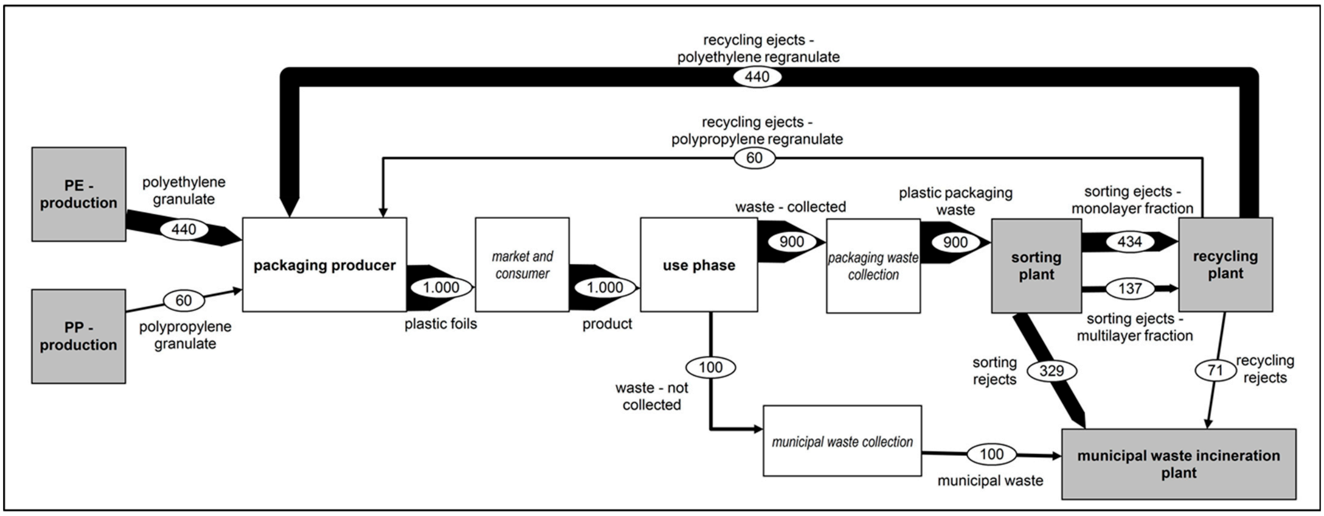

Figure A6. Material flows—Scenario 5—Recycling Goals 2025.

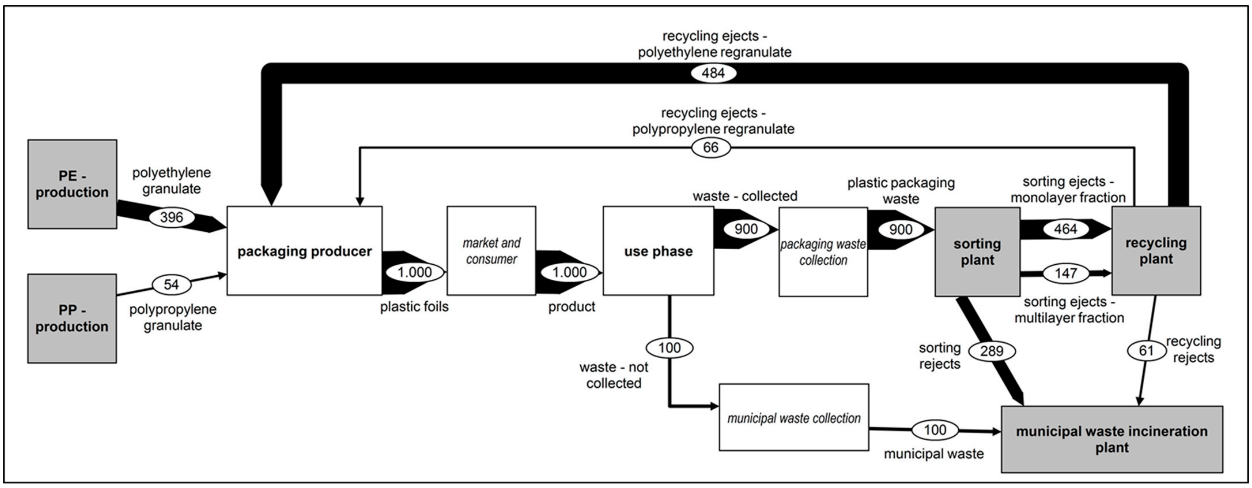

Figure A7. Material flows—Scenario 6—Recycling Goals 2030.

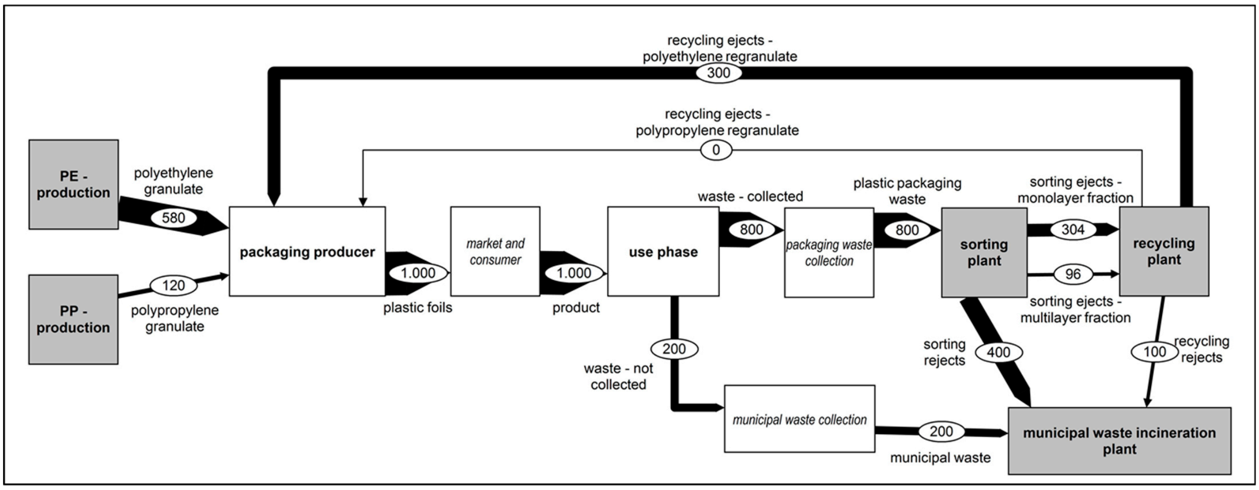

Figure A8. Material flows—Scenario 7—State Of the Art.

Appendix C

In Appendix C the input consumption concerning the output for the calculations is depicted.

Table A1. Production data of the film manufacturing process as a data basis for packaging production [16].

Walter Kunststoffe GmbH—Gunskirchen					
			Mass [t/a]		
	Input Granulate	**Input Regranulate**	**Input—Other Raw Materials, Operating Supplies**	**Input—in Total**	**Output**
2016	2500	5000	8600	16,100	16,085
2017	3000	6500	10,125	19,625	17,910
2018	3000	6500	10,125	19,625	20,110
			Operating Resources (OR)		
		Electricity [kWh]			
2016		6,000,000			
2017		6,500,000			
2018		6,500,000			
OR/t-output 2016		373			
OR/t-output 2017		363			
OR/t-output 2018		323			
OR/t-output average		**353**	**[kWh/t]**		
		1.27	**[MJ/kg]**		

Appendix D

Appendix D shows the input, output fractions and output residual fractions of the plants which were the basis for the calculations.

Table A2. Data collection and calculation of the relevant sorting process parameters [5,16,19,26].

Saubermacher Dienstleistungen—AG				
		Mass [t/a]		
	Input	**Output Target Fraction—LDPE**	**Output Target Fraction**	**Output Residual Fraction**
2016	27,660	3250	8309	19,321
2017	30,360	3260	10,576	19,797
2018	28,820	3720	11,017	17,908
		Operating Resources (OR)		
	Electricity [kWh]	**Electricity [kWh]**	**Gas [kWh]**	**Water [m^3]**
2018	1,354,000,000	1,354,000	7459	
OR/t-input	46,981	46.98	0.26	
Brantner Sort4you GmbH				
		Mass [t/a]		
	Input	**Output Target Fraction—Plastic Films**	**Output Target Fraction**	**Output Residual Fraction**
2016	16,683	972	6788	10,579
2017	18,388	1044	7380	10,626
2018	18,734	1179	6795	12,390
		Operating Resources (OR)		
		Electricity [kWh]	**Gas [kWh]**	**Water [m^3]**
2018		2,004,000		
OR/t-input		106.97		
Tiroler Recycling GmbH & Co KG				
		Mass [t/a]		
	Input	**Output Target Fraction—Plastic Films**	**Output Target Fraction**	**Output Residual Fraction**
2016	19,800	1827	7260	12,989
2017	21,420	1841	6937	14,460
2018	23,404	1805	6991	15,415
		Operating Resources (OR)		
		Electricity [kWh]	**Gas [kWh]**	**Water [m^3]**
2018		1,180,000	63,830	
OR/t-input		50.42	2.73	
Energie AG Oberösterreich Umwelt Service GmbH				
		Mass [t/a]		
	Input	**Output Target Fraction—Plastic Films**	**Output Target Fraction**	**Output Residual Fraction**
2016	20,529	1774	7105	13,424
2017	18,829	1535	7118	11,711
2018	24,088	1607	7968	16,120
		Operating Resources (OR)		
		Electricity [kWh]	**Gas [kWh]**	**Water [m^3]**
2018		1,560,000		
OR/t-input		64.76		
Öko-Institut e.V.				

Table A2. *Cont.*

Saubermacher Dienstleistungs—AG				
		Mass [t/a]		
	Input	Output Target Fraction—LDPE	Output Target Fraction	Output Residual Fraction
			Operating Resources (OR)	
		Electricity [kWh]	Gas [kWh]	Water [m^3]
OR/t-input		50		
Emile Van Eygen				
		Operating Resources (OR)		
		Electricity [kWh]	Gas [kWh]	Water [m^3]
OR/t-input		64.7		
Resource averages—input related				
Electricity	**63.97**	**[kWh/t]**	**0.23**	**[MJ/kg]**
Gas	**1.49**	**[kWh/t]**	**0.11**	**[g/kg]**

Table A3. Data collection and calculation of the sorting depth [5,16,19,26].

Sorting Depth—Residual Fraction (Output Residual Fraction/Input)				Average
	2016	**2017**	**2018**	
Saubermacher Dienstleistungs—AG	70%	65%	62%	66%
Brantner Sort4you Gmbh	63%	58%	66%	62%
Tiroler Recycling GmbH & Co KG	66%	68%	66%	66%
Energie AG Oberösterreich Umwelt Service GmbH	65%	62%	67%	65%
Sorting Depth—Residual Fraction				**65%**
Sorting Depth—Target fraction	**35%**			
Van Eygen, 2018	33%			
Average—Target fraction	**34%**			

Appendix E

Appendix E shows the mass flow analysis conducted by Van Eygen in 2018 in detail.

Table A4. Excerpt of the mass flow analysis results [5].

		PET Bottles		Hollow Bodies Small					Hollow Bodies Large			Films Small			
		Total Mass (t)	PET Mass (t)	**Total Mass (t)**	HDPE Mass (t)	PP Mass (t)	PS Mass (t)	PVC Mass (t)	**Total Mass (t)**	HDPE Mass (t)	PP Mass (t)	**Total Mass (t)**	LDPE Mass (t)	LLDPE Mass (t)	PVC Mass (t)
F1.01	PET Bottles	**45,487**	45,487	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F1.02	Hollow Bodies Small	**0**	0	**49,176**	14,064	26,948	8094	70	**0**	0	0	**0**	0	0	0
F1.03	Hollow Bodies Large	**0**	0	**0**	0	0	0	0	**18,308**	8262	10,046	**0**	0	0	0
F1.04	Films Small	**0**	0	**0**	0	0	0	0	**0**	0	0	**69,428**	65,001	4384	43
F1.05	Films Large	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F1.06	EPS Large	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F1.07	Others	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F2.01	Separately Collected Waste	**29,557**	29,557	**22,239**	6414	12,280	3513	32	**7853**	3544	4309	**51,964**	49,495	2437	32
F2.02	Municipal Solid Waste	**14,884**	14,884	**24,390**	6938	13,302	4116	34	**6505**	2935	3569	**16,413**	14,573	1830	10
F2.03	Bulky/Commercial Waste	**1046**	1046	**2546**	711	1366	466	3	**3950**	1782	2167	**1051**	934	117	1
F3.01	Sorted Plastics (Food-Grade)	**20,151**	20,151	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.02	Sorted Plastics	**4291**	4291	**10,356**	4317	4740	1299	0	**5738**	3235	2504	**17,391**	16,877	514	0
F3.03	Mixed Plastics	**52**	52	**121**	21	77	23	0	**22**	3	18	**353**	333	20	0
F3.04	Mixed Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.05	Medium Calorific	**445**	445	**1033**	182	655	192	3	**184**	27	157	**3005**	2835	167	3
F3.06	Sorting Residues	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.07	High Calorific	**4619**	4619	**10,729**	1893	6808	1999	29	**1909**	279	1630	**31,214**	29,449	1736	29
F3.08	WtE MSW	**12,503**	12,503	**20,487**	5828	11,173	3457	29	**5464**	2466	2998	**13,787**	12,241	1537	9
F3.09	WtE B/C	**537**	537	**1308**	365	702	239	2	**2028**	915	1113	**540**	479	60	0
F3.10	MP MSW	**2381**	2381	**3902**	1110	2128	659	6	**1041**	470	571	**2626**	2332	293	2
F3.11	WtE MSW	**509**	509	**1239**	346	665	226	2	**1922**	867	1055	**512**	454	57	0
F3.12	Sorted Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.13	Mixed Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.14	Mixed Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.15	Medium Calorific	**1949**	1949	**3468**	982	1884	597	5	**1998**	902	1096	**2116**	1879	236	1
F3.16	High Calorific	**796**	796	**1416**	401	769	244	2	**816**	368	448	**864**	767	96	1
F3.17	Residues	**145**	145	**257**	73	140	44	0	**148**	67	81	**157**	139	17	0
F4.01	Food-Grade Re-Granulate	**9351**	9351	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F4.02	Re-Granulate	**11,002**	11,002	**8892**	4001	3839	1052	0	**5026**	2998	2028	**12,422**	12,055	367	0
F4.03	Mixed Re-Granulate	**42**	42	**97**	17	62	18	0	**17**	3	15	**283**	267	16	0
F4.04	Residues	**4096**	4096	**1488**	320	916	251	0	**717**	237	479	**5040**	4889	151	0
F4.05	Off Gas	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F4.06	Slag	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F4.07	Off Gas	**15,049**	15,049	**25,944**	7266	14,230	4412	36	**9552**	4256	5296	**19,204**	17,216	1975	12
F4.08	Residues	**384**	384	**351**	92	184	73	2	**123**	54	69	**244**	218	25	1
F4.09	Off Gas	**9274**	9274	**13,449**	2582	8385	2453	29	**3399**	874	2525	**36,652**	34,666	1958	28
F4.10	In Product	**237**	237	**184**	33	109	41	2	**44**	11	33	**466**	440	25	1

Table A4. *Cont.*

		PET Bottles		**Hollow Bodies Small**					**Hollow Bodies Large**			**Films Small**			
		PET Bottles		**Hollow Bodies Small**					**Hollow Bodies Large**			**Films Small**			
		Total Mass (t)	PET Mass (t)	**Total Mass (t)**	HDPE Mass (t)	PP Mass (t)	PS Mass (t)	PVC Mass (t)	**Total Mass (t)**	HDPE Mass (t)	PP Mass (t)	**Total Mass (t)**	LDPE Mass (t)	LLDPE Mass (t)	PVC Mass (t)
F1.01	PET Bottles	**45,487**	45,487	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F1.02	Hollow Bodies Small	**0**	0	**49,176**	14,064	26,948	8094	70	**0**	0	0	**0**	0	0	0
F1.03	Hollow Bodies Large	**0**	0	**0**	0	0	0	0	**18,308**	8262	10,046	**0**	0	0	0
F1.04	Films Small	**0**	0	**0**	0	0	0	0	**0**	0	0	**69,428**	65,001	4384	43
F1.05	Films Large	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F1.06	EPS Large	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F1.07	Others	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F2.01	Separately Collected Waste	**29,557**	29,557	**22,239**	6414	12,280	3513	32	**7853**	3544	4309	**51,964**	49,495	2437	32
F2.02	Municipal Solid Waste	**14,884**	14,884	**24,390**	6938	13,302	4116	34	**6505**	2935	3569	**16,413**	14,573	1830	10
F2.03	Bulky/Commercial Waste	**1046**	1046	**2546**	711	1366	466	3	**3950**	1782	2167	**1051**	934	117	1
F3.01	Sorted Plastics (Food-Grade)	**20,151**	20,151	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.02	Sorted Plastics	**4291**	4291	**10,356**	4317	4740	1299	0	**5738**	3235	2504	**17,391**	16,877	514	0
F3.03	Mixed Plastics	**52**	52	**121**	21	77	23	0	**22**	3	18	**353**	333	20	0
F3.04	Mixed Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.05	Medium Calorific	**445**	445	**1033**	182	655	192	3	**184**	27	157	**3005**	2835	167	3
F3.06	Sorting Residues	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.07	High Calorific	**4619**	4619	**10,729**	1893	6808	1999	29	**1909**	279	1630	**31,214**	29,449	1736	29
F3.08	WtE MSW	**12,503**	12,503	**20,487**	5828	11,173	3457	29	**5464**	2466	2998	**13,787**	12,241	1537	9
F3.09	WtE B/C	**537**	537	**1308**	365	702	239	2	**2028**	915	1113	**540**	479	60	0
F3.10	MP MSW	**2381**	2381	**3902**	1110	2128	659	6	**1041**	470	571	**2626**	2332	293	2
F3.11	WtE MSW	**509**	509	**1239**	346	665	226	2	**1922**	867	1055	**512**	454	57	0
F3.12	Sorted Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.13	Mixed Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.14	Mixed Plastics	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F3.15	Medium Calorific	**1949**	1949	**3468**	982	1884	597	5	**1998**	902	1096	**2116**	1879	236	1
F3.16	High Calorific	**796**	796	**1416**	401	769	244	2	**816**	368	448	**864**	767	96	1
F3.17	Residues	**145**	145	**257**	73	140	44	0	**148**	67	81	**157**	139	17	0
F4.01	Food-Grade Re-Granulate	**9351**	9351	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F4.02	Re-Granulate	**11,002**	11,002	**8892**	4001	3839	1052	0	**5026**	2998	2028	**12,422**	12,055	367	0
F4.03	Mixed Re-Granulate	**42**	42	**97**	17	62	18	0	**17**	3	15	**283**	267	16	0
F4.04	Residues	**4096**	4096	**1488**	320	916	251	0	**717**	237	479	**5040**	4889	151	0
F4.05	Off Gas	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F4.06	Slag	**0**	0	**0**	0	0	0	0	**0**	0	0	**0**	0	0	0
F4.07	Off Gas	**15,049**	15,049	**25,944**	7266	14,230	4412	36	**9552**	4256	5296	**19,204**	17,216	1975	12
F4.08	Residues	**384**	384	**351**	92	184	73	2	**123**	54	69	**244**	218	25	1
F4.09	Off Gas	**9274**	9274	**13,449**	2582	8385	2453	29	**3399**	874	2525	**36,652**	34,666	1958	28
F4.10	In Product	**237**	237	**184**	33	109	41	2	**44**	11	33	**466**	440	25	1

Appendix F

Appendix F shows the Input and Output values researched in the report from Neubauer et al. from 2020. Here the input and output values from the evaluated plants are shown in the respective tables.

Table A5. Data collection and calculation of the relevant recycling process parameters [5,16,19].

Walter Kunststoffe GmbH—Wels				
		Mass [t/a]		
	Input	**Input Plastic Films**	**Output Granulate**	**Output**
2016	22,400	20,500	15,000	22,000
2017	23,600	22,000	16,000	23,000
2018	25,200	23,500	18,000	24,500
		Operating Resources (OR)		
		Electricity [kWh]	**Diesel [kWh]**	**Water [m^3]**
2016		14,611,000	414,000	40,416
2017		18,270,000	426,000	40,669
OR/t-input 2016		652.28	18.48	1.80
OR/t-input 2017		774.15	18.05	1.72
OR/t-input plastic films 2016		596.95	16.91	1.65
OR/t-input plastic films 2017		721.67	16.83	1.61
Steinbeis PolyVert GmbH—Mitte (Kruschitz GmbH—Kühnsdorf)				
		Massen [t]		
	Input	**Input Plastic Films**	**Output Granulate**	**Output**
2018	20,233	3343	12,973	16,813
		Operating Resources (OR)		
		Electricity [kWh]	**Diesel [kWh]**	**Water [m^3]**
2018		9,863,000	429,000	
OR/t-input 2018		487.47	21.20	
OR/t-input plastic films 2018		80.54	3.50	
Öko-Institut e.V.				
		Operating Resources (OR)		
	Electricity [kWh]	**Diesel [kWh]**		**Water [m^3]**
OR/t-input	1100			0.50
Emile Van Eygen				
		Operating Resources (OR)		
	Electricity [kWh]	**Diesel [kWh]**		**Water [m^3]**
OR/t-input	650			5.25
Resource Averages—Input Related				
Electricity	**629.83**	**[kWh/t]**	**2.27**	**[MJ/kg]**
Diesel	**12.41**	**[kWh/t]**	**1.27**	**[g/kg]**
Water	**2.25**	**[m^3/t]**	**2.25**	**[dm^3/kg]**

Table A6. Data collection and calculation of the recycling yield [5,16,19].

	Recycling Yield (Output Granulate/Output)				**Average**
	2016	**2017**	**2018**		
Walter Kunststoffe GmbH—Wels	68%	70%	73%		70%
Steinbeis PolyVert GmbH—Mitte			77%		77%
Öko-Institut e.V.				72%	72%
Emile Van Eygen				71%	71%
			Average—target fraction		73%

Appendix G

Appendix G shows the vehicle usage, their respective workload and the distance covered by the respective vehicle as used in the calculation.

Table A7. Data basis and evaluation of the transport model. 0 GLO: Truck, Euro 5, 14–20 t gross weight/11.4 t payload capacity (GaBi); X GLO: Truck-trailer, Euro 0–6 mix, 34–40 t gross weight/27t payload capacity (GaBi) [16,27,28].

Fraction	**Transport Data according to Öko-Institut e.V. et al., 2016 Route**	**Vehicle (Own Assumption)**	**Workload [%]**	**Distance [km]**
W-C	Use phase → Packaging waste collection	0	50	10
PW	packaging waste collection → Sorting plant	X	75	100
S-MO/ML	Sorting plant → Recycling plant	X	83	255
W-S	Sorting plant → Municipal waste incineration plant	X	90	50
W-R	Recycling plant → Municipal waste incineration plant	X	75	200
W-NC	Use phase → Municipal waste collection	0	50	10
MW	Municipal waste collection → Municipal waste incineration plant	X	75	100
Transport Model Austria—Selected Locations				
Basic material manufacturer			[Intern number]	
	Borealis Polyolefine GmbH		1	
Packaging producer				
Composite films for plastic packaging	Lenzing Platsics GmbH & Co KG		21	
	LPS GMBH LUPOTHERM		22	
packaging films of plastic	LPS GMBH LUPOTHERM			
	Coveris Kufstein		23	
	Mondi Styria		24	
	TECHNOFLEX PACKAGING		25	
Sorting plant				
	TRG GmbH		31	
	Saubermacher Dienstleistungs AG		32	
	ZENTRALE Energie AG Oberösterreich Umwelt Service GmbH		33	
	Brantner Österreich GmbH Wölblin		34	
Recycling plant				
	Walter Kunststoffe GmbH—Wels		41	
	Steinbeis PolyVert GmbH (Kruschitz)—Mitte		42	
	Ecoplast Kunststoffrecycling GmbH		43	
Municipal waste incineration plant				
	Müllverbrennungsanlage Spittelau—Hundertwasser		51	
	FCC Zistersdorf Abfall Service GmbH		52	
	Abfallverwertung Niederösterreich GmbH & Co		53	
	Energie- u Abfallverwertungs GesmbH		54	
	Kärntner Restmüllverwertung		55	
	Energie AG Oberösterreich Umwelt Service GmbH Lenzing		56	
	Fernheizkraftwerk Linz-Mitte		57	
	Energie AG Oberösterreich Umwelt Service GmbH Wels		58	

Table A7. *Cont.*

Fraction	Transport Data according to Öko-Institut e.V. et al., 2016 Route				Vehicle (Own Assumption)	Workload [%]	Distance [km]
	Optimized Transport Distances		**Distance [km]**				
	from	**to**	**Google Maps**	**Average**		**Workload**	
Basic material manufacturer to Packaging producer	1	21	260				
	1	22	314			(Own assumption and literature)	
	1	23	428				
	1	24	200				
	1	25	262	**293**		**90%**	
Sorting plant to Recycling plant	31	41	316				
	32	43	29				
	33	41	160				
	34	41	17				
	Literature		255	**156**		**83%**	
Recycling plant to Packaging producer	41	21	53				
	41	22	103				
	41	23	220				
	42	24	89				
	41	25	54	**104**		**90%**	
Sorting plant to Municipal waste incineration plant	31	56	271				
	32	54	71				
	33	57	14				
	34	53	27				
	Literature		50	**87**		**90%**	
Recycling plant to Municipal waste incineration plant	41	58	3				
	42	55	89				
	43	54	89				
	Literature		200	**95**		**75%**	

References

1. PlasticsEurope. Plastics-the Facts 2019: An Analysis of European Plastics Production, Demand and Waste Data. 2019. Available online: https://plasticseurope.org/wp-content/uploads/2021/10/2019-Plastics-the-facts.pdf (accessed on 25 January 2022).
2. Brandt, B.; Pilz, H. The Impact of Plastic Packaging on Energy Consumption and Greenhouse Gas Emissions in Europe: Executive Summary. 2011. Available online: https://kunststoff-initiative.com/wp-content/uploads/2021/03/ausw_v_kunststoffverp_a_ev_u_thg_in_eu.pdf (accessed on 25 January 2022).
3. European Union. *Directive 94/62/EC of the European Parliament and of the Council of December 20, 1994 on Packaging and Packaging Waste: Packaging Directive*; European Union: Brussels, Belgium, 2018.
4. Koinig, G.; Rutrecht, B.; Friedrich, K.; Barretta, C.; Vollprecht, D. Latent Recycling Potential of Multilayer Films in Austrian Waste Management. *Polymers* **2022**, *14*, 1553. [CrossRef] [PubMed]
5. Van Eygen, E. *Management of Plastic Waste in Austria: Analysis of the Current Situation and Determination of Optimisation Potential from an Ecological Point of View*; TU Vienna: Vienna, Austria, 2018.
6. Vollmer, I.; Jenks, M.; Roelands, M.; White, R.; Harmelen, T.; Wild, P.; Laan, G.; Meirer, F.; Keurentjes, J.T.F.; Weckhuysen, B.M. Beyond mechanical recycling: Giving new life to plastic waste. *Angew. Chem. Int. Ed.* **2020**, *59*, 15402–15423. [CrossRef] [PubMed]
7. Maeurer, A.; Martin, S.; Otto, B. Method for Recycling Plastic Materialsand Use Thereof. U.S. Patent No. 8,138,232, 20 March 2012.
8. Walker, T.; Frelka, N.; Shen, Z.; Chew, A.; Banick, J.; Grey, S.; Kim, M.S.; Dumesic, J.; Van Lehn, R.; Huber, G. Recycling of multilayer plastic packaging materials by solvent-targeted recovery and precipitation. *Sci. Adv.* **2020**, *6*, eaba7599. [CrossRef]
9. Villanueva, A.; Eder, P. *End-of-Waste Criteria for Waste Plastic for Conversion: Technical Proposals: Final Report: Technical Proposals*; Last Checked on: 25.01.2022; Publications Office of the European Union: Luxembourg, 2014. [CrossRef]
10. Frischknecht, R. *Textbook of Life Cycle Assessment*; Springer Spectrum: Berlin/Heidelberg, Germany, 2020. [CrossRef]
11. Choi, B.; Yoo, S.; Park, S. Carbon Footprint of Packaging Films Made from LDPE, PLA, and PLA/PBAT Blends in South Korea. *Sustainability* **2018**, *10*, 2369. [CrossRef]

12. Volk, R.; Stallkamp, C.; Steins, J.J.; Yogish, S.P.; Müller, R.C.; Stapf, D.; Schultmann, F. Techno-economic assessment and comparison of different plastic recycling pathways: A German case studies. *J. Ind. Ecol.* **2021**, *25*, 1318–1337. [CrossRef]
13. Knappe, F.; Reinhardt, J.; Kauertz, B.; Oetjen-Dehne, R.; Buschow, N.; Ritthoff, M.; Wilts, H.; Lehmann, M. *Technical Potential Analysis to Increase Plastic Recycling and the Use of Recyclates (Final Report)*; Umweltbundesamt Deutschland: Heidelberg, Germany, 2021; ISSN 1862-4804.
14. Jönkkäri, I.; Poliakova, V.; Mylläri, V.; Anderson, R.; Andersson, M.; Vuorinen, J. Compounding and characterisation of recycled multilayer plastic films. *J. Appl. Polym. Sci.* **2020**, *137*, e49101. [CrossRef]
15. Kaiser, K.; Schmid, M.; Schlummer, M. Recycling of Polymer-Based Multilayer Packaging: A Review. *Recycling* **2018**, *3*, 1. [CrossRef]
16. Neubauer, C.; Stoifl, B.; Tesar, M.; Thaler, P. *Sorting and Recycling of Plastic Waste in Austria: Status 2019*; Umweltbundesamt Österreich: Vienna, Austria, 2021; ISBN 978-3-99004-565-7.
17. Lacy, P.; Rutqvist, J. *Waste to Wealth: The Circular Economy Advantage*; Palgrave Macmillan: New York, NY, USA, 2016.
18. Horodytska, O.; Valdés, F.; Fullana, A. Plastic flexible films waste management—A state of art review. *Waste Manag.* **2018**, *77*, 413–425. [CrossRef] [PubMed]
19. Öko-Institut, E.V.; Dehoust, G.; Möck, A.; Merz, C.; Gebhardt, P. Environmental Potential of the Separate Collection and Recycling of Recyclable Materials in the Dual System: Balance of Environmental Impacts. 2016. Available online: https://www.gruener-punkt.de/fileadmin/Files/Downloads/PDFs/16-09-21_OEko-Institut_Abschlussbericht_LCA-DSD.PDF (accessed on 25 January 2022).
20. Pachauri, R.K.; Mayer, L. (Eds.) *Climate Change 2014: Synthesis Report*; Intergovernmental Panel on Climate Change: Geneva, Switzerland, 2015; ISBN 978-92-9169-143-2.
21. PE International. Handbook for Life Cycle Assessment (LCA): Using the GaBi Education Software Package. 2010. Available online: https://gabi.sphera.com/fileadmin/gabi/tutorials/Paperclip_Tutorial_Handbook_4.4.pdf (accessed on 25 January 2022).
22. Eurostat Data Browser. Packaging Waste by Waste Management Measures: Statistics. 2022. Available online: https://ec.europa.eu/eurostat/databrowser/view/ENV_WASPAC__custom_1271915/default/table?lang=de (accessed on 25 January 2022).
23. Eurostat. EU Exports of Recyclables to China Fall Sharply. 2020. Available online: https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20200709-01 (accessed on 25 January 2022).
24. PlasticsEurope. Plastics—The Facts 2020: An Analysis of European Plastics Production, Demand and Waste Data. 2020. Available online: https://plasticseurope.org/wp-content/uploads/2021/09/Plastics_the_facts-WEB-2020_versionJun21_final.pdf (accessed on 25 January 2022).
25. Bundesministerium für Klimaschutz, Umwelt, Energie, Mobilität, Innovation und Technologie (BMK), Vienna Austria. (2020) The Inventory of Waste Management in Austria: Status Report 2020 (Reference Year 2018), Federal Ministry for Climate Protection, Environment, Energy, Mobility, Innovation and Technology. Status Report. Available online: https://www.wko.at/service/ooe/umwelt-energie/BAWP_Statusbericht_2020_4.pdf (accessed on 25 January 2022).
26. BDEW Energiemarkt Deutschland (2019), BDEW Bundesverband der Energie-und Wasserwirtschaft e.V., Berlin, Germany. Available online: https://www.bdew.de/service/publikationen/bdew-energiemarkt-deutschland-2019/ (accessed on 25 January 2022).
27. FCIO—Fachverband der Chemischen Industrie Österreichs (2022), Produkte und Hersteller—FCIO Website. Available online: https://www.fcio.at/chemische-industrie/produkte-und-hersteller/ (accessed on 25 January 2022).
28. Bundesministerium für Nachhaltigkeit und Tourismus (BMNT), 2017; Bundesabfallwirtschaftsplan 2017 Teil 1. Available online: https://www.arge.at/Downloads/2_BAWPL_2017_Teil_1.pdf (accessed on 25 January 2022).

3.2 Publication 5

Research Paper 5:

"Influence of Reflective Materials, Emitter Intensity and Foil Thickness on the Variability of Near-Infrared Spectra of 2D Plastic Packaging Materials"

Koinig, Gerald; Friedrich, Karl; Rutrecht, Bettina; Oreski, Gernot; Barretta, Chiara; Vollprecht, Daniel (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.

Annotation on the doctoral candidate's contribution to this publication:

The general concept of the publication was designed by the doctoral candidate. Afterwards, the relevant scientific literature on the subject was reviewed by the doctoral candidate. The publication was then written by the author of the doctoral thesis. The internal review process was done with the consultation of the co-authors Karl Friedrich, Gerald Koinig, Chiara Barretta and supervisors Daniel Vollprecht and Gernot Oreski.

Waste Management 144 (2022) 543–551

Contents lists available at ScienceDirect

Waste Management

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

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

ARTICLE INFO

Keywords:
2D plastic packaging
Near-infrared
Sensor-based sorting
Background material
Transflection

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.

https://doi.org/10.1016/j.wasman.2021.12.019
Received 30 June 2021; Received in revised form 7 October 2021; Accepted 9 December 2021
Available online 1 April 2022

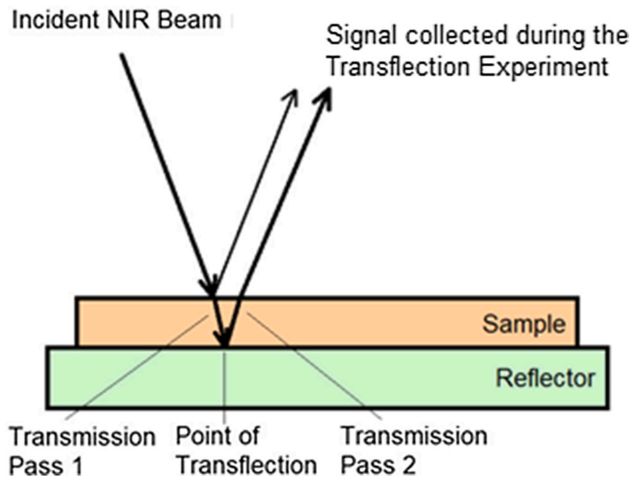

Fig. 1. Scheme of the transflection measurement principle.

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

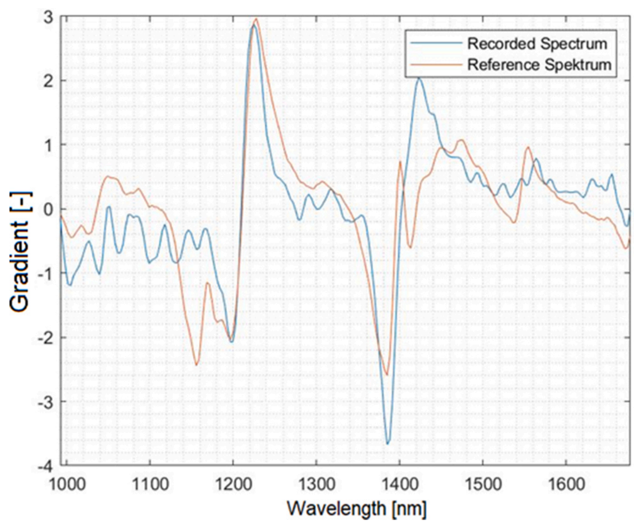

Fig. 2. Comparison between the PE reference spectrum (orange) and a PE foil spectrum (blue).

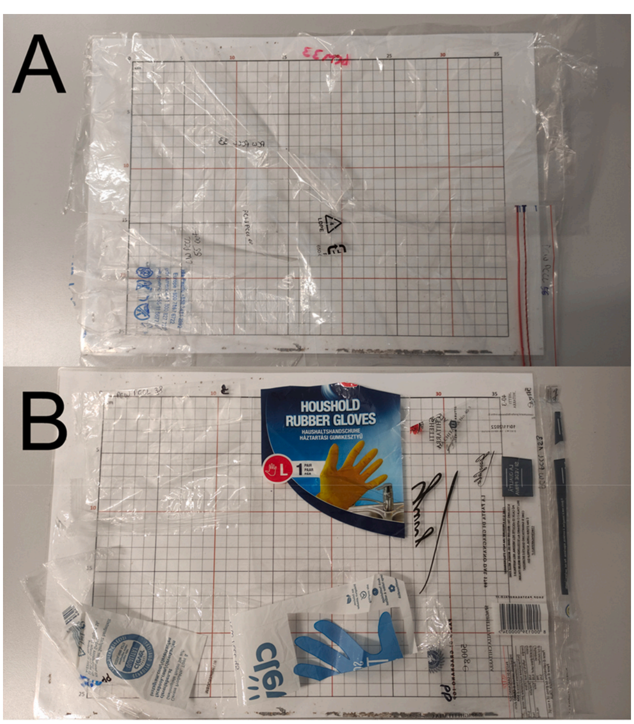

Fig. 3. Depiction of all Samples, A) PE B) PP.

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 sampleś 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

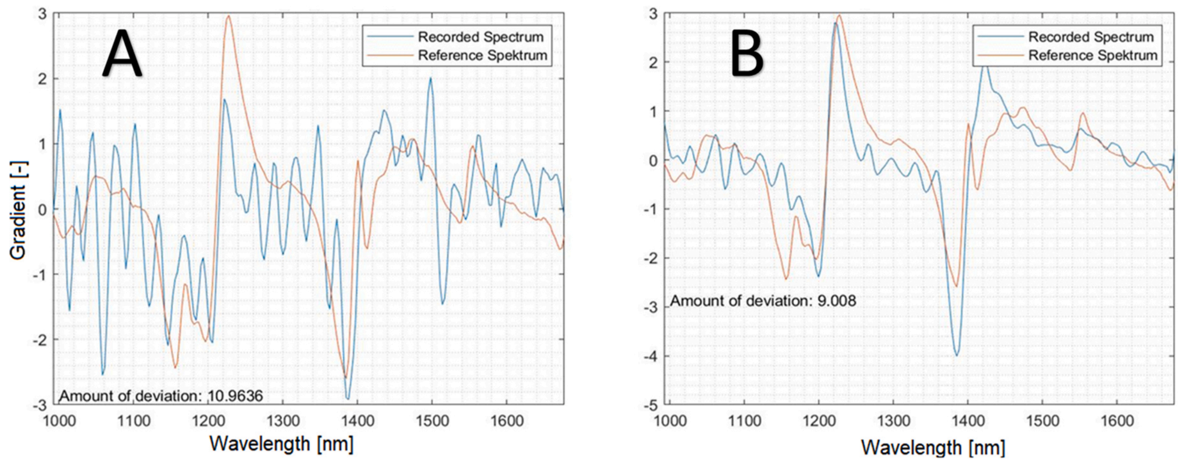

Fig. 4. Increasing fidelity to the PE reference spectrum of two spectral images taken without reflective background[A] and with a reflective copper background [B]

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

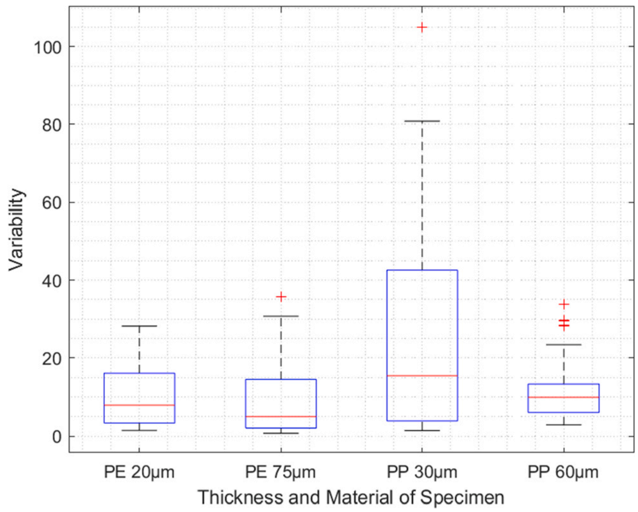

Fig. 5. Influence of spectral variability depending on thickness and material.

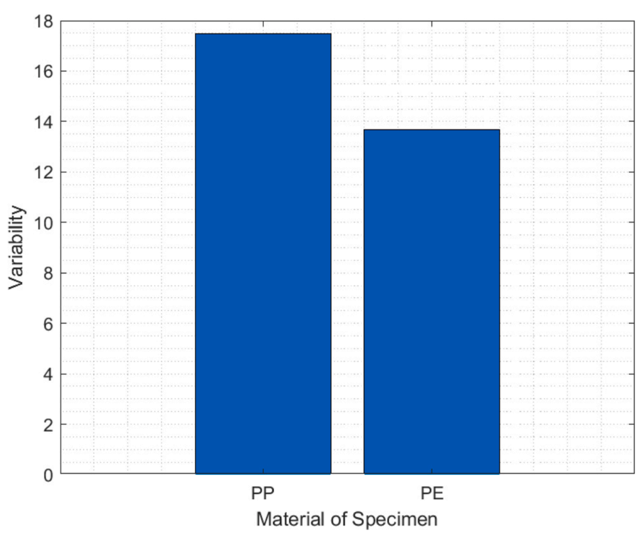

Fig. 6. Difference in average variability depending on specimen material.

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

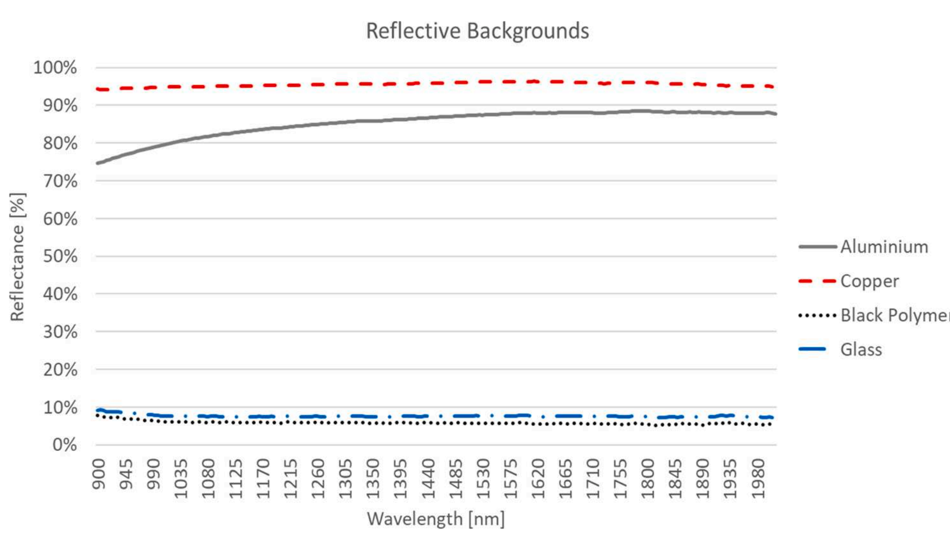

Fig. 7. Reflectance of chosen reflector materials.

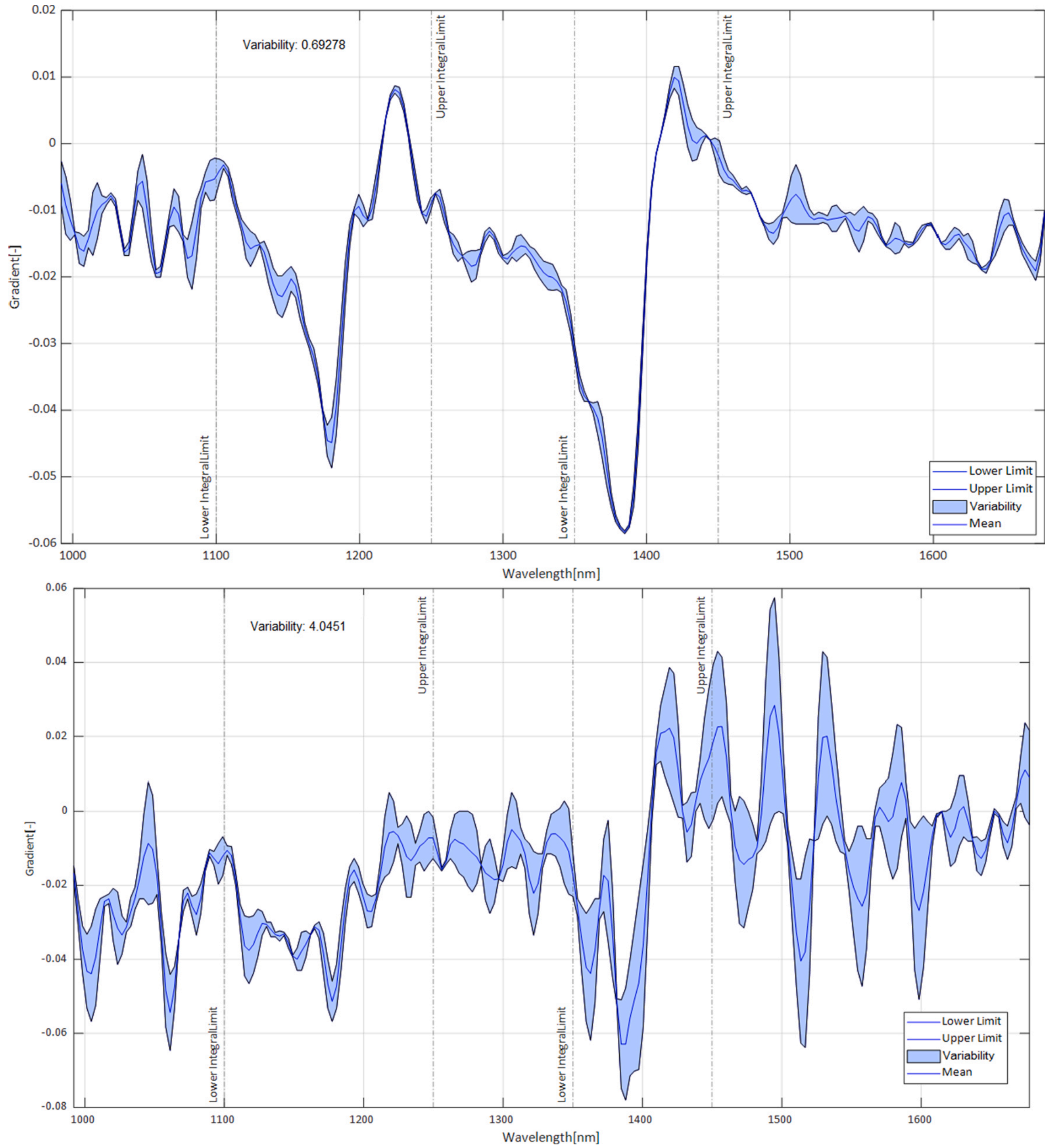

Fig. 8. Reduction in spectral variability due to increased reflectivity of background material and subsequent measurement in transflection. A) No reflector B) Copper reflector.

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

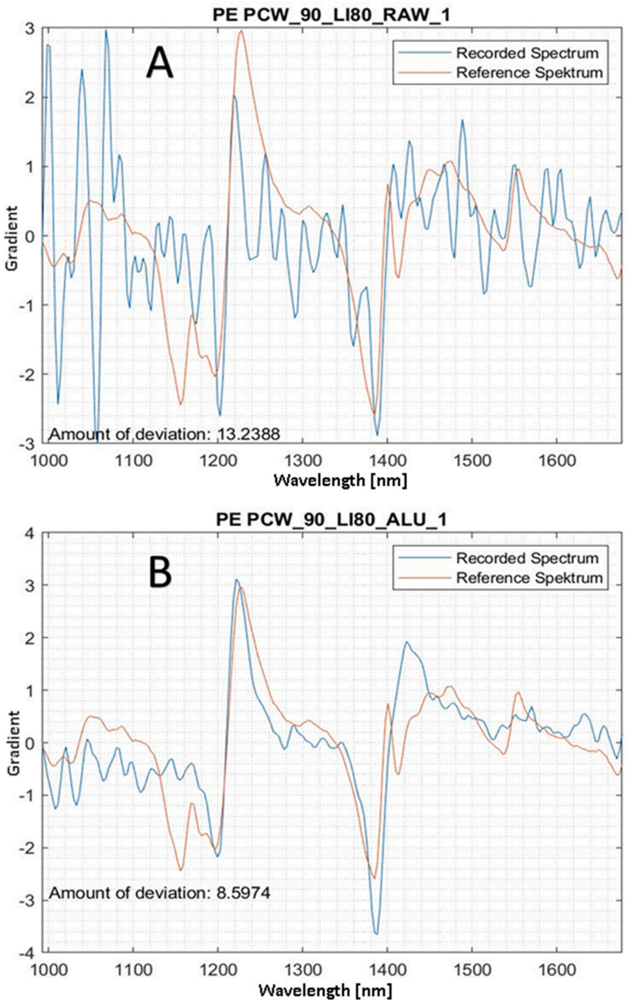

Fig. 9. Reduction in spectral deviation from the reference spectrum due to the effect of reflector material, A) No reflector B) Aluminium reflector.

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

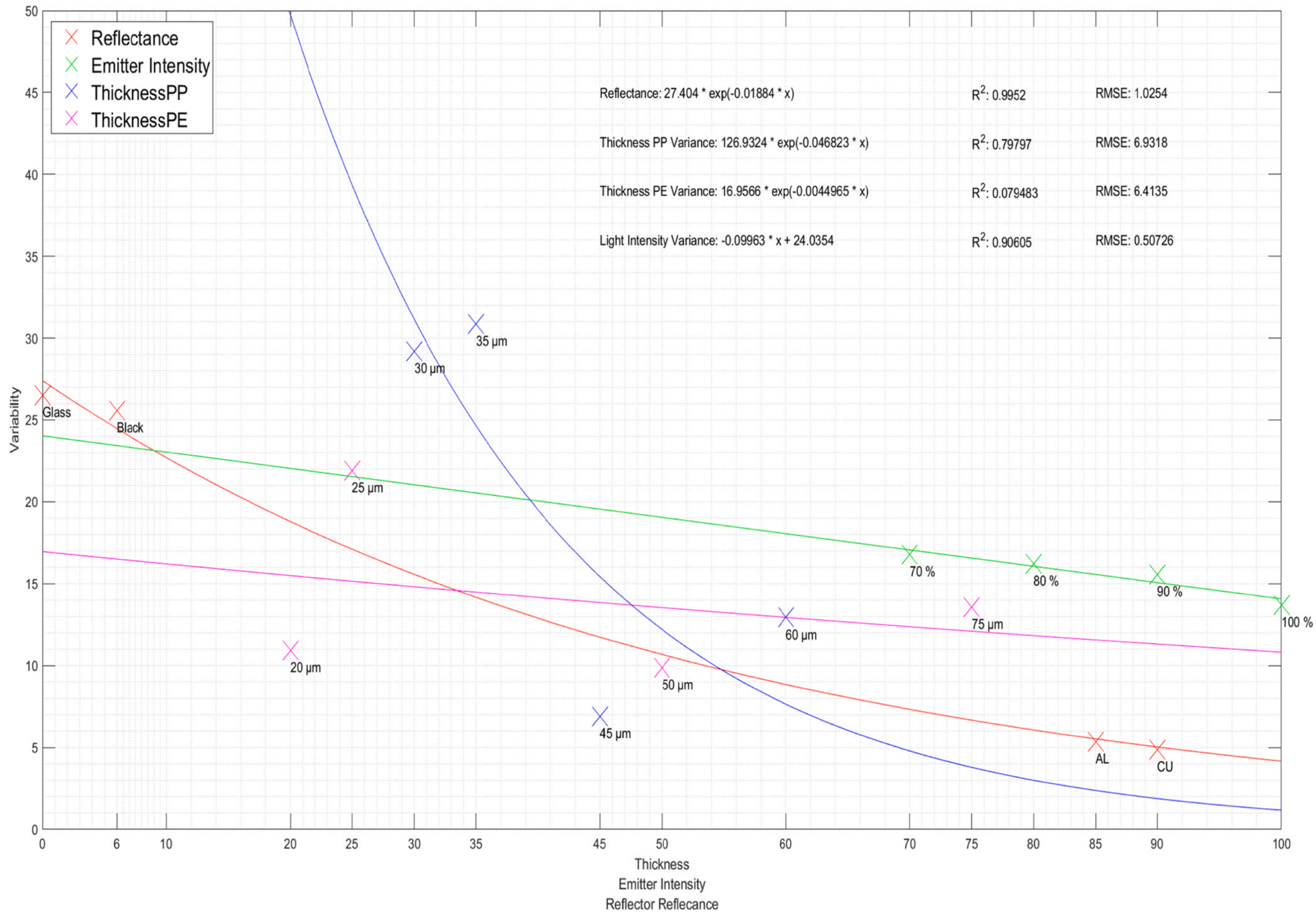

Fig. 10. Statistical evaluation of the effect changing various parameters has on the spectral variability.

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.

Funding

This work was funded by the province of Styria and Zukunfsfonds Steiermark.

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.

References

Chen, X., Kroell, N., Feil, A., Pretz, T., 2020. Determination of the composition of multilayer plastic packaging with NIR spectroscopy. DETRITUS - Multidisciplinary journal for Waste Resources and Residues 13, 62–66. https://doi.org/10.31025/2611-4135/2020.14027.

Cui, Y.X., 2011. Study and Development of near-Infrared Reflective and Absorptive Materials for Energy Saving Application. Carlton University, Ottawa, Ontario. ISBN: 978-0-494-87749-4. Doctoral thesis.

Burns, D., Ciurczak, E., 1992. Handbook of Near-Infrared Analysis. Marcel Dekker, New York. ISBN 9780824786571.

Faris, F., Thorniley, M., Wickramasinghe, Y., Houston, R., Rolfe, P., Livera, N., Spencer, A., 1991. Non-invasive in vivo near-infrared optical measurement of the penetration depth in the neonatal head. Clin. Phys. Physiol. Meas. 12 (4), 353–358.

Frauenhofer IVV (2021). Kunststoffrecycling - CreaSolv® Prozess. Frauenhofer-Institut für Verfahrenstechnik und Verpackung. https://www.ivv.fraunhofer.de/de/recycling-umwelt/kunststoff-recycling.html#creasolv (accessed on 17 September 2021).

Kaiser, K., Schmid, M., Schlummer, M., 2018. Recycling of Polymer-Based Multilayer Packaging: A Review Recycling, 3 (1), 1. https://doi.org/10.3390/recycling3010001.

Küppers, B., Schloegl, S., Oreski, G., Pomberger, R., Vollprecht, D. (2019). Influence of surface roughness and surface moisture of plastics on sensor-based sorting in the near infrared range. Waste Management & Research. 2019;37(8):843-850. doi: 10.1177/0734242X19855433.

Masoumi, H., Safavi, S., Khani, Z., 2012. Identification and classification of plastic resins using near-infrared reflectance spectroscopy. Int. J. Mech. Ind. Eng. 6 (2012), 213–220. https://doi.org/10.5281/zenodo.1076916.

Manley, M., 2014. Near-infrared spectroscopy and hyperspectral imaging: non-destructive analysis of biological materials. Chem. Soc. Rev. 43 (24), 8200–8214. https://doi.org/10.1039/c4cs00062e.

Niaounakis, M., 2020. Recycling of Flexible Plastic Packaging. Elsevier Inc. ISBN: 978-0-12-816335-1. doi: 10.1016/C2018-0-00076-6.

Padalkar, M., Pleshko, N., 2015. Wavelength-dependent penetration depth of near infrared radiation into cartilage. The Analyst 140 (7), 2093–2100. https://doi.org/10.1039/c4an01987c.

Pasquini, C., 2003. Near Infrared Spectroscopy: fundamentals, practical aspects and analytical applications. J. Braz. Chem. Soc. 14 (2), 198–219. https://doi.org/10.1590/S0103-50532003000200006.

Unilever, 2020. Our solution for recycling plastic sachets takes another step forward. https://www.unilever.com/news/news-and-features/Feature-article/2018/our-solution-for-recycling-plastic-sachets-takes-another-step-forward.html (accessed on 17 September 2021).

Jeszenszky, É., Kocsányi, L., Richter, P., 2004. Eliminating the interference pattern in near-infrared spectra used for identification of thin plastic foils. Appl. Spectrosc. 58 (6), 693–697. https://doi.org/10.1366/000370204872953.

Lammertyn, J., Peirs, A., De Baerdemaeker, J., Nicolaï, B., 2000. Light penetration properties of NIR radiation in fruit with respect to non-destructive quality assessment. Postharvest Biol. Technol. 18 (2), 121–132. https://doi.org/10.1016/S0925-5214(99)00071-X.

Reich, G., 2005. Near-infrared spectroscopy and imaging: basic principles and pharmaceutical applications. Adv. Drug Deliv. Rev. 57 (8), 1109–1143. https://doi.org/10.1016/j.addr.2005.01.020.

Waste Framework Directive, 2008. Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2018 on waste and repealing certain Directives.

Woidasky, J., Lang-Koetz, C., Heyde, M., Wiethoff, S., Sander, I., Schau, A., Moesslein, J., Fahr, M., Richards, B., Turshatov, A., Sorg, F. (2018). Tracer Based Sorting – Innovative Sorting Options for Post Consumer Products. Recy- & Depotech 2018, In Proceedings of the 14th Recy- & DepoTech Conference, 07 November – 09 November 2018, Leoben, AVAW Eigenverlag: Leoben, Austria, pp. 105–110, ISBN 978-3-200-05874-3.

3.3 Publication 6

Research Paper 6:

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

Koinig, Gerald; Kuhn, Nikolai; Barretta, Chiara; Friedrich, Karl; Vollprecht, Daniel (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), p. 3926. DOI: https://doi.org/10.3390/polym14193926.

Annotation on the doctoral candidate’s contribution to this publication:

The general concept of the publication was designed by the doctoral candidate and discussed in contribution with the author Nikolai Kuhn. The relevant software was programmed by the author of the doctoral thesis. The relevant scientific literature on the subject was reviewed by the doctoral candidate. The publication was then written by the author of the doctoral thesis. The internal review process was done with the consultation of the co-authors, Nikolai Kuhn, and supervisor Daniel Vollprecht.

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

check for updates

Citation: Koinig, G.; Kuhn, N.; Barretta, C.; Friedrich, K.; Vollprecht, D. Evaluation of Improvements in the Separation of Monolayer and Multilayer Films via Measurements in Transflection and Application of Machine Learning Approaches. *Polymers* **2022**, *14*, 3926. https://doi.org/10.3390/polym14193926

Academic Editor: Leon Chernin

Received: 18 July 2022
Accepted: 15 September 2022
Published: 20 September 2022

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.

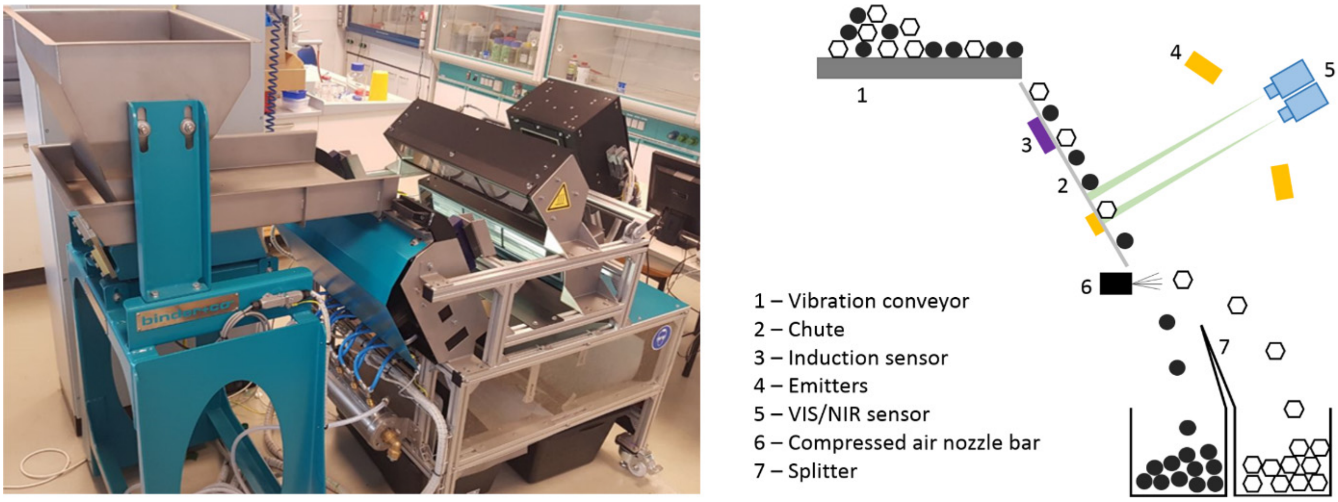

Figure 2. Experimental sensor-based sorting setup with the use of near-infrared spectroscopy.

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.

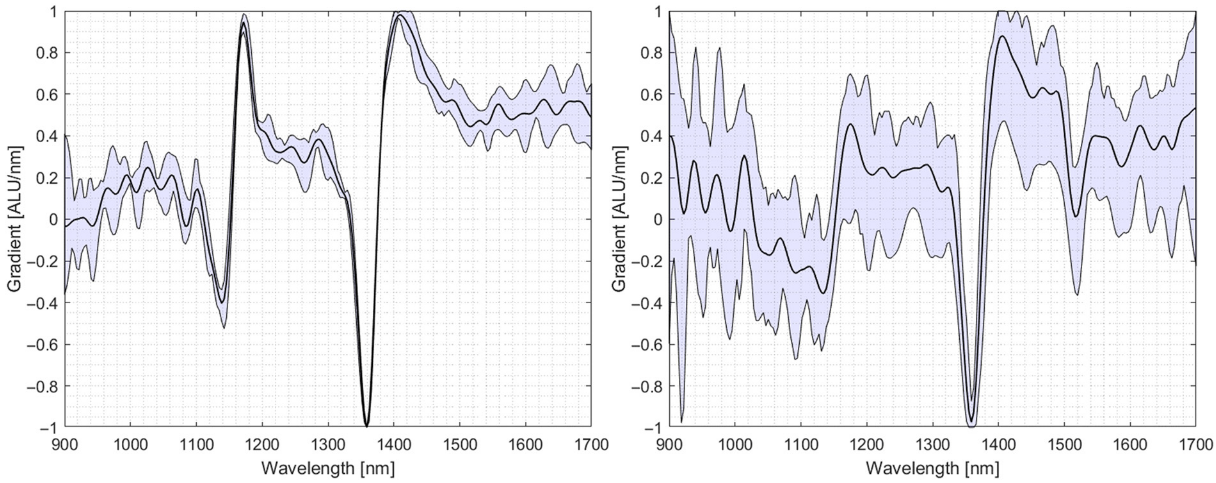

Figure 3. Comparison of spectral variability and characteristic peaks of a PE film when measured in transflection (**left**) and measured in reflectance (**right**).

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.

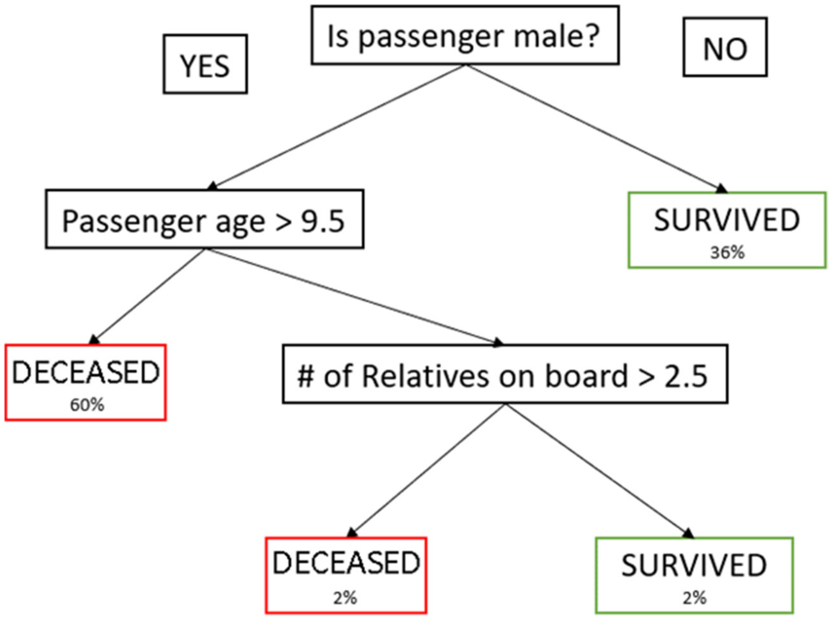

Figure 4. Example of a decision tree.

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.

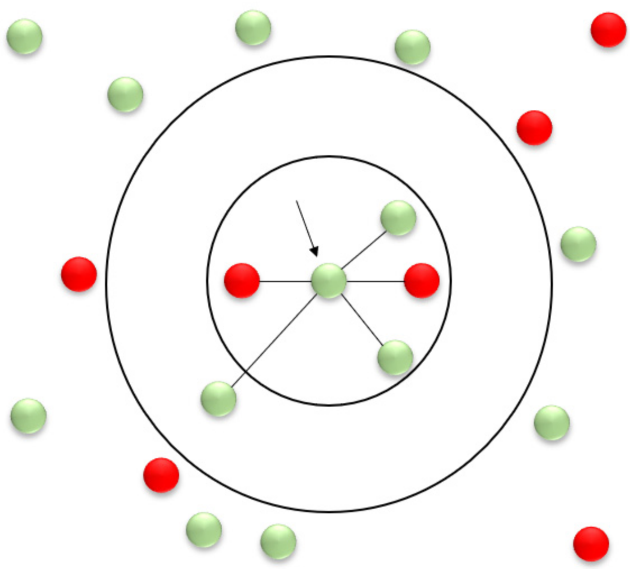

Figure 5. Example for k-nearest neighbour classification using k = 5 neighbours.

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.

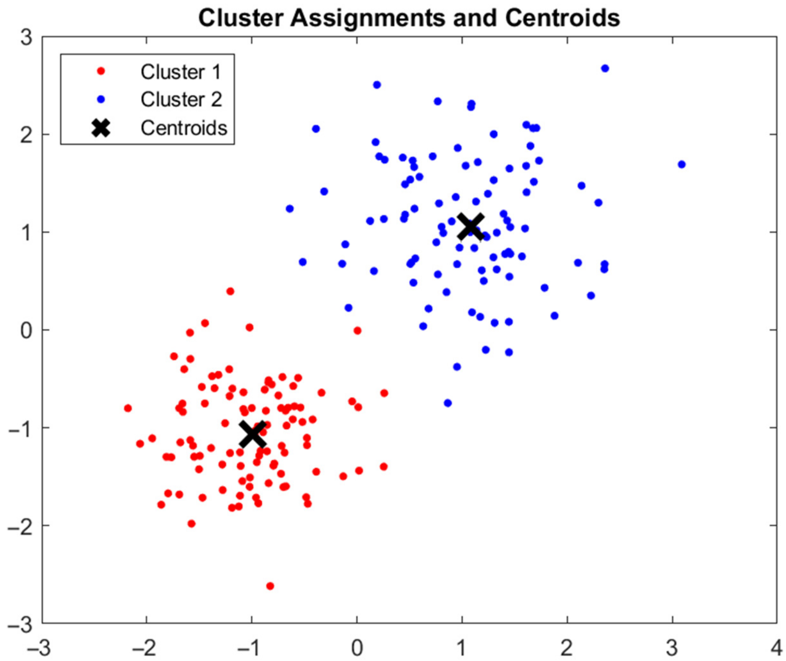

Figure 6. Example of a k-clusters clustering problem.

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].

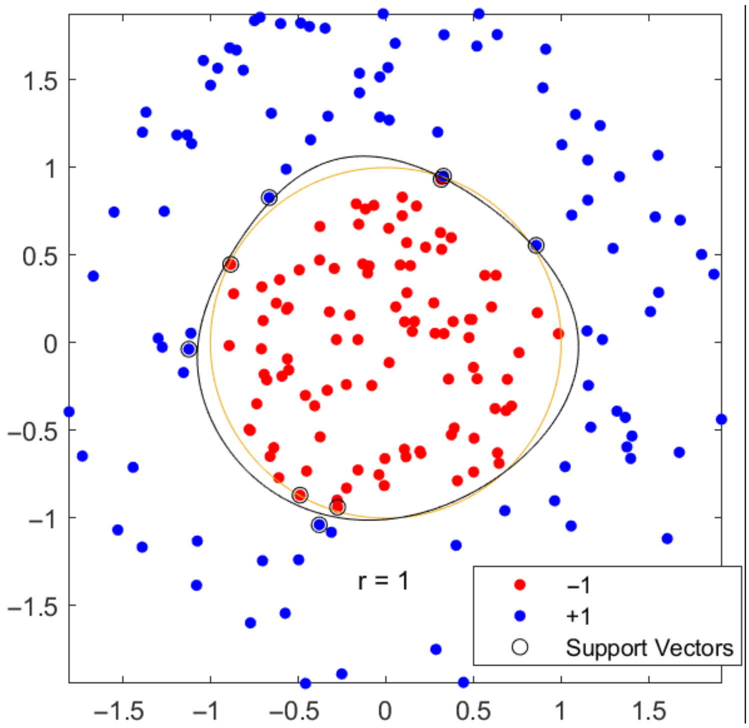

Figure 7. SVM classification using a nonlinear hyperplane and the classification result and the used support vectors to create the hyperplane.

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.

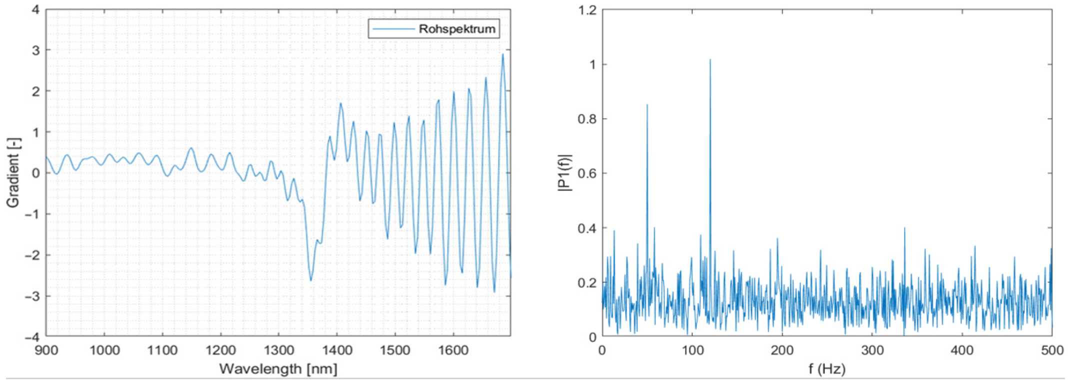

Figure 8. Spectral and Fourier depiction of a noisy signal.

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.

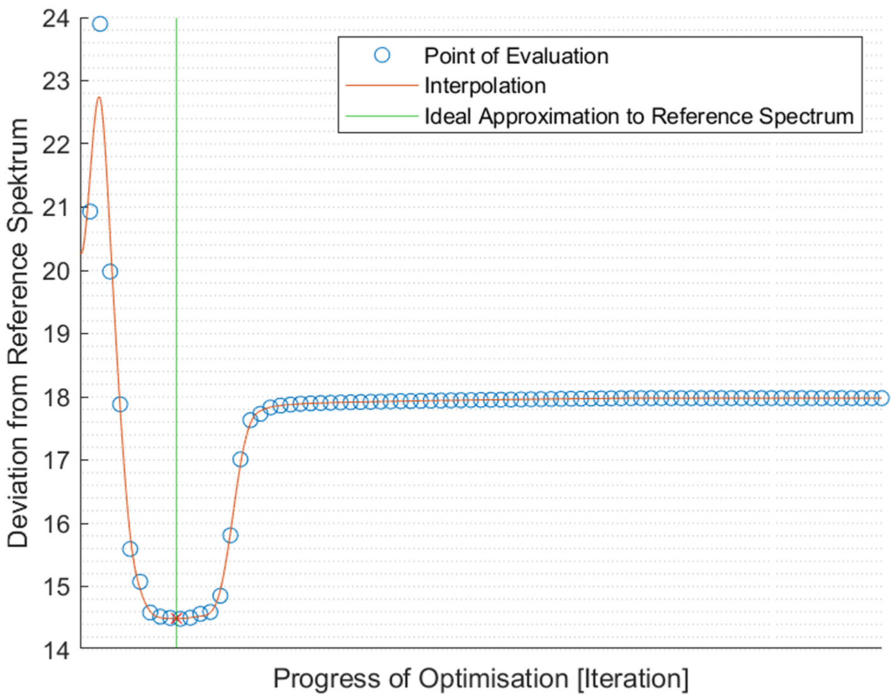

Figure 9. Progress of the optimisation over the deviation of the resulting spectrum from the reference spectrum.

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.

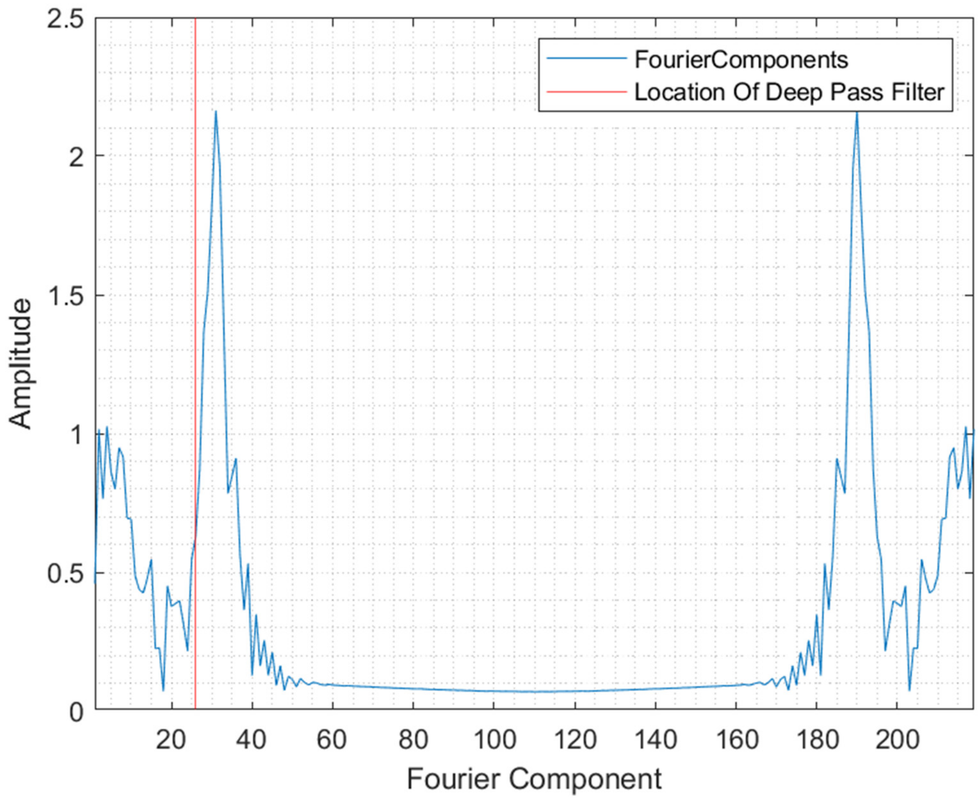

Figure 10. Fourier representation of the original spectrum.

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.

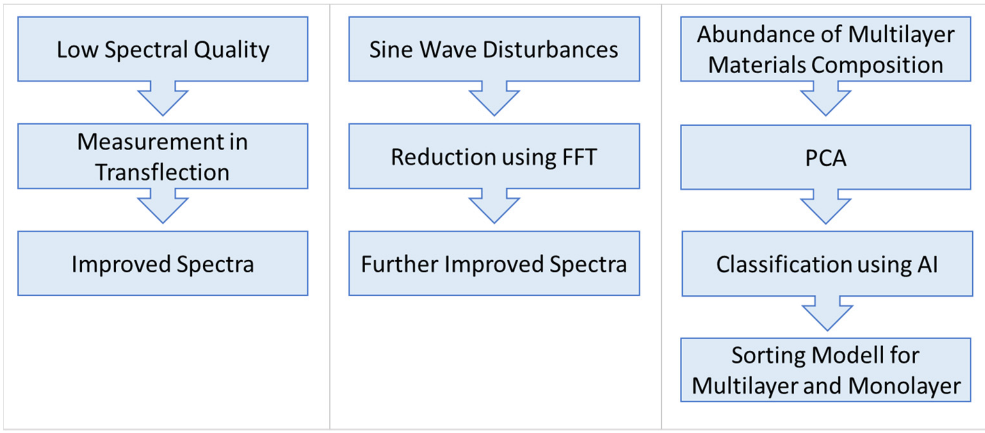

Figure 11. Summary of encountered problems when sorting films and the applied solutions.

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.

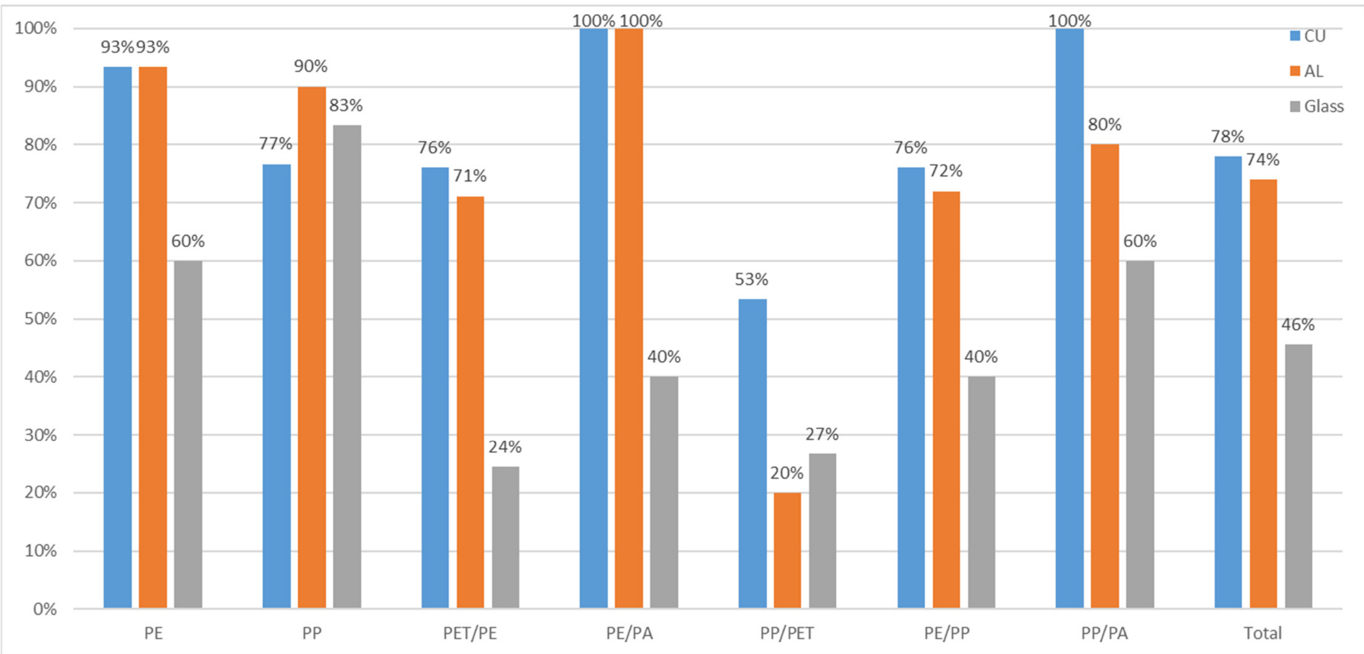

Figure 12. Detection rate with different reflectors concerning different materials.

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.

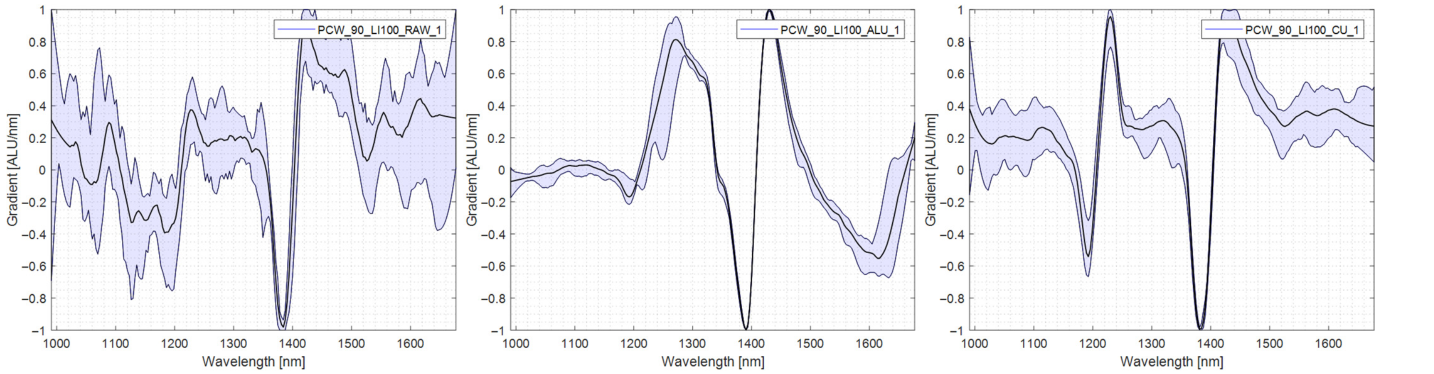

Figure 13. Comparison PE spectra, **left**: no reflector, middle: aluminium reflector, **right**: copper reflector.

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.

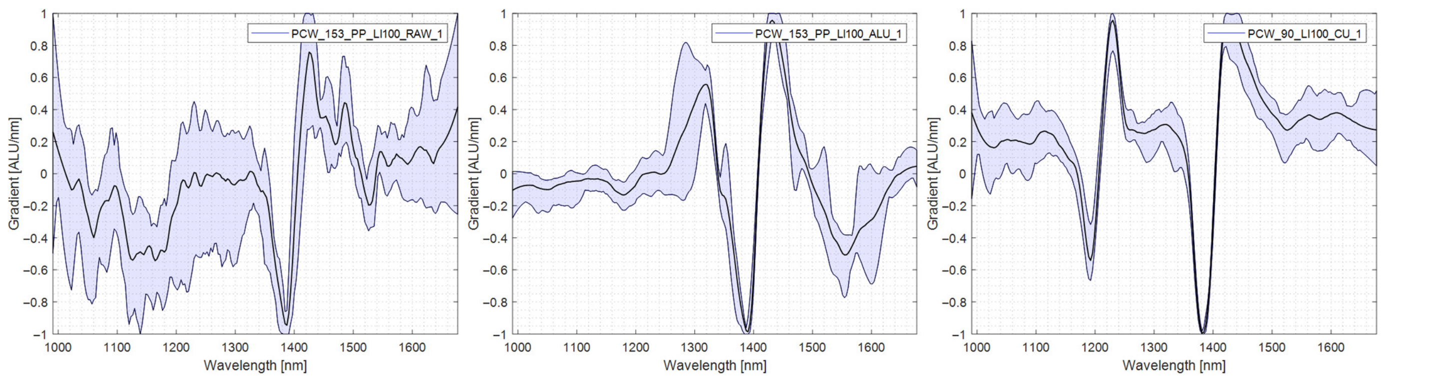

Figure 14. Comparison of PP spectra, **left**: no reflector, middle: aluminium reflector, **right**: copper reflector.

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.

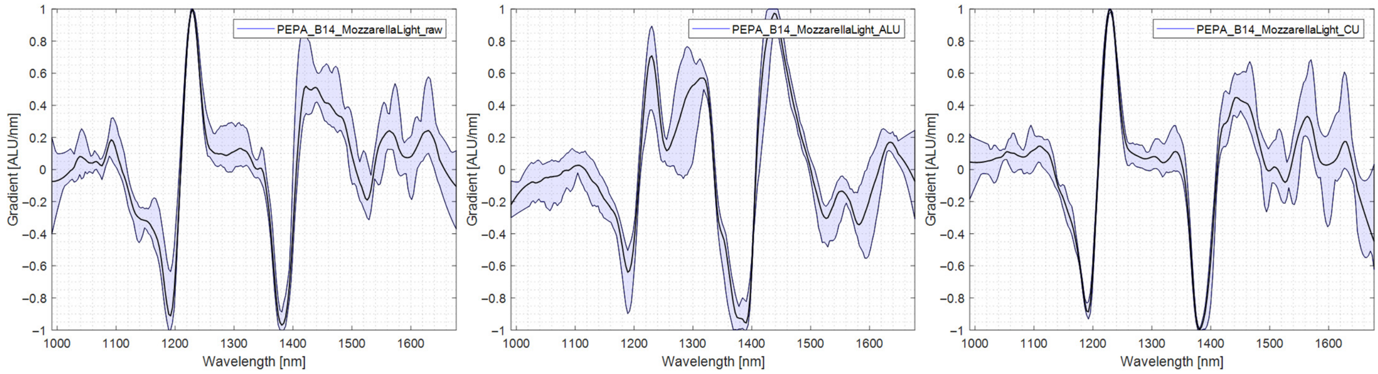

Figure 15. Comparison of PE/PA spectra, **left**: no reflector, middle: aluminium reflector, **right**: copper reflector.

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.

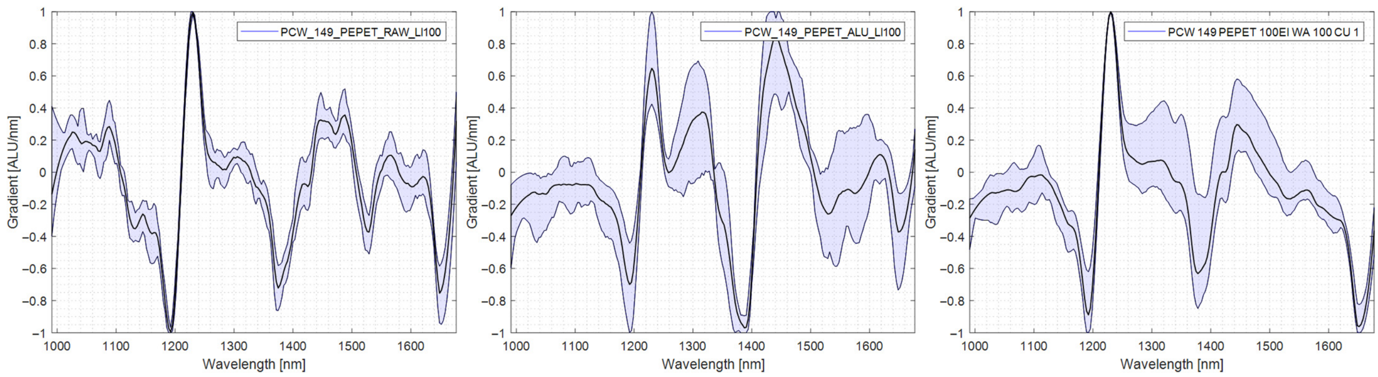

Figure 16. Comparison PE/PET spectra, left: no reflector, middle: aluminium reflector, right: copper reflector.

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.

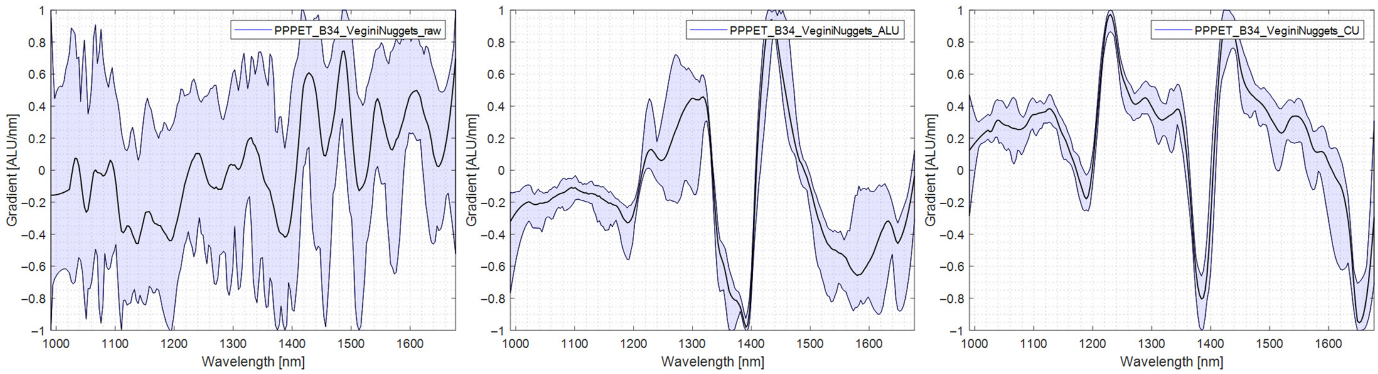

Figure 17. Comparison PP/PET spectra, left: no reflector, middle: aluminium reflector, right: copper reflector.

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.

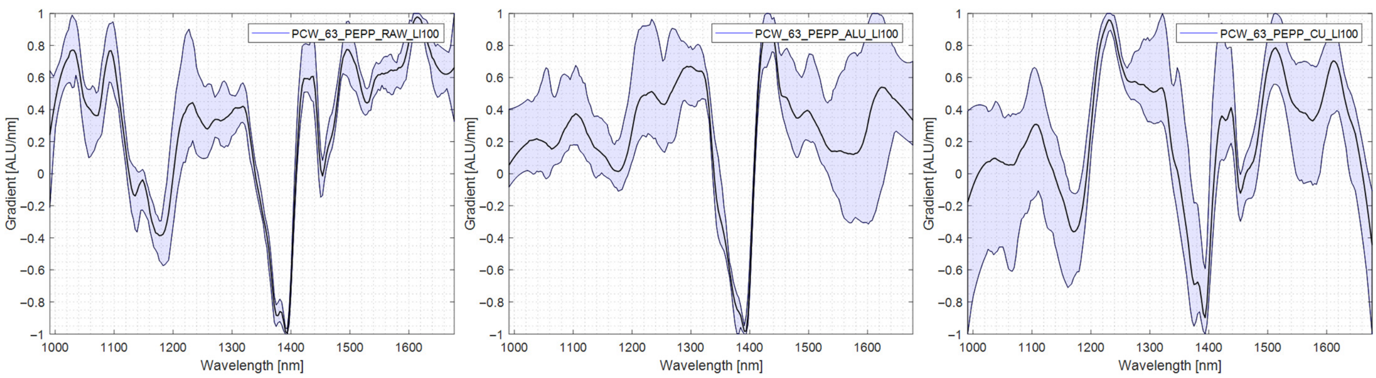

Figure 18. Comparison PE/PP spectra, left: no reflector, middle: aluminium reflector, right: copper Reflector.

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.

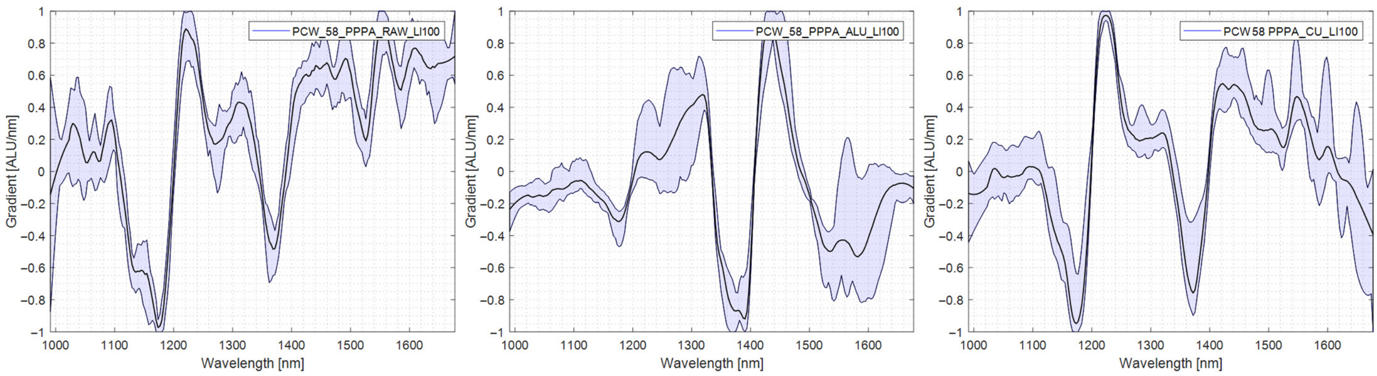

Figure 19. Comparison PP/PA spectra, left: no reflector, middle: aluminium reflector, right: copper reflector.

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.

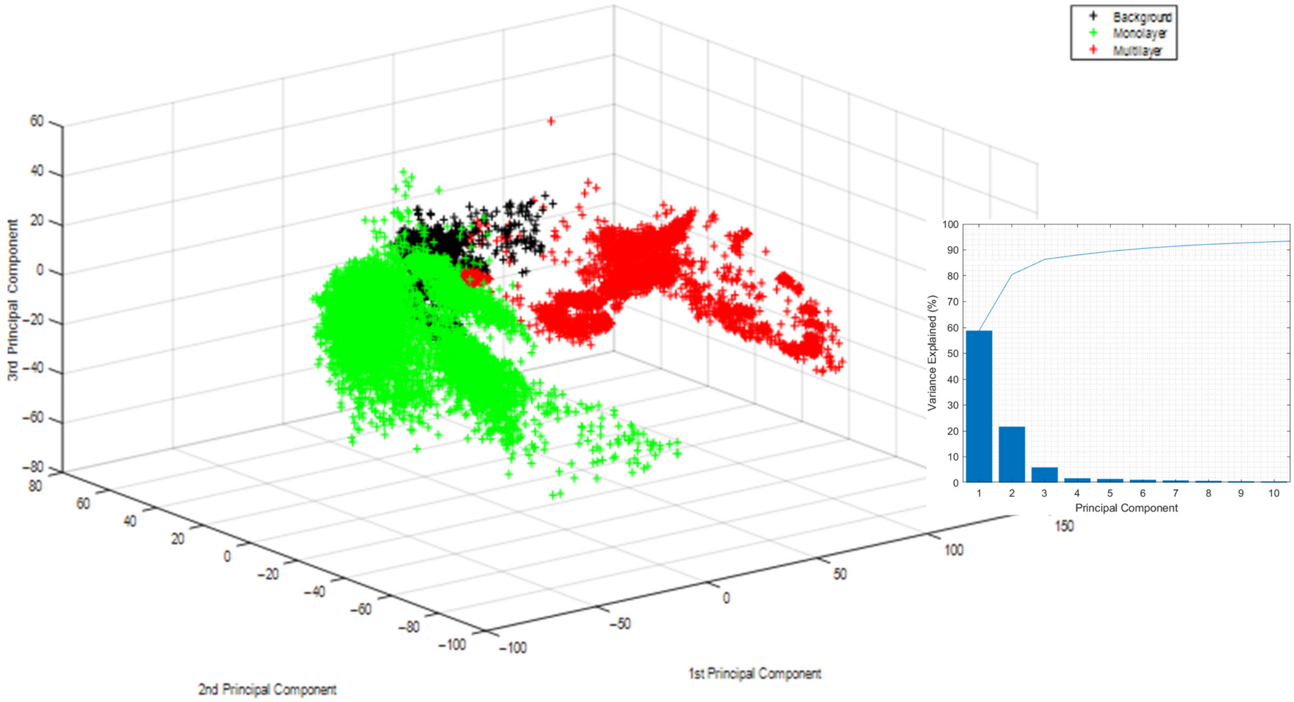

Figure 20. Result of the principal component analysis of approximately 17,000 spectra of monolayer, multilayer and background material to discern their sortability.

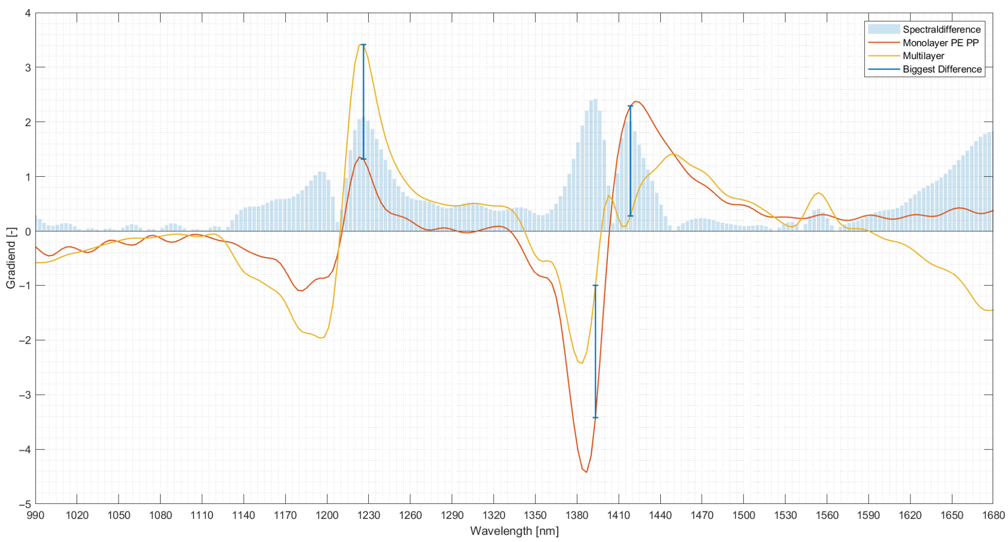

Figure 21. Differences in the mean spectra of multilayer and monolayer materials.

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%

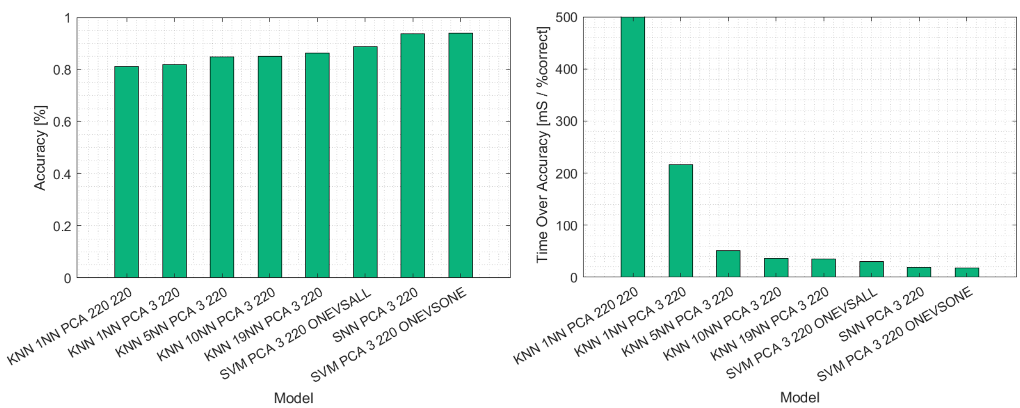

Figure 22. Comparison of the different machine learning algorithms used for classifying monolayer and multilayer materials in the test set.

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.

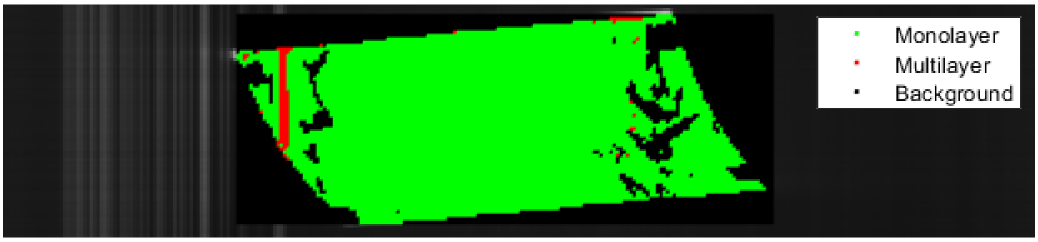

Figure 23. Classification of a PE monolayer film with the SNN.

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.

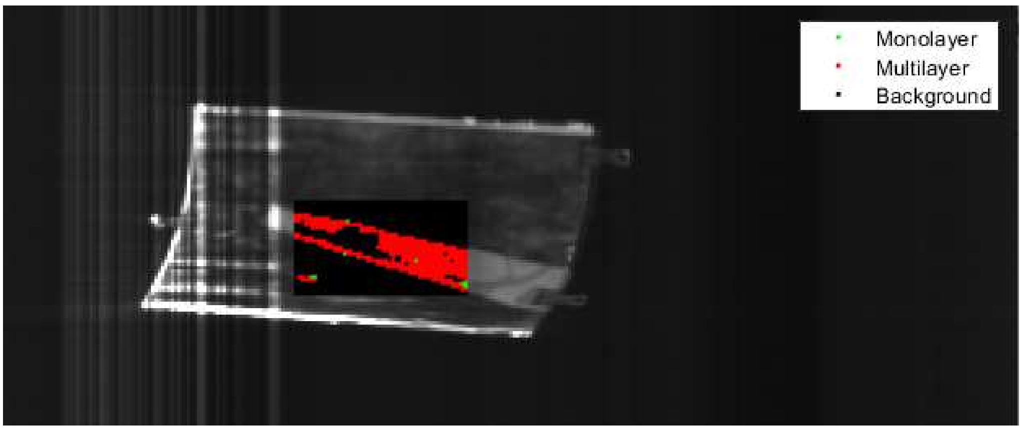

Figure 24. Classification of PE/PET multilayer film with the SNN.

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.

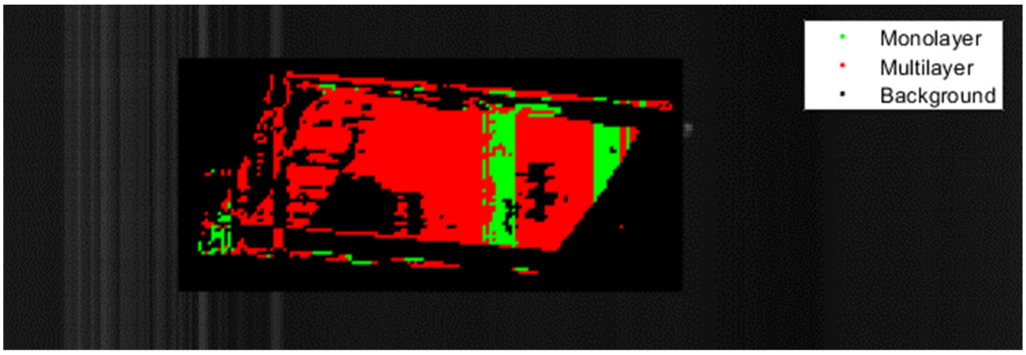

Figure 25. Classification of PE/PP multilayer film with the SNN.

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.

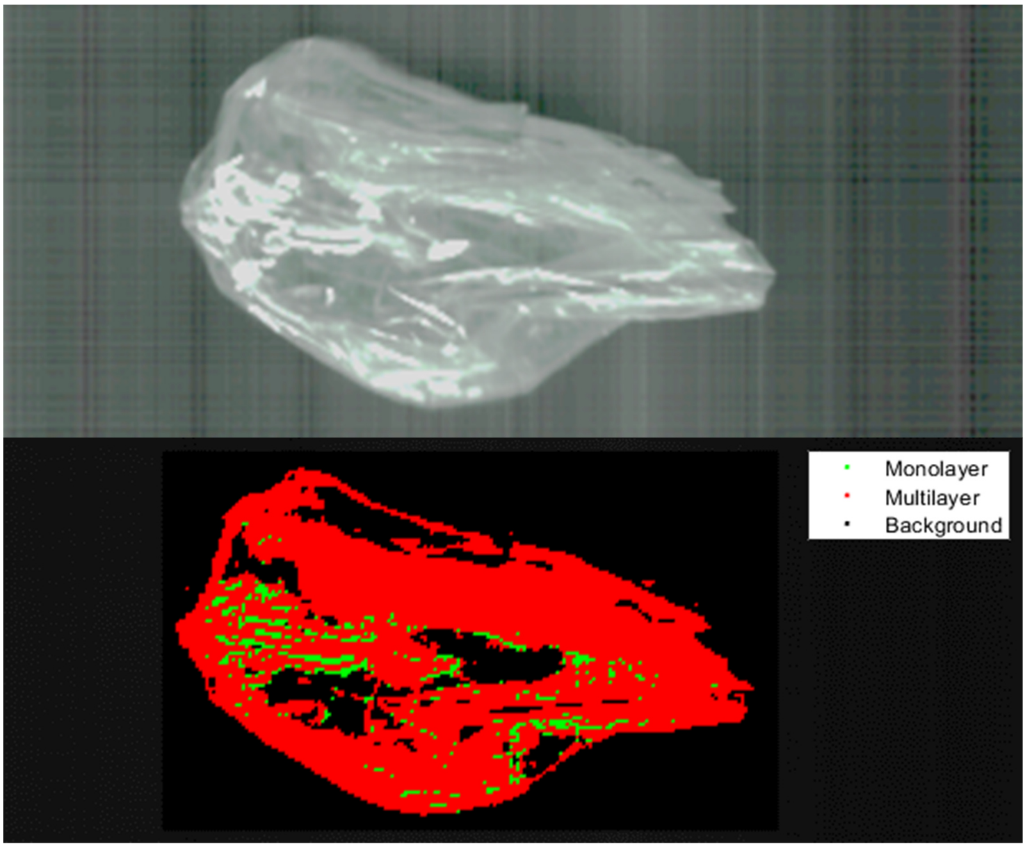

Figure 26. Classification of a cheese packaging film not used in training and testing with the SNN.

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.

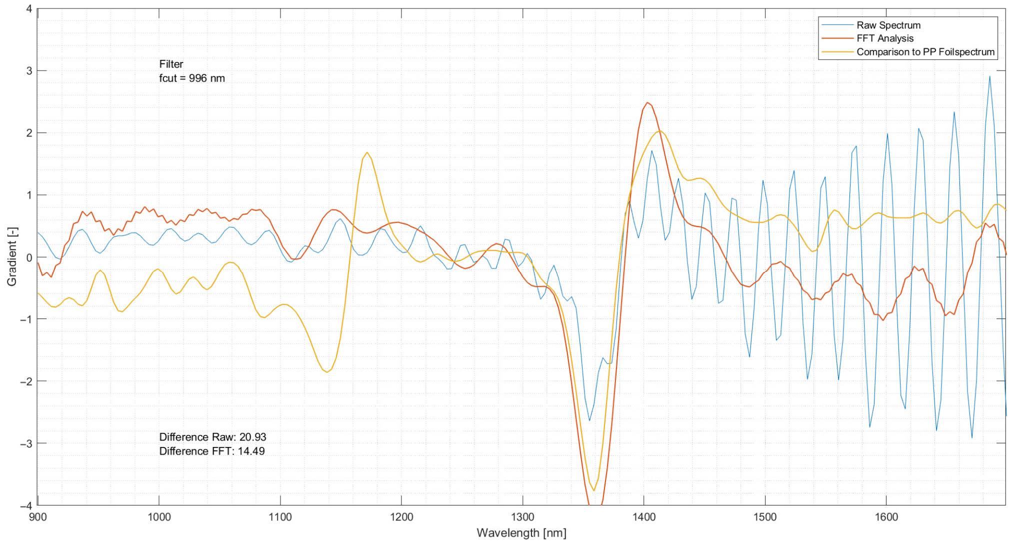

Figure 27. Difference between the raw spectrum (blue) and an improved spectrum (red) and their comparison to a reference spectrum (yellow).

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.

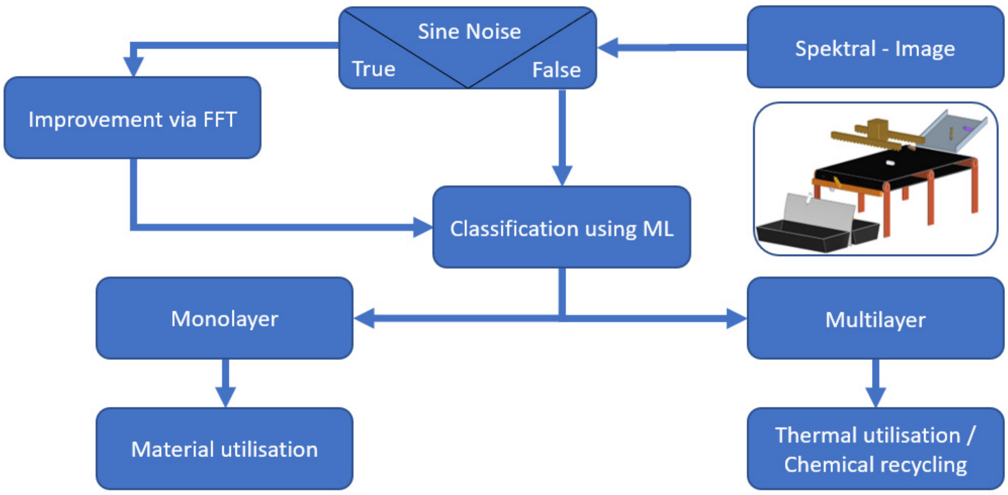

Figure 28. Integrated film recycling process.

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.

Funding: This work was funded by the province of Styria and Zukunftsfonds Steiermark for the project “Multilayer Detection” (project number 1314).

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.

References

1. Van Eygen, E.; Laner, D.; Fellner, J. Circular economy of plastic packaging: Current practice and perspectives in Austria. *Waste Manag.* **2018**, *72*, 55–64. [CrossRef] [PubMed]
2. Koinig, G.; Rutrecht, B.; Friedrich, K.; Barretta, C.; Vollprecht, D. Latent Recycling Potential of Multilayer Films in Austrian Waste Management. *Polymers* **2022**, *14*, 1553. [CrossRef] [PubMed]
3. PlasticsEurope Deutschland e., V. 2019. Available online: https://plasticseurope.org/wp-content/uploads/2021/10/2019-Plastics-the-facts.pdf (accessed on 17 July 2022).
4. Directive (EU) 2018/851 of the European Parliament and of the Council. 30 May 2018. Available online: https://www.eea.europa.eu/policy-documents/directive-eu-2018-851-of (accessed on 17 July 2022).
5. Siesler, H.W.; Kawata, S.; Heise, H.M.; Ozaki, Y. *Near-Infrared Spectroscopy: Principles, Instruments, Applications*; John Wiley & Sons: Hoboken, NJ, USA, 2002.
6. Eisenreich, N.; Rohe, T. Infrared Spectroscopy in Analysis of Plastics Recycling. In *Encyclopedia of Analytical Chemistry*; Meyers, R.A., Ed.; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2006. [CrossRef]
7. Chen, X.; Kroell, N.; Feil, A.; Pretz, T. Determination of the composition of multilayer plastic packaging with NIR spectroscopy. *Detritus—Multidiscip. J. Waste Resour. Residues* **2020**, *13*, 62–66. [CrossRef]
8. Jeszenszky, E.; Kocsányi, L.; Richter, P. Eliminating the interference pattern in near-infrared spectra used for identification of thin plastic foils. *Appl. Spectrosc.* **2004**, *58*, 693–697. [CrossRef] [PubMed]
9. Pfaendner, R.; Herbst, H.; Hoffmann, K.; Sitek, F. Recycling and restabilization of polymers for high quality applications. An Overview. *Angew. Makromol. Chem.* **1995**, *232*, 193–227. [CrossRef]
10. Gonzalez Viejo, C.; Fuentes, S.; Torrico, D.; Howell, K.; Dunshea, F.R. Assessment of beer quality based on foamability and chemical composition using computer vision algorithms, near infrared spectroscopy and machine learning algorithms. *J. Sci. Food Agric.* **2018**, *98*, 618–627. [CrossRef] [PubMed]
11. Morellos, A.; Pantazi, X.-E.; Moshou, D.; Alexandridis, T.; Whetton, R.; Tziotzios, G.; Wiebensohn, J.; Bill, R.; Mouazen, A.M. Machine learning based prediction of soil total nitrogen, organic carbon and moisture content by using VIS-NIR spectroscopy. *Biosyst. Eng.* **2016**, *152*, 104–116. [CrossRef]
12. Kaiser, K.; Schmid, M.; Schlummer, M. Recycling of Polymer-Based Multilayer Packaging: A Review. *Recycling* **2018**, *3*, 1. [CrossRef]
13. Mumladze, T.; Yousef, S.; Tatariants, M.; Kriūkienė, R.; Makarevicius, V.; Lukošiūtė, S.-I.; Bendikiene, R.; Denafas, G. Sustainable approach to recycling of multilayer flexible packaging using switchable hydrophilicity solvents. *Green Chem.* **2018**, *20*, 3604–3618. [CrossRef]
14. Friedrich, K.; Koinig, G.; Pomberger, R.; Vollprecht, D. Qualitative analysis of post-consumer and post-industrial waste via near-infrared, visual and induction identification with experimental sensor-based sorting setup. *MethodsX* **2022**, *9*, 101686. [CrossRef]
15. Cui, Y.X. *Study and Development of Near-Infrared Reflective and Absorptive Materials for Energy Saving Application*; Canadian theses = Thèses canadiennes; Library and Archives Canada; Bibliothèque et Archives Canada: Ottawa, ON, Canada, 2011.
16. McKelvy, M.L. Infrared Spectroscopy: Introduction. In *Encyclopedia of Analytical Chemistry*; Meyers, R.A., Ed.; John Wiley & Sons, Ltd.: Hoboken, NJ, USA, 2006. [CrossRef]

17. Koinig, G.; Friedrich, K.; Rutrecht, B.; Oreski, G.; Barretta, C.; Vollprecht, D. Influence of reflective materials, emitter intensity and foil thickness on the variability of near-infrared spectra of 2D plastic packaging materials. *Waste Manag.* **2022**, *144*, 543–551. [CrossRef] [PubMed]
18. Nguyen, Q.H.; Ly, H.-B.; Ho, L.S.; Al-Ansari, N.; van Le, H.; van Tran, Q.; Prakash, I.; Pham, B.T. Influence of Data Splitting on Performance of Machine Learning Models in Prediction of Shear Strength of Soil. *Math. Probl. Eng.* **2021**, *2021*, 4832864. [CrossRef]
19. Küppers, B.; Schloegl, S.; Oreski, G.; Pomberger, R.; Vollprecht, D. Influence of surface roughness and surface moisture of plastics on sensor-based sorting in the near infrared range. *Waste Manag. Res. J. Int. Solid Wastes Public Clean. Assoc. ISWA* **2019**, *37*, 843–850. [CrossRef] [PubMed]
20. Rinnan, Å.; van den Berg, F.; Engelsen, S.B. Review of the most common pre-processing techniques for near-infrared spectra. *TrAC Trends Anal. Chem.* **2009**, *28*, 1201–1222. [CrossRef]
21. Yadav, S.; Shukla, S. Analysis of k-Fold Cross-Validation over Hold-Out Validation on Colossal Datasets for Quality Classification. In Proceedings of the 2016 IEEE 6th International Conference on Advanced Computing (IACC), Bhimavaram, India, 27–28 February 2016; IEEE: Piscataway, NJ, USA, 2016; pp. 78–83. [CrossRef]
22. Durmus, B.; Güneri, Ö. Analysis and detection of Titanic survivors using generalized linear models and decision tree algorithm. *Int. J. Appl. Math. Electron. Comput.* **2020**, *8*, 109–114. [CrossRef]
23. Peterson, L. K-nearest neighbor. *Scholarpedia* **2009**, *4*, 1883. [CrossRef]
24. Beyer, K.; Goldstein, J.; Ramakrishnan, R.; Shaft, U. When Is "Nearest Neighbor" Meaningful? In Proceedings of the Database Theory—ICDT'99, Jerusalem, Israel, 10–12 January 1999; Goos, G., Hartmanis, J., van Leeuwen, J., Beeri, C., Buneman, P., Eds.; Lecture Notes in Computer Science. Springer: Berlin/Heidelberg, Germany, 1999; Volume 1540, pp. 217–235. [CrossRef]
25. Suthaharan, S. Support Vector Machine. In *Integrated Series in Information Systems: Machine Learning Models and Algorithms for Big Data Classification*; Suthaharan, S., Ed.; Springer: New York, NY, USA, 2016; Volume 36, pp. 207–235. [CrossRef]
26. Masoumi, H.; Safavi, S.M.; Khani, Z. Identification and Classification Of Plastic Resins Using Near Infrared Reflectance Spectroscopy. *Int. J. Mech. Ind. Eng.* **2012**, *6*, 213–220. [CrossRef]
27. Burns, D.A.; Ciurczak, E.W. *Handbook of Near-Infrared Analysis*; CRC Press: Boca Raton, FL, USA, 2007. [CrossRef]

4 Summary of Results

This doctoral thesis entails six publications covering the two phases of this research, "Waste Management Analysis" and "Process Optimisation", with each publication building upon the findings of its predecessors. The research questions defined in chapter 1.3, "Scope of Investigations", are answered below as a summary.

4.1 Waste Management Analysis Phase

Research Paper 1:

"Latent Recycling Potential of Multilayer Films in Austrian Waste Management"

This publication concerns itself with the current prevalence of film packaging in the separate collection of lightweight packaging. It portrays a hand-sorting trial to determine the percentage of plastic waste that is film packaging. Further, the packaging is catalogued according to their usage. In addition, the film packaging undergoes classification with Fourier transform infrared spectroscopy (FTIR) to determine the percentage of multilayer packaging within the film fraction. Based on these results, this publication shows the latent recycling potential in film packaging that can be used to reach the mandatory recycling rates.

Research questions:
(1a) How prevalent is film packaging in Austrian lightweight packaging at the start of the investigations?
Film packaging represents 69,000 t of Austria's annually produced 300,000 t lightweight packaging, i.e. 23 %. In this publication, hand sorting trials have been conducted to deepen the understanding of how prevalent film packaging is in the input fraction of a sorting facility in Austria. The results of the hand sorting trial of plastic packaging could support the results of existing studies, which suggested that of the 170,000 t of separate collected waste in Austria, 30% by weight is flexible 2D plastic packaging.

(1b) What percentage of film packaging are multilayer films?
FTIR analysis of these films further revealed that 31% of all films are made of polyethene (PE), 39% polypropene (PP), 11% polyethene–polyethene terephthalate, and 8% polyethene–polypropene. Based on the FTIR analysis, the percentage of multilayer films in the evaluated fraction was 20 %.

(1c) What are the most common applications for multilayer films disposed of via the separate collection of lightweight packaging?
Cataloguing the film material showed that the most prevalent use of multilayer film packaging is carrier bags, pet food packaging and sanitary products. 30%, 18% and 8% of all multilayer packaging were used for these applications, respectively. In addition, the types of packaging most likely to be made up of two or more layers of film were evaluated. This evaluation showed that 100% of evaluated cases of dairy products and coffee packaging was made of multilayer films. Following these applications is meat packaging, where over 80% of all packaging were made of multilayer films.

(1d) How would increased film recycling affect the overall recycling rate?
It was calculated that improved sorting of films could increase the Austrian recycling rate from 25.7% to 35.5%. This approach enables the recycling of single-layer films by avoiding contamination with foreign substances introduced by multilayer films, which affect the

mechanical properties of the recyclates. In addition, the potential increase in the recycling rate was calculated if multilayer films were recycled. Including mechanical or chemical recycling schemes to recycle multilayer films would raise the recycling rate to 38.9%.

Research Paper 2:

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

This publication serves as a review of the relevant technologies in the field of sensor-based sorting. This review analyses the most important technologies, such as near-infrared, visual, x-ray fluorescence, and laser-induced breakdown spectroscopy. In addition, the most common sorter configurations, such as a chute sorter, belt sorter and robot-aided sorting, are depicted in detail in this publication. All evaluated sensor systems are comprised in a lookup table, depicting the capabilities of the sensor technologies. This review was used to determine the sensor technology with the highest potential for film sorting and subsequent industrial applications.

Research questions:
(2a) What is the current state of the art, and what is the best practice in sensor-based waste sorting?
Currently, an array of sorting technologies is used in waste management to sort incoming material. These sorting methods depend on the specific differences in material properties to enable a separation into the desired fraction. This publication has undertaken a comprehensive overview of the available sorting techniques to gain an overview of the most common sensor-based sorting techniques. Among these is sorting via electromagnetic induction, using the electrical conductivity for separating materials. Sensor-based waste sorting is commonly applied in the sorting and processing of scrap, electronic waste, construction residue, commercial waste and glass.

Laser-Induced-Breakdown-Spectroscopy (LIBS) is based on the material's elemental composition. Heating the sample's surface induces conversion into plasma. The plasma emits a light spectrum that can then be used to differentiate metal alloys and sort scrap metal.

Near Infrared Spectroscopy (NIRS) is based on the interaction between the near-infrared radiation and the material's molecular structure. The excitation of the molecules by the near-infrared radiation leads to absorption in specific bands that produce characteristic spectra, which are, among others, commonly applied to separate packaging waste, household waste, commercial waste, sorting of recyclables and the end-of-life recycling of vehicles.

Visual Spectroscopy (VIS) works by detecting visible light colour, and samples are then characterised based on colour, brightness, reflectivity, and transparency. This technology is commonly used to separate waste paper, recyclables, glass, and construction site residue.

X-ray Fluorescence Spectroscopy (XRF) depends on the specimen's elemental composition. When the specimen is exposed to the radiation, a fluorescence characteristic of the substance is produced, which can be used to identify different alloys or to sort glass.

(2b) Which currently available technique shows the highest potential for improving the sortability of film packaging waste?

The most common technologies were compared for their cost, effectiveness, and ease of application. This comparison led to eliminating all X-Ray-based sorting mechanisms due to the need for extensive radiation protection and the procuring of expensive equipment. LIBS was excluded for similar reasons and, in addition, the application of LIBS to polymer sorting is inhibited by the similarity of the elemental composition of polymers. The remaining sorting methods, VIS, induction sorting, and NIRS, underwent further evaluation of their potential to improve the sortability of film packaging waste. Induction sorting can be used to separate films with a metallic layer as these metallic layers pose a problem in the recycling process and need to be removed. VIS sorting can aid in producing a single colour film fraction to improve the marketability of recyclates. NIRS is a staple in the waste processing sector, is widely applied, does not need special safety equipment, and is able to handle high throughput rates.

Improving the sorting of films with these types of sensor-based sorting technology shows great promise for improving the waste management of lightweight film packaging.

<u>**Research Paper 3:**</u>

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

This publication details the selected methods and the underlying working principles used in this doctoral thesis. The methods described in this paper address the development of sorting models for a specific near-infrared, visual spectroscopy, and induction sensor. Specifically, the methods used to create sorting models are described and validated with plastic and metal wastes.

Research question:

(3a) What are the working principles behind the sorting techniques best applicable to film sorting?

The concluded process when sorting in VIS had nine steps. The first two steps entail adjusting lighting settings, white calibration, and black calibration. The third step consists of creating a basic classification program. In the fourth step, specimens are recorded, and the respective colour of the pixels are assigned to the classification classes. In step five, the material to be classified is applied to the sorting aggregate and sorted into the created colour classes. Here, the classification success of the particles is measured, and the sorting model is adjusted as needed. The previous steps were all completed on a PC. Step seven involves transferring the created model to the sorting aggregate for usage during a sorting trial. This sorting trial represents step eight. After the sorting trial is completed, the ejected and rejected fractions are evaluated, and the sorting success is measured by manually sorting and weighing the fractions.

Applying NIRS is similar to conducting sorting trials with VIS. The first step consisted of correcting the white and black calibration. After completing this step, the NIR spectral images of representative specimens are taken. From these images, spectra are chosen, and material classes are created. These materials classes are combined into a sorting model, with which the input fraction is sorted. This sorting is conducted via compressed air. After the sorting trial is concluded, the created fractions are again sorted by hand, and the sorting success is evaluated by weighing or counting the fractions as applicable.

When sorting with induction, no sorting model is created. Instead, the parameters for the induction sensor are calibrated to enable classification and ejection. These parameters include the detector's sensitivity, the delay time (defined by the delay between detection and activation of the high-pressure nozzles), the minimum blowout time, and the minimum size of an object to trigger ejection. Further, scaling of the detected object and activating proximity nozzles can be toggled.

4.2 Process Optimisation Phase

Research Paper 4:

"Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison"

This publication evaluates the environmental impact of film recycling. In detail, the resulting Global Warming Potential and the Depletion of Abiotic Fossil Fuels (ADPF) are quantified. Different scenarios depicting improved collection, sorting, and recycling of film packaging are compared with the current situation. Further, the resulting environmental impact of reaching the postulated recycling goals in film recycling is quantified. The overarching goal of this publication is to compare the thermal valorisation of film packaging waste to the recycling of this fraction regarding the resulting environmental impact. This comparison is used to aid in deciding whether the mechanical recycling of films is a goal worth achieving from an environmental perspective.

Research questions:
(4a) Can mechanical recycling of films reduce the environmental impact of film packaging?
The results in this publication showed that the general trend towards mechanical recycling of films reduces the environmental footprint of film packaging. In this publication seven scenarios have been compared. Each scenario depicts improvements in one area of film packaging recycling and is compared against the status quo.

With each scenario, the environmental impact of film packaging has decreased over its lifecycle. Increased collection of film packaging decreased the load of the municipal waste incineration plant only in a limited way. This limited decrease in incinerated film packaging is due to a lack of suitable sorting facilities to separate mono- from multilayer films. This lack of a recycling route for film packaging necessitates thermal recovery of the film fraction that is separated during the separation process. At this point, the improved sorting of film packaging that was looked at in this publication decreased the environmental impact of film packaging by enabling the separation of mono- and multilayer films.

By separating the multilayer fraction from the monolayer materials, this fraction can be used as feedstock, eliminating the current need for thermal recovery of these monolayer films. This reduction in thermally recovered lightweight packaging reduced the environmental impact of film packaging substantially.

(4b) Is mechanical recycling of films ecologically viable despite the reduction in thermally recovered energy from film waste?
One concern in reducing the amount of thermally recovered film packaging was the resulting decrease in produced power and heat. This decrease would entail the need for other forms of electricity and heat production, which would offset the reduction in CO_2 emissions. The results showed that the driving forces for the environmental impact are the production and waste incineration of film packaging, which are the most significant contributors to the Global Warming Potential (GWP).

Reducing the incineration resulted in reducing the necessity for virgin film production and reducing the environmental impact of film packaging. The results for energy recovery were similar: After calculating the environmental impact of the otherwise recovered energy from thermal recovery with the energy mix used in Austria, the results showed that a reduction in thermal recovery and subsequent increase in other energy production would lead to an overall decrease in the environmental impact of film packaging. Regarding quantifying reduced incineration's impact, the GWP has been calculated for the functional unit of 1,000 kg of packaging film.

The calculated GWP of the Status Quo was 3,237 kg CO_2-eq. and an ADPF of 54,759 MJ for the functional unit of 1,000 kg of film packaging. Improvements in the film packaging waste collection reduced the GWP by 6%. Improving the separation of monolayer films from the film fraction and subsequently introducing them into the recycling scheme reduced the GWP by 63%. Simulated recycling of all film packaging would reduce the GWP by 90%, leaving 335 kg CO_2-eq for the examined functional unit of 1,000 kg film packaging.

The usage of regranulates from film recycling in film packaging production enables this reduction by reducing the amount of virgin materials that need to be manufactured and the environmental impact that accompanies this production. This theoretical substitution eliminates the need to produce virgin materials and, thus, reduces the production-related effects to zero. Optimising all steps in the recycling process eliminates the need for incineration and leaves primary energy production as the predominant emission source of the residual GWP.

(4c) How will reaching the postulated recycling goals in film recycling impact the global warming potential and depletion of abiotic fossil fuels?

The impact of reaching the postulated recycling goals for 2025 and 2030, respectively, has been calculated. The optimisations necessary to reach the 2025 recycling goal in collection rate, sorting and recycling would yield in a reduction of the GWP of 34%. This reduction entails an absolute reduction to 2,124 kg CO_2-eq for the functional unit. In terms of the ADPF, reaching the 2025 recycling goals would yield a reduction of 36% in ADPF compared to the status quo.

The postulated recycling rate of 55% by 2030 surpasses the goals set for 2025. As such, the resulting reduction in GWP would also increase. The GWP could be reduced by 40% if the recycling goals are met by further optimisation of the collection, sorting and recycling processes. This reduction results in 1,944 kg CO_2-eq for the functional unit. In terms of the ADPF, reaching the goals postulated for 2030 would reduce the ADPF by 42% compared to the status quo, resulting in an absolute ADPF for each functional unit of 32,028 MJ.

Research Paper 5:

"Influence of Reflective Materials, Emitter Intensity and Foil Thickness on the Variability of Near-Infrared Spectra of 2D Plastic Packaging Materials"

This publication concerns the limitation of near-infrared spectroscopy when handling thin materials such as film packaging. Since this technology relies on near infrared radiation interacting with the material, thin thicknesses pose a problem because little to no interaction can occur. The lack of interaction leads to spectra that contain no characteristics of the material and are thus of no value to the classification process. This publication showcases new adaptations to existing sorting aggregates and the increased spectral quality that can be achieved.

Research questions:
(5a) What hardware adaptions mitigate the lack of spectral information when sorting films with near-infrared technology?
The lack of spectral information is mainly caused by two mechanisms. One is the effect of low material thickness, which inhibits the interaction of the material and the near-infrared radiation. The second is caused by the material properties itself. The often glossy and crinkled surface leads to overexposed pixels while destructive interferences produce overlying noise and thus further blur the spectral information content.

The resulting improvement in spectra quality was defined by the deviation of the spectra from a reference spectrum and the spectra's variability. Various experiments have been conducted to find the most relevant factors that define spectral quality. A relevant factor was the material thickness, further confirming the notion that low spectral quality is a result of low material thickness.

Another relevant factor was the illumination intensity. Raising the intensity of the infrared emitter increased the spectral quality. Another effective way to increase spectral information content was raising the reflectivity of the background on which the materials were recorded, enabling measurement in transflection.

(5b) What changes provide the most significant improvement in spectral quality?
A statistical evaluation of all sorting process parameters revealed the most important changes. The greatest improvement in spectral quality could be seen when a reflective background was introduced. This reflective background replaces the standard transparent background and enables measurement in transflection. This method of measuring the films' spectra increases the interaction between film and radiation and produces spectra with little to no variability. Measurement in transflection further reduces spectral noise and yields spectra with the typical characteristics of the evaluated material.

(5c) How can existing Near-infrared Sorting aggregates be adapted to improve film sorting?
The adaption of existing near-infrared sorting aggregates must be completed with minimal investment concerning time and labour and minimal disturbance of the daily processes. This publication showcases the adaptation of an existing chute sorter to incorporate measurements in transflection. This adaption has been designed to be reversible, not to hinder aggregate usage in conventional transmission measurements.

A reflective background has to be installed to implement transflection measurement, and this reflective background needs to be highly reflective of near-infrared radiation. The experiments conducted in this publication and the reviewed literature point to metallic backgrounds. Theoretically viable materials include gold, copper, and aluminium. Out of these materials only copper and aluminium are applicable in a waste sorting plant due to the high cost and unsuitable mechanical properties of gold. These materials are resilient and relatively inexpensive and deliver the best cost-to-performance ratio. These metallic backgrounds are highly reflective in the relevant wavelengths and increase the spectral information content.

Implementing these reflective backgrounds in a chute sorter is comparatively easy to achieve. Given the measurements of the sorter, a reflective plate has been laser-cut to fit the existing aggregate. As a final step, the sorter's illumination settings and white calibration were modified to accommodate the background's increased reflectivity.

Research Paper 6:

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

This publication concerns the residual issues when sorting film packaging in near-infrared. One issue is the plethora of existing film combinations in multilayer packaging. The high number of possible combinations of materials makes creating a sorting model challenging because every material combination exhibits a characteristic spectrum that has to be accounted for in the sorting model. In this publication, machine learning sorting models are evaluated based on their capability to sort multilayer- and monolayer materials based on overlying differences in the spectra. The results show that it is possible to apply machine learning techniques to the data and to sort film packaging without explicitly teaching the sorting model every material combination present in the input fraction. In addition, frequency analysis methods are evaluated to present a method to further increase the information in the spectra of films by eliminating overlying noise.

Research question:
(6a) Can data-driven methods further facilitate the sorting of film packaging?
Data-driven methods were evaluated for their feasibility in classifying multilayer and monolayer films. These classifications should be produced independently from the material composition of the film. Classifying films this way would enable the separation of film materials without creating sorting models for every layer combination. Preliminary trials have shown that characteristic differences between the spectra of mono- and multilayer films exist, and these differences are independent of the actual material composition. The applied principal component analysis of the film spectra revealed three principal spectral areas as components, which explained over 80% of the variance present in the data. These components were in the ranges of 1,230 nm, 1,380 nm – 1,410 nm and 1,410 nm – 1,440 nm. These specific wavelengths are regions of interest for the classification and show that sufficient material independent information is present in the spectral data to enable separation.

(6b) Can Fast Fourier Transformation automatically improve spectral quality?
Fast Fourier Transformation has been applied to spectra exhibiting sinus wave noise. This noise results from destructive interferences due to the low material thickness. Fast Fourier Transformation can represent the spectra in the form of Fourier components. Prior to the

reconstruction of the spectra via inverse Fourier Transformation, the Fourier components are evaluated for their information content. Only Fourier components containing relevant information should be used for the reconstruction. Finding these relevant Fourier components by hand is time-consuming and laborious. Thus, this process has been automated. Reconstruction is performed after automatically checking the contribution of all Fourier components to a valuable spectrum and implementing a filter. This filter removes all Fourier components that do not improve the reconstructed spectrum. With this automatic selection of Fourier components for reconstruction, improving spectra via Fast Fourier Transformation to eliminate sine wave noise in line is feasible.

(6c) Can machine learning techniques separate monolayer- from multilayer materials without explicitly teaching the sorting aggregate to recognise the spectra of all present multilayer compositions?

The results of this publication have shown that sufficient material independent information is present in the spectra data to make separation via machine learning approaches feasible. Further investigation has shown that only a small number of machine learning techniques are suitable for this task. After evaluating the available possibilities, k-Nearest Neighbour, Support Vector Machines and Neural Networks were chosen for further trials. Before teaching the sorting model, extensive tests were conducted to determine the correct feature engineering. Additionally, all spectra were smoothened via a gaussian smoothing algorithm, normalised and the first derivative taken. With this data, the training of the models was started, and the trained models were tested on an independent set of spectra. Here, the neural network needed the shortest training time, delivered the most accurate prediction, and performed extraordinarily well even on completely new spectral material. Complemented with the fast prediction speed, these results lead to the preliminary conclusion that a shallow neural network is most capable to perform in-line classification of film material on an existing near-infrared sorter.

5 Summary and Discussion of Results

This chapter critically analyses the results and findings obtained in this dissertation. Further, the results are put into context and compared with existing findings.

It was shown in publication 1 that there is substantial potential for improvement in the recycling of films. For the first time, the proportion of multilayer material in the separate collection of packaging waste in Austria was quantified. The resulting 20% are similar to the findings in of Jannick et al., 2022 in Germany. At the same time, the findings prove that the problem of insufficient sorting and sortability of film packaging still exists. However, the root cause of these issues cannot only be found in the waste management sector and political decisions but lies also in limitations in the sorting technologies currently available to film sorting. The decision to increase film sorting relies on the existence of reliable, efficient, and cost-effective sorting methods to separate film packaging. Presently, film sorting via NIRS is hindered by the material properties of film packaging, such as low material thickness and an overabundance of film compositions. The resulting issues in creating a clean monomaterial film fraction need to be overcome before a substantial increase in the recycling rate of films is feasible. In this thesis, the previously described technological limitations were solved by increasing the spectral quality and deriving new sorting methods for film recycling. These solutions were based on a thorough analysis of existing sorting methods and the existing composition of film packaging in the Austrian waste stream.

Publications 2 and 3 reviewed the available technologies and their application. The scope of the reviews lies primarily in the hardware of sensor-based sorting techniques. At the time, the inherent limitations of film packaging meant that existing sensor-based sorting techniques were unable to detect film packaging (Bauer et al., 2021). Existing recycling systems are geared towards the recycling of mono materials, and thus, thermal recovery is the main route currently available for film packaging (Ragaert et al., 2017; Kaiser et al., 2018; Riedl, 2018). The comparison of existing technology showed that NIRS had the most potential for film packaging. At the time, first solutions were being formulated to overcome the restrictions in film sorting with NIR. During the course of this thesis, these solutions were implemented to increase the capabilities of NIR film sorting.

Publication 5 showcased improvements to an existing near-infrared sorting aggregate. These improvements are shown to enhance the classification of film packaging. Despite being in industrial use since 1990, NIRS is still undergoing continuous and substantial improvements (Gupta, 2018). These improvements in the hardware and software alike are making NIR devices smaller, more intelligent, more accurate and more useable (Rani et al., 2019; Hu et al., 2022; Chunting et al., 2022). Improvements like these facilitate the adoption of NIRS for tasks hitherto erroneously deemed unsuitable. Publication 5 focuses on the effects adaptations to the measuring geometry have on spectral quality. The spectral quality was assessed offline. Previous findings showed that thin polymer films exhibit interferences, and publication 5 added a thickness range for the occurrence of these interferences in PP (Jeszenszky et al., 2004). The publication did not offer a way to decrease these interferences apart from increasing the material's thickness or the reflectance of the sorting chute. These issues were taken up in publication 6, which expands on the findings of publication 5.

Publication 6 conducted an inline sorting trial separating mono- from multilayer films. This sorting trial compared the standard sorting method with an adapted sorting aggregate. The sorting aggregate was improved via the enhancements proffered in publication 5. Publication

6 further proposes using machine learning techniques to facilitate the separation of mono- and multilayer films. In addition, publication 6 demonstrates a particular usage of the Fast Fourier Transformation to increase spectral quality through an automated removal of unnecessary spectral components and subsequent reconstruction of the spectrum. All proposed methods were conducted offline. While the computing time of the shown methods was evaluated, no inline experiments applying the methods to live recorded spectra were performed.

During the course of this work, uncertainty persisted whether an increase in the mechanical recycling of films would benefit the environmental goals. These concerns were driven by the fact that an increase in the share of recycled film would reduce the feedstock available for thermal recovery. This could therefore increase the use of fossil fuels for the generation of heat and electricity (Fellner & Brunner., 2022). Therefore, publication 4 used a comprehensive LCA to show the potential reduction in GWP and ADPF through the adoption of increased film recycling. This publication aimed to gauge the environmental practicality of increased mechanical recycling of film packaging concerning greenhouse gas emissions. The change in the recovery path from thermal recovery to mechanical recycling entails a change in emissions and resource depletion that were compared in this article. This publication adds to the existing array of LCA for plastic packaging that have ranked the influence of methodological choices, assessed the environmental impact of multilayer film from biopolymers and evaluated modifications in the packaging for their environmental impact (Toniolo et al., 2013; Garrain et al., 2011; Siracusa et al., 2011). The findings in publication 4 concentrate on Austrian waste and are based on data available for processes and facilities within the Austrian waste management, polymer production and energy (supply) system. As such, they are limited to the Austrian situation. A comparison of the Austrian situation to its neighbour states or an evaluation of Austria's role in the European context of international waste management and the resulting transport was outside the scope of this publication.

As the Austrian energy mix is mainly based on renewables, such as hydropower, an increase in energy consumption for production does not add substantial greenhouse gas emissions. At the time of writing, the reactivation of coal power plants is being discussed. Consequently, this situation may change in the future. Changes in the Austrian energy provision system may necessitate a revaluation of the environmental reasonableness of increased recycling.

6 Outlook and Further Research

Further improvements to film packaging will be part of the ongoing project “Flex4Loop”. Results from this project may show that the existing packaging solutions are exaggerated in terms of thickness and the application of metallic layers for the expected protection capabilities. No research has been conducted on how much packaging is minimally necessary to guarantee product protection and shelf life of foodstuff. Furthermore, it has to be seen whether the enhanced sorting capabilities of NIRS can offset the deprecation of spectral information caused by the trend to thinner packaging material and if the recyclability of these packaging materials can thus be maintained.

In addition to finding the ideal way of packaging while still retaining recyclability, the findings in this thesis are the basis for further research in “Flex4Loop”. The increased understanding of film spectra in NIR and the enhanced spectral information due to the improved measuring methods are used to gauge whether film packaging that is currently deemed “Not Recyclable”, can be detected, and ejected from the waste stream via NIRS. New packaging is being developed under the principles of minimal material use. Shelf-life trials with newly developed packaging are conducted to show how prevalent overpackaging is, and how packaging can be changed to achieve a better ratio between packaging and product. Further, these studies may reveal that many packaging types, like metallised films, which are difficult to recycle, may not be necessary to achieve the required shelf life. These new minimalistic packaging are then evaluated for their sortability and recyclability with the sorting techniques developed in Multilayer Detection.

Figure 4:Concise description of the research projects flex4loop and Multilayer Detection showing their different goals, synergies, and common aims.

LCA is increasingly recognised as a critical concept and method to support sustainable transformation. LCA plays a relevant role in decision support, striving for a holistic assessment of environmental impacts. The performed LCA delivered a holistic view of the effects of increased film recycling on Austria. A more in-depth analysis must be performed to gauge the impact of possible strategic decisions and provide a stable basis of argument in the political arena.

Further applications of the proposed improvements in detection geometry need to be evaluated in a broader array of NIR sorting aggregates. These trials may include the implementation of sorting models tailored to separating films by layer composition to consider the ideal combination of prediction accuracy and computational requirements. Bearing in mind the continuous improvements in AI-aided waste management, the sorting software enhancing the capabilities of NIRS may emerge even further. The waste management sector needs to stay well informed about these developments.

To assess the technological readiness level (TRL) of the new developments shown in this doctoral thesis, the TRL proposed by the European Commission in 2014 were used. These levels categorise the readiness of the technology in question into nine levels. For these levels, the following definitions apply. TRL 1 – basic principles observed, TRL 2 – technology concept formulated, TRL 3 – experimental proof of concept, TRL 4 – technology validated in lab, TRL 5 – technology validated in relevant environment (industrially relevant environment in the case of key enabling technologies), TRL 6 – technology demonstrated in relevant environment (industrially relevant environment in the case of key enabling technologies), TRL 7 – system prototype demonstration in operational environment, TRL 8 – system complete and qualified, TRL 9 – actual system proven in operational environment (competitive manufacturing in the case of key enabling technologies; or in space) (European Commission, 2015).

The relevant developments in this thesis, namely the software-based enhancement of film classification and the hardware-based enhancements via film measurement in transflection, were ranked as TRL 4 and TRL 6, respectively. The software developments, entailing the Fast Fourier Transformation improvement of spectral data and the application of machine learning methods to classify film packaging, were shown to work offline in a laboratory setting. At the time of writing, applying these techniques to spectral images recorded on the NIR sorter inline is impossible due to computational limitations and the difficulties inherent in implementing a program that utilises the GigeCam / GenICam Interface to gain direct access to useable data directly from the near-infrared detector. Once these limitations are overcome, trials validating and demonstrating the usage of FFT to enhance the spectral quality of thin film packaging and the subsequent application of a custom classifier to separate film packaging inline will be implemented, potentially raising the TRL from 4 to 6.

The hardware-based improvements in the classification of film spectra were validated in small trials on the sensor-based sorter used in this thesis and with statistical comparison as portrayed in publication 4. Further, larger scale trials were conducted to compare the separation success when applying transflection to the sorting success when classifying in reflectance. This comparison showed the merits of transflection classification of film packaging in general and the superiority of the copper reflector when compared to a reflector made from aluminium. The TRL of the hardware-based improvements was thus estimated to be 6, because the technology was validated and demonstrated on a near infrared sorter, commonly used in industrial waste management.

Before TRL 7 can be reached, however, the hardware-based improvements need to be tested further on NIR sorting aggregates employing conveyor belts. Complications arising in the implementation of transflection measurement on belt-based sorters will need to be evaluated and overcome, prior to the incorporation of transflection measuring in the operational environment of NIR sorters and finally reaching TRL 7.

Figure 5 gives a short summary of the relevant TRL points for the software- and hardware-based improvements to NIR based film sorting. The steps deemed necessary to further the TRL for the respective developments are depicted in the figure.

Monitoring the origin of packaging waste and the impacts of political and economic changes needs to continue, and this continuation of monitoring can deliver vital data for policymaking. In addition to the origin of plastic waste, monitoring social and economic factors may prove crucial for strategic decisions and investment in emerging technologies on the Austrian as well as European level. Ongoing evaluation of the development of film recycling needs to be conducted to ensure that the latent potential to increase the recycling rate through increased film recycling sees realisation.

In conclusion, should film packaging recycling continue to be sufficiently researched, the emerging use of these resources may prove vital in decreasing the environmental impact and improving the circular economy of plastic packaging.

Software Based Improvements

	Technology Readiness Level
1	Basic principles observed
	Jeszenszkyand Wanjun have shown that FFT can improve spectral quality and that machine learning is a viable addition to SBS.
2	Technology concept formulated
	Publication 6 showed the application of FFT and Machine Learning to enhance spectral quality. It further formulates an algorithm for automatic application.
3	Experimental proof of concept
	Publication 6 showed that spectral quality and classification can be enhanced through FFT and Neural Networks
4	Technology validated in lab
	Spectral recordings of real materials were enhanced using FFT and film objects were classified using ML algorithms offline.
5	Technology validated in relevant environment
	Sorting of film packaging with known composition needs to be conducted to validate the application of inline application of FFT and Neural Net Classification of films.
6	Technology demonstrated in relevant environment
	Large scale sorting trials need to be conducted to validate the application of inline application of FFT and Neural Net Classification of films.
7	System prototype demonstration in operational environment
	NIR Sorter with FFT Spectra improvement and NN Classification needs to be demonstrated with real waste material.
8	System complete and qualified
	Necessary purity and yield from a waste stream need to be achieved with the system.
9	Actual system proven in operational environment
	FFT and AI Classification is implemented in film sorting process and achieves postulated yield and purity.

Hardware Based Improvements

	Technology Readiness Level
1	Basic principles observed
	Chen et al. have shown that measurements in transflection are possible on an laboratory scale NIR setup.
2	Technology concept formulated
	The concept of using NIR in transflection for film sorting was formulated during the Multilayer Detection project proposal.
3	Experimental proof of concept
	Experiments shown in publication 4 statistically confirmed the positive effect of measurement in transflection on film spectra.
4	Technology validated in lab
	Publication 4 conducted trials with spectra taken from waste specimen to validate the spectral enhancement of film packaging with NIR transflection.
5	Technology validated in relevant environment
	In Line adaptation of existing NIR sorting aggregate were applied in publication 4. Here the enhanced spectra were validated.
6	Technology demonstrated in relevant environment
	Larger scale sorting trials comparing transflection sorting of film packaging to reflection sorting were conducted in publication 6.
7	System prototype demonstration in operational environment
	NIR Sorter with transflection measurement needs to be demonstrated with real waste material.
8	System complete and qualified
	Necessary purity and yield from a waste stream need to be achieved with the system implementing transflection measurement.
9	Actual system proven in operational environment
	Transflection sorting is implemented in waste sorting process and achieves postulated yield and purity.

Figure 5: Estimation of the Technological Readiness Level of the applied developments for the enhancement of film spectra

7 References

APK AG: 2020. Maschinen von BKG® spielen eine Rolle bei der Circular Economy, indem aus Mehrschichtverpackungen hergestelltes, hochwertiges Polyamid im Newcycling®-Prozess granuliert wird [online]. Available online at https://www.apk-ag.de/maschinen-von-bkg-im-einsatz-beim-newcycling/, (Accessed on 25. October 2022)..

Bauer, Anna-Sophia; Tacker, Manfred; Uysal-Unalan, Ilke; Cruz, Rui M. S.; Varzakas, Theo; Krauter, Victoria (2021): Recyclability and Redesign Challenges in Multilayer Flexible Food Packaging-A Review. In Foods (Basel, Switzerland) 10 (11). DOI: 10.3390/foods10112702.

Briassoulis, Demetres; Tserotas, Philippos; Hiskakis, Miltiadis (2017): Mechanical and degradation behaviour of multilayer barrier films. In Polymer Degradation and Stability 143, pp. 214–230. DOI: 10.1016/j.polymdegradstab.2017.07.019.

Chen, Huazhou; Xu, Lili; Ai, Wu; Lin, Bin; Feng, Quanxi; Cai, Ken (2020): Kernel functions embedded in support vector machine learning models for rapid water pollution assessment via near-infrared spectroscopy. In The Science of the total environment 714, p. 136765. DOI: 10.1016/j.scitotenv.2020.136765.

Chen, Xiaozheng; Kroell, Nils; Wickel, Jan; Feil, Alexander (2021): Determining the composition of post-consumer flexible multilayer plastic packaging with near-infrared spectroscopy. In Waste management (New York, N.Y.) 123, pp. 33–41. DOI: 10.1016/j.wasman.2021.01.015.

Dahlbo, Helena; Poliakova, Valeria; Mylläri, Ville; Sahimaa, Olli; Anderson, Reetta (2018): Recycling potential of post-consumer plastic packaging waste in Finland. In Waste management (New York, N.Y.) 71, pp. 52–61. DOI: 10.1016/j.wasman.2017.10.033.

Dilkes-Hoffman, Leela Sarena; Pratt, Steven; Laycock, Bronwyn; Ashworth, Peta; Lant, Paul Andrew (2019): Public attitudes towards plastics. In Resources, Conservation and Recycling 147, pp. 227–235. DOI: 10.1016/j.resconrec.2019.05.005.

European Commission: Technology readiness levels (TRL); Extract from Part 19 - Commission Decision C(2014)4995" (PDF). ec.europa.eu. 2014. (Accessed on 25. October 2022).

European Union: EU, 2008, Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2008 on waste and repealing certain Directives, OJ L 312, 22.11.2008, p. 3-30.

Eurostat, Generation of waste by waste category, hazardousness and NACE Rev. 2 activity, Statistical office of the European Union. Available online at https://ec.europa.eu/eurostat/databrowser/view/ENV_WASGEN$DEFAULTVIEW/default/line?lang=en, (Accessed on 25. October 2022).

Eurostat, Recycling rates for packaging waste Statistical office of the European Union (2022), Retrieved From https://ec.europa.eu/eurostat/databrowser/view/TEN00063/default/line?lang=en&category=env.env_was.env_wasst; (Accessed on 25. October 2022).

Feil, Alexander; Pretz, Thomas (2020): Mechanical recycling of packaging waste. In : Plastic Waste and Recycling: Elsevier, pp. 283–319.

Fellner, Johann; Brunner, Paul H. (2022): Plastic waste management: is circular economy really the best solution? In J Mater Cycles Waste Manag 24 (1), pp. 1–3. DOI: 10.1007/s10163-021-01340-2.

Frauenhofer-Institut für Verfahrenstechnik und Verpackung IVV: Frauenhofer-Institut für Verfahrenstechnik und Verpackung IVV Mehrschicht-Verpackungen mit dem CreaSolv® Prozess recyceln [online]. Available online at https://www.ivv.fraunhofer.de/de/recycling-umwelt/kunststoff-recycling.html#creasolv (Accessed on 25. October 2022).

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.

Friedrich, Karl (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.

Garraín, D., Vidal, R., Martínez, P., Franco, V., & Cebrián-Tarrasón, D. (2007, August). LCA of biodegradable multilayer film from biopolymers. In 3rd International Conference on Life Cycle Management.

Gonzalez Viejo, Claudia; Fuentes, Sigfredo; Torrico, Damir; Howell, Kate; Dunshea, Frank R. (2018): Assessment of beer quality based on foamability and chemical composition using computer vision algorithms, near infrared spectroscopy and machine learning algorithms. In Journal of the science of food and agriculture 98 (2), pp. 618–627. DOI: 10.1002/jsfa.8506.

Gradus, Raymond H.J.M.; Nillesen, Paul H.L.; Dijkgraaf, Elbert; van Koppen, Rick J. (2017): A Cost-effectiveness Analysis for Incineration or Recycling of Dutch Household Plastic Waste. In Ecological Economics 135, pp. 22–28. DOI: 10.1016/j.ecolecon.2016.12.021.

Gupta, V. P. (Ed.) (2018): Molecular and laser spectroscopy. Advances and applications. Amsterdam, Netherlands: Elsevier. Available online at http://www.sciencedirect.com/science/book/9780128498835.

Hu, Jinquan; Yang, Huihua; Zhao, Guoliang; Zhou, Ruizhi (2022): Research on Online Rapid Sorting Method of Waste Textiles Based on Near-Infrared Spectroscopy and Generative Adversity Network. In Computational intelligence and neuroscience 2022, p. 6215101. DOI: 10.1155/2022/6215101.

Jeszenszky, Eva; Kocsányi, Lászlo; Richter, Péter (2004): Eliminating the interference pattern in near-infrared spectra used for identification of thin plastic foils. In Applied spectroscopy 58 (6), pp. 693–697. DOI: 10.1366/000370204872953.

Kaiser, Katharina; Schmid, Markus; Schlummer, Martin (2018): Recycling of Polymer-Based Multilayer Packaging: A Review. In Recycling 3 (1), p. 1. DOI: 10.3390/recycling3010001.

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.

Koinig, Gerald; Grath, Elias; Barretta, Chiara; Friedrich, Karl; Vollprecht, Daniel; Oreski, Gernot (2022): Lifecycle Assessment for Recycling Processes of Monolayer and Multilayer Films: A Comparison. In Polymers 14 (17), p. 3620. DOI: 10.3390/polym14173620.

Koinig, Gerald; Rutrecht, Bettina; Friedrich, Karl; Barretta, Chiara; Vollprecht, Daniel (2022): Latent Recycling Potential of Multilayer Films in Austrian Waste Management. In Polymers 14 (8). DOI: 10.3390/polym14081553.

Kranert, Martin (2017): Einführung in die Kreislaufwirtschaft. Wiesbaden: Springer Fachmedien Wiesbaden.

Kroell, Nils; Chen, Xiaozheng; Greiff, Kathrin; Feil, Alexander (2022): Optical sensors and machine learning algorithms in sensor-based material flow characterization for mechanical recycling processes: A systematic literature review. In Waste management (New York, N.Y.) 149, pp. 259–290. DOI: 10.1016/j.wasman.2022.05.015.

Li, Chunting; Chen, Huazhou; Zhang, Youyou; Hong, Shaoyong; Ai, Wu; Mo, Lina (2022): Improvement of NIR prediction ability by dual model optimization in fusion of NSIA and SA methods. In Spectrochimica acta. Part A, Molecular and biomolecular spectroscopy 276, p. 121247. DOI: 10.1016/j.saa.2022.121247.

Mancini, Manuela; Mircoli, Alex; Potena, Domenico; Diamantini, Claudia; Duca, Daniele; Toscano, Giuseppe (2020): Prediction of pellet quality through machine learning techniques and near-infrared spectroscopy. In Computers & Industrial Engineering 147, p. 106566. DOI: 10.1016/j.cie.2020.106566.

Masoumi, Hamed & Safavi, Seyed Mohsen & Khani, Z. (2012).: Identification and classification of plastic resins using near infrared reflectance spectroscopy. In International Journal of Mechanical and Industrial Engineering 6, pp. 213–220. Available online at https://www.researchgate.net/publication/285330830_Identification_and_classification_of_plastic_resins_using_near_infrared_reflectance_spectroscopy, (Accessed on 25. October 2022).

Mohn, J.; Szidat, S.; Fellner, J.; Rechberger, H.; Quartier, R.; Buchmann, B.; Emmenegger, L. (2008): Determination of biogenic and fossil CO(2) emitted by waste incineration based on (14)CO(2) and mass balances. In Bioresource technology 99 (14), pp. 6471–6479. DOI: 10.1016/j.biortech.2007.11.042.

Niaounakis, Michael (2020): Recycling of flexible plastic packaging. Oxford, United Kingdom, Cambeidge, MA: William Andrew is an imprint of Elsevier (PDL handbook series). Available online at https://www.sciencedirect.com/science/book/9780128163351.

Pauer, Erik; Tacker, Manfred; Gabriel, Viktoria; Krauter, Victoria (2020): Sustainability of flexible multilayer packaging: Environmental impacts and recyclability of packaging for bacon in block. In Cleaner Environmental Systems 1, p. 100001. DOI: 10.1016/j.cesys.2020.100001.

Plasticeurope: 2019. Plastics - the Facts 2019 [online]. An analysis of European plastics production, demand and waste data. https://plasticseurope.org/wp-content/uploads/2021/10/2019-Plastics-the-facts.pdf, (Accessed on 25. October 2022).

Ragaert, Kim; Delva, Laurens; van Geem, Kevin (2017): Mechanical and chemical recycling of solid plastic waste. In Waste management (New York, N.Y.) 69, pp. 24–58. DOI: 10.1016/j.wasman.2017.07.044.

Rani, Monika; Marchesi, Claudio; Federici, Stefania; Rovelli, Gianluca; Alessandri, Ivano; Vassalini, Irene et al. (2019): Miniaturized Near-Infrared (MicroNIR) Spectrometer in Plastic Waste Sorting. In Materials (Basel, Switzerland) 12 (17). DOI: 10.3390/ma12172740.

Riedl F.: Recyclingherausforderung Multi-Layer? Neuartiges Aufbereitungsverfahren bietet Lösungen. In: Pomberger R., Adam J., Aldrian A., Kranzinger L., Lorber K., Neuhold S., Nigl T., Pfandl K., Sarc R., Schwarz T., et al., editors. Vorträge-Konferenzband zur 14. Recy & DepoTech-Konferenz: Tracer Based Sorting–Innovative Sorting Options for Post Consumer Products. Abfallverwertungstechnik & Abfallwirtschaft Eigenverlag; Leoben, Austria: 2018. pp. 269–274.

Schmidt, Jannick; Grau, Laura; Auer, Maximilian; Maletz, Roman; Woidasky, Jörg (2022): Multilayer Packaging in a Circular Economy. In Polymers 14 (9). DOI: 10.3390/polym14091825.

Shoushtarian, Mehrnaz; Alizadehsani, Roohallah; Khosravi, Abbas; Acevedo, Nicola; McKay, Colette M.; Nahavandi, Saeid; Fallon, James B. (2020): Objective measurement of tinnitus using functional near-infrared spectroscopy and machine learning. In PLoS ONE 15 (11), e0241695. DOI: 10.1371/journal.pone.0241695.

Siracusa, Valentina; Rosa, Marco Dalla; Romani, Santina; Rocculi, Pietro; Tylewicz, Urszula (2011): Life Cycle Assessment of multilayer polymer film used on food packaging field. In Procedia Food Science 1, pp. 235–239. DOI: 10.1016/j.profoo.2011.09.037.

Tartakowski Z. Recycling of packaging multilayer films: New materials for technical products. Resour. Conserv. Recycl. 2010;55:167–170. doi: 10.1016/j.resconrec.2010.09.004. Available online at https://ideas.repec.org/a/eee/recore/v55y2010i2p167-170.html, , (Accessed on 25. October 2022).

Toniolo, Sara; Mazzi, Anna; Niero, Monia; Zuliani, Filippo; Scipioni, Antonio (2013): Comparative LCA to evaluate how much recycling is environmentally favourable for food packaging. In Resources, Conservation and Recycling 77, pp. 61–68. DOI: 10.1016/j.resconrec.2013.06.003.

Van Eygen, Emile; Feketitsch, Julia; Laner, David; Rechberger, Helmut; Fellner, Johann (2017): Comprehensive analysis and quantification of national plastic flows: The case of Austria. In Resources, Conservation and Recycling 117, pp. 183–194. DOI: 10.1016/j.resconrec.2016.10.017.

Van Eygen, Emile; Laner, David; Fellner, Johann (2018): Circular economy of plastic packaging: Current practice and perspectives in Austria. In Waste management (New York, N.Y.) 72, pp. 55–64. DOI: 10.1016/j.wasman.2017.11.040.

Van Eygen, Emile; Laner, David; Fellner, Johann (2018): Integrating High-Resolution Material Flow Data into the Environmental Assessment of Waste Management System Scenarios: The Case of Plastic Packaging in Austria. In Environmental science & technology 52 (19), pp. 10934–10945. DOI: 10.1021/acs.est.8b04233.

Waste Framework Directive. Directive 2008/98/EC of the European Parliament and of the Council of 19 November 2018 on waste and repealing certain Directives. Available online: https://eur-lex.europa.eu/legalcontent/ EN/TXT/?uri=celex:32008L0098; , (Accessed on 25. October 2022).

Xia, Wanjun; Jiang, Yanping; Chen, Xiaohong; Zhao, Rui (2022): Application of machine learning algorithms in municipal solid waste management: A mini review. In Waste management & research: the journal of the International Solid Wastes and Public Cleansing Association, ISWA 40 (6), pp. 609–624. DOI: 10.1177/0734242X211033716.

Zhang, Mengsheng; Zhang, Bo; Li, Hao; Shen, Maosheng; Tian, Shijie; Zhang, Haihui et al. (2020): Determination of bagged 'Fuji' apple maturity by visible and near-infrared spectroscopy combined with a machine learning algorithm. In Infrared Physics & Technology 111, p. 103529. DOI: 10.1016/j.infrared.2020.103529.

8 List of Abbreviations

ADPF	Depletion of Abiotic Fossil Fuels
AI	Artificial Intelligence
ALU	Arbitrary Light Units
ATR	Attenuated Total Reflectance
AVAW	The Chair for Waste Processing Technology and Waste Management
CED	Cumulative Energy Requirement
CO_2	Carbon Dioxide
DFT	Discrete Fourier Transformation
FFG	Österreichische Forschungsförderungsgesellschaft (Austrian Research Promotion Agency)
FFT	Fast Fourier Transformation
FTIR	Fourier-transform infrared spectroscopy
GWP	Global Warming Potential
HDPE	High Density Polyethylene
HSB	Hue Saturation Brightness
HSI	Hyperspectral Imaging
iDFT	Inverse Discrete Fourier Transformation
iFFT	Inverse Fast Fourier Transformation
kNN	K Nearest Neighbour Algorithm
LCA	Life Cycle Analysis
LCI	Life Cycle Inventory
LDPE	Low Density Polyethylene
LIBS	Laser Induced Breakdown Spectroscopy
LLDPE	Linear Low Density Polyethylene
MFA	Material Flow Analysis
MIT	Massachusetts Institute of Technology
MMI	Man Machine Interface
MPP	Multilayer Plastic Packaging
MSW	Municipal Solid Waste
NIRS	Near Infrared Spectroscopy
PA	Polyamide
PBAT	Polybutylene Adipate Terephthalate
PCCL	Polymer Competence Center Leoben

PCW	Post Consumer Waste
PDMS	Polydimethylsiloxane
PE	Polyethene
PET	Polyethene Terephthalate
PLA	Polylactic Acid
PLC	Programmable Logic Controller
PMMA	Polymethylmethacrylate
PP	Polypropylene
RDF	Residue Derived Fuel
RGB	Red Green Blue
RIA	Robotics Industries Association
RMSE	Root Mean Squared Error
SBS	Sensor Based Sorting
SCW	Separately Collected Waste
SNN	Shallow Neural Network
ST	Pellenc Selective Technologies
STAN	Substance Flow Analysis
SVM	Support Vector Machine
SWIR	Short Wavelength Infrared
TPU	Thermoplastic Polyurethane
TRL	Technology Readiness Level
VIS	Visual Spectroscopy
WFD	Waste Framework Directive
Wt	Weight-related percentage
wt%	Weight-Related Percentage
XRF	X-Ray Fluorescence Spectroscopy
XRF	X-Ray Fluorescence Spectroscopy
XRT	X-Ray Transmission
XRT	X-Ray Transmittance