Chair of Metal Forming

Doctoral Thesis

Digitalization and Digital Transformation in the Austrian Metal Forming Industry

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AFFIDAVIT

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

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

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

Date 07.05.2021

Signature Author
Benjamin James Ralph

‘Born to lose. Live to win.’

-Ian Fraser ‘Lemmy’ Kilmister

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Kurzfassung

Seit der Einführung des Konzepts Industrie 4.0 im Jahr 2011 lässt sich ein stetiger und nachhaltiger Paradigmenwechsel im industriellen Produktionsumfeld beobachten. Damit verbundene technologische Konzepte wurden häufig in der Literatur untersucht sowie in einer Vielzahl unterschiedlicher Industriesparten umgesetzt. Ein Großteil dieser Veröffentlichungen geht jedoch nicht ausreichend auf die umformtechnische Industrie ein.

Um diesen Industriezweig bei der digitalen Transformation zu unterstützen, wurde in erster Instanz eine Literaturrecherche, ergänzt durch Experteninterviews, durchgeführt. Des Weiteren wurde eine repräsentative Befragung innerhalb der österreichischen Umformindustrie durchgeführt und ausgewertet. Als Ergebnis dieser Befragung kann festgehalten werden, dass der Digitalisierungsgrad im Vergleich zu anderen Branchensegmenten wesentlich geringer ist. Neben dem relativ hohen Anteil an KMUs ist ein oftmals nicht mehr zeitgemäßer Maschinenpark der Hauptgrund für diesen Umstand. Um diese Unternehmen mit entsprechenden Lösungen zu unterstützen, wurden drei Maschinensysteme unterschiedlichen digitalen Reifegrades digitalisiert und in eine eigens entwickelte Layer-Architektur integriert. Dazu wurden zwei verschiedene industrietaugliche Datenerfassungssysteme (DAQ) eingesetzt.

Die Komplexität von Umformoperationen ergibt sich aus mikrostrukturellen Änderungen im jeweiligen Werkstück, basierend auf dem Einfluss von Temperatur, komplexen mechanischen Zuständen und dem umgebenden tribologischen System. Die Finite-Elemente-Analyse (FEA) ist ein weit verbreitetes Werkzeug zur Vorhersage von Prozessparametern, um kosten- und arbeitsintensive praktische Versuche zu reduzieren. Dennoch ist eine direkte Integration in die Produktion in der Mehrzahl der Umformprozesse nicht realisiert, da der Rechenaufwand oft zu hoch ist bzw. entsprechende Schnittstellen noch nicht ausreichend entwickelt sind. Um die Produktivität weiter zu steigern und mögliche Lösungen für dieses Problem aufzuzeigen, wurden drei Lösungsansätze entwickelt.

In vielen Fällen kann die FEA durch nicht-komplexe Algorithmen ersetzt werden. Dieser Ansatz wurde am Versuchswalzwerk des Lehrstuhls für Umformtechnik umgesetzt, woraus ein Prädiktor für die teilautomatisierte Prozessanpassung resultierte. Zusätzlich wurde ein einfacher maschineller Lernalgorithmus (MLA) entwickelt, der die Vorhersagen entsprechend neuer Daten aus durchgeführten Walzprozessen anpasst.

Um die Möglichkeiten der FEA-Integration in einen Produktionsprozess zu demonstrieren, wurde ein digitaler Schatten (DS) für den ECAP Prozess entwickelt. Dieser ist in der Lage, Reibungszustände in Abhängigkeit von vorgegebenen Eingabeparametern aus dem Maschinenbetriebssystem zu prognostizieren. Zusätzlich wurde ein FEA-basierter Python-Algorithmus zur Vorhersage von Eigenspannungen nach dem Kugelstrahl-Prozess entwickelt. Dieser Algorithmus demonstriert, wie die FEA in Kombination mit Open-Source-Programmierumgebungen und einfachen MLA den jeweiligen Mitarbeiter bei der Auswahl geeigneter Prozessparameter unterstützen kann.

Umformtechnische Prozesse sind ein entscheidender Teil der industriellen Wertschöpfungskette. Um das Vernetzungspotential innerhalb dieser aufzuzeigen, wurde ein holistischer Integrationsansatz für die Einbettung verschiedener Prozesssimulationen in ein übergeordnetes Logistiksystem entwickelt.

Zusätzlich wurde eine Stakeholder-orientierte Vorlesung für die interdisziplinäre Ausbildung von Studierenden designt. Diese Vorlesung berücksichtigt moderne pädagogische Theorien und ist auf die Anforderungen der österreichischen Umformtechnikbranche zugeschnitten. Die entwickelte Layer Architektur, welche eine in Python programmierte Bearbeitungsebene enthält, bietet hierfür interessierten Studierenden die Möglichkeit, ihre Programmierkenntnisse in einer realistischen Fertigungsumgebung zu trainieren.

Abstract

Since the introduction of the Industry 4.0 concept in 2011, a steady and persistent paradigm shift in the industrial production environment can be observed. Related technological concepts have been frequently studied in the literature as well as implemented in a variety of different industrial sectors. However, a majority of these publications do not sufficiently address the metal forming industry.

In order to support this industry sector in its digital transformation, a literature review was conducted in the first instance, supplemented by expert interviews. Furthermore, a representative survey within the Austrian metal forming industry was executed and analyzed. As a result of this survey, it can be stated that the degree of digitization is significantly lower compared to other industry segments. In addition to the relatively high proportion of SMEs, one of the main reasons for this circumstance is often outdated production machinery. In order to support these companies with appropriate solutions, three machine systems with different levels of digital maturity were digitized and integrated into a newly developed layer architecture. Two different industry-standard data acquisition systems (DAQ) were used for this purpose.

The complexity of forming operations results from microstructural changes in the respective workpiece, based on the influence of temperature, complex mechanical conditions and the surrounding tribological system. Finite element analysis (FEA) is a widely used tool for predicting process parameters to reduce costly and labor-intensive practical trials. Nevertheless, direct integration into production has not been realized in the majority of forming processes, as the computational effort is often too high or corresponding interfaces are not yet sufficiently developed. In order to further increase productivity and to identify possible solutions to this problem, three approaches have been elaborated.

In many cases, FEA can be replaced by non-complex algorithms. This approach was carried out on the experimental rolling mill of the Chair of Metal Forming, resulting in a predictor for a semi-automated process adaptation. In addition, a simple machine learning algorithm (MLA) was established to adjust the predictions according to new data from performed rolling processes.

To demonstrate the capabilities of FEA integration into a production process, a digital shadow (DS) for the ECAP process was devised. This DS is capable of predicting friction conditions as a function of given input parameters from the machine operating system. In addition, an FEA-based Python algorithm was evolved to predict residual stresses after the shot peening process. This algorithm demonstrates how FEA, in combination with open-source programming environments and simple MLA can assist the respective operator in selecting appropriate process parameters.

Forming processes are a critical part of the industrial value chain. In order to reveal the potential of open-interface networks within this, a holistic integration approach for embedding different process simulations into a higher-level logistics system has been developed.

In addition, a stakeholder-oriented lecture was designed for the interdisciplinary education of students. This lecture takes into account modern pedagogical theories and is tailored to the requirements of the Austrian metal forming industry. The presented layer architecture, which includes a processing layer programmed in Python, offers interested students the opportunity to train their programming skills in a realistic manufacturing environment.

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Abbreviations

AI	Artificial Intelligence
CMS	Condition Monitoring System
CPLS	Cyber Physical Logistics System
CPPS	Cyber Physical Production System
DAQ	Data Acquisition
DM	Digital Model
DS	Digital Shadow
DT	Digital Twin
ECAP	Equal-Channel-Angular-Pressing
ERP	Enterprise Resource Planning
FEA	Finite Element Analysis
FVA	Finite Volume Analysis
F_{sm}	Mean value of simulated Force
F_{exm}	Force measured by a machine system
GUI	Graphical User Interface
HMI	Human Machine Interface
IL	Chair of Industrial Logistics
i.s.	In situ
LLL	Life Long Learning
LVDT	Linear Variable Differential Transformer
M	Institute of Mechanics
MES	Manufacturing Execution System
MF	Chair of Metal Forming
ML	Machine Learning
MUL	Montanuniversität Leoben
NFM	Chair of Nonferrous Metallurgy
NIST	National Institute of Standard and Technology
OEE	Overall Equipment Effectiveness
PLC	Product Life Cycle
QM	Quality Management
R&D	Research and Development
SCADA	Supervisory Control and Data Acquisition

SFL	Smart Forming Lab
SME	Small and Medium Sized Enterprises
STS	Structured Text Format
TMTS	Thermo-mechanical Treatment Simulator
XRD	X-Ray Diffraction

List of publications

The following peer reviewed research papers and conference proceedings serve as a fundament for this thesis. All mentioned manuscripts are a result of the authors work at the Chair of Metal Forming at the Montanuniversität Leoben and are attached in A (Associated publications).

(A 1) Publication 1	B.J. Ralph, M. Stockinger: 'Digitalization and Digital Transformation in Metal Forming: Key Technologies, Challenges and Current Developments of Industry 4.0 Applications', in: *XXIX. Colloquium on Metal Forming*, pp. 13-23, 03.2020, ISBN: 978-3-902078-26-1.
(A 2) Publication 2	B.J. Ralph, A. Schwarz, M. Stockinger: 'An Implementation Approach for an Academic Learning Factory for the Metal Forming Industry with Special Focus on Digital Twins and Finite Element Analysis', in: *Procedia Manufacturing*, 45, pp. 253-258, 04.2020, DOI: 10.1016/j.promfg.2020.04.103.
(A 3) Publication 3	A. Schwarz, B.J. Ralph, M. Stockinger: 'Planning and implementation of a digital shadow for the friction factor quantification of the ECAP process using a grey box modeling approach and finite element analysis', in: *Procedia CIRP*, 99, pp. 237-241, 01.2021, DOI: 10.1016/j.procir.2021.03.035.
(A 4) Publication 4	B.J. Ralph, K. Hartl, M. Sorger, A. Schwarz-Gsaxner, M. Stockinger: 'Machine Learning Driven Prediction of Residual Stresses for the Shot Peening Process Using a Finite Element Based Grey-Box Model Approach', in: *Journal of Manufacturing and Materials Processing,* 5(2), 39, 04.2021, DOI: 10.3390/jmmp5020039.
(A 5) Publication 5	B. J. Ralph, M. Sorger, B. Schödinger, H.-J. Schmölzer, K. Hartl, M. Stockinger: Implementation of a Six-Layer Smart Factory Architecture with Special Focus on Transdisciplinary Engineering Education, in: *Sensors*, 21(9), 2944, 04.2021, DOI: 10.3390/s21092944.
(A 6) Publication 6	B. J. Ralph, C. Pacher, M. Woschank: 'Conceptualization of the Lecture 'Digitalization and Digital Transformation in Metal Forming' based on Implications from Contemporary Teaching and Learning Theories', in: *Proceedings of the 2nd African International Conference on Industrial Engineering and Operations Management*, pp. 703-712, 12.2020, ISBN: 978-1-7923-6123-4.
(A 7) Publication 7	B. J. Ralph, M. Woschank, C. Pacher, M. Murphy: Evidence-based Redesign of Engineering Education Lectures: Theoretical Framework and Preliminary Empirical Evidence, under review (20.04.2021) in: *European Journal of Engineering Education.*

(A 8) Publication 8	B.J. Ralph, M. Sorger, K. Hartl, A. Schwarz, F. Messner, M. Stockinger: Transformation of a rolling mill aggregate to a Cyber Physical Production System: from sensor retrofitting to machine learning, under review (22.03.2021) in: *Journal of Intelligent Manufacturing.*
(A 9) Publication 9	B.J. Ralph, M. Woschank, P. Miklautsch, A. Kaiblinger, C. Pacher, M. Sorger, H. Zsifkovits, M. Stockinger: MUL 4.0: Systematic Digitalization of a Value Chain from Raw Material to Recycling, accepted in *Procedia Manufacturing,* 04.2021, DOI: tba.

Additionally, five bachelor thesis and two master thesis were supervised by the author during his work.

Bachelor Thesis:

1. M. Mayer: Möglichkeiten der Eigenspanungsmessung an Aluminiumbauteilen mittels Bohrlochmethode, 06.2020.
2. B. Schödinger: Digitalisierte in situ Leistungsmessung einer CNC Drehmaschine auf Basis aktueller praxisorientierter Automatisierungstechnologien, 09.2020.
3. A. Paulik: Abstraktion komplexer Geometrien für die mikromechanische Modellierung von Formstoffsystemen, 02.2021.
4. B. Skall: Entwicklung eines digitalen Modells für die rechenzeitoptimierte 3D-Simulation des Kugelstrahlprozesses mit Abaqus und Python, 02.2021.
5. J. Rieder: Optimierung eines digitalen Modells für den Einsatz als Digitaler Schatten in der Produktion auf Basis des Kugelstrahlprozesses und FEA, 04.2021.

Master Thesis:

1. M. Sorger: Digitalisierung eines Walzwerks mit der Retrofitting Methode, 09.2020.
2. H.-J. Schmölzer: Development of an open source project management tool with integrated PPS-data using SQL and PHP, 03.2021.

Furthermore, two additional manuscripts were published:

B.J. Ralph: Ein Beitrag zur numerischen Simulation von mechanischen Formsandeigenschaften, in: *Gießerei-Rundschau*, 66, pp. 6-12, 02.2019. (not peer-reviewed)

M. Woschank, B.J. Ralph, A. Kaiblinger, P. Miklautsch, C. Pacher, M. Sorger, H. Zsifkovits, M. Stockinger, S. Pogatscher, T. Antretter, H. Antrekowitsch: MUL4.0 – Digitalisierung der Wertschöpfungskette vom Rohmaterial bis hin zum Recycling, in: Berg- und hüttenmännische Monatshefte (BHM), 167(5), pp. 1-6, 06.2021, DOI: tba

1 Introduction

Metal forming is characterized as reshaping metallic components without adding or removing material. As a result, the forming process leads to a permanent deformation of the respective workpiece [1,2]. To achieve this objective, high loads and corresponding stresses are frequently required, which has a direct impact on the forming industry: to be able to sustain profitable, high volume production lines have to be executed in order to amortize the heavy and capital committing machinery necessary. In the past decades, an additional approach to achieve economic success was offshoring of production facilities to low-wage countries [3,4].

However, this strategy was not applicable for all parts of the metal forming industry. In highly-specialized sectors (e.g. aviation, aerospace, parts of the automotive sector), significant know-how about materials science, mechanical engineering and technical mechanics is necessary to achieve the superior material quality respective customers demand. As a result, a majority of these manufacturers extended their production capacity in high-wage countries. Due to these developments, this industry sector is heavily exposed to its business environment and other global impacts (e.g. the ongoing Covid-19 crisis, punitive tariffs) [5,6].

The persistent digitalization and digital transformation, heavily accelerated during the last two decades, offers opportunities for these companies to significantly enhance their economic success and market position by increasing their operational efficiency. This paradigm change, often addressed by the terminology Industry 4.0 (I 4.0), which was introduced by the German government in 2011 [7], can, if properly applied, result in an improved Overall Equipment Effectiveness (OEE). Despite this positive advantage, the possibility of negative impacts by a decreasing necessity of human labour has to be addressed [8–11]. The sustainable shift in knowledge requirements for blue collar as well as engineering experts in a digitalized manufacturing environment cannot be neglected [12–15]. If the training of respective human capital can be executed successfully, this possible threat on employment can even be switched, as an increasing amount of metal processing companies decide to backshore their production facilities to high-wage countries [3,4,16,17]. As digitalization decreases the cost of manual labour for these companies, highly skilled experts and their know-how becomes more important [18–21]. Additionally, the required technical skills as well as job descriptions and corresponding roles of these experts change, which leads to a shift in engineering education at academic institutions as well as applicable life-long learning (LLL) concepts for already employed engineers and technicians mandatory [22–24].

For these reasons, this thesis proposes a novel and holistic approach to address the possibilities and threats of this paradigm shift due to the fourth industrial revolution explicitly for the Austrian metal forming sector. To be able to accomplish this goal, a literature study as well as a quantitative survey to identify the degree of digitalization in this segment was executed. The results of this work are presented in section two and serve as a basis for further elaboration. From this analysis, the resulting research questions to be elaborated in this work were derived. Section three describes how these research questions were addressed, including the intended contributions of the published manuscripts to answer these questions. In section four, the contribution to the decrease of the defined research gap and scientific contribution by the respective work is pointed out and discussed, followed by a conclusion and an outlook in the fifth chapter.

2 State of the art, identified research gap and resulting research questions

The impact of the fourth industrial revolution on manufacturing operations and the corresponding industry is elaborated widely in current literature [25–30]. However, there is still a lack of terminology standardization present [31]. Furthermore, the definition of key technologies varies depending on the industry sector. To be able to identify research gaps within the Austrian metal forming industry segment, an initial literature study was carried out [32]. This study was additionally complemented by personal interviews with domain experts from the Austrian metal forming environment, mainly conducted at the XXXVIII. Colloquium on Metal Forming[1]. The analysis of the current literature as well as these expert interviews revealed that the following key technologies are or will be important in the near future for this sector [32]:

1. Cyber Physical Production Systems (CPPS),
2. Industrial Internet of Things (IIoT),
3. Digital Models (DM), Digital Shadows (DS), Digital Twins (DT),
4. Big Data Technologies and
5. Cloud-Computing.

In this work, CPPS are defined on the basis of the definition from Cardin [33], as this definition is the most accepted in this research field according to Wu et al. [34]. In Publication A 8, the author extended this definition for the specific needs of the Austrian metal forming industry by adding two additional components (Table 1, IV. And V.) [35].

Table 1. Definition of CPPS derived from [33,34]. The corresponding publication can be found in A 8 [35].

No.	Criteria
I.	CPPS are superordinate systems within systems.
II.	CPPS consist of cooperative elements, those connect with each other situationally appropriate, on and between all different levels within the production environment, from the processes itself, through involved machines up to overlaying networks, e.g. MES or ERP-systems.
III.	CPPS enhance decision making processes in real-time in a resilient and robust way, with respect to time as well as foreseen and unforeseen events
IV.	CPPS in the Austrian metal forming environment have to provide sufficient Human Machine Interfaces (HMIs), tailored to the requirements of the respective operator and coworkers

[1] The XXXVIII. Colloquium on Metal Forming was conducted on March 23-27 2019 in Zauchensee Austria, whereas the author participated as organizational manager.

V.	CPPS in the metal forming industry have to be especially resilient to harsh manufacturing environments (e.g. dirt, high temperatures) under consideration of relatively short amortization times

IIoT suffers from the same lack of unified definition as CPPS. For the purpose of this work, the author defines this term according to Boyes et al. [36]:

'A system comprising networked smart objects, cyber-physical assets, associated generic information technologies and optional cloud or edge computing platforms, which enable real-time, intelligent, and autonomous access, collection, analysis, communications, and exchange of process, product and/or service information, within the industrial environment, so as to optimise overall production value. This value may include; improving product or service delivery, boosting productivity, reducing labour costs, reducing energy consumption, and reducing the build-to-order cycle.'

The definition of the terms DM, DS and DT can be concretized, as the difference between these three definitions can be explained by the automated connectivity between a digital and physical entity, as illustrated in Figure 1 [37].

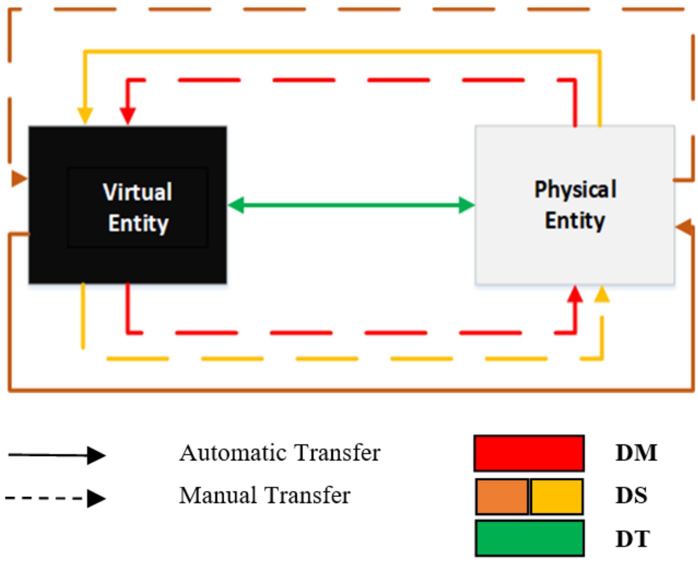


Figure 1. Definition of DM, DS and DT by the dependability of automatic data transfer [32,37]

Regardless of the level of connectivity, a differentiation has to be attained depending on the physical domain to be mirrored. While DTs on supply chain or MES level can be seen as state of the art, progress in dealing with complex process simulations (e.g. FEA, Finite Volume Analysis (FVA)) is right at the beginning in the metal processing environment [38]. Another important point to consider in this context is the amount of data available for the production process to be virtually mirrored. While data-driven models and corresponding ML algorithms can have major advantages and are therefore able to substitute complex, real-physics based (white-box) models in a significant amount of different processes, low-volume and high-variety metal forming operations can often not benefit from these advantages. Therefore, the integration of white-box models and their combination with data-driven approaches (grey-box models) are able to add significant advantage to these kind of operations.

Big Data Technologies are defined in a variety of publications, whereas the number of criteria that have to be fulfilled varies [39–41]. In this work, the author refers to data as Big Data if the definition according to Zikopoulos [42] and validated by Ghasemaghaei [43], whereas three conditions have to be accomplished in order to define a data set as Big Data, is fulfilled:

- a data volume of at least one Petabyte,
- a variety of data within the set including structured, unstructured and semi-structured data,
- different velocities of data flow (discrete and continuous processing) [42].

Cloud computing is holistically defined according to the National Institute of Standard and Technology (NIST) as follows [44]:

'A model for enabling convenient, on-demand network access to a shared pool configurable computing resources (e.g. networks, servers, storage, application, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction.'

The metal forming industry in Austria can further be characterized as highly heterogeneous, with a huge variety of production processes, organizational structures and sizes. Nevertheless, potential challenges that arise in a majority of respective companies were identified and are summarized in Table 2 [32].

Table 2. Identified challenges in the Austrian metal forming environment to overcome for a successful and sustainable digital transformation [32].

Definition	Description	Challenges for a successful digital transformation in Austrian's metal forming industry
Retrofitting	Upgrading of machine systems for the integration into a digitalized production environment	The upgrading process requires time and know-how; due to the high amount of SME's the cost factor is crucial; the accuracy of existing sensors and actuators has to be validated initially
HMI	Interaction between humans and machine systems	Developing tools (e.g. Graphical User Interfaces (GUIs)) that serve specific target groups in the manufacturing environment
Digital twin integration (process level)	Bilateral automated data communication between the digital and the physical domain	Due to often complex process parameters, Finite Element Analysis (FEA) simulations are widely used as DMs. Transformation of these DMs to DSs and finally DTs requires specific skills; For a successful transformation, open interface based horizontal integration is required
Vertical integration	The connectivity between different data layers in a production environment (e.g. Manufacturing Execution	The connectivity has to be ensured; reliability of gathered data has to be warranted; Change management and

	System (MES), Supervisory Control and Data Acquisition (SCADA), Enterprise Resource Planning (ERP))	commitment of respective employees is mandatory and must be trained
Data security	Appropriate data security approaches tailored to data type and sensitivity	Data has to be categorized according to the grade of sensitivity; a sustainable data framework has to be implemented and maintained through all business levels; employees have to be trained and sensitized
Interdisciplinarity and education	Interdisciplinary know-how for the efficient communication above boundaries and to enable transdisciplinary high-performance teams; required education to perform this	Domain experts in the different engineering fields have to be able to communicate (e.g. mechanical engineers, material scientists, electrical engineers); due to digitalization, fundamentals of programming and network technologies have to be known to successfully transform the production operations on long term

For a further concretization and knowledge gap identification, a quantitative survey was sent out to 200 Austrian companies operating in the metal forming field, whereas 32.00 % (64 companies) were completed and categorized as valid due to no significant difference between early and late responses [45,46]. The result of this study is released in Publication 7 (A 7) and illustrated additionally in Table 3. The operationalization of the respective items was done by a five-point Likert scale from 1 (e.g. not agree) to 5 (e.g. fully agree).

Table 3. Degree of digitalization in the Austrian metal forming industry: valid responses (A 7).

Item	Text	N	Min.	Max.	Mean	Std. Dev.
DIG_1	All production processes that occur are recorded by a higher-level ERP system.	64	1	5	3.33	1.574
DIG_2	All production processes that occur are controlled and timed automatically using an MES system, PPS, or ERP system with similar functionality.	64	1	5	2.69	1.457
DIG_3	The machines used all have at least one interface to higher-level systems (SCADA on MES/ERP).	64	1	5	2.72	1.397
DIG_4	Captured processes and general production data are stored and processed via cloud solutions.	64	1	5	1.97	1.403
DIG_5	Data can be made fully available through an interface for external use by other applications such as business intelligence.	64	1	5	2.47	1.345

DIG_6	Internet of Things solutions are used on a large scale in production (e.g., IIoT gateways, transmission using IoT protocols such as MQTT).	64	1	5	1.81	1.296
DIG_7	Collected data is analyzed using big data technologies.	64	1	5	1.81	1.332
DIG_8	Important production processes are modeled with simulation programs (e.g., finite element simulation).	64	1	5	2.36	1.396
DIG_9	The visual representation of production data is structured and user-friendly.	64	1	5	2.64	1.289
DIG_10	All production processes are fully described by means of standards.	64	1	5	3.25	1.297
DIG_11	Finite element simulations are used for troubleshooting as well as process optimization.	64	1	5	2.23	1.488
DIG_12	Simulations interact directly with a higher-level production system (e.g., SCADA, MES, ERP)	64	1	5	1.80	1.311
DAT_1	Process data is archived completely digitally.	64	1	5	3.45	1.126
DAT_2	All production processes include controls and auditing bodies to ensure conformity with internal and external requirements.	64	1	5	3.56	1.320
DAT_3	Quality controls are fully digitized and archived.	64	1	5	3.17	1.279
DAT_4	(Short-term) changes in the production plan are fully and transparently integrated into the existing control systems.	64	1	5	2.97	1.357
DAT_5	Process data is collected completely automatically.	64	1	5	2.42	1.206
DAT_6	In the event of a failure of the production control system, production can be carried out completely manually if necessary (until repairs are made).	64	1	5	3.78	1.362
DAT_7	The provision of data for internal purposes is completely digital.	64	1	5	3.25	1.113
DAT_8	The data collected is transparent and used for analysis and comparison.	64	1	5	3.00	1.141
DAT_9	The value chain (purchasing, logistics, production, sales, after-sales service) is fully digitized and can be viewed transparently by all areas of the company.	64	1	5	2.83	1.121
DAT_10	Data is always the basis for improving the business process.	64	1	5	3.31	1.220
DAT_11	Sufficient IT security is ensured at all digital levels (data security and protection of all systems).	64	1	5	3.84	1.224
ATT_1	There is a clearly defined digitization strategy in the company.	64	1	5	2.83	1.077
ATT_2	There is a dedicated person responsible for digitization issues (internal or external).	64	1	5	2.86	1.435

ATT_3	The management level promotes the digital transformation in the company in a credible manner and believes that progressive digitization will ensure the company's success in the long term.	64	1	5	3.33	1.235
ATT_4	Digitization solutions that have already been implemented make an important contribution to business success, especially during the ongoing Corona crisis.	64	1	5	3.36	1.302
ATT_5	Digitization solutions that have already been implemented have increasingly led to redundancies in your company in the past.	64	1	5	2.09	1.519
ATT_6	Workers and employees in the company fully welcome digitization and digital transformation in the company.	64	1	5	3.13	.968
ATT_7	The productivity of your company is much higher than that of your competitors.	64	1	5	2.95	.785
ATT_8	The economic success of your company (profit) is significantly higher than that of your competitors.	64	1	5	2.92	.841
DIG	Mean from DIG_1 to DIG_12	64	1	5	2.42	.898
DAT	Mean from DAT_1 to DAT_11	64	1	5	3.24	.792
ATT	Mean from ATT_1 to ATT_8	64	1	5	2.93	.735

The analysis and contextualization of this survey led the author to the following conclusion:

1. Cloud solutions are not heavily used in this industry segment (DIG_4).
2. IIoT and Big Data solutions are hardly applied in this industry segment (DIG_6, DIG_7).
3. FEA is utilized in the industry segment (DIG_11), but rarely connected into superordinate layers, as well as other types of simulations (DIG_12).
4. Management as well as technicians welcome the digital transformation and support the process.

Based on the implications from the survey as well as the initial literature study and executed expert interviews, the author elaborated three research questions:

I. **How can existing machine systems and proprietary manufacturing-process-related software solutions be efficiently and effectively integrated into a digitalized metal forming environment?**
II. **How can metal forming related process simulations (e.g. based on FEA) be automated and integrated in a digitalized metal forming environment?**
III. **How can the digital transformation in the Austrian metal forming industry be further enhanced and sustained?**

(II) is a direct result of conclusion (3). Due to the authors practical experience and communications with domain experts from this industry sector, the reason for this issue can be found in a lack of non-proprietary integration of machine systems as well as nonsufficient DAQ (e.g. due to a lack of adequate sensors). Therefore, in order to successfully create DSs and DTs,

(I) has to be answered first. In comparison to other industry segments, the metal forming sector has a considerably lower degree of digitalization. For this reason, the answer of (III) supports respective companies in decrease this gap and help them to remain profitable.

3 Methodological approach

Due to the complexity and interdisciplinarity of the topic elaborated in this work, a mixed methods approach was chosen [47]. As described in section 2, an initial quantitative and qualitative literature study was executed. Based on the implications of this study, qualitative expert interviews were carried out. For a further concretization, a quantitative survey based on the conclusions of the previous approaches was designed and executed. The identified research gaps where then formulized and transformed into the final research questions. Figure 2 summarizes this approach graphically.

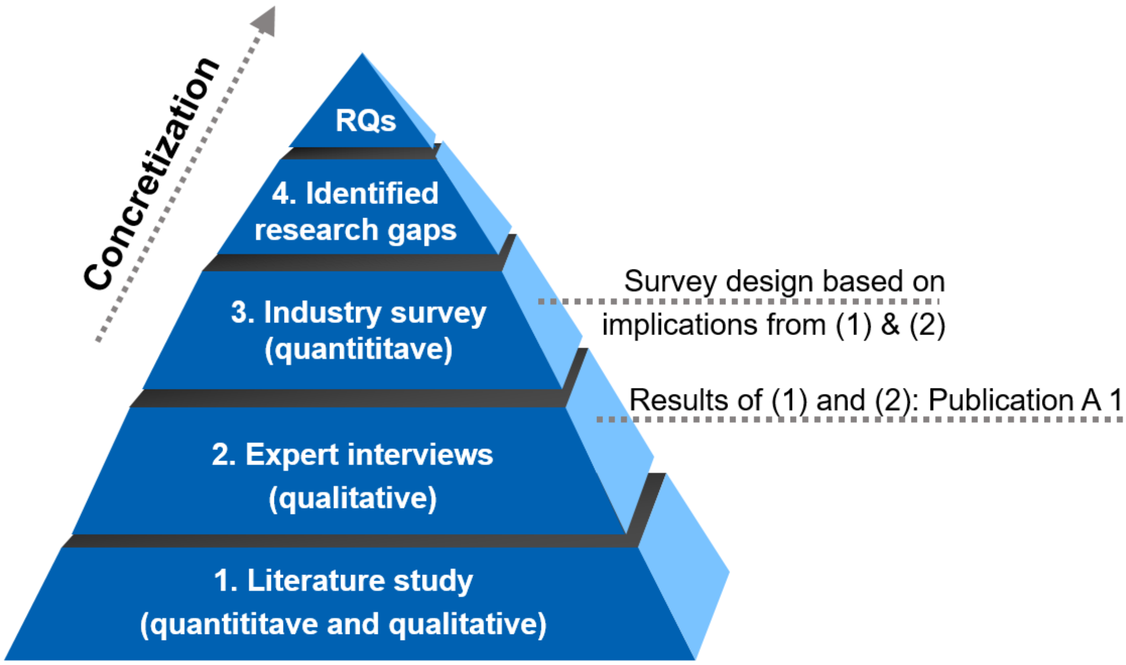


Figure 2. Methodological approach: obtainment of resulting research questions (RQs).

The following subsections describe the methodology and contribution of the publications A 2 to A 9 to the answer of the elaborated research questions.

3.1 Answering research question (I): contribution and methodology

To be able to answer the first research question, three different case studies were developed, whereas each case study can be defined as an extension of the previous one, resulting in a comprehensible demonstration of possible solutions of the issues addressed by (I). The investigated aspects are summarized in Table 4.

Table 4. Contributions to the answer of (I).

No.	Case study	Addressed issues	Corresponding publications
3.1.1	Development of a framework for a smart factory including a proof of concept for the digitization of a metal forming aggregate based on high frequency DAQ and FEA	Planning of a smart factory layout tailored to the metal forming environment; demonstration of possible disadvantages of proprietary software solutions; pointing out the advantage of a second open-interface DAQ to a system under special consideration of required sampling rates for metal forming and corresponding Quality Management (QM) processes; proposal for the integration of FEA based DTs into a smart factory environment	A 2
3.1.2	Building a low-cost resilient six-layer architecture based smart factory: proof of concept by integrating a proprietary CNC-lathe machine system & integration of an additional high-frequency DAQ into the resulting smart factory layout	Demonstration of a low-cost approach for metal forming processes that do not require high-frequency sampling rates; integration of a condition monitoring system (CMS) and an interactive project management tool; Integration of high-frequency measurements into this open interface layer architecture (based on 3.1.1); pointing out the possibilities of incorporating different DAQ systems into a superordinate low-cost main processing layer	A 5
3.1.3	Transformation of a rolling mill into a CPPS	Demonstration of a complete digitization and digitalization approach based on low-cost technologies: from sensor retrofitting to ML; validation of the smart factory architecture developed by connecting a rolling mill system into this framework	A 8

3.1.1 Development of a smart factory framework including an open interface digitization approach for a Thermo-mechanical treatment simulator based on high-frequency DAQ and the integration of FEA into the productive flow

Within this case study the possibility of digitizing and digitalizing the thermo-mechanical treatment simulator (TMTS) Gleeble 3800 by using an iba DAQ system (ibaPDA) was demonstrated. In the industrial metal forming environment, a significant amount of processes require a high frequency DAQ to be able to operate with data in a sophisticated way. This circumstance is especially important within the QM or Research and Development (R&D), as microstructural characterization under consideration of forming conditions (e.g. high temperature, complex stress states) is crucial for resulting quality assessment as well as process improvement. The presented DAQ is capable of up to 100 kHz sampling rate and is installed parallel to the proprietary DAQ of the machine system. In A 2, a comparison between both systems was carried out additionally, demonstrating the difference between raw data (data gathered by the iba DAQ without further processing) and the proprietary software initially used. This comparison is shown for the resulting data from a thermocouple by an exemplary tensile test [48].

Furthermore, an initial framework for the implementation of a smart factory framework, based on the iba DAQ system is proposed. Within this initial proposal, the possibility of connecting FEA based process simulations into this system is additionally pointed out, illustrated for the Equal-Channel-Angular-Pressing (ECAP) machine system at the Chair of Metal Forming (Figure 3) [48].

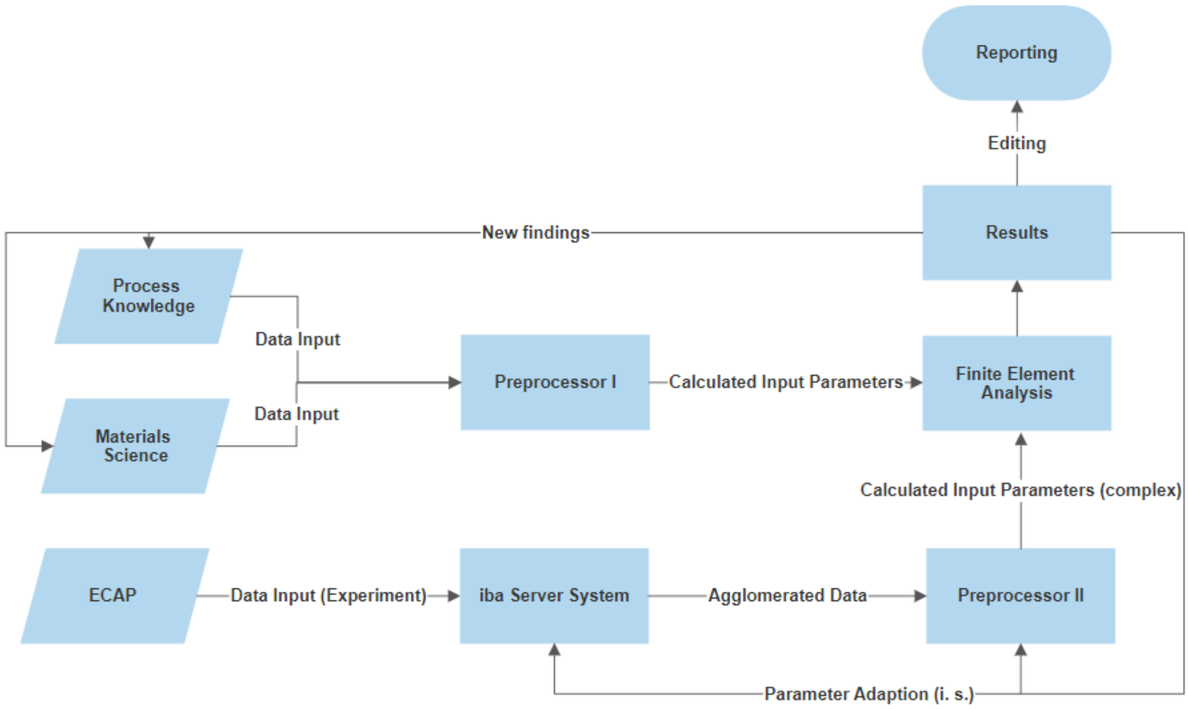


Figure 3. Initial DT framework for the integration of FEA-based simulations into the productive flow: exemplary demonstration for the ECAP machine system [48].

3.1.2 Building a low-cost resilient six-layer architecture based smart factory: proof of concept by integrating a proprietary CNC-lathe and further integration of an additional high-frequency DAQ system

This case study shows the development of a six-layer architecture serving as a basis for a metal forming related smart factory. The DAQ system used is based on a low-cost industrial solution provided by Wago. In order to demonstrate the practicability of this framework, a CNC-lathe was integrated into this setup by the application of a three-phase current and voltage measurement, which automatically publishes captured data into a structured text (STS) programmed front end GUI and back-end pre-processor. The pre-processed data from the Wago

DAQ is published into the server architecture and embedded into an additional GUI using Python. Figure 4 illustrates the digitization and data flow from the current transformer to the refined data storage [49].

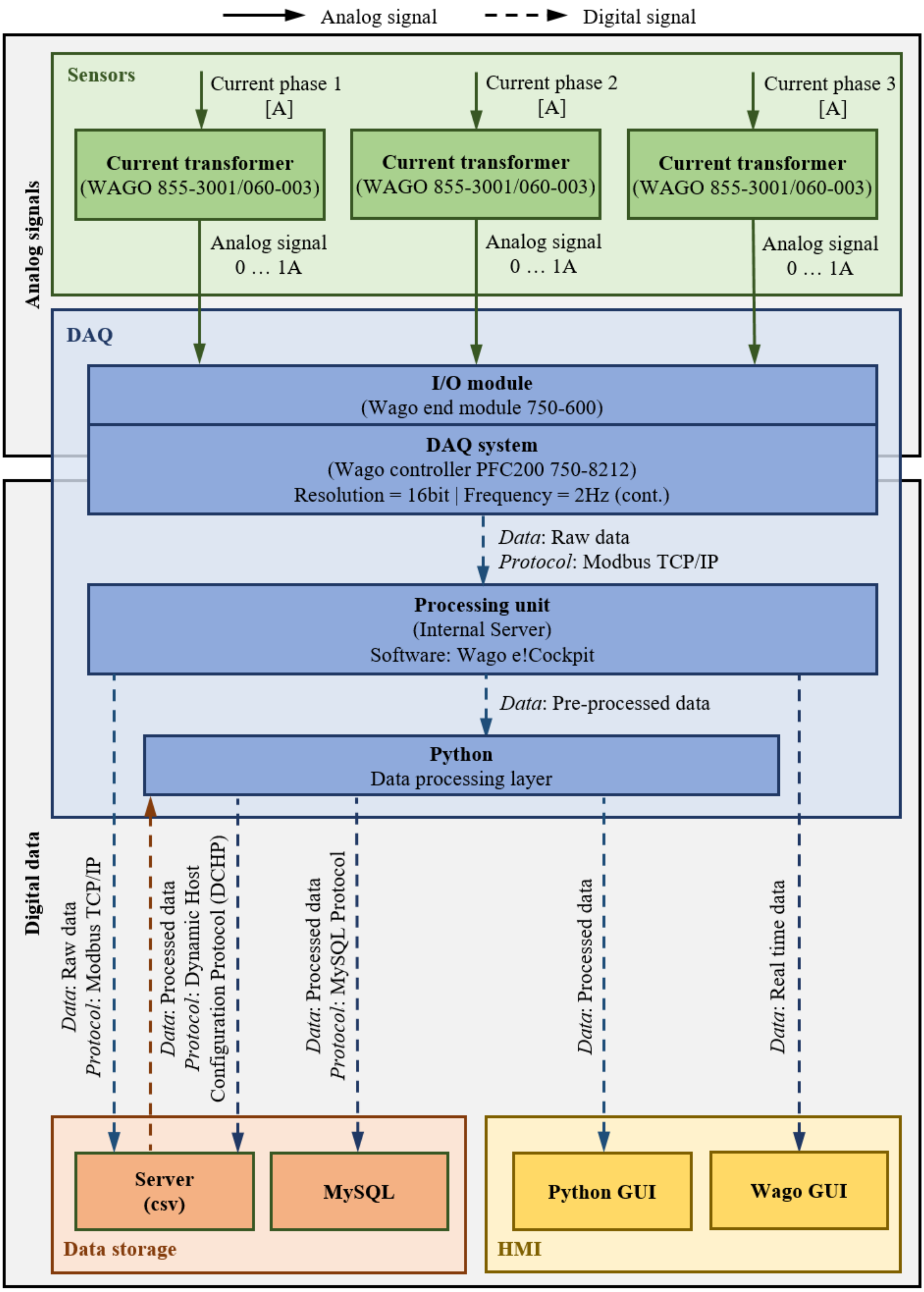


Figure 4. Data flow from the added three-phase current and voltage measurement unit to the Python main processing layer [49].

The resulting processed data is directly connected with the superordinate project management system, which is coupled to a MySQL database management system. The login to this tool is additionally restricted based on defined rights for different categories of users, taking into account data security and transparency issues [49]. Figure 5 illustrates the resulting layer architecture schematically.

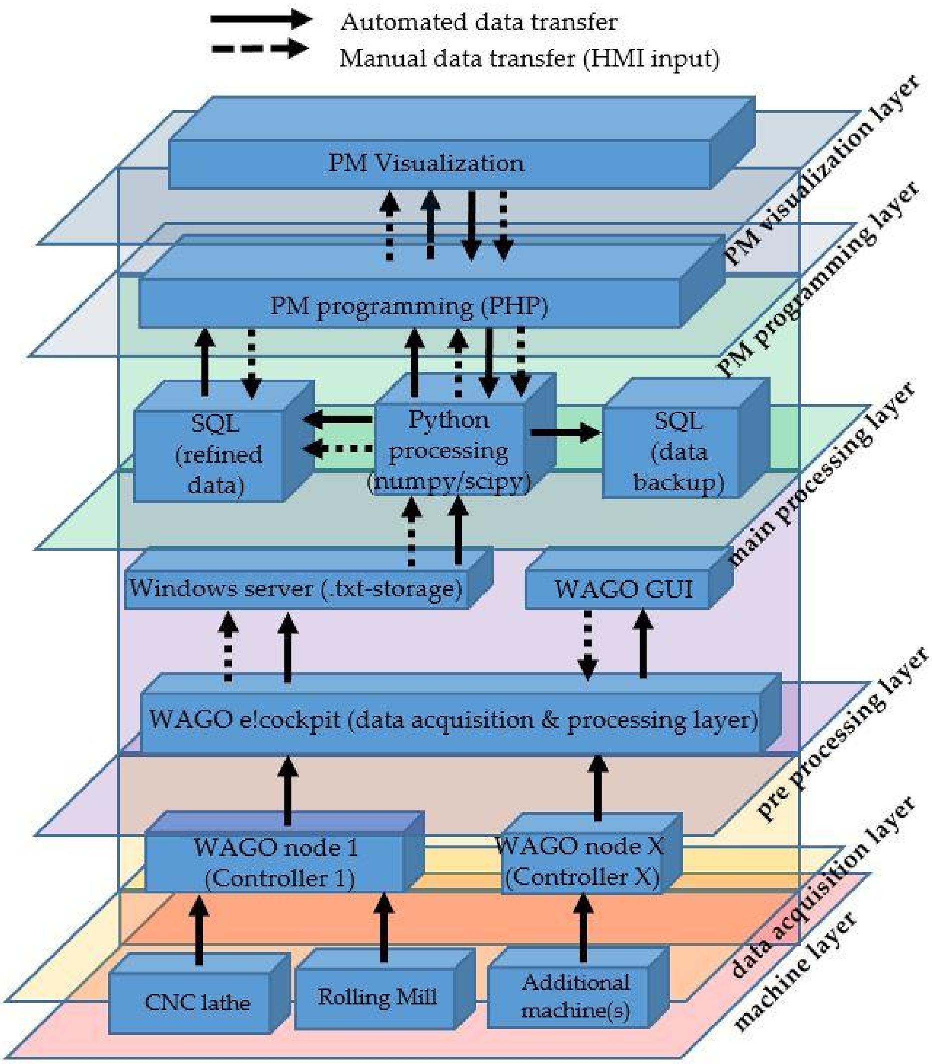


Figure 5. Resulting six-layer architecture [49].

Within this case study, the first focus was set on the possibility of integrating low-cost and most important, non-proprietary interfaces, which is mandatory for designing and upscaling a smart factory in practice [49].

Additionally, the open-interface high-frequency DAQ (3.1.1) was inserted into this layer-architecture. Figure 6 illustrates the resulting data flow from the initial sensors to the iba system as well as the assimilation into the smart factory layout [49].

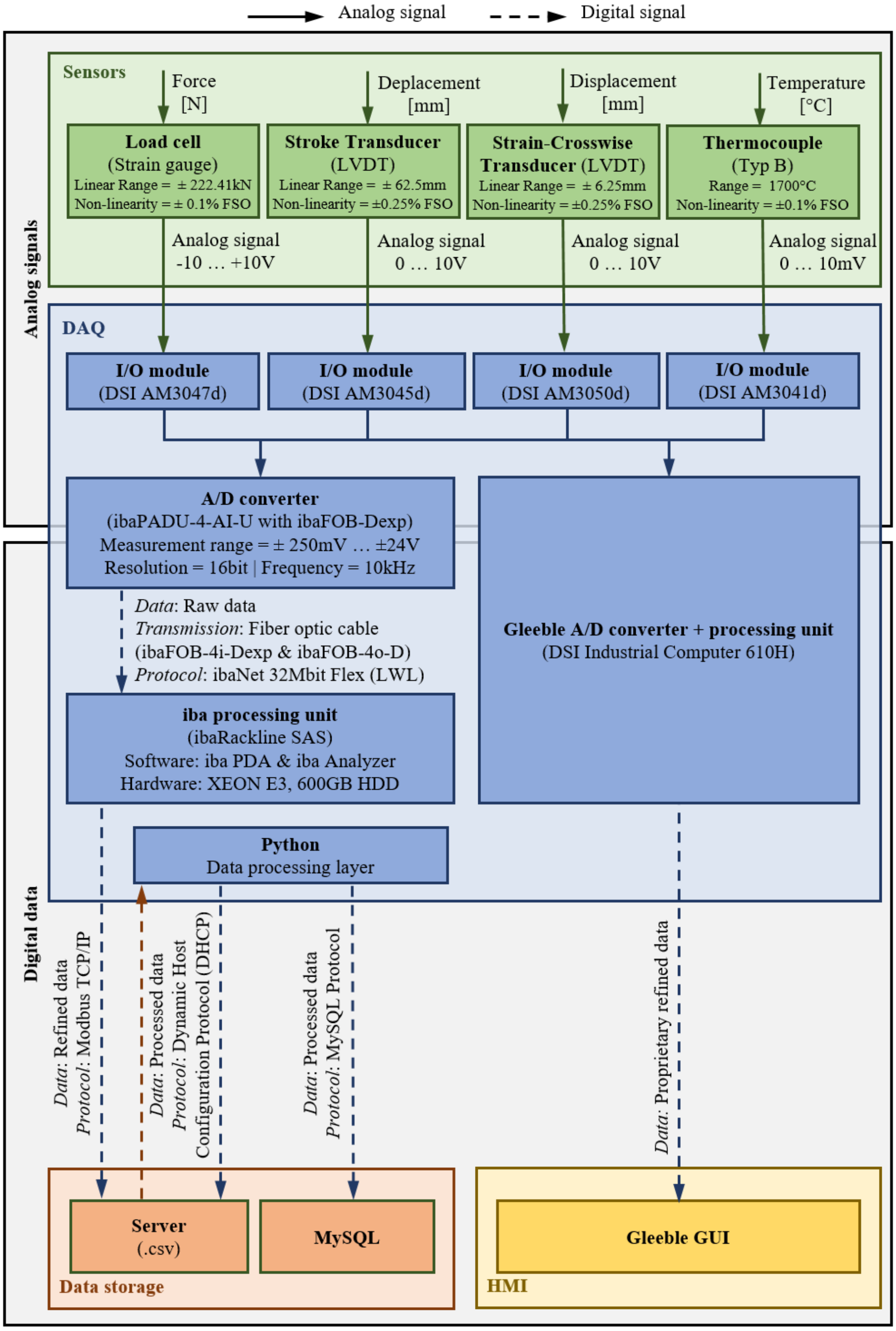


Figure 6. Digitization and data flow from the Gleeble sensors to the superordinate Python layer and proprietary software [49].

3.1.3 Transformation of a rolling mill into a CPPS

Based on the smart factory layout introduced in 3.1.2, this case study strives to present interested domain experts from industry and engineering students a framework on how to include outdated metal forming machines into a digitalized environment. For this purpose, the rolling mill aggregate at the Chair of Metal Forming, built in 1954, was retrofitted with appropriate sensors (two load cells, a linear variable differential transformer (LVDT) and a magnetic multiturn encoder) and integrated into the network using the same Wago controller as in 3.1.2. Based on this digitization setup (Figure 7), a statistical experimental setup was planned and executed, resulting in more than 1900 process steps providing data for a further analysis by using a Python open source environment. The DAQ sampling rate in this case was capped to 500 Hz, providing sufficient data sets for further analysis. Within this experimental setup, three alternative rolling schedules with two different friction states and three varying widths each were executed [35].

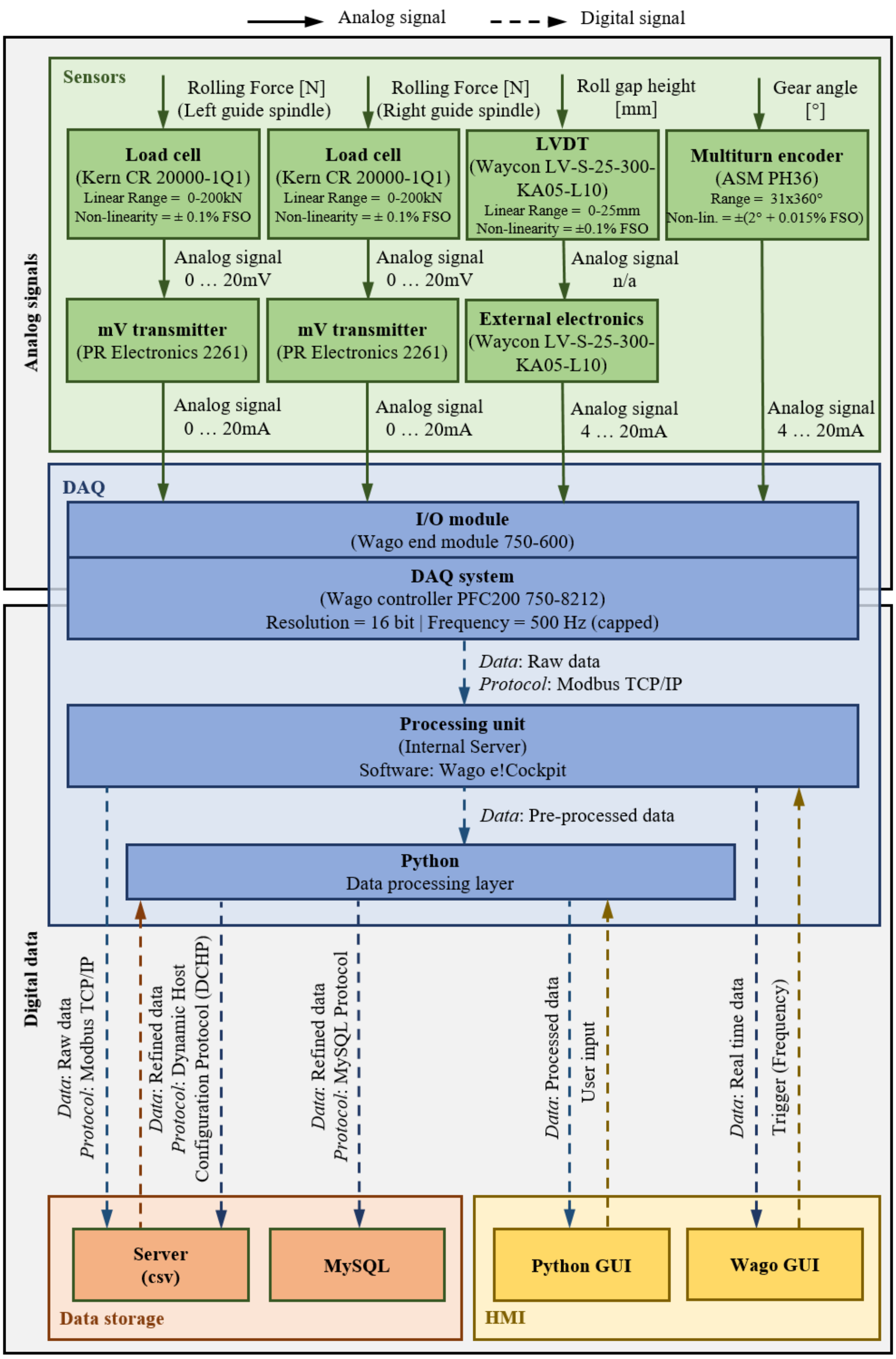


Figure 7. Digitization and data integration of the rolling mill system using the infrastructure introduced in 3.1.2 (A 8) [35].

To demonstrate the possibility of low-cost open source technologies, a rolling mill schedule predictor was developed. This predictor was initially calibrated on commercially pure aluminum, but can be extended for other materials based on the same logic. The Python logic uses linear interpolation and extrapolation based on given data points, leading to a comprehensive prediction for interested parties. For the sake of practicability, a corresponding open-source GUI was developed, demonstrating the algorithm for (future) domain experts (Figure 8). Furthermore, by implementing additional data sets from practical experiments, the system is able to learn and correct the prediction, resulting in a simple example for ML in the industrial context [35].

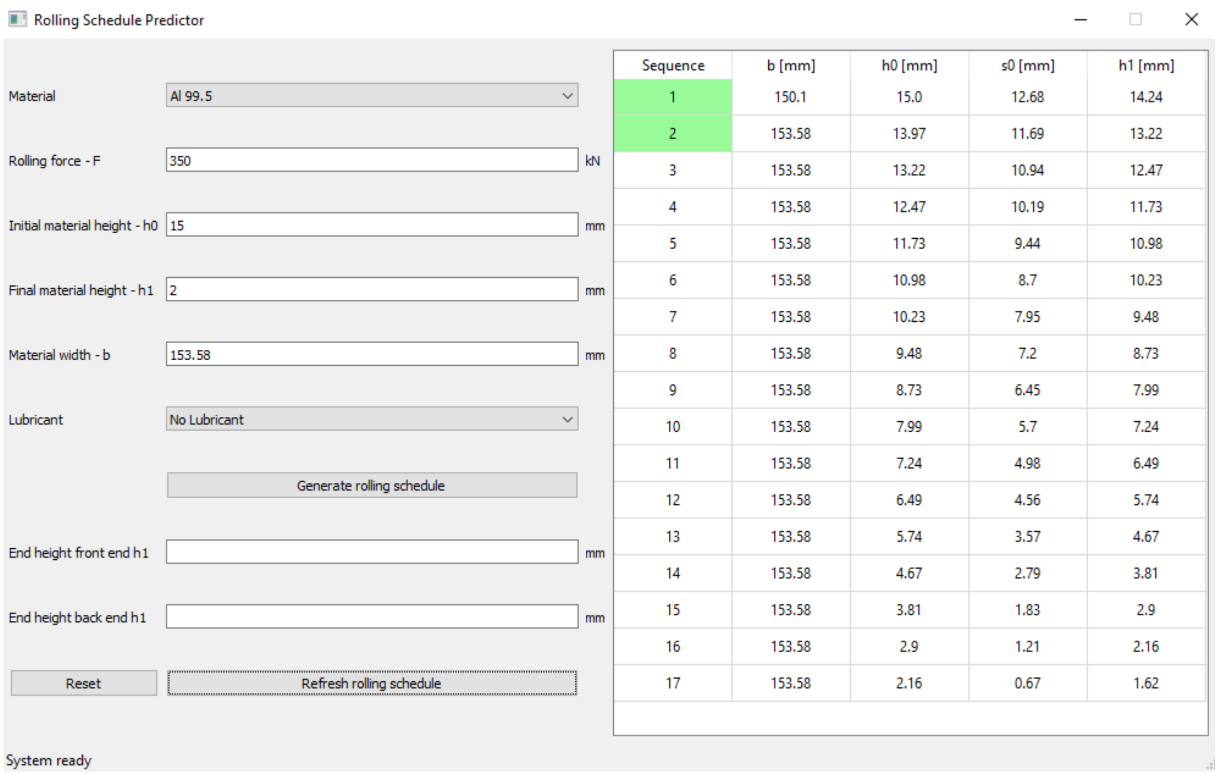


Figure 8. Resulting GUI for the rolling mill schedule predictor. The green highlighted sequences imply that the user has entered additional data after the first sequence, leading to an automated adaption of upfollowing sequences (A 8) [35].

3.2 Answering research question (II): Methodology and contribution

To be able to answer the second research question, two case studies for the integration of efficient FEA simulations into a production operation were created. The first study describes the development of a DS whereas the second development is a DM that can be used to increase overall manufacturing operation efficiency by decreasing the amount of practical experiment with supporting FEA. For both frameworks, a use case was developed to demonstrate practicability. Additionally, two different FEA programs were used for this exhibition, both widely utilized in industrial practice. In order to further consider a larger perspective, a third use case for the digitalization of the value chain, supported by FEA and Finite Volume Analysis (FVA) was developed. This case demonstrates the benefit of superordinate connection of the integration of sophisticated numerical simulation tools for the product lifecycle of a metal good, from the initial casting to recycling. Table 5 shows the contributions of corresponding publications for these developments.

Table 5. Contributions to the answer of (II).

No.	Case study	Addressed issues	Corresponding publications
3.2.1	Development of a DS for the friction factor quantification during the ECAP process	Demonstration of the superior usage for the optimization of process steps	A 3
3.2.2	Residual stress prediction for the shot peening process using FEA and Python based ML	Demonstration of the advantages of optimized FEA in combination with an open-source programming environment	A 4
3.2.3	MUL 4.0: systematic digitalization of a value chain – from raw material to recycling	Demonstrating the advantages of non-proprietary interfaces and suitable numerical simulation tools for the optimization of the value chain	A 9

3.2.1 Development of a DS for the friction factor quantification during the ECAP process

Within this case study, a grey-box approach for the determination of the resulting friction state after the ECAP process was developed. The focus was set on the integration of the FEA program Simufact® into a Python based preprocessor. Substantiated on input data (back pressure p, pressing velocity v, initial billet temperature T_s) provided by a Profinet interface, Python pre-processes the resulting data and automatically triggers the prebuild FEA. The prebuild simulation operates with given input parameters and varying friction coefficients, until the mean value of the simulated force (F_{sm}) lies within a defined range of the actual force measured by the machine system (F_{exm}). The resulting information about the friction state during the process can then be further used for an adaption of lubrication. As the results are stored within the server infrastructure at the Chair of Metal Forming, a time dependent parameter comparison can additionally be made (e.g. for predictive maintenance algorithms). Figure 9 shows the concept for this DS schematically [50].

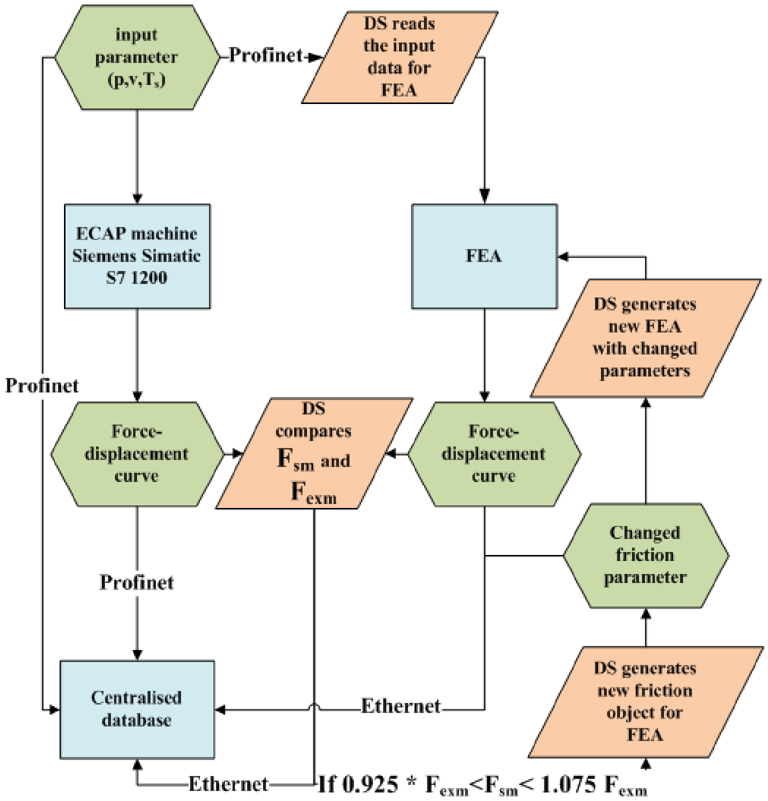


Figure 9. DS concept for the ECAP machine system [50].

3.2.2 *Residual stress prediction for the shot peening process using FEA and Python*

This framework shows a different approach on the possible integration of FEA into a manufacturing environment. In this case, the user is able to insert desired results after a specific process, which triggers a Python logic to calculate the required input parameter based on a database developed with FEA. The method is similar to what is described in 3.1.3. The solely difference is, that underlying data for the logic comes from a numerical simulation instead of practical experiments. Furthermore, a different ML-algorithm was developed, which is capable of including data sets from practical experiments into the initially FEA based database. The procedure is practically demonstrated on the example of the shot peening process, which is widely used in the metal forming environment as a mechanical surface treatment [51]. As in 3.1.3, a GUI for the prediction of desired material behavior after the respective process was developed, supporting domain experts and operators to decide which process parameters should be deployed. Additionally, a ML-algorithm based on the same Python environment as within the main processing layer was evolved. This algorithm is capable of implementing data sets from different practical experiments to increase the predictor's accuracy [52]. Figure 10 visualizes the generation of the initial database using the FEA program Abaqus® directly within the Python environment. For this initial development, the input parameters shot velocity, the underlying material model of the target workpiece as well as the radius and material of the spheres to be shot on the respective workpiece were varied, resulting in the automatic execution of over 350 simulations. Supplementary post-processing before the storage of the results in the database was also carried out within Python.

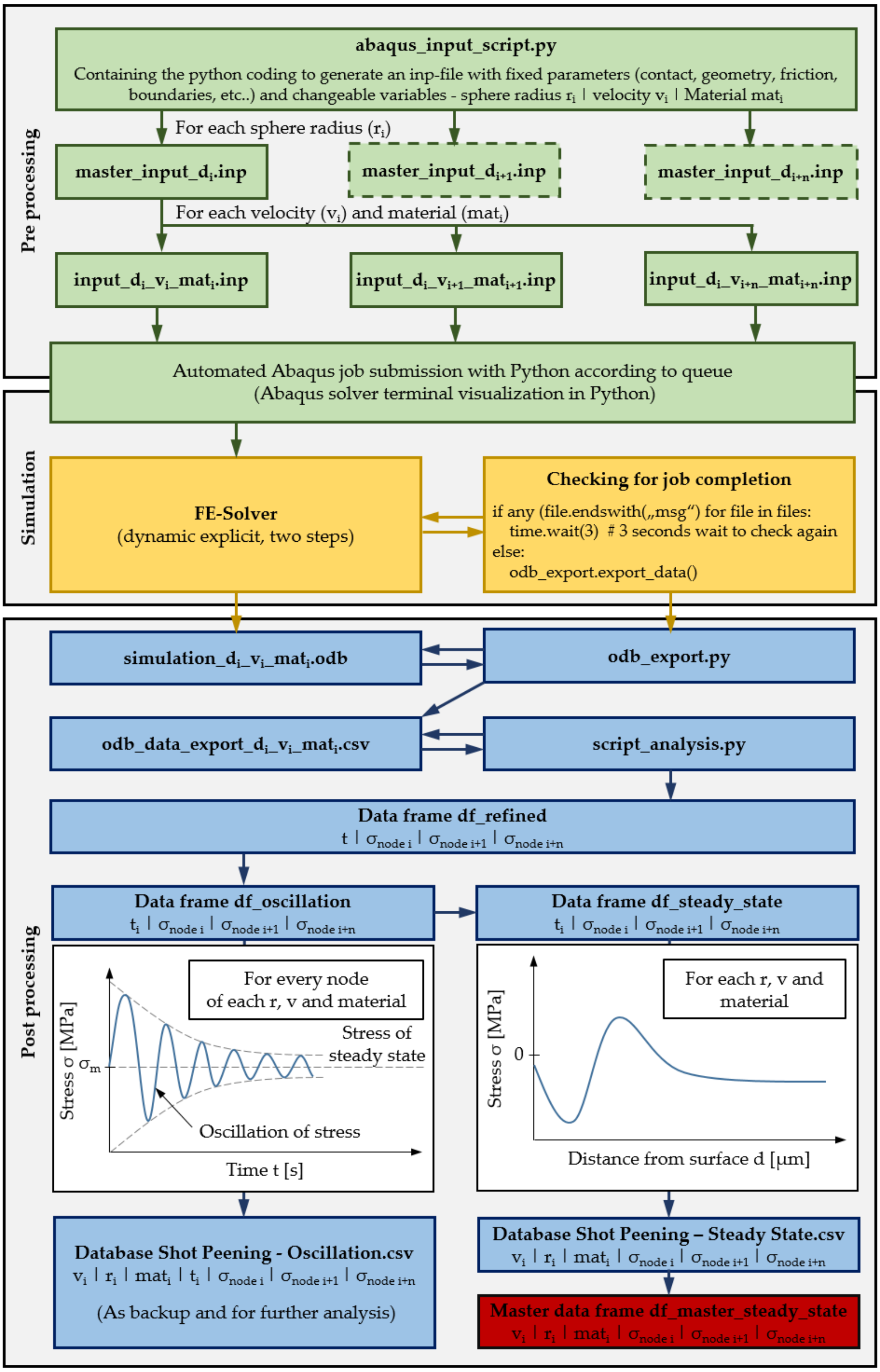
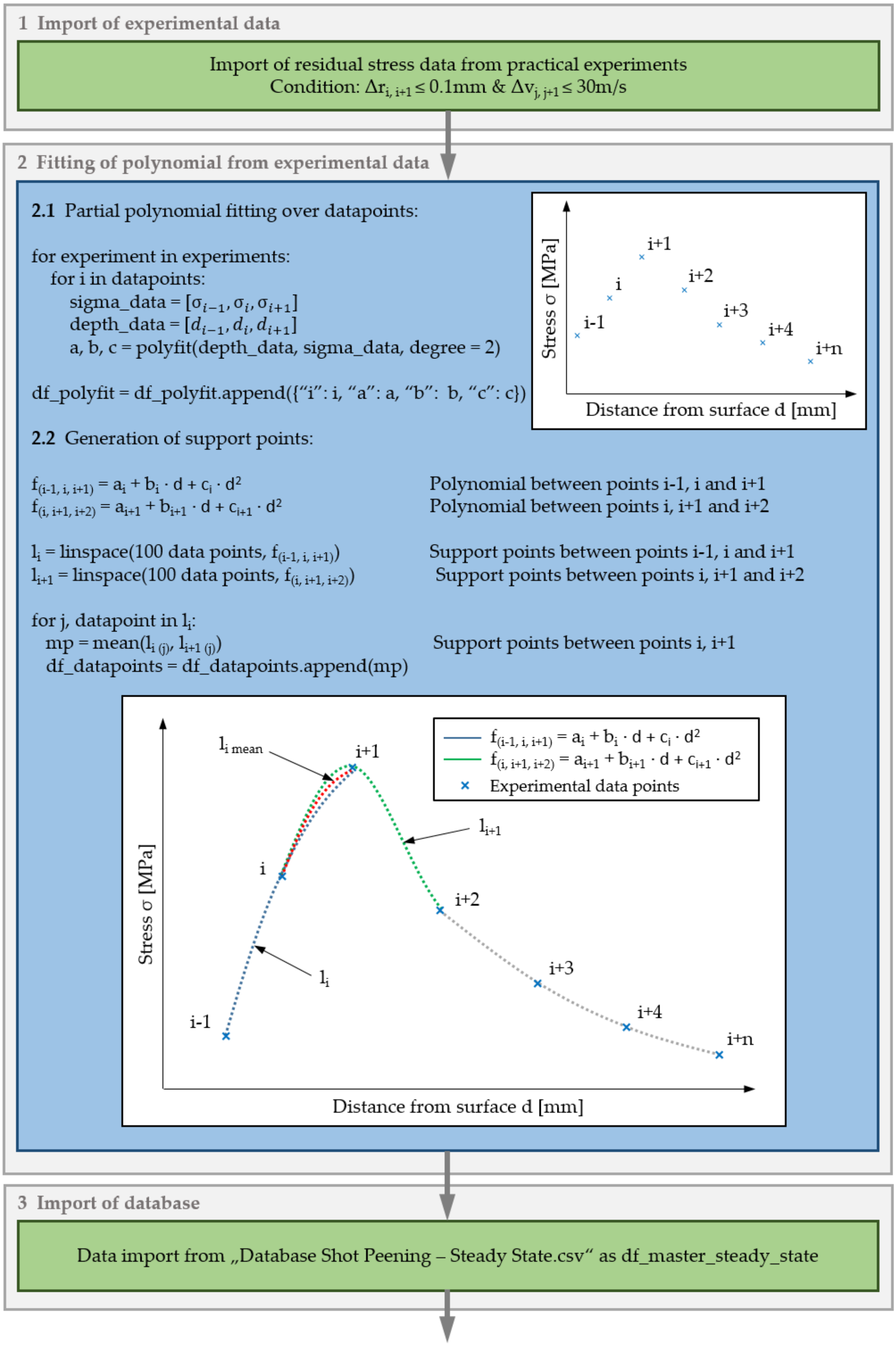


Figure 10. Automated FEA set-up and data analysis using Abaqus® and Python [52].

For the respective GUI, a similar logic as in the rolling mill case study (3.1.3) was used. For the inclusion of data sets from practical experiments into the same database, a second order interpolation approach was chosen. The logical concept behind this approach is additionally visualized in Figure 11. This method can be used for the integration of all different kinds of experimental data into a FEA based database. By adapting the initial overruling condition (Figure 11, section 1), the presented case can be directly extended for other more or less complex physical interrelationships.



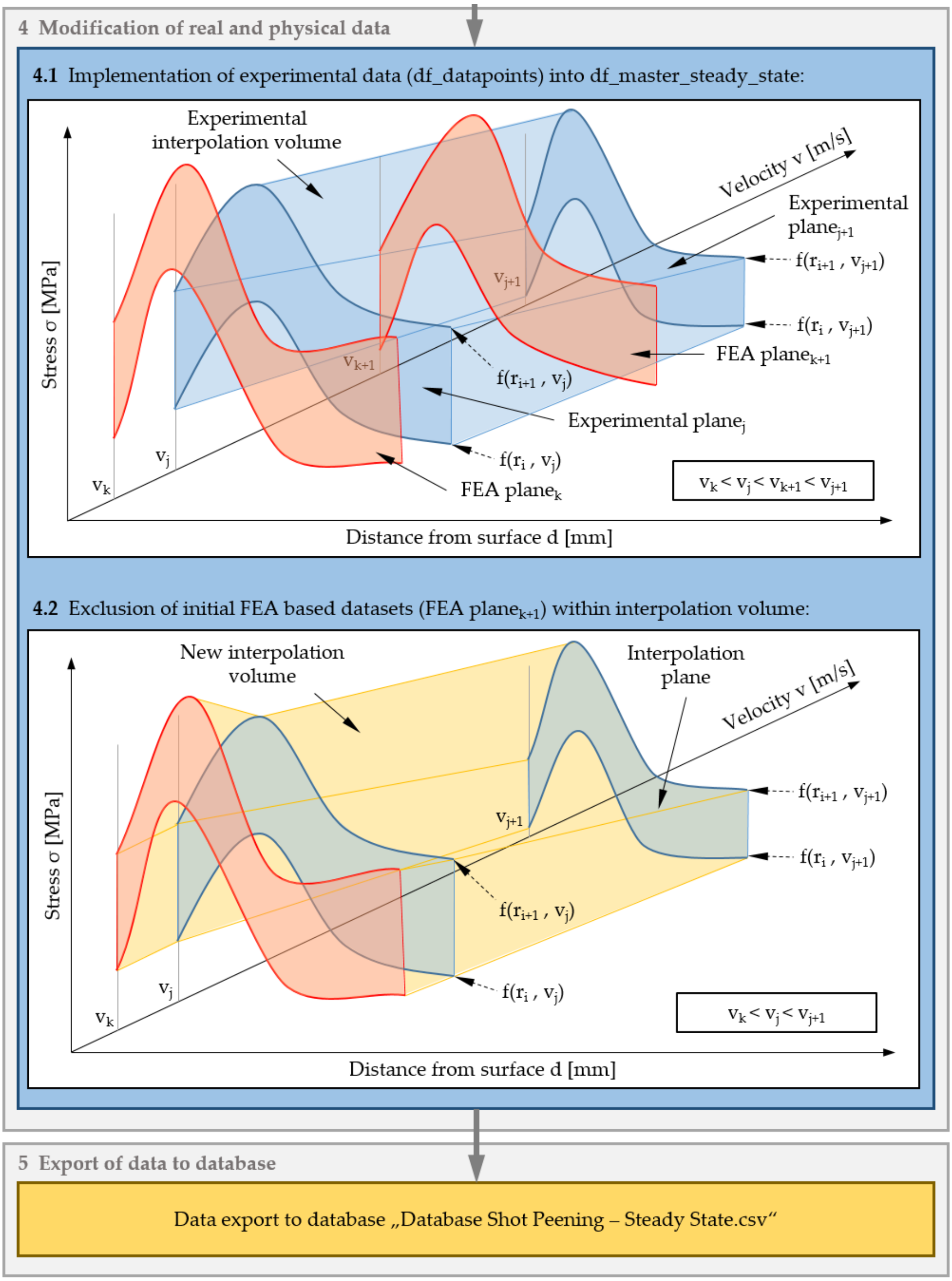


Figure 11. Python based ML-approach for the integration of practical experiments into the FEA based database to increase the predictors' accuracy [52].

3.2.3 MUL 4.0: systematic digitalization of a value chain – from raw material to recycling

The MUL 4.0 project is an interdisciplinary approach co-initiated by the author at the Montanuniversität Leoben (MUL). Within this project, three academic chairs at the MUL (Chair of Metal Forming (MF), Chair of Industrial Logistics (IL), Chair of Nonferrous Metallurgy (NFM)) and the Institute of Mechanics (M) developed a cooperative approach to digitalize the value chain. For a first use case an aluminum alloy, casted at the NFM, was chosen. After the casting process, which will be supported by a FVA serving as a DT, the resulting billet is forehanded to the MF, where different forming and quality control related processes will be executed. At the MF, FEA based DTs will be included for each corresponding process step, supervised by M. After a simulated product life, the resulting part will be remelted at the NFM again, to conclude the cycle of the value chain. As a result, a DT for each involved process step should be implemented. To demonstrate the full potential of this process related DTs, the supply chain related data from theses simulations (e.g. estimated throughput time) will be extracted and inserted in a superordinate Cyber Physical Logistic System (CPLS), which is currently in establishment at the IL. Figure 12 shows a blueprint of this project proposal, including different HMIs for supervision, adaption and demonstration purposes [53].

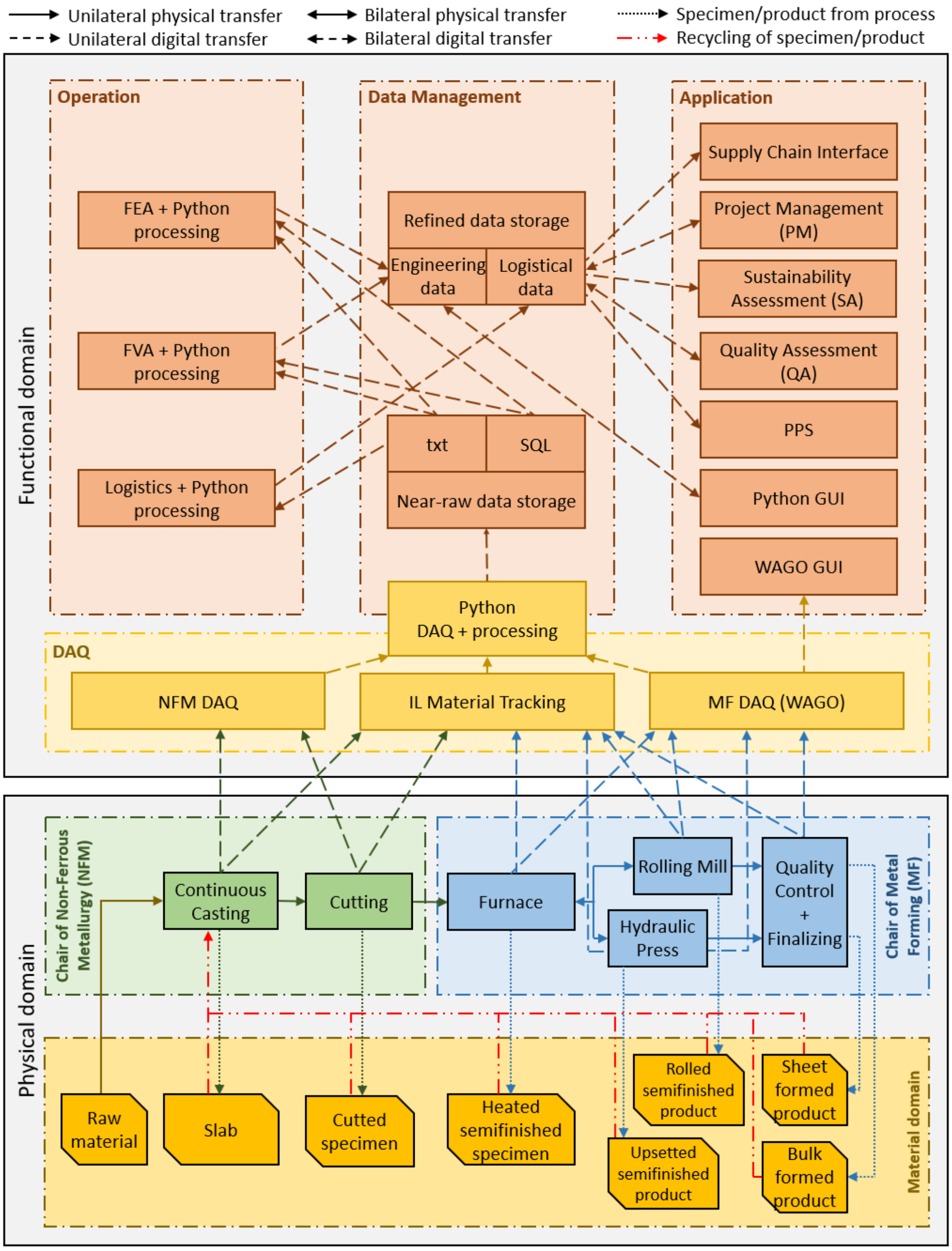


Figure 12. Physical and functional domain blueprint for the MUL 4.0 project [53].

3.3 Answering research question (III): Methodology and contribution

For the answer of the third and from the authors point of view, most important research question, the work elaborated in the previous subsections has to be considered. The case studies described in section 3.1 and 3.2 result in a smart factory tailored to the metal forming industry, therefore entitled as Smart Forming Lab (SFL). Based on this evolvement, the transition to the industrial practice and therefore the acceleration of the digital transformation process in the Austrian metal forming environment can be achieved. Interested domain experts from industry are able to learn within the SFL by cooperation (e.g. joint projects). To reach a sustainable impact in the industry, engineering students who will possibly work as future domain experts in this field have to be sensitized about these new technologies. Moreover, by teaching these students in an interdisciplinary and modern way, the ability for LLL should be enhanced due to this framework, which is mandatory in this rapid developing environment [54]. Within case study 3.3.1, the initial framework for such an academic course, including scope and workload, was developed. In 3.3.2, an adaption based on the implications of the actual knowledge of students as well as the implications from the industry was executed.

Table 6. Contributions to the answer of (III).

No.	Case study	Addressed issues	Corresponding publications
3.3.1	Development of an academic course for the transdisciplinary education of engineering students with special focus on digitalization and digital transformation in metal forming	Demonstration of the implementation of a framework for transdisciplinary engineering education at the MUL by using state-of-the-art pedagogical approaches; definition of the respective scope for an efficient basics course on digitalization and digital transformation with special focus on the metal forming environment	A 6
3.3.2	Implementation of a stakeholder oriented adaption of the lecture concept for the transdisciplinary engineering education	Closing the knowledge gap for future domain experts to accelerate digital transformation in Austrian's metal forming industry; inclusion of the LLL concept to support a sustainable and continuous improved knowledge transfer from participants to respective potential employers	A 7

3.3.1 Development of the lecture 'Digitalization and Digital Transformation': Definition of scope and initial framework

As illustrated in Table 6, a framework for a transdisciplinary academic course was planned at the MUL. This lecture should instruct the fundamentals of the digitalization and digital transformation in metal forming [55]. The initial concept was derived from the author's knowledge and experience gained and described in section 2, 3.1 and 3.2. For the initial design, the lecture was split into four different modules, two theoretical and two practical parts. Table 7 gives a brief overview about the scope and planned workload distribution, which is determined with 2.5 European Credit Transfer System (ECTS) points [55–57].

Table 7. Design of the initial framework for the lecture 'Digitalization and Digital Transformation in Metal Forming' [55].

Module I: Digitalization –Theoretical Part: Face to face and online (Timeframe: 4x1h, 2x2h, 1x3h, 1x6h, 1x15h)			
Topics: Introduction and enhancement of awareness for chances and issues of digitalization in the metal forming industry (1); Fundamentals of automation in the metal processing industry, including retrofitting and digitization (2); Fundamentals of networking technologies: state of the art protocols and data management, including retrofitting and IT-security (3); CPPS and HMI in the metal forming environment (4); DT and DS in metal forming related operations, including AI and Big Data (5)			
Objectives: Knowledge of the most important definitions and differences in metal forming related digitalization key technologies; Enhancement of the ability to communicate with IT-domain experts in the manufacturing environment; Understand the possible advantages of digitalization technologies			
Content	**Methods**	**Material**	**Duration**
(1)	Face to face lecture; group discussion	PPT; Handouts, video	1h
(2)	Moodle based e-learning; online script; actual research papers; videos	PDFs, videos	2h
(3)	Moodle based e-learning; actual research papers; videos; practical tutorials	Online tutorials; PDFs; videos	2h
(4)	Moodle based e-learning; online script; actual research papers; videos	PDFs, videos	1h
(5)	Moodle based e-learning; online script; actual research papers; videos	PDFs; Handouts, video	3h
Module II: Digitalization – Practical Part: Face to face (Timeframe: 1x1h, 1x2h, 1x3h)			
Topics: Explanation and practical demonstration of the fundamentals of automation and networking technologies via a six-layer digitalization framework, including DS, DT and AI (6); Practical demonstration of a suitable implementation approach for CPPS and HMI, illustrated by the Chair's retrofitted experimental cold rolling mill, using a variety of different software (7); Demonstration of practical open source IIoT solutions, demonstrated on operating machine hour counters and related project management implementations at different forming aggregates (8)			

Objectives: Knowledge transaction from theory into practical implementation; Deepening the understanding for the purpose of knowing the fundamentals of digitalization as a future domain expert

Content	Methods	Material	Duration
(6)	Face to face lecture; group discussion	Different forming aggregates and infrastructure at the Smart forming lab	3h
(7)	Face to face lecture; group work; group discussion	Smart forming labs digitalization environment, including cold milling aggregate and different software	2h
(8)	Face to face lecture; group discussion	Demonstration of the Smart forming lab's six layer architecture and the advantages of digitalized project management	1h

Module III: Digital Transformation – Theoretical Part: Face to face (Timeframe: 1x2h)

Topics: Major issues regarding the implementation of digitalization technologies in the metal forming environment (9); The importance of top-down and bottom-up change management (10); Practical change management approaches in the metal forming industry (11)

Objectives: Understanding the fundamentals and purpose of change management in metal processing manufacturing; Raise awareness for the most important challenges arising with digital transformation on the different layers of management; Knowledge about practical approaches to overcome the most common resistance in a sustainable way

Content	Methods	Material	Duration
(9)	Face to face lecture;	PPT; board	1h
(10)	Interactive face to face lecture; group discussion	PPT; board	0.5h
(11)	Interactive face to face lecture; group discussion	Board;	0.5h

Module IV: Digital Transformation – Practical Part: Face to face (Timeframe: 1x20h, 1x2.5h)

Topics: Developing a strategy and operational approach to successfully run a digitalization project (12); Summarizing and presenting the elaborated solution in an appropriate way (13)

Objective: Participants are able to run a digitalization project in the metal forming industry successfully

Content	Methods	Material	Duration
(12)	E-learning, group work;	Lecture material;	20h
(13)	Presentation	PPT, board, video	2.5h

3.3.2 *Further adaption and redesign of the initial lecture design based on initial student's knowledge and requirements from industry*

To tailor the learning objectives to the requirements of the industry, the survey described in Table 3 was used for a focus shift on current issues in the metal forming environment and thus increasing employability of respective students. Furthermore, a second quantitative survey was sent to students at the MUL, in order to gather data about their knowledge on recent developments in digitalization and digital transformation (A 7). The results showed a significant knowledge gap between industry requirements and initial knowledge of participants. Furthermore, the difference between distinct engineering disciplines at the MUL as well as studying progress (e.g. bachelor vs. master students) is not significant for this purpose and can therefore be neglected (A 7). For this reason, the lecture is accessible for all interested students in the engineering field. This approach results in an additional benefit for the core disciplines in the metal forming environment, as different point of views and lessons learned from other technical fields (e.g. mining, applied geosciences) can point out out-of-the-box solutions. Figure 13 visualizes the concretized pedagogical approach of the redesigned lecture.

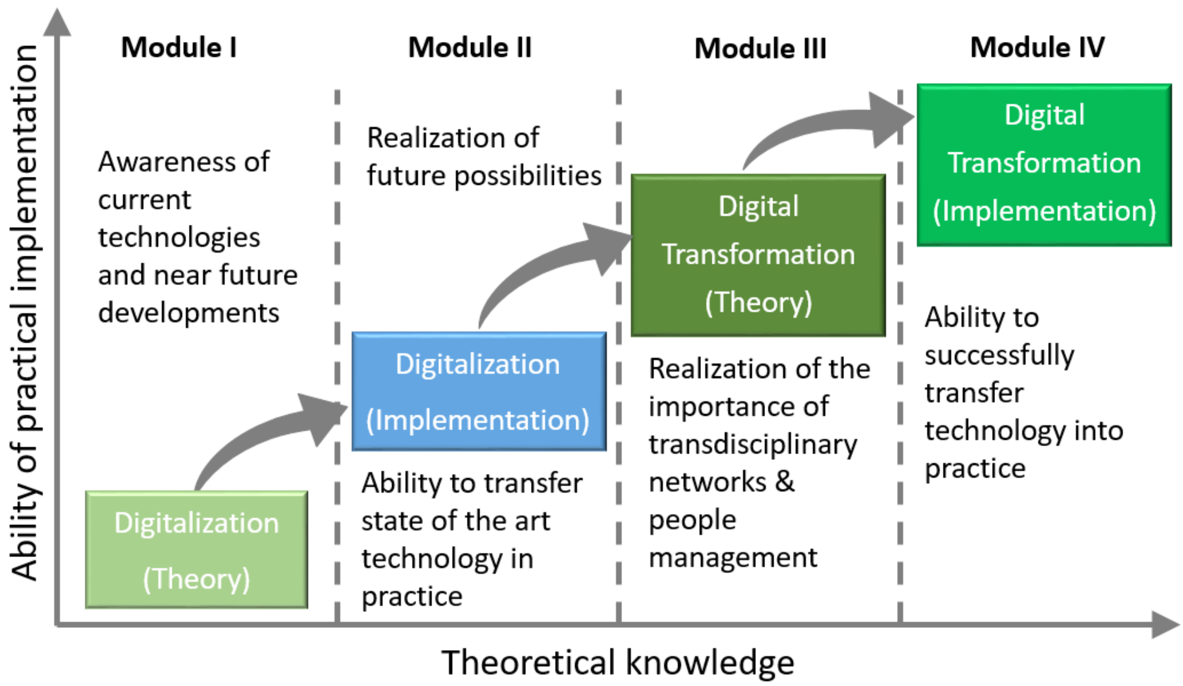


Figure 13. Definition of modules and corresponding learning outcomes of the redesigned lecture (A 7).

To ensure a continuous improvement of this teaching framework in terms of education techniques and scope, a methodology was developed (Figure 14), which can further be used for updating other lectures in a transdisciplinary field (A 7).

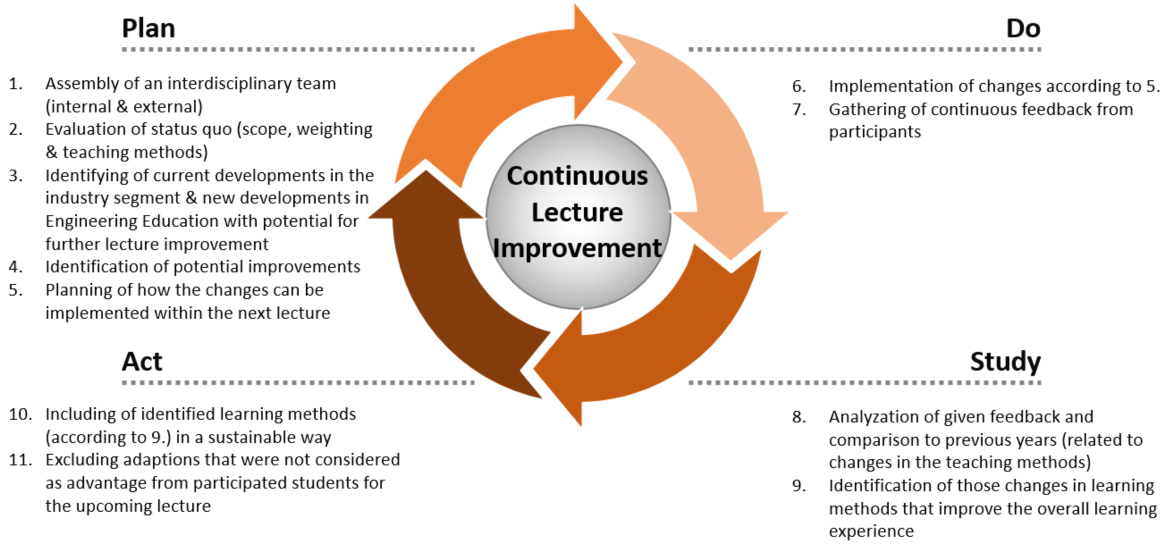


Figure 14. 11 step PDSA cycle for the continuous improvement of a transdisciplinary lecture, derived from the work of Deming [58] and Shewhart [59] (A 7).

4 Results and discussion

This thesis strives to support the scientific research field of digitalization and digital transformation by answering three research questions elaborated from current literature, expert interviews and practical developments in Austria's metal forming industry. For this purpose, eight case studies, two quantitative surveys and a proposed framework for the interdisciplinary connection of digitalization technologies were developed. To answer research question (I), a SFL was established, which points out different possibilities of integrating machine systems of different age, degree of automation and digitalization as well as complexity into a digitalized production environment. For the purpose of practicability, two different DAQ systems were developed initially, both operating on industry standards and extendable by simple adaptions. These progressions are crucial in first instance, as production architectures are often proprietary solutions, resulting in an artificial threshold for a truly efficient digitalized production system [49]. To overcome these barriers and demonstrate the advantages of open-interfaces, Python was used wherever applicable as a main processing layer for further data processing. Based on the conceived Python layer, further low-cost open-source technologies for the integration of a directly connected project management tool and database management system were integrated, serving as a basis for the demonstration of advantages of open-source technologies. Finally, a low-cost user-friendly CPPS was elaborated, highlighting the possibilities of open-source technologies (A 8) [35]. In conclusion, the resulting SFL shows solution approaches for a majority of practical challenges in the Austrian metal forming sector.

Due to the heavy usage of FEA in this industry segment, the answer of research question (II) is another important contribution to the research field. Within this thesis, three different approaches for the automated integration of complex numerical simulations into the metal forming environment were proposed:

- The integration of FEA into a DS for the optimization of a complex metal forming process, demonstrated by a simplified FEA on an ECAP process machine system [50];
- The integration of FEA for optimizing initial process parameters and reduce costs by decreasing the required amount of practical experiments, demonstrated by a prevalent mechanical surface treatment process with a supporting ML algorithm formulated within the Python environment [52];
- A proposal of how FEA and FVA can be utilized on a superordinate supply chain level to further optimize the product-manufacturing lifecycle, demonstrated on the MUL 4.0 project from the casting of a nonferrous material to its recycling (A 9).

The developments resulting from these case studies significantly contribute to the acceleration of the digital transformation process, as they point out a variety of possibilities which can be directly applied in industrial practice. The hardware and software implemented was chosen based on the following requirements:

- Industrial standards in terms of resilience in a harsh manufacturing environment;
- Easy-to-use for respective workers and domain experts by parallel development of corresponding front-end and back-end GUIs;
- Open-interface and open-source solutions wherever applicable under consideration of other postulated requirements;

- As low-cost as possible to reduce the financial barrier for the implementation of these digitalization solutions [49].

Despite the technical solutions developed within this work, a sustainable way for the knowledge transfer from the SFL into the industrial practice has to be ensured. For this purpose, a transdisciplinary lecture was designed, taking into account recent developments of Austria's metal forming industry and initial knowledge of potential participants. Within these lecture, future domain experts are trained and educated in the field of digitalization. Due to the use of mainly open-source software in the SFL, respective students are able to work alongside with domain experts from industry to further develop the framework and include additional machine systems and complementary software solutions, resulting in an increase of theoretical and practical knowledge [49].

5 Conclusion and outlook

This thesis describes the development and implementation of a six-layer architecture for the development of a SFL at the MUL. To accomplish this architecture, two different open-interface DAQ systems were introduced and connected by using the open-source programming environment of Python. To consider the specific challenges of the Austrian metal forming industry segment, a special focus is set on the integration of machine systems of different degrees of automation and complexity into this framework. To support the digitalization in this specific sector, comprehensible ML algorithms were devised, supporting the integration of FEA into the productive flow on different levels. To transfer the gathered knowledge from the academic into the industrial environment, a transdisciplinary academic course was planned and adapted to the requirements of the industry as well as potential participants from academic institutions.

In order to take full advantage from the architecture and engineering education framework, the platforms introduced offer the possibility of a further development from the academic as well as industrial position. Additionally, the introduced architecture with embedded case studies offer industrial experts the possibility to learn and improve in a non-critical environment, e.g. without having to worry about producing errors in their operating system at work. This possibility is especially important for SMEs in the metal forming sector, as adequate practical learning possibilities are rarely given in this working environment. The educational framework developed within this work can be further adjusted as training courses for respective employees on different levels, supporting their companies by building up the knowledge of their key personnel for an efficient planning, implementation and operation of a digitalized production chain. By using relatively low-cost industrial standard components and mainly open-source and open-interface software solutions, the smart forming layer architecture created can be transferred to industrial practice without high implementation costs. The combination of demonstrating reasonable priced hardware and showing how this hardware can be used adequately in a comprehensible way can therefore significantly contribute to a successful digital transformation in this industry sector.

The digitalized supply chain proposal developed within the MUL 4.0 framework will be pursued in the near future, extending the potential advantages of digitalization technologies. As the proposed CPLS is based on purely open-interface technology, additional supply chain domains, e.g. mining, conveying technology, can be integrated into this system. After the initial go-live, a further enhancement of already included processes and operations can be executed, e.g. a variety of different alloys, produced within different casting processes or additional material testing methods. The network itself, as well as the underlying open-interface programs can be further expanded and increased in terms of efficiency and effectiveness. While the initial objective of the implemented ML-logic was to create a comprehensible and therefore easy-to-learn environment for unexperienced parties, the Python environment used is capable of implementing more complex algorithms. This condition, paired with the high amount of data obtainable from real industrial processes at the different chairs and institutes of the MUL, can further be used for the training of (future) data scientists.

The concepts and case studies executed within this work therefore serve as a reliable fundament for further digitalization and digital transformation activities in and beyond the metal processing environment and additionally contribute significantly to a future-proof transdisciplinary engineering education in Austria.

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A Associated publications

The following chapter contains the publications A 1 to A 9, according to the chapters 1 - 5.Within each subsection, a table describing the authors contribution to the respective manuscript is provided.

A 1 Publication 1

B.J. Ralph, M. Stockinger: ‘Digitalization and Digital Transformation in Metal Forming: Key Technologies, Challenges and Current Developments of Industry 4.0 Applications’, in: *XXIX. Colloquium on Metal Forming*, pp. 13-23, 03.2020, ISBN: 978-3-902078-26-1.

Author contributions

1. B. J. Ralph: literature study, conceptualization, methodology, interviews, visualization, writing-first draft, writing - review and editing
2. M. Stockinger: resources, writing - review and editing

DIGITALIZATION AND DIGITAL TRANSFORMATION IN METAL FORMING: KEY TECHNOLOGIES, CHALLENGES AND CURRENT DEVELOPMENTS OF INDUSTRY 4.0 APPLICATIONS

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ABSTRACT: The conception of Industry 4.0 in 2011 marked the beginning of a new era of industrial manufacturing. Since then, data-driven decision making and smart networks supported by artificial intelligence have led to a continuous change in working environments in production. Nevertheless, there are many companies that have not fully exploit the potential of the fourth industrial revolution. To a considerable extent, this can be attributed to a low level of automation. This circumstance often results from financial or process-related restrictions and affects not only the production facilities but also the sensitive IT infrastructure. The lack of automation is therefore often compensated by expert knowledge and experience. The fear of job loss due to disruptive technologies is a further contribution to the significant delay in the digital transformation of such companies. Companies in the metal forming industry are particularly affected by this development. This paper describes the key technologies of digitalization and provides an outlook to possible solutions for specific challenges during the next years in the manufacturing and especially metal forming industry environment.

KEYWORDS: Industry 4.0; Metal Forming; Smart Production; Digital Factory; Cyber Physical Production Systems; Industrial Internet of Things; Big Data; Cloud Computing; Digital Twin; Finite Element Analysis;

1 INTRODUCTION

Since the German government introduced the term "Industry 4.0" in 2011, a lot of scientific research focused on the development and forms of its key components [1,2]. In most of these works, several problems arise with regard to the practical application of Industry 4.0 (I 4.0) technologies in the metal forming industry. In summary, there is a clear incoherence between theoretical digital maturity levels and practical work validated by case studies. Especially for smaller batch sizes, apart from conventional mass production, many recommended implementation approaches are not feasible at the current state of the art [3]. In addition, there are hardly any publications that significantly consider the integration of complex numerical simulations, which are widely used in forming technology practice, into such I 4.0 strategies. This paper gives an overview of current digitalization technologies which are already used in forming technology or at least have the potential to be implemented in the near future. In addition, the potential challenges in this industry sector are discussed.

2 KEY TECHNOLOGIES

The following subchapters are dedicated to core technologies of the fourth industrial revolution that are of the highest relevance from the perspective of current scientific publications [1,2,3,4,5,6,7]. Despite the large number of publications concerning these technologies, there is still no uniform terminology [8]. For this reason, the most recent scientific publications in sophisticated journals are cited for the definition of the terms. Although Additive Manufacturing (AM) is considered a part of I 4.0 in most current publications [9], it will not be discussed in detail in this paper. From the metal forming point of view, additive manufacturing is a special production technique, which was strongly driven by I 4.0 technologies, but is not absolutely necessary in order to completely digitalize forming technology companies.

2.1 GENERIC INFRASTRUCTURE

To create a uniform operationalization of the I 4.0 concepts, various reference models were developed. One of the most comprehensive and promising for further adaptations is the Reference Architectural Model Industrie 4.0 (RAMI 4.0) [10]. This model is an extension of the Smart Grid Architecture Model (SGAM) and takes into account the often complex requirements of planning, implementation and operation of a smart factory [11]. In addition to the consideration of the hierarchical level and the layer level known from classic automation technology, this model also considers value stream and asset life cycle in the third dimension [10]. Fig. 1 schematically shows the basic configuration of this concept.

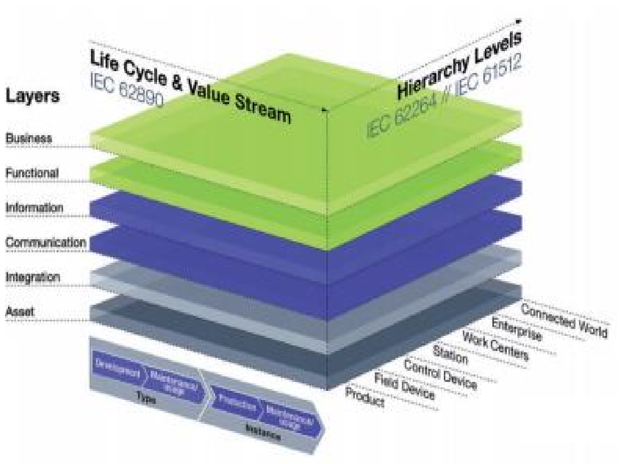

Figure 1: RAMI 4.0 concept [12]

An essential aspect of the digital transformation and thus of I 4.0 is the vertical as well as the horizontal integration along the supply chain. These are described by the hierarchy levels (horizontal integration) and layers (vertical integration). In the Life Cycle and Value Stream dimension, both the initial implementation and further optimization can be quickly visualized and discussed, as required [12]. Depending on requirements, this model can be adapted at will and is therefore suitable for all types of production processes and manufacturing companies [10,13,14].

2.2 CYBER PHYSICAL PRODUCTION SYSTEMS (CPPS)

Cyber Physical Systems (CPS) were first mentioned in a workshop of the American National Science Foundation in 2006 [15]. The terminology of this concept has been concretized several times in recent years. In general, CPS refers to systems that acquire, store, analyze and process data via Internet technologies (Internet of Things (IoT)) and in the context of the integration of the real physical and virtual world, including human machine interaction. It is also seen as one of the essential building blocks of the fourth industrial revolution [1,2]. A further development and specially adapted extension for production is the so-called CPPS. In addition to the interaction of computer science, information and communication technologies as well as human machine interface known from the CPS concept, automation technology is also taken into account more explicitly [16]. For this purpose, instruments of classical automation technology, e.g. sensors, actuators or fieldbus interfaces are combined with modern information technology hardware and software [17,18,19]. The classic hierarchical structure of the well-known automation pyramid is replaced by a decentralized structure [20], starting above the field and control level (Fig. 2).

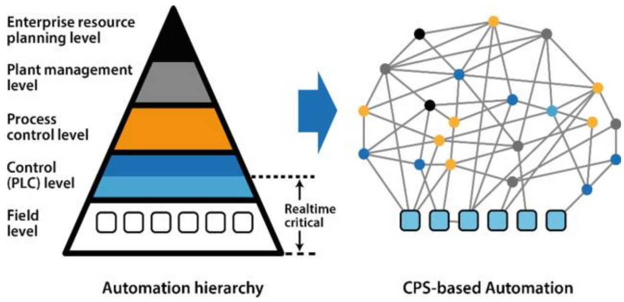

Figure 2: CPPS – Scheme [22]

Due to the increasing spread of in memory technologies on the Enterprise Resource Planning (ERP) and Business Intelligence (BI) level as well as more sophisticated Management Executions Systems (MES) in the metal forming Industry, the use of this technology will also increase in the future [21]. The challenge regarding the high amount of different interfaces plays an important role in this context. According to the current state of research, OPC Unified Architecture (OPC UA) seems to be the first standard communication protocol framework for communication in the mostly heterogeneous machine data environment. This format is open source, constantly developing and compatible with almost all file formats. Furthermore, adaptations can be made via a corresponding Graphical User Interface (GUI) using Python or C++ [23]. OPC UA is therefore seen as key technology of Industrial Internet of Things (IIoT), which can be seen as one of the main enabler of CPPS (**2.3**).
The inconsistency of scientific publications concerning I 4.0, HMI, CPS and CPPS can be illustrated by the following Figure 3. While publications on the theory and terminology of CPS almost exclusively see Human Machine Interface (HMI) as an integral part, this topic is often seen as a separate focus and therefore outstanding add-on (**3.2**). Also the definition of CPPS is often difficult to differentiate from CPS. In this paper, with reference to the metal forming industry, CPPS is nevertheless considered as a superordinate system, which adds sophisticated HMI Technologies and simulations to the CPS.

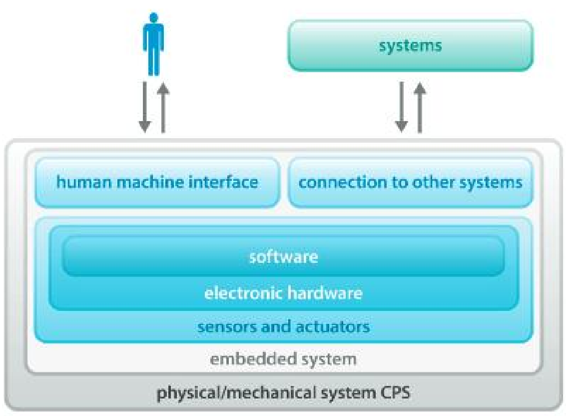

Figure 3:Commonly used definition of CPS [16]

Within the context of the metal forming industry, this would imply that CPPS takes into account digital shadows and digital twins in addition to HMI technologies [24].

2.3 INDUSTRIAL INTERNET OF THINGS (IIOT)

According to the current state of research, the term IIoT can be regarded as an evolution of the IoT concept [25]. Starting with the first significant mention in recognized journals in 2013, there has been an exponential increase in publications over the years, as demonstrated by Liao et al. [26] until 2017, whereby articles from the Scopus, IEEE Xplore and Science Direct databases were collected in detail and analyzed using data denoising, data confirmation, data enrichment and data categorization. Despite this, there are still various definitions of IoT in 2018 [26]. The underlying reasons for this can often be attributed to different approaches due to the interdisciplinary nature of digitalization. In general, it can be postulated that the term IoT has developed in most cases from the Fieldbus technology known from automation technology. These process automation protocols were and are still partly used today for the implementation of the Supervisory Control and Data Acquisition (SCADA) control level (Fig. 2, Process Control Level), which then forwards agglomerated information to the MES level above. This interface is also one of the main drivers for the development of the fourth industrial revolution. SCADA systems in most cases include not only simple sensors and actuators but also Programmable Logic Controllers (PLCs), management consoles and Proportional-Integral-Derivative (PID) controllers. These were passed on and processed using the Fieldbus protocol format. The main challenge in this case is the heterogeneity of these protocols. The IEC-61158-1 and other known standards include over 18 different families of fieldbus protocols, e.g. modBus, ProfiNet, CANbus, EtherCAT and many more. This heterogeneous protocol landscape leads to extremely complex systems, especially for companies with long system life and machine heterogeneity. Due to the spread of the Internet in the industrial context, it was also necessary to include Internet protocol standards in this mostly already complex system. For the manufacturing industry, the term IoT can therefore be seen as a structured and standardized layer architecture that provides standardized Internet protocols (IPv4 and IPv6) as a superior instance for further processing while simplifying complex SCADA systems as much as possible. This abstraction is made possible by the integration of gateways or data transformation using, for example, IPv6 over Low Power Wireless Personal Area Networks (6LoWPAN7) [27]. One of the most promising recommended data protocol format for pure machine communication in production is Message Queuing Telemetry Transport (MQTT), as it provides particularly efficient storage and thus reduces the resulting amount of data. Another example is the Extensible Messaging and Presence Protocol (XMPP), which was designed specifically for HMI communication [28]. Fig. 4 shows some further file formats which are currently in use according to the current state of literature on all levels of a fully digitalized factory [29].

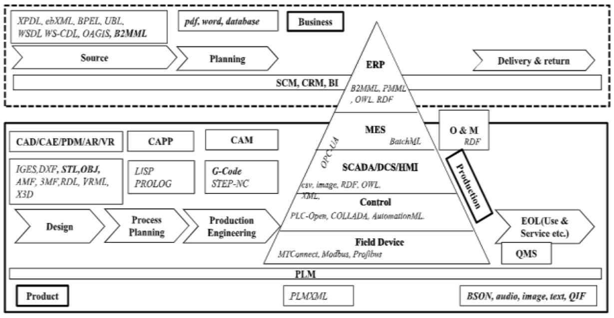

Figure 4: Smart Manufacturing systems and various data formats [29]

2.3.1 Tracking Technologies

The basic prerequisite for the use of an IIoT environment are so-called Smart Parts. These subsystems, which are often also often referred to as Intelligent Parts, Products or Machines, refer to sensors and/or actuators mounted directly on the product or machine, which enable the localisation of all entities involved in the production process. While machines are usually integrated via integrated controllers and gateways based on them, this approach is often difficult to execute for semi-finished products or starting materials. For this application, a variety of different technologies are used, from intelligent image recognition to Radio Frequency Identification (RFID) [30], Bluetooth and WiFi technologies [31], or (for mostly smaller quantities) manual input into the system via HMI. It is important to note that the full potential can hardly be exploited without supply chain-wide tracking technologies. This concept is also often referred to as Logistics 4.0 [32], but in terms of the technologies used and the purpose, it can be considered a subset of I 4.0 [33,34]. The full potential of I 4.0 and the Smart Production concept can only be achieved by fulfilling these technologies, so a separate consideration and naming from the metal forming industry´s point of view does not seem necessary.

2.3.2 IT Security

Cyberattacks have been common practice since the mass suitability of the Internet. Parallel to the increasing use of IIoT technology in manufacturing companies, attacks on their IT infrastructure are also on the increase. Already 2014, the manufacturing industry was the main target of spear pishing attacks [35]. Another well-known example of cyber physical attacks is the "WannaCry" ransomware virus, which drove a large number of automotive factories to a standstill in 2017 [36]. Such cyberattacks range from theft and manipulation to the deletion of sensitive production data. Intellectual property is also affected [37]. Especially in European and American metal forming industry, in which internal know-how is in many cases an essential component of competitiveness, such an attack can threaten the existence of a company. It should also be noted that the legal basis for successfully defending against data transfer is often not sufficient to protect intellectual property rights [38]. Sensitization and the involvement of IT security experts can help companies to identify and avoid potential dangers through well thought-out IT risk management. Additionally, there are several frameworks developed by experts, which support the development and implementation of cybersecurity solutions, e.g. as part of or under consideration of the RAMI 4.0 concept [39].

2.4 DIGITAL TWINS

The terminology of Digital Twins, like most of the technologies mentioned above, is not always clear defined. Originally first mentioned in 2002 in the context of Product Lifecycle Management (PLM), various fields of application and interpretations have led to a diverse development in the use of this term. In general, a Digital Twin is defined as the virtual, digital equivalent of a physical existing product [40]. However, this definition is insufficient for practical applications in the metal forming industry.
The first differentiation is based on the field of application. In metal forming technology there are two main application areas for this concept: i.) Digital twins as a representation of the production process over parts or the entire production chain, and ii.) Digital twins as a representation of one or a manageable number of process steps for the production of a semi-finished or finished product. In ii.) the focus is mainly on numerical simulation, e.g. Finite Element Analysis (FEA). The mapping of the process chain according to definition i.) is an important aspect in production plan optimization, but does not differ significantly from the general manufacturing industry. There are also a large number of large-scale industrial solutions, often coupled or as an integral part of modern MES systems. Definition ii.) is of particular interest. In this case a Digital Twin can be defined as a digital representation of processes, which are often based on complex material science and process engineering interactions [24]. For this reason, this article will refer to definition ii.) when using Digital Twin terminology.

2.4.1 Degree of Process Intervention

Another necessary differentiation is the distinction between "actual" Digital Twins (DT), Digital Shadows (DS) and Digital Models (DM). A Digital Model is a digital copy of a real physical entity, but completely without automatic data exchange between the virtual and the real object [41], e.g. an FEA of an existing forming process. This definition is mostly unambiguous in current literature and therefore needs no further concretization.
There are different definitions for DS in comparison. In general, it can be postulated that at least one of the two data connections between real and virtual objects is automated [41]. However, there are definitions where one of the two connections is explicitly defined as manual and the other as automatic [42]. Due to the lack of traceability and for reasons of generalizability, the first definition will be chosen as the basis for further considerations.
A Digital Twin is therefore a digital image of a real physical entity, which automatically transfers data bidirectional between both instances [41]. The differences between these three definitions are schematically visualized in Fig. 5.

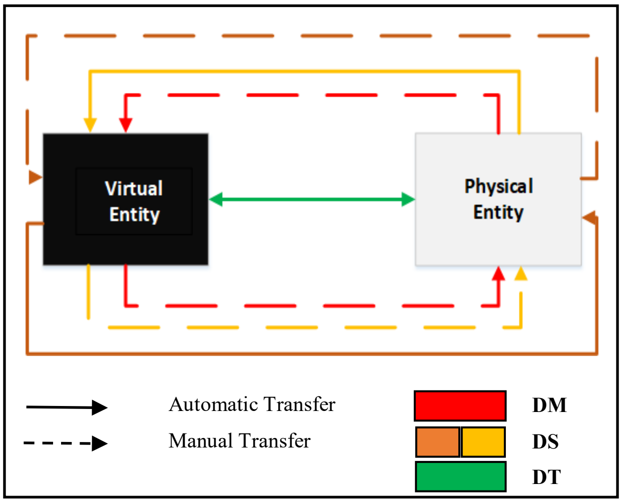

Figure 5: Comparison of Data Connectivity: DM/DS/DT

A large number of scientific publications define DT as virtual objects, which are in some way connected to a real object. This approach is mainly used for case studies and implementation approaches [41,42,43]. From this it can be concluded that especially in the field of modeling in manufacturing, theoretical progress and practical implementation diverge substantially.

2.4.2 Modeling Techniques

Furthermore, a distinction must be made between the origin of data used to model a DM, DS or DT. The consideration of digital twins on the basis of real material-physical laws is only one of two general approaches in the metal forming industry. Another approach, but one that is rather rarely used in the development of companies in heavy industry, is the creation of such a twin with strongly restricted or, in extreme cases, without the inclusion of material physics. Such approaches are based on stochastic methods and find correlations and thus descriptive variables directly from process and sensor data analysis. Multiple digitalization solutions, which e.g. connect on the SCADA level in production control, use a mixture of both approaches: complex material-physical models are coupled to the process and existing material models are optimized under the supervision of experts with the support of Artificial Intelligence (AI). In this case the stochastic part of process modelling consists primarily in the reduction of the complex real-physical models. Nevertheless, it should be the ambition of the metal forming industry to understand the underlying scientific relationships even after abstraction. In the context of I 4.0 and Smart Production, the mixture of real-physical laws and thus comprehensible calculations, called White Box Modeling (WBM), and calculations that are no longer comprehensible for a domain expert (stochastically calculated modelling that is decoupled from the physical problem, called Black Box Modeling (BBM)) is referred to as Grey Box Modeling (GBM). GBM approaches are becoming increasingly popular and represent the tool of choice for many manufacturing companies, in which also the greatest (near) future potential with regard to the further spread of DS and DT in production is represented [24,44]. Fig. 6 shows the GBM approach schematically.

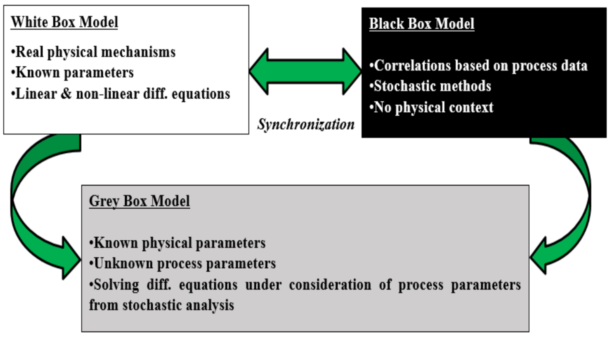

Figure 6: GBM approach for the metal forming industry [24]

2.5 BIG DATA AND ANALYTICS

Data is the fundamental basis of all I 4.0 technologies. In order for effective usage of data generated in a production process, it must meet certain criteria. The big data concept summarizes the problems that arise when handling recorded data in an industrial context in defined criteria. The number of these criteria again varies depending on the scientific publication [45,46,47], but in general production is based on three criteria, the 3 V of Big Data (Fig. 6), which is lately scientifically substantiated from M. Ghasemaghaei [48]. If these criteria are fulfilled, the term Big Data is accurate.

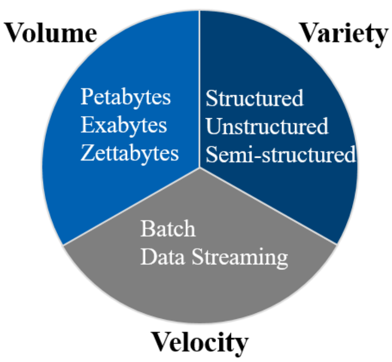

Figure 7: IBM Big Data characteristics [49]

Volume refers to the continuously increasing amount of data, whereby in most cases only from petabytes (equivalent to 1000 terabytes) onward, a truly large amount of data is assumed. Considering a fully digitalized factory in which all machines and the entire logistics communicate with each other using IIoT, CPPS, MES and an ERP System, data volumes of this magnitude can be reached even in medium-sized companies [50].
Considering the volume, the variety of the data is also a challenge. Data from different heterogeneous resources, e.g. IIoT Gateways, Customer Relationship Management (CRM) or Supplier Relationship Management (SRM) Tools, in most cases lead to a data structure that is difficult to handle [51]. In heavy industry in particular, offline parallel structures are also a problem, as data is often not entered into the digitalization system at all or only insufficiently (e.g. missing database maintenance).
The third challenge is to provide the required data at the required velocity. This problem seems to be the biggest challenge especially in the forming technology practice, considering e.g. DS or DT approaches. Also with regard to innovation this point seems to be the most critical one [52].
A variety of infrastructures have also been developed for Big Data applications. In general, the necessary architecture can be divided into six different layers. For each of these layers, different software and database developments should be preferred.
Among the most widely used is the Apache Hadoop framework developed in Java. This is a scalable tool for centrally operating software applications and is based on Google's MapReduce algorithm, which enables the efficient clustering of computing processes for processing large amounts of data. Fig. 8 shows an example of the process from tapping data from coupled machines to visualization of the analyzed data via HMI.

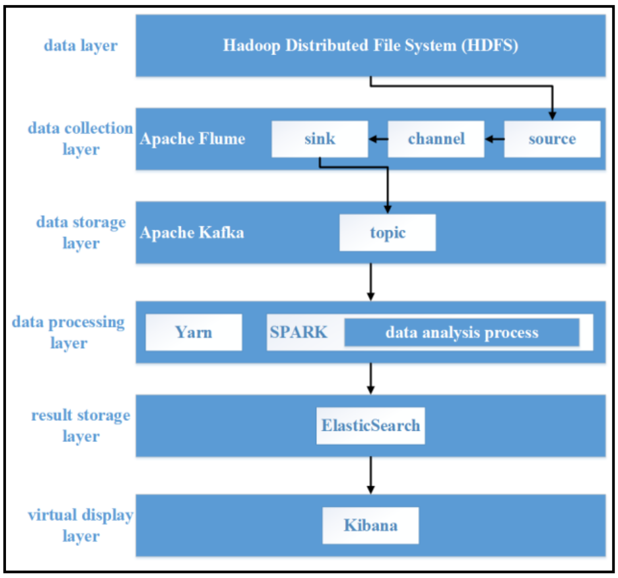

Figure 8: Example of a big data architecture framework [53]

The data from e.g. IIoT Gateways or directly from the machine controller is sent to the Hadoop Distributed File System (HDFS). The second step is a real-time monitoring of the file systems using e.g. Apache Flume. These are then collected in real-time and sent to (in this example) Apache Kafka in agglomerated form. Apache Kafka then acts as an interface for loading and exporting data streams to preferred third party systems. In the following layer, e.g. Yarn or Apache SPARK can be used for package management of JavaScript and Node.js. This layer is also responsible for the actual data analysis. Besides e.g. streaming functionality they also include machine learning, deep learning and graph processing tools. Applications can be written directly with Java, Scala, Python, R or SQL. The fact that SPARK and Hadoop (HDFS, Yarn) applications have partially overlapping functions must be considered. On one hand, SPARK does not have its own file management and is therefore relying on HFDS or similar technology (e.g. Cassandra, HBase). On the other hand, SPARK can perform most calculations in memory, which leads to an outperformance of traditional Hadoop MapReduce platforms in most cases [54]. Nevertheless, which architecture is chosen depends on the preference of those responsible for implementation and the specific use case. The results in this use case are then stored in ElasticSearch as NoSQL. Kibana is a browser-based, open-source analysis platform, and a practical example for a program in the final big data layer that allows to search and visualize the data stored in e. g. ElasticSearch [53,54].

2.6 CLOUD COMPUTING

The definition of cloud computing varies depending on considered application area. The National Institute of Standard and Technology (NIST) refers in a very general way to the following definition to the cloud computing terminology, as "*a model for enabling convenient, on-demand network access to a shared pool configurable computing resources (e.g. networks, servers, storage, application, and services) that can be rapidly provisioned and released with minimal management effort or service provider interaction"* [55]. According to Mell and Grants [55], the common architecture of a cloud solution consists of five essential characteristics, three service models and four deployment models (Fig. 9). It is considered outsourcing of data storage, usually accompanied by corresponding Service Level Agreements (SLAs).

On demand self-service is the definition for the possibility of customers of a cloud service to automatically access required resources, e.g. storage capacities, without additional human interaction. Broad network access enables customers to access all agreed resources with a variety of heterogeneous client platforms (e.g. smartphones, tablets, workstations). The resources provided by the provider are used by a large number of customers, who have limited possibilities to localize the physical data storage (resource pooling). Rapid elasticity refers to the ability of the provider to adapt its provided resources highly flexibly to the requirements of customers (e.g. upscaling). Another part of the essential characteristics is the possibility for the user to monitor and analyze his provided data streams and to request reports (measured service). As usual in many sub-areas of IT services, pay-per-use models are usually used for this purpose (e.g. for extended reporting possibilities, data volume (per time unit)).

In order to be able to use the advantages of such a service offer as effectively as possible, some providers also offer to adopt a corresponding big data architecture (SaaS, PaaS). The advantages, especially for smaller manufacturing companies, lie in the reduced in house expert know-how and required infrastructure (IaaS) required in this area [55, 56].

Private clouds are exclusively used by one organization, divided into e. g. business units, managed by internal IT, external organizations or a combination of both. Community clouds are provided for a defined community that share common interests, e.g. security requirements. It can be operated and owned by one or more organizations in the community, a third party, or a combination of both. Public clouds are infrastructures which are provided for open use by GOs, NGOs or academic organizations. Hybrid clouds consist of two or more different cloud infrastructures (public, community, private) that remain unique entities, but are connected by a single standardized framework technology. This enables a fast and relatively simple exchange of data between individual entities involved [55].

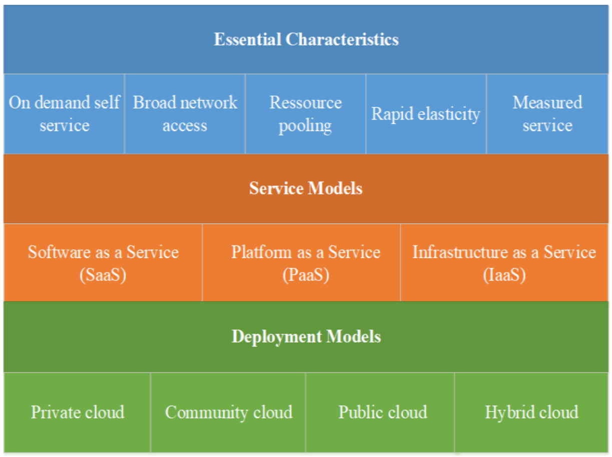

Figure 9: Cloud computing terminology after NIST [55]

3 POTENTIAL CHALLENGES

The metal forming industry in general is characterized by a high degree of heterogeneity. It includes a variety of production processes, materials, machine systems, but also organizational structures and sizes. In addition, there is currently no Austria-wide umbrella organization which represents companies assigned to this industrial sector as a unit. The heterogeneity in all these cases also results in a reduced number of publications that address the requirements within this technical discipline. Digitalization and digital transformation are topics that have been in the focus of a large number of interest groups in recent years. Nevertheless, a large number of developed concepts and case studies are not applicable to a significant part of the metal forming industry. For this reason, this chapter deals with what the author believes to be the greatest challenges in metal forming technology in relation to digitalization and digital transformation, supported by current scientific publications. Despite the technical component, also industrial-economical and partly also legal components are considered.

3.1 RETROFITTING

Retrofitting in the context of the fourth industrial revolution is defined as the upgrading of machine systems to make them viable for I 4.0 applications. In scientific publications, this process is usually based on the planning, implementation and validation of suitable infrastructure, communication and applications. In general, the goal of these procedures is to turn machines with older technologies into fully functional CPPS. This enables them to connect to existing IIoT networks and big data applications. Considering the high degree of heterogeneity, especially in metal forming industry, this seems to be one of the main challenges in implementing a smart production unit (fully digitalized production). Some work in this field deals with the creation of standardized frameworks, which should allow a structured approach for retrofitting. However, in the case of forming technology, these frameworks are either too general to directly initiate necessary steps (e.g. no suitable recommendation of defined interfaces, hardware, software (SW)) [57] or too specific (only suitable for a defined use case [58]). Based on renowned publications between 2014 and 2018 [59,60,61], Lins et al. [57] summarized the requirements for successful conversion of older systems to full CPPS, by retrofitting in a partially digitalized environment, in 13 points (Table 1, modified by the author). For the first-time digitalization in a non-industry 4.0 environment, a similar procedure can be followed once at least IIoT technology has been implemented. Recommendations for a first-time introduction of IIoT are the provision of high speed internet coverage and the server architecture required for local data processing. Sufficient resources for sustainable IT security should also be considered. Big data applications and mostly embedded artificial intelligence systems as well as the associated data expenditure must be taken into account in the planning stage. The storage location of the data volume should also be defined in the planning phase (locally or via cloud (**2.6**)). An essential point is also the choice of IT standards used (e.g. MQTT, OPC UA, MES, general layer architecture). Appropriately trained personnel must be considered if not available in the own company (for planning, implementation and also ongoing operation and maintenance).

Table 1: Retrofit approach for the development of a CPPS for an existing I 4.0 environment [57]

	Infrastructure
1	Identification and visualization of requirements and potential improvements, for each sub-process and machinery to retrofit
2	Adding of suitable IIoT Devices directly to the selected machinery (e.g. smart sensors)
3	Adding associated, but not directly connected IIoT Devices to the machinery (e.g. IIoT gateways)
	Communication
4	Identification and visualization of existing communication technologies and protocols with I 4.0 standard, if applicable (e.g. MQTT protocols)
5	Integration of existing not integrated communication technologies in an I 4.0 network (e. g. through IIoT gateways)
6	Integration of communication management, avoiding usage of a network manager for different communication types
7	Support for IIoT networks (e.g. I 4.0 specialists)
8	Implementation of real-time communication between all production levels (most important between SCADA and MES level)
	Application
9	Identification and visualization of existing, implemented software and applications and required software/applications for running I 4.0 applications on the system to retrofit
10	Adding of interfaces for the connection of not I 4.0 SW and applications to I 4.0 SW and applications (e.g. connections to cloud)
11	Integration of existing not I 4.0 ready SW to I 4.0 applications which are part of existing CPPS (e.g. OPC UA interfaces from SPS)
12	Implementation of monitoring applications for the supervising of all generated data of the retrofitting system in conjunction with added IIoT devices (HMI via various GUIs)
13	Implementation of remote access technology for the users of the CPPS

3.2 HUMAN MACHINE INTERACTION (INDUSTRY 5.0)

HMI technologies are in the focus of current research. Some recognized researchers in the field of digitalization also refer to this focus as Industry 5.0 [62]. In this case it is not only about the purely technical component, but primarily about interaction challenges in human-robot collaboration. In the metal forming industry, the author believes that the interaction between complex process-optimizing algorithms and employees involved is a particular challenge in this context, which must be considered when implementing an I 4.0 solution in the manufacturing process [63,64].

3.3 DIGITAL TWIN INTEGRATION

In the metal forming industry, the simulation of processes and the resulting material behavior is of high importance. Important process parameters (e.g. material flow, temperature range, force required) as well as the resulting material characteristics (e.g. strength, residual stress, temperature resistance) can be supported by the use of FEA to replace costly and uneconomical practical tests. Furthermore, theoretical process planning and process optimization can be investigated and validated quickly and cost-effectively. Due to the advancing digitalization and the use of I 4.0 technologies, it is also possible to use FEA in the form of digital twins for in situ process optimization. The biggest challenges are the efficient programming and abstraction of corresponding FEAs to make such a process synchronous calculation possible. Furthermore, the automated integration of FE programs into the IT architecture of a digital factory is only possible by means of standardized interfaces. However, the difficulty of programming such interfaces can vary greatly depending on the supplier [24].

3.4 VERTICAL INTEGRATION

From a purely production engineering perspective, vertical integration offers one of the greatest potentials for optimizing production processes. Successfully considered already in the planning phase, it can support greenfield approaches (completely new planning of digital factories) to make economic sense in the first place. When it comes to the digitalization of existing factories (brownfield approach), a transparent vertical, but also horizontal integration can quickly become complex. This is caused, among other aspects, by historically grown IT and machine infrastructure, but also by organizational structures. For this reason, in many cases a multitude of measures are necessary to successfully implement a transparent integration. In addition to the selection of suitable personnel, suitable hardware and software, the accompanying use of change management techniques is also unavoidable in most cases.

3.5 DATA SECURITY AND LEGAL ASPECTS

The use of big data and artificial intelligence applications in the metal forming industry may be outsourced to external providers, if there is a lack of human resources. Many of these providers also include in their scope of services the physical storage of data to be analyzed from the production process. In addition to the advantages of lower administrative and personnel costs, there are numerous risks associated with this approach. In many cases the physical storage of data takes place in specially designed server farms, which are often operated in countries that are subject to fundamentally different legal obligations. For this reason, a legal examination of contracts with third party providers regarding data security and also data ownership rights must be taken into account when implementing such applications (**2.5**, **2.6**).

3.6 INTERDISCIPLINARITY AND EDUCATION

The implementation of a holistic digitalization solution generally requires a high level of interdisciplinary expertise. In addition to traditional engineering knowledge of forming processes, basic knowledge of network technology, programming languages, production logistics and industrial economics is required, even when outsourcing to third parties. Smart Production concepts also require a change in the organizational structure. According to a personal interview of the author with a well-known consulting company in heavy industry, the greatest challenges in the implementation of Industry 4.0 technologies are not the provision and use of modern technologies, but rather the inadequate coordination of those responsible for production and the internal IT department. These departments often have too limited resources to plan, implement and maintain a digitalization solution. It is therefore recommended to involve the responsible persons as early as possible. Depending on the size of the company, more and more companies are also using a separate instance for the digital transformation of production. The most prominent example of this approach is the role of the Chief Digital Officer (CDO). In most cases, the CDO does not replace the IT manager, but is deployed in parallel to him specifically for innovations in the area of the fourth industrial revolution. The combination of top-down commitment through the implementation of such functions in the organizational structure, and the promotion of bottom-up commitment through the use of change management at all hierarchical levels, significantly increases the probability of a company's successful digital transformation. In order to be able to meet the increasing demand for qualified specialists in the future from today's perspective, appropriate training and further training measures must be developed. Figure 10 shows an example of the knowledge required in the field of digital and advanced analytics (DnA) for a company in heavy industry [65].

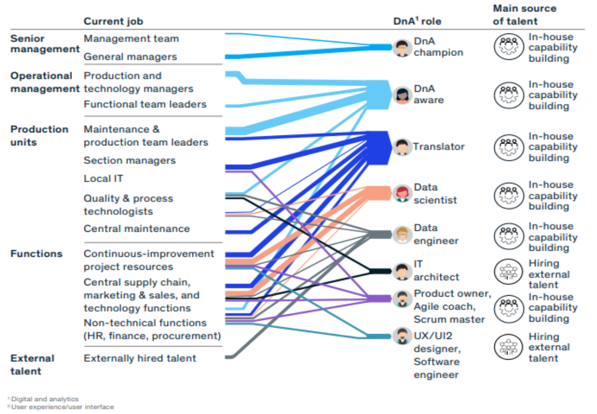

Figure 10: Required Skills for Data Analytics in heavy industry [65].

4 CONCLUSION AND OUTLOOK

The challenges listed in Chapter 3 represent major obstacles to the success and competitiveness of the Austrian metal forming industry. In addition, it must always be taken into account that even the simplest form of digitization can only bring an advantage if the preceding process is mastered and capable. Traditional concepts of Lean Management must therefore always be considered as an initial instance. It should also be ensured in advance that manual and automated data, which are digitized or fed into a digitalization system, are complete and valid.

Digitalization and digital transformation are research priorities of a large number of academic and private research institutions. For this reason, several research priorities regarding digitalization were set at the Chair of Metalforming. Since 2019, in cooperation with the company ibaAG, the Chair of Metalforming has been working on the networking of the most important in-house forming technology aggregates [66]. Furthermore, the possibilities of integrating an FEA-based digital twin into a Smart Production Lab are being investigated in the context of a dissertation. This is done in cooperation of the University of Leoben and the FH Joanneum, University of Applied Sciences. In 2020, the Chair of Metalforming will also develop a digital shadow at SCADA level using Simatic S7 1200 control and Simufact FEA. Furthermore, a quantitative survey of the digital maturity level of the metal forming industry in Austria will be carried out by 2021. Within the framework of this survey, potential correlations between economic success and the degree of digitalization will also be determined. In the field of academic education, digitalization in the context of the metal forming industry will also be a major focus in 2021. In this context, the digitalization projects at the chair, for practical illustration of theory, will also be included. These projects should make an important contribution to preserve and expand the competitiveness of the Austrian metal forming industry.

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A 2 Publication 2

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Author contributions

1. B. J. Ralph: literature study, conceptualization, methodology, practical implementation, visualization, writing, project administration

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3. M. Stockinger: resources, writing – review and editing, supervision

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An Implementation Approach for an Academic Learning Factory for the Metal Forming Industry with Special Focus on Digital Twins and Finite Element Analysis

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Abstract

The requirements for the planning, implementation and operation of an academic learning factory vary depending on the specific area of the respective institution. This paper provides an approach for the planning and implementation of such a factory, specifically tailored to the requirements of the metal forming industry. This learning factory will then be operated at the Chair of Metalforming at the Montanuniversität Leoben (MUL). The objective is to monitor and control forming units of different technological maturity in a common system. The industrial software used, ibaPDA for data logging and ibaAnalyzer for automated further processing, is widespread in practice and enables students to learn the required skills as close to practice as possible. In addition, Analog to Digital (A/D) converters and machine hour counters will be implemented to illustrate the retrofitting approach in practice. For the planning and implementation of Digital Shadows and Digital Twins, common Finite Element (FE) simulation programs will be used and the possibilities of connectivity between machines, simulation programs and automation software will be demonstrated. The project presented here should thus make an important contribution to the training of future specialists with special consideration of the increasing interdisciplinarity in manufacturing technology.

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Keywords: Learning Factory; Digital Twin; Industry 4.0; Digitalization; Smart Factory

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1. Introduction

Due to the increasing complexity in manufacturing technology, the share of required interdisciplinary expertise in the field of academics is increasing [1]. In most cases, understanding of the fundamentals of mechanical engineering and materials science is no longer sufficient in industrial practice. Future engineers also need a broad understanding of information technology and, above all, network technology interrelationships [2]. For this reason, more and more universities are deciding to implement learning factories, which should make it easier for future experts to acquire the interdisciplinary core competencies addressed and thus prepare them for future professional challenges [3]. In order to cope with this development, the Chair of Metalforming at the Montanuniversität Leoben (MUL) is developing such a factory within the framework of a digitization and digitalization project, specially tailored to the needs of the metal forming industry. The primary aim of this learning factory is to network the most important forming aggregates, from the servo-hydraulic press to the Thermo-Mechanical Treatment Simulator (TMTS). In addition, the latest laser ultrasonic technology for the quantification of microstructural changes in formed material samples is to be integrated into this network. The main objective is to show interested students the optimization potentials which result from the coupling of such a system. Furthermore, it will be possible to create Digital Shadows (DS) and, in long term, Digital Twins (DT) [4] by in-situ coupled FE simulation. Another essential aspect of this project is to demonstrate the possibility of numerical and statistical evaluation to students and other interested parties. In the following chapters, the steps required for the successful planning and implementation of such a factory are explained. The first step is to determine the required IT infrastructure based on the machine systems to be networked. Second, the planned or already implemented software packages and interfaces are described. Finally, the possible coupling of an FE simulation and thus the creation of a DS and DT is discussed. Referring to the morphology of learning factories described by Abele et al. [5], the system presented in this paper should have the characteristics shown in Table 1 after completion.

Table 1. Characterization of the presented Learning Factory, adopted from Abele et al. [5].

Four characteristics of Learning Factory morphology	Type of the Learning Factory at the Chair of Metalforming
Operating model	Academic usage, internal funds, teaching by teaching staff at the chair
Purpose and targets	Education of mechanical engineering, metallurgy, industrial logistics and industrial data science students, academic research focused on metal forming
Process	Development of new production processes, from casted semi-finished product to the finished product, process optimization using FE simulation
Didactics	Main focus of teaching: brownfield approach (retrofitting), network technology, integration of FE simulation in a digital factory environment.

2. Infrastructure

A feasibility study was carried out in the first planning phase to ensure the most efficient and effective implementation possible. In the first instance, those machines were selected which are expected to have the highest impact on teaching operations and future-oriented research. The assessment favored the forming simulators (FS) Servotest TMTS and the DSI Gleeble 3800 system. In order to facilitate internal project planning, machines with high capacity utilization were selected for connection by means of an operating hour counter (OHC). This should give students and other interested parties an insight into production planning and the basics of data acquisition for efficient project management. The Band Saw Machine (BSM), Electric Wire Discharge Machine (EWDM), Water Jet Trimming System (WJTS), Milling Machine and Computerized Numerical Control (CNC) controlled lathe were selected for this purpose. In addition, two machine systems were considered, both of which are currently in the final design phase. The first one is a laser ultrasonic measuring system (LUS) which, coupled to the DSI Gleeble hot forming simulator, enables in situ (i. s.) evaluation of the change in the microstructure of the tested material. The second machine system is a specially designed system for the practical application of Equal Channel Angular Pressing (ECAP) technology. Table 2 lists all machines considered in the first planning phase. The type of connection from the machine specific Control System (CS) is also defined.

Table 2. Selected machine systems and type of connection for integration into the digitalization network.

Machine System	Description	Connection Type
Servotest TMTS	HSCT (T, t, Φ, $\dot{\Phi}$)	A/D, directly from CS
DSI Gleeble 3800	FS (T, t, Φ, $\dot{\Phi}$)	A/D, directly from CS
LUS	i. s. MS (T, t, Φ, $\dot{\Phi}$)	LabVIEW
ECAP-System	MS (T, t, Φ, $\dot{\Phi}$)	SIMATEC S7 1200
WJTS	Cutting Operations (t)	OHC (A/D)
Emco Turn E 65	CNC Lathe (t)	OHC (A/D)
Fanuc Robocut	EWDM (t)	OHC (A/D)
Deckel FP 2	Milling Machine (t)	OHC (A/D)
MEP	BSM (t)	OHC (A/D)

The systems shown in Table 2 are connected to the iba main computation and storage unit by means of the defined connections. This server system operates independently of the internal server structure of the chair of Metalforming and is able to automatically forward evaluations and, depending on the type of connection, to intervene and regulate the current process.

3. Scheduling and Implementation Approach

After selecting the machines to be connected, the sequence was defined. This was done under consideration of complexity, availability and the planned usage of the considered systems for current and upcoming projects in the near future. After successful commissioning of the measuring control computer, the DSI Gleeble system was selected in the first instance. The A/D connection was made primary via analog measuring boards of the DSI Server System. In case of the temperature signal, which is absolutely necessary for the recording, there was no analog measuring board available. Therefore, the signal was tapped directly at the input signal of the system computer. In any case, sufficient shielding of the cable connection used must be ensured. In this case, insufficient shielding leads to significant scattering in the measurements, which cannot be fully compensated by using suitable statistical methods. Fig. 1. (a) shows the comparison of a dilatometer curve, captured directly on the DSI testing machine using an A/D converter and post-processed with the digitizing software (red) and captured and post-processed with DSI's own software (blue). Fig. 1. (b) shows a hot tensile test recorded in the same configuration. Both tests work with different analog input signals, therefore the entire bandwidth of the digitized signals can be displayed in these evaluations.

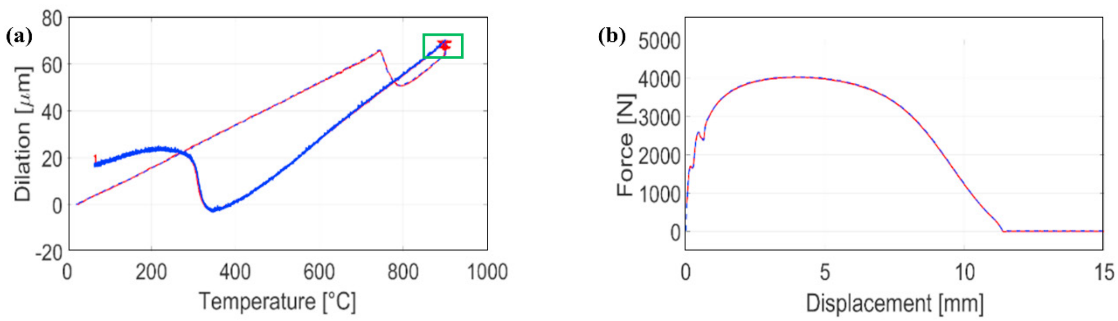

Fig. 1. (a) Dilation Curve for a bainitic steel; (b) Hot tensile test for a bainitic steel. Blue line: Original Gleeble. Red Line: Iba system.

The analog signal output of temperature and dilation leads to strong noise (Fig. 1. (a), green frame), while the force and displacement signals correlate significantly. This noise is a result of the relatively strong fluctuations of the voltage tapped on the DSI server system. In order to be able to prove the validity of the measurement, this section (Fig. 1. (a), green frame), is again examined in detail for correlation in Fig. 2. The electrical voltage generated by the temperature change on the test specimen is in the single-digit millivolt range. A measuring range of up to 2000 °C must be covered from this very small analog measuring range. As a result, voltage fluctuations in the range of 10^{-3} Volt lead to temperature fluctuations of ± 250 °C.

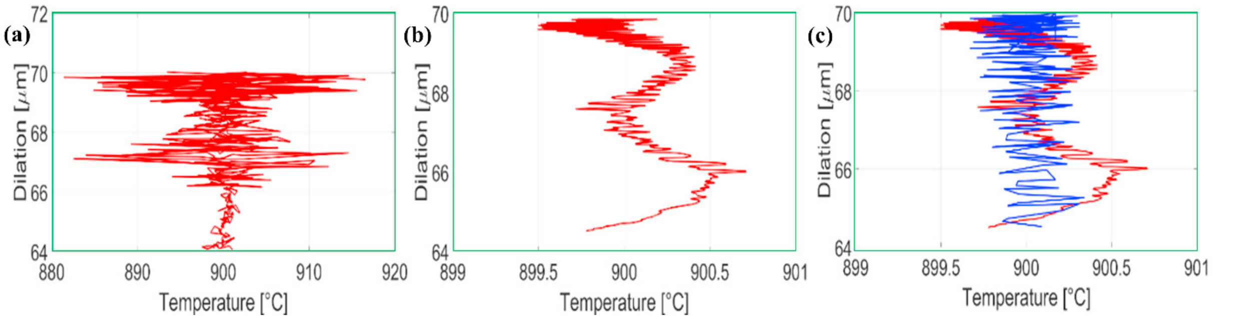

Fig. 2. Scatter of the holding range; (a) without post-processing; (b) with post-processing; (c) Comparison between (b) with the DSI evaluation.

In order to minimize the influence of measurement errors, calibrations at different temperatures were repeatedly carried out. In spite of these measures, the dispersion in the range mentioned in Fig. 1. (a) cannot be completely eliminated due to the necessity of keeping the temperature constant in this area for almost two minutes during the experiment, leading to a significantly larger number of data pairs in this range. In order to evaluate whether the dispersion shown in Fig. 2. (a) can be detected due to the voltage signal fluctuations only or if there is also a deviation of the mean value, the moving mean value was calculated in Fig. 2. (b) over all entries of the [11821 x 2] data matrix. The first minimum of the smallest scatter band results from the moving average over 2000 points (Fig. 2. (b)). By plotting this modified data curve in direct comparison with the evaluation of the DSI software (Fig. 2. (c)), maximum temperature deviations of 0.9 °C can be detected.

Fig. 3 shows an overview of the planned learning factory. The two machine systems which are currently in the final construction phase were considered as mentioned before.

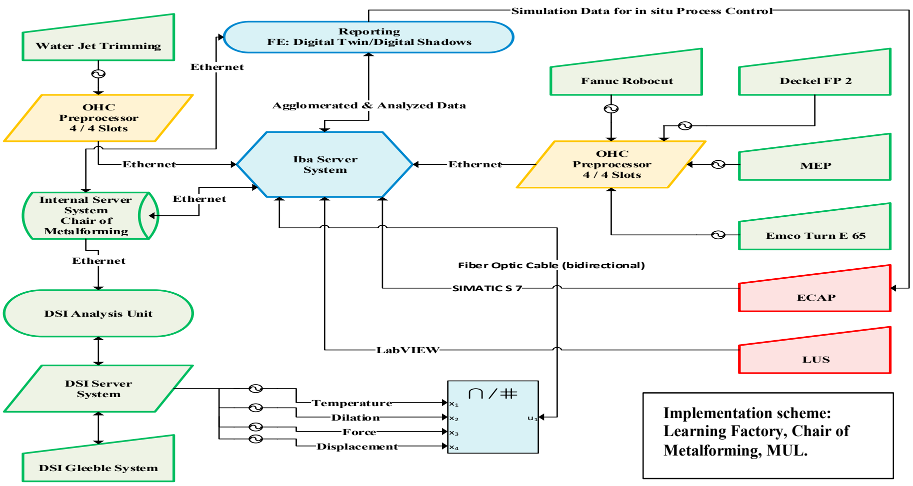

Fig. 3. Learning Factory Concept on the Chair of Metalforming, MUL. Green: in use. Red: in construction. Yellow: Not yet implemented.

A major advantage of using the central digitizing unit is the possibility of fully automated processing of raw data. These data can also be forwarded fully automatically to predefined users via email or other web technologies. These functions are independent of the specific machine software and thus guarantee full compatibility also in the future. In addition, both the maintenance and the learning of the operation are considerably simplified due to the reduction to one main system. Furthermore, the integrated software is able to assign important budgeting data for the accounting of specific work packages by means of the OHC shown in Fig. 3 and the possible assignment of project data and involved employees. The calculation of machine hour rates for involved systems for example can be carried out automatically due to the higher accuracy of data obtained. Other important key production figures such as Overall Equipment Effectiveness (OEE) can be made transparent too, another advantage is the systematic data storage of all process data. The automated allocation to defined storage locations leads to the reduction of memory redundancies. The increased memory requirement due to continuous process data recording can thus be compensated to a significant extent by more efficient data management.

4. Digital Twin Approach and General Usage of Finite Element Analysis

On the basis of the digital learning factory, it is also possible to model DT. The basic prerequisite for this is a data transfer rate and data processing which, including all latencies and other loss times, functions faster than the process to be simulated. The biggest challenge in this case is the data processing, since it includes not only the processing of the input measurement signals, but also the automated calculation of a coupled simulation and the return of the calculations to the original system. For this reason, the efficient programming of such a model is of utmost importance. The reduction of complexity must be carried out until this restriction is met, without losing the required accuracy [6]. For the modeling of a DT for the automated process control of the ECAP system, the Grey Box modeling approach is used [7]. In the metal forming industry, the white box approach for the simulation of processes and material properties is currently used mainly. In this case, all input data and process parameters are based on physical relationships. In contrast, a black box approach only uses statistically generated data without a physical background [8]. Although there is a high level of material and process-specific know-how in forming technology, there are still parameters which are too complex to be defined precisely enough with white box models due to the multitude of influencing factors [9], e.g. the coefficient of friction. This coefficient is complex in almost all cases in a real process environment [10]. The determination of such core parameters using real-time coupled process data acquisition can thus make an important contribution to more efficient and effective simulation.

In this case, parameters that cannot be calculated directly from scientific contexts are calculated via the automated data evaluation of the iba system and transferred to the coupled finite element analysis as input variables. Fig. 4 schematically illustrates the Grey Box approach for the creation of a DT for the ECAP system.

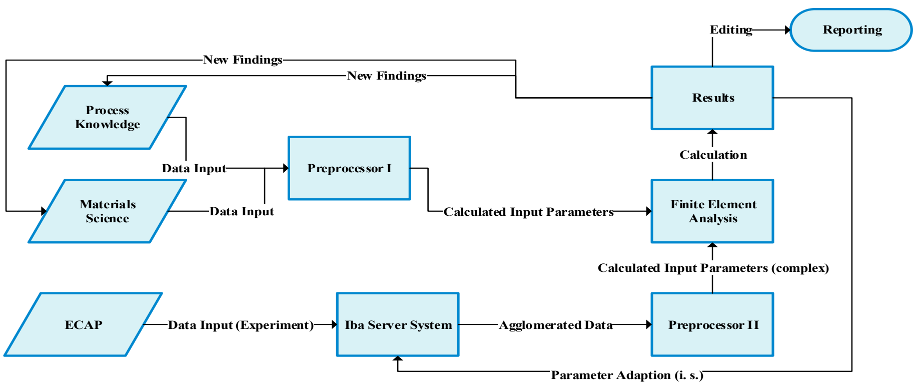

Fig. 4. DT concept for the ECAP system under consideration of the Grey Box modelling approach.

The corresponding Finite Element Analysis (FEA) is created in the FE simulation program Simufact forming, which is also widely used in industrial practice. The handling is relatively intuitive, which accelerates the learning of required skills for prospective experts. In order to create a complete and valid DT, it is also necessary to include a model of the microstructure of the tested material in the calculation. Particularly in the ECAP process, the structural change in the course of forming makes a significant contribution to a valid calculation.

As a preliminary stage for the DT, a DS is created. In contrast to the DT, the in situ parameter adaptation is not used in first instance. In order to ensure the general validity and required accuracy of the data obtained from the digitalization system, a manual check will be first performed by comparing the simulation result with the corresponding test. If the results of the FEA are valid, the feedback, still missing for a DT, will be implemented subsequently.

5. Conclusion and Outlook

The development of academic learning factories in the metal forming industry is still in its initial state. The concepts presented here are intended to generate an important contribution to the training and deepening of interdisciplinary knowledge. Engineering students receive an insight into the potentials of digitization and digitalization through specially designed courses. Starting with IT-supported shop floor project management, which is implemented with the help of iba software solutions, the planning, allocation and accounting of work packages can be made transparent. Using the example of the DSI Gleeble System's analog measurement signal sampling and the subsequent automated data processing with the iba system, essential contents and special features in the connection of analog measurement signals can also be examined with special consideration of interference influences. In combination with the following coupling of the Servotest TMTS, the retrofitting approach can be illustrated. The connection of the ECAP machine system based on the SIMATIC S 7 1200 control system is also intended to illustrate the connection of modern control systems to a digital network. The possibility of intervening in an ongoing process and the resulting potentials will also be illustrated using DT. Special emphasis will be placed on the underlying programming, FEA and the selection of suitable software programs that are relevant in practice. By explaining the theory behind this Academic Learning Factory, as well as practical exercises in the field of modeling, programming, control, design and project planning, future graduates and other interested parties from research and industry will gain a broad spectrum of knowledge about current concepts of digitalization in the metal forming industry.

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A 3 Publication 3

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Author contributions

1. A. Schwarz: experimental setup, conceptualization, methodology, data curation, writing – initial draft preparation, writing – review and editing

2. B. J. Ralph: literature study, conceptualization, methodology, project administration, writing – initial draft preparation, writing – review and editing

3. M. Stockinger: resources, writing – review and editing

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Planning and implementation of a digital shadow for the friction factor quantification of the ECAP process using a grey box modeling approach and finite element analysis

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Abstract

This paper describes the possibility of analytical friction factor generation using a Grey Box modelling approach. A preprocessor is used, which automatically collects measured data via a Smart Production Network and calculates the effective friction coefficient as a function of all significant process parameters of the Equal-Channel-Angular-Pressing (ECAP) process using a data-driven evaluation algorithm. The results of this calculation are then automatically implemented in an efficiently programmed finite element analysis. This Digital Shadow then serves as the basis for the implementation of a Digital Twin, which is described shortly at the end.

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Keywords: Digital shadow; Digital twin; Smart factory; Digitalisation; Finite element analysis

Nomenclature

ECAP	equal channel angular pressing
FEA	finite element analysis
DS	digital shadow
SPD	severe plastic deformation

1. Introduction

In recent years, the demands for improved mechanical properties of construction materials, especially in the areas of lightweight design, have increased considerably. In addition to conventional methods for improving mechanical properties such as alloying or heat treatment, severe plastic deformation (SPD) is also researched intensively in the last four decades [1–4]. Processing materials by SPD technologies leads to a significant reduction in grain size, which results in improved mechanical properties like yield strength or ultimate tensile strength. One of the most prominent SPD methods is equal channel angular pressing (ECAP) [5]. With this method, it is possible to produce bulk material with a considerably refined grain-sized. A well-lubricated billet is inserted into a die and repeatedly pressed through two intersecting channels. The square section of the workpiece does not change in the process. The deformation in the narrow plastic zone through simple shear leads to shear banding in the material. These localised shear bands firstly develop into subgrains, and with further plastic deformation turn into a homogeneous refined grain structure [6]

There are various parameters such as die geometry, chemical composition and temperature, which affects the resulting microstructure of the processed workpiece [7]. Additionally, the friction between die and workpiece is of high importance, because it strongly affects the resulting deformation mode and therefore the homogeneity of the microstructure as well as the final grain size. Furthermore, the necessary force to press the billet through the die is also critically affected by the friction [8]. There are many experimental methods to determine friction coefficients for different friction models. Ideally, the friction coefficients should be determined in an experiment

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which simulates similar conditions than the real process, for example, sliding distance and normal pressure [9, 10]. This fact makes it difficult to determine generally valid coefficients of friction for different processes, which is especially important as they are necessary for accurate finite element analysis.
Digitalisation in manufacturing processes becomes more prominent every day. The possibility to achieve higher levels of productivity through the utilisation of the newest sensor technologies and the vast amount of data they deliver is in the manufacturers best interest [11]. A digital shadow can be defined as a digital model coupled to the state of an existing physical process. A one-way data flow is realised, which means a change of state in the physical process leads to a change of state in the digital model[12]. These systems offer various applications for manufacturing processes, for example, improved maintenance prediction [13] and production planning [14].
This paper focuses on the proof of concept to automatically determine the friction coefficient with the use of a finite element analysis of the ECAP process coupled to a digital shadow. First, the reference FEA model used for the digital shadow is described. Secondly, the conception and implementation of the digital shadow are discussed. Finally, the results of the automatic determination of the friction coefficient, and the future prospects of this project are shown.

2. Finite element analysis of the ECAP process

A reduced thermomechanically coupled finite element model of the ECAP process was developed in the simulation software SimufactForming 15. The model resembles a new ECAP testing rig, which is currently under construction at the chair of metal forming. This machine has two individually controllable hydraulic cylinders with a pressing force of 50 tons each. One of them acts as the main plunger while the second one is used for a defined back pressure on the specimen (back-pressure plunger). The latter offers the possibility to improve the homogeneity of the resulting microstructure as well as the processability of the material [15]. Furthermore, the back-pressure plunger acts as a moveable bottom wall inside the die. This design of the ECAP process leads to reduced friction on the bottom side of the specimen. In the new machine, the pressing speed can be varied between 0.1 and14.5 mm/s while the tools can be heated up to a maximum temperature of 450°C.

The simulation setup was realised in 3D as a 2D model leads to non-tolerable inaccuracies because of the different frictional conditions between the specimen and the die walls [16]. The main plunger presses the workpiece from the square entry canal into the exit canal with an angle between the canals of 90°. The cross-section of the billet is 15x15 mm, the length is 145 mm. The age hardenable aluminium alloy EN-AW-6082 was used as reference material for the simulations. The flow curves used for these calculations are determined using the thermo-kinetic software package MatCalc. The friction is described by the shear friction model:

$$\tau_R = m * \frac{k_f}{\sqrt{3}} \tag{1}$$

where τ_R is the frictional shear stress, m the constant friction factor and k_f the yield stress of the deformed material. As a consequence of the moving bottom wall, the relative velocity between the billet and the bottom wall is zero, which results in a frictionless contact. The contact between the back-pressure plunger and the specimen was defined as glued and the friction coefficient was set to zero, to model this behaviour adequately.
Besides the friction factor, the pressing speed (v), the applied back pressure (p) and the initial billet temperature are the critical process parameters for this FEA. The specimen has been meshed with hexahedron elements with an element size of 1.5 mm. An automatic remeshing criterion was defined to avoid problems with strongly distorted elements during the calculation. Figure 1 shows the FEA model at 50% process time, indicating the effective plastic strain of the workpiece.
The values used for the reference simulation for this study can be found in table 1. The total run time for one simulation was about 40 minutes. This model serves as the starting point for the digital shadow.

Table 1. Input values of the reference simulation

Parameter	Value
Constant back pressure p	30 MPa
Constant pressing speed v	5 mm/s
Displacement of the main plunger	130 mm
Initial temperature T	20 °C
Friction coefficient m	0.16

3. Digital Shadow

The digital shadow (DS) is realised via Python. For the data handling the Pandas package is used within the python script. An overview of the functionality of the DS can be seen in figure 2. As soon as an experiment on the ECAP machine is started the Siemens Simatic 1200 PLC sends the input data (pressing speed, back-pressure, initial billet temperature, lubricant and material) via Profinet to a directory in the institute's smart factory database. The principle design of the smart factory of the organisation is described in [17]. The DS automatically reads the input data and generates a new finite

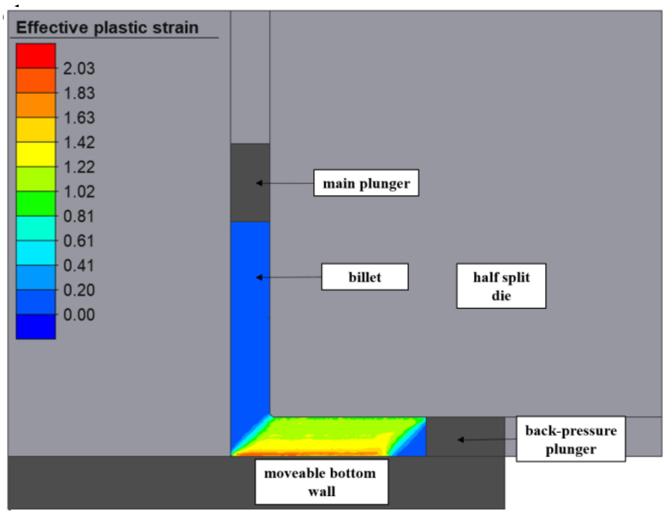

Fig 1. FEA model of the ECAP process at 50% process time

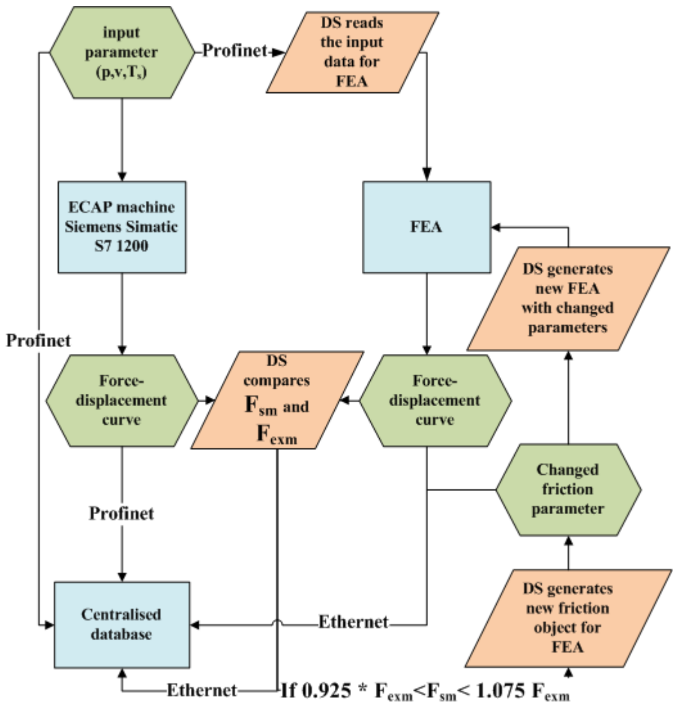

Fig 2. Concept of the digital shadow

simulation based upon the model described before, but including the input parameters from the experiment. After the initialisation, the DS transfers the input files of the calculation to the smart factory's database and starts the calculation.

After the finished simulation, the DS generates the force-displacement curves, smoothes them, using the rolling average method with a boxcar window, and calculates the mean value of the resulting force values. The smoothing is crucial due to excessive noise in the data, which results from necessary remeshing during the simulation, as well as unstable contact conditions between the workpiece and the canal edge in the die. Figure 3 shows the original and the smoothed curve of the reference simulation.

The mean value of the force-displacement curves derived from the smoothed simulation F_{sm} and the actual experiment F_{exm} are compared between each other. An abort criterion is introduced:

$$0.925 * F_{exm} > F_{sm} > 1.075 * F_{exm} \qquad (2)$$

If the abort criterion is met, the actual friction coefficient was found during the simulation. Otherwise, the DS generates a new calculation with the same input parameters except for a changed friction coefficient. The new friction coefficient is reduced if the mean force of the simulation was too high to meet the abort criterion, or increased if the force values were too low. The DS keeps iterating the simulation with new friction values until the abort criterion is met, and the ideal friction coefficient was found. Depending on the difference between the two compared values, the program decides how strongly the new friction coefficient should be changed in order to keep the number of iterations to a minimum and to speed up the process. After every iteration, the generated force-displacement data, as well as the newly assigned friction coefficient, are transferred to the database for further analysis. This setup produces a vast amount of data from one single

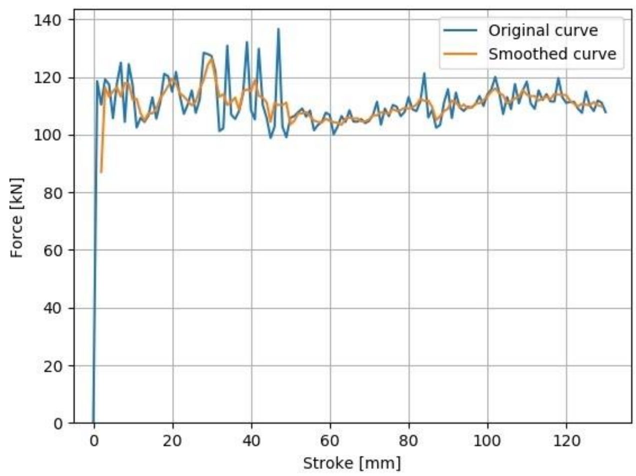

Fig 3. Comparison between the original and smoothed curve of a simulation

experiment, which gets collectively stored on the centralised database of the organisation:

- Experimental input parameters and specimen description
- Experimental values (force-displacement curves, temperature-time curves)
- Simulation input files of every iteration
- Force displacement curves of every iteration
- Determined friction coefficient

4. Results

Since the ECAP machine is not yet fully operational, a generic force-displacement curve was generated to serve as experimental test data for this study. With this data, a proof of concept of the friction factor quantification was investigated. The generic force-displacement curve, as well as the resulting curves from the different simulations, can be seen in Figure 4. After five iterations, the abort criterion was met, and a best-fitting friction factor of m = 0.08 was determined. Table 2 shows the collected values of the generated friction coefficients, as well as the corresponding force mean values for the different simulations. It can be seen that the coefficient

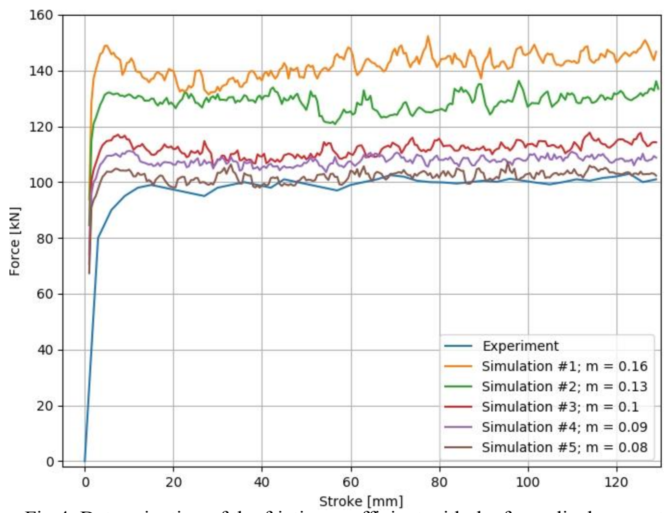

Fig 4. Determination of the friction coefficient with the force displacement curves of the experiment and simulations

value change per iteration is reduced from 0.3 per iteration to 0.1, the closer the simulation data is to the specified force values.

Furthermore, the results from figure 4 and table 2 clearly show the influence of the friction factor on the necessary force to press the billet through the die. The reduction of m from initially 0.16 to the final value of 0.08 shows a reduction of mean force from 141.81 to 101.95 kN. The deviation between the quasi-experiment and the final simulation is 5.32 kN which equals a difference of 5.5%. The reason for this strong friction dependence is the large surface area of the processed billet, which is continuously in contact with the die. The considerable high frictional force acts in the opposite direction as the primary hydraulic plunger and thus the pressing force increases rapidly with increased friction. After an initial peak, the force quickly saturates at a constant level. This characteristic is in contrast to the force-displacement curves of the ECAP process without applied back-pressure. They show a decrease after the peak load before the required load rises again. This is because of geometrical disorders (e.g. dead zone at the lower conjunction of the entry and exit canal) and different contact behavior on the top and bottom side of the billet because of different frictional effects [18]. In this model, the applied back-pressure prevents the dead zone formation in the die and assures that the billet is in contact with the die in the exit channel throughout the whole process. Consequently, the pressing force quickly settles on a specific level.

Table 2. Mean values and friction coefficients of the simulations and the experiment

Data	Friction coefficient	Mean force value [kN]
Experiment	-	96.63
Simulation #1	m= 0.16	141.81
Simulation #2	m= 0.13	128.74
Simulation #3	m=0.1	111.72
Simulation #4	m=0.09	107.46
Simulation #5	m=0.08	101.95

5. Conclusion

This study showed a practical use of a digital shadow in manufacturing. A proof of concept of generating the corresponding friction factor of a specific tribological setup was investigated, using a finite element analysis model for the ECAP process with applied back-pressure and moveable bottom wall, coupled with a digital shadow. This system enables the determination of the friction coefficient in a process-specific manner, and therefore reduces time-consuming and expensive tests. The data generated during one experiment, gets stored collectively on the centralised database of the smart factory The vast amount of available data is an optimal prerequisite for further investigations regarding predictive maintenance and big data handling.

6. Outlook

The system described in this study serves as a starting point for further digitalisation of the process. Several steps to upgrade and improve the models are:

6.1. Verification of the results

The FEA model shall be verified, as soon as there is data from the finished ECAP machine. For this verification, billets of the alloy used in the simulations (EN-AW-6082) will be processed, and the acquired data will be compared to the results of the simulations of the finite element model.

6.2. Specification of different tribological systems

After the verification, different tribological systems can be specified using the described digital shadow. The friction coefficient depends on the pairings of alloys and lubricants, as well as on the process parameters. With careful analysis of the microstructure and the force-displacement curves, optimal lubricants can be found for the ECAP process.

6.3. Extending the functionality of the simulation model

For experiments at elevated temperatures, six heating elements are placed at the entry canal of the die. This ensures reduced energy consumption during the process because not the whole die has to be heated. The drawback of this setup is that the heating time, as well as the power input to completely heat through the workpiece, is difficult to determine. The finite element model shall be expanded, thus it is able to calculate the heating of the specimen inside die.

A microstructural model for the ECAP process is in development as well. With this model, the development of the grain structure during the pressing is simulated, and mechanical properties, as well as the mean final grain size of the processed billets can be evaluated.

6.4. Predictive maintenance

The collected data on the database shall be used for forecasting ongoing tool damage and therefore allow predictive maintenance applications. When a new billet is pressed through the ECAP die, the digital shadow will check the database for already conducted simulations and experimental data. If relevant data is available, the script can detect significant differences between the force-displacement curves, which can be indicated as a sign of beginning tool damage. A warning will then be sent to the machine operator.

6.5. Further automatic analysis of simulation results

Besides the determination of the friction coefficient, the digital shadow can be improved to analyse other simulation results than the force-displacement data. This includes for example strain and stress analysis as well as temperature development of the billet during the pressing.

6.6. Digital Twin

This digital shadow serves as a preparation for the future implementation of a digital twin for the ECAP machine. A digital twin allows the two-way data flow between the physical and digital object, which results in a direct model-based control of the machine. The optimisation of the current FE model is the first step to achieve a Digital Twin because currently, the calculation time is too long for in-line modelling. One possibility to use an in-line model as a digital twin is to simulate the heating of the sample while the sample is actually heated in the tool. Direct measurement of the workpiece temperature is not possible in the experiment, so the required heating time and power can be determined from a verified simulation model. Finally the Digital Twin can start the physical experiment as soon as the desired starting temperature is reached.

In addition, further optimisations can be carried out on the basis of this digital twin, such as the inclusion of microstructure material models. Through bilateral coupling and through metallographic methods and quickly verifiable analysis of the material parameters, it will also be possible to optimise existing simulation parameters for FEAs for numerous metallic materials. For these reasons, this approach can not only help to optimise the ECAP process but also to optimise the numerical simulation of various materials.

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A 4 Publication 4

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Author contributions

1. B. J. Ralph: conceptualization, data curation, methodology, project administration, software, validation, visualization, writing – original draft, writing – review and editing

2. K. Hartl: investigation, writing – original draft, writing – review and editing

3. M. Sorger: data curation, formal analysis, software, visualization

4. A. Schwarz – Gsaxner: investigation, writing – review and editing

5. M. Stockinger: resources, supervision

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Article

Machine Learning Driven Prediction of Residual Stresses for the Shot Peening Process Using a Finite Element Based Grey-Box Model Approach

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Abstract: The shot peening process is a common procedure to enhance fatigue strength on load-bearing components in the metal processing environment. The determination of optimal process parameters is often carried out by costly practical experiments. An efficient method to predict the resulting residual stress profile using different parameters is finite element analysis. However, it is not possible to include all influencing factors of the materials' physical behavior and the process conditions in a reasonable simulation. Therefore, data-driven models in combination with experimental data tend to generate a significant advantage for the accuracy of the resulting process model. For this reason, this paper describes the development of a grey-box model, using a two-dimensional geometry finite element modeling approach. Based on this model, a Python framework was developed, which is capable of predicting residual stresses for common shot peening scenarios. This white-box-based model serves as an initial state for the machine learning technique introduced in this work. The resulting algorithm is able to add input data from practical residual stress experiments by adapting the initial model, resulting in a steady increase of accuracy. To demonstrate the practical usage, a corresponding Graphical User Interface capable of recommending shot peening parameters based on user-required residual stresses was developed.

Keywords: python scripting; residual stresses; shot peening; finite element analysis; digitalization; machine learning; smart factory

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1. Introduction

For the design of dynamically load-bearing components, a certain safety risk is minimized by increasing the service life and improving its estimation. A key aspect in this context is the selected material and its long-term stability under dynamically oscillating loads [1–3]. Numerous machining end contour processes included in the manufacturing of critical components such as milling, turning, or drilling lead to residual tensile residual stresses on the surface. These stresses are counterproductive for the fatigue resistance; therefore, further surface treatment is essential for these components.

There are several mechanical surface treatment technologies available today, pursuing the objectives of implementing residual compressive stresses close to the surface, as well as introducing a work hardened layer. A well-known example is deep rolling, a low-cost method that achieves a comparatively smooth surface, but is limited to elementary, usually rotation-symmetrical geometries [4]. This technique is mainly used for components that require frictionless sliding, where good surface quality is critical for wear. Another alternative is laser shock peening, an efficient method to introduce compressive residual stresses at four times the depth of shot peening [5]. This is achieved by high-energy laser pulses that introduce a shock wave into the material that exceeds the material's yield strength and causes localized deformation. Although this method is gaining popularity, the investment in such a system is a high-cost proposition. Moreover, the long process times are currently not suitable for an efficient application in production [6]. Additionally, the ball burnishing or roller burnishing method produces a particularly smooth surface [5,7–9]. A related method developed by Lambda Technologies Group is low plasticity burnishing, which is capable to introduce significant residual compressive stresses while initiating comparatively low work hardening. This assists in ensuring permanent compressive stresses when components are used in higher temperature applications. This method has the further advantage that it can be integrated into a variety of machining systems, e.g., CNC lathes [10–14].

Even though there is a strong effort in establishing new and optimizing well-known surface treatment methods, shot peening still is the standard procedure in the manufacturing environment. Irrespective of the mechanical surface treatment chosen, specific knowledge and therefore respective data about suitable process parameters is mandatory to obtain the required results.

To receive a comprehensive data set for the shot peening process, it is mandatory to obtain a significant amount of valid data. This approach requires the execution of an unreasonable amount of practical experiments per workpiece material/sphere material combination. Furthermore, the same amount of upfollowing experiments to receive valid residual stress profiles would have to be carried out. By substituting practical tests with Finite Element Analysis (FEA)-based simulations, this disproportionate effort can be avoided.

The effectiveness of FEA for production processes can be further increased by using state of the art digitalization technologies, taking into account user, processes, and materials [15–17]. One possibility to achieve this objective is the implementation of robust machine learning algorithms. In order to do so, a first decision has to be made regarding the nature of the respective algorithm. In general, three methods are defined: reinforcement learning (RL), unsupervised learning (UL), and supervised learning (SL) [18]. According to more recent work, there are different subordinate algorithms available, which can be used within one or more of these three main techniques [19,20]:

RL: Genetic Algorithms, Simulated Annealing, and Estimated Value Functions;

UL: Decision Tree Analysis (DTA), Rule-Based Learners, Instance-Based Learners, Artificial and Bayesian Neural Networks (NN), as well as Naïve Bayesian Approaches;

SL: Support Vector Machines, DTA, Rule-Based Learners, Instance-Based Learners, Genetic Algorithms, Artificial and Bayesian NN, and Naïve Bayesian Approaches.

For the prediction of residual stresses after the shot peening process, the authors decided to use a SL algorithm, as the nature of this technique is a continuous learning from data provided by an external knowledgeable source. The accuracy of this algorithm depends on internal knowledge about the expected results and, most important, comprehensible input data [19,21,22].

To achieve accurate data sets serving as an input for this kind of simulation, a suitable material model based on reliable material data from practical experiments must be chosen. Therefore, it is essential to implement real-physics-based input variables, which must be obtained under similar conditions as the process to be modeled.

2. Fundamentals of the Shot Peening Process and Corresponding FEA

In order to increase the fatigue strength, shot peening is applied as a standard procedure in the production process for structural materials. This method contributes to the service life enhancement of cyclic loaded components [23]. The most notable advantages of shot peening compared to other surface hardening treatments are the good process quality, reproducibility, and applicability to a wide range of materials and component geometries [3]. During the process, the surface of the component is impacted by spheres at high velocities. As a result of the momentum transfer, work hardening is increased directly on the surface which reduces the probability of crack initiation. The plastic deformations induced by the spheres also generate residual compressive stresses in the material to a certain depth. These stresses are the main inhibitors of crack propagation due to the prevention of crack tip opening and thus increase the fatigue strength. However, this surface treatment does not always contribute to a work piece's service life extension rather than a reduction, as König investigated for Waspalloy in [24]. Although increasing the degree of coverage from the impacting spheres can increase the magnitude of resulting residual stresses, this additional loading for higher strength materials at the surface may contribute to a higher probability of initiating cracks. Therefore, it is crucial to be aware of the influential variables of the process before it is applied in practice. The process itself is variable in numerous aspects, such as the sphere's material and geometry, as well as the impact velocity and the coverage [25,26]. The average sphere radius is about 0.4 mm and they are commonly made of glass, ceramic, cast iron, or steel. A prerequisite for the sphere's material is the higher hardness compared to the shot-peened material. A higher difference between the sphere's and the target's hardness yield higher resulting residual compressive stresses [27]. Additionally, larger sphere radii result in the maximum compressive stresses occurring deeper in the material [28].

In order to achieve the maximum effect on service life extension through this process, these parameters must be optimally adjusted to the material. The maximum achievable residual compressive stresses and the depth of penetration into the material are decisive, since the residual compressive stresses inside the material are balanced by tensile residual stresses in a certain depth. Additionally, the dislocation density introduced by this surface treatment needs to be observed concerning the resulting material behavior. On the one hand, this can prevent the crack initiation [29], on the other hand, it may contribute to the brittleness of certain materials and thus drastically reduce their service life, especially in corrosive environments [30]. To experimentally analyze the residual stresses inside the material, destructive and therefore expensive examinations based on X-ray diffraction (XRD) or using the hole drilling method have to be performed in practice. A time and cost-saving alternative to physical experiments is the numerical simulation, which allows the determination of favorable parameters for the optimal result in advance. In addition, stresses on the surface and in depth of the material can be analyzed to provide a better comprehension of the effectiveness of the process. Several studies have been carried out using FEA to simulate the shot peening treatment. The approaches to simulate this process vary widely in different publications. In [31], Edberg et al. designed a three-dimensional FEA simulation, comparing a visco-plastic strain hardening formulation to a elasto-plastic one analyzing a single shot. This study revealed that the visco-plastic model overestimated the resulting residual stresses by a factor of 1.5. In [32], Majzoobi et al. used a three-dimensional set up applying multiple shot impacts and investigated the shot velocity and coverage effects on the resulting residual stresses. The investigations of Meguid et al. in [33] included the separation distance of the spheres and its impact on the residual stress profile as well as the frictional behavior of AISI 4340. A comparison between the resulting values of an axisymmetric and a three-dimensional numeric model on an aluminum target was conducted by Han et al. in [34] where high emphasis was attached to the interaction of the sphere and the target as well as suitable boundary conditions for the FEA. In [35], Schwarzer et al. investigated the influence of the sphere's impact angle on the resulting residual stresses while Hong et al. focused on the loss of kinetic energy of the spheres as a result of alternating impact angles in [36]. In [37], Mylonas and Labeas addressed a reasonable relation between the quantity of impacts needed in order to receive the results of experimentally obtained residual stress profiles but still reduce computational time. The approach of reducing computational time is also applied in this study by the usage of a two-dimensional setup for the simulation, in order to provide a beneficial tool for the industry, taking into account the results of previous works mentioned in this section.

3. Fundamentals and Behavior of EN-AW-6082 T6 under Dynamic Conditions

The material investigated in this study is the age-hardenable EN-AW-6082 aluminum alloy, which is one of the most essential alloying systems for the usage in lightweight construction due to its balanced properties and good formability. The chemical composition of the used alloy is shown in Table 1.

Table 1. Chemical composition of examined aluminum alloy EN-AW-6082.

Chemical Composition of EN-AW-6082 (wt. %)							
Si	Fe	Cu	Mn	Mg	Cr	Zn	Ti
0.87	0.42	0.08	0.57	0.66	0.02	0.2	0.02

The alloy achieves its strength values primarily through the precipitation of the so-called β-Phase Mg_2Si, and further phases such as $AlSi_6Mg_3Fe$ and $Al_{15}(FeMn)_3Si_2$ with suitable ageing after solution heat treatment. Since particularly Mn particles increase the strength of the alloy, while negatively influencing ductility, a homogenization annealing is carried out before forming in practice [38]. The duration of homogenization annealing increases the effect on the reshaping and distribution of particles and therefore reduces the yield stress for extrusion [39]. The highest strength is achieved with the T6 treatment, which consists of a solution heat treatment between 793 K and 813 K for 30 min to one hour in order to dissolute the alloying elements in the matrix. Subsequent quenching creates a supersaturated condition which is immediately followed by the artificial heating treatment, ranging between 423 K and 443 K for 5–20 h, resulting in a peak of precipitation [40–45]. It is common to consider strain-rate sensitivity for the determination of processing parameters and processing maps, as it has a significant impact on fracture behavior [46]. However, the existence of metastable precipitates causes a change in mechanical properties to higher strength values with a reduction in ductility.

EN-AW-6082 also exhibits deficiencies, especially with regard to fatigue resistance under cyclic loading. When used as a component in a chlorine-containing environment such as near industrial production facilities, the corrosion-resistant passive coating cannot withstand the incorporation of chlorine ions in the passive layer. This increases the probability of pitting corrosion. The crack initiation enhanced by this effect leads to a facilitated crack growth under dynamic loading [2]. In order to increase the fatigue strength, shot peening is applied as a standard procedure in the production process for this alloy.

The initial microstructure of the investigated material is shown in Figure 1. The specimen was prepared by electrolytic polishing using the Barker etching method [47]. The microstructure shows a non-textured grain structure with uniform grain size. The emphasis on the age-hardened condition, which is investigated in the present case, is essential in the case of shot peening, since this treatment is applied as a last processing step after heat treatment.

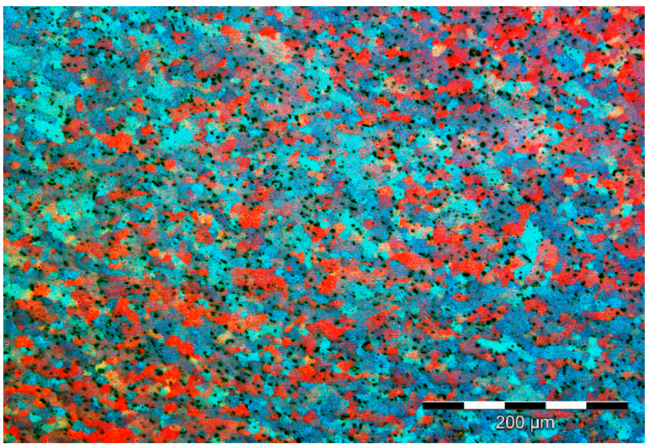

Figure 1. Initial microstructure of the EN-AW-6082 specimens investigated.

4. The Johnson–Cook Material Model

In order to simulate impact problems such as shot peening, material models are commonly used to represent the material's behavior in the most accurate possible way. Especially for high dynamic impacts, using FEA to model this process is an efficient and effective solution. The most important aspect in this context is the strain rate dependency of a material. Many constitutive models deal with material behavior by dislocation motions and their interactions with lattice defects. For many industrial processing related applications, these models are exceedingly complex and require material data with limited accessibility. Others, such as the Zerilli–Armstrong model, contain a simpler structure, but still include factors that are elaborate to determine, such as initial grain size [48]. In order to provide simplicity and convenience to the user, the Johnson–Cook (JC) material model is establishing itself as the most commonly used material model for impact problems, since it takes both strain rate and thermal softening behavior into account. Nevertheless, it is kept simple, consisting of three terms and five material parameters which are arranged as visualized in (1) [49].

$$\sigma = \left(A + B\varepsilon_p^n\right)\left[1 + C\ln\left(\frac{\dot{\varepsilon}_p}{\dot{\varepsilon}_0}\right)\right]\left[1 - \left(\frac{T - T_t}{T_m - T_t}\right)^m\right] \tag{1}$$

The first term refers to strain hardening during plastic deformation including the plastic strain ε_p, the yield strength of the quasi-static condition A, the strain hardening constant B, as well as strain hardening exponent n. The second term relates to the material's behavior under different strain rates with the strain rate sensitivity coefficient C as a result of different strain rates $\dot{\varepsilon}_p$ normalized to a quasi-static strain rate $\dot{\varepsilon}_0$. The third term describes the material behavior under temperature influence including the reference temperature T_t, the melting temperature T_m, and the thermal softening exponent m [49]. The localized strain acquired through the shot peening process is limited, resulting in a small energy input due to the deformation process, even at high strain rates. For this reason, the thermal input due to the plastic deformation of the impinging spheres at the surface is neglected in the JC material model for this framework. Therefore, (1) can be reduced by the third term, resulting in (2).

$$\sigma = \left(A + B\varepsilon_p^n\right)\left[1 + C\ln\left(\frac{\dot{\varepsilon}_p}{\dot{\varepsilon}_0}\right)\right] \tag{2}$$

The parameters of the first term can be determined by using (3).

$$\ln(\sigma - A) = n \cdot \ln(B\varepsilon) \tag{3}$$

A can be derived from the initial flow curve under quasi-static conditions. The slope n can be determined graphically by plotting a trend line while B can be expressed by solving the exponential function. The parameter C includes tests for higher strain rates. To receive C, (2) has to be arranged as demonstrated in (4).

$$\frac{\sigma}{(A + B\varepsilon^n)} = 1 + C \cdot ln\left(\frac{\dot{\varepsilon}}{\dot{\varepsilon}_0}\right) \tag{4}$$

By plotting the left term of (4) against the logarithmic strain rate ratio, C can be obtained directly from the resulting trend line.

Particular attention is required for the comparison of the determined material parameters with literature values, especially the quasi-static strain rate used ($\dot{\varepsilon}_0$), as this value often varies in a range between 10^{-4} and 1 s^{-1}. Another disadvantage regarding literature-based JC parameters is the test setup used to determine these values. For quasi-static stresses, the tensile test is usually selected in literature for the simplicity of the method. For particularly high strain rates, the strain rate sensitivity is frequently determined using the Split-Hopkinson pressure or tensile bar [50]. It should be noted that the stress states differ in these test methods. The main disadvantage of tensile tests is the instability of the deformation due to geometric deconsolidation processes after the ultimate tensile strength is reached. In contrast, the upsetting test provides steady strain hardening. The critical aspect here, in addition to the frictional conditions at the dies, is the barreling of the specimen. As a result of this phenomenon, the uniaxial load state cannot be ensured [51]. The comparison of the determined material parameters with those from literature revealed deviations in the values. One reason might be that some of the tests performed were carried out under tensile stress conditions. Besides, there might be differences between the chemical compositions of the materials studied. Slight differences in the heat treatment route for the T6 condition could also be responsible for these divergences. For this reason, separate tests should be carried out with the specific material used, in order to eliminate these variations. The different parameters from the literature are listed in Table 2, whereas temperature is not listed due to the lack of definition within the investigated publications. Accordingly, it is essential to arrange the test setup in such a way that it comes closest to real conditions of usage. For the simulation of shot peening processes, the upsetting test is most similar to the compressive stresses introduced by the spheres at the surface. For low degrees of deformation, uniaxial deformation can be also provided, which is why the experiments carried out in this study are based on this principle.

Table 2. Material parameters for the JC model for EN-AW-6082 T6 from literature sources.

	A [MPa]	*B* [MPa]	*C* [-]	*n* [-]	*m* [-]	$\dot{\varepsilon}_0$ [s^{-1}]
[52]	250.00	243.60	7.47×10^3	0.17	1.31	1.0
[53]	305.72	304.90	4.37×10^3	0.68	-	10^{-3}
[50]	277.33	307.93	3.2×10^3	0.69	1.28	10^{-4}

5. Experimental Setup

For the determination of the material parameter of the investigated alloy EN-AW-6082 T6, cylindrical samples with a diameter of 8 mm and an initial height of 12 mm were obtained from an extruded rod material. To receive the T6 condition, all specimens were solution-annealed at 803 K for one hour, followed by water quenching. After these steps, age hardening at 443 K for another five hours was carried out. For the determination of realistic material parameters, the specimens were compressed longitudinal to the extrusion direction at room temperature on the Gleeble 3800 thermal-mechanical Simulator, using the Hydrawedge module at constant strain rates of 1 s^{-1}, 10 s^{-1}, and 100 s^{-1}. The Hydrawedge module is especially designed for the simulation of forging and forming processes requiring a high strain rate, as it is capable of significantly reducing ringing of the hydraulic ram. The capability of high-speed deformations allows the generation of flow curves, which are relevant for the shot peening process. As shown within Figure 2, a graphite foil was additionally placed between both contact surfaces to reduce the friction between specimen and anvil, thus ensuring a uniform stress state during compression.

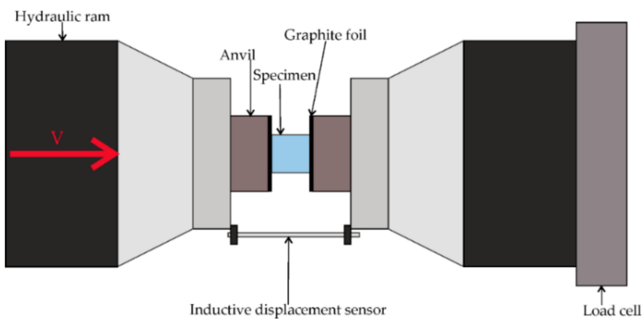

Figure 2. Experimental setup for the obtainment of JC material parameters.

Table 3 shows the resulting JC parameters, derived from the practical experiments and calculated according to Section 4. The experiments were carried out until a strain of 0.035 was reached, as higher strains are not relevant considering the shot peening process.

Table 3. Material parameters for the JC model for EN-AW-6082 T6 obtained from practical experiments.

A [MPa]	B [MPa]	C [-]	n [-]	m [-]	$\dot{\varepsilon}_0$ [s^{-1}]
385.02	116.01	7.97×10^3	0.50	-	1.0

6. FEA Setup and Resulting Data Mining Algorithm

For the implementation of the initial state white box model, a fundamental Abaqus input script was defined in first instance. This script contains all necessary input parameters for the simulation model to be automated and is scripted within the Abaqus Python environment. Table 4 shows a brief overview of the most important variables changeable within this input script.

Table 4. Variables changeable within the Python input script.

Input Variable	Functionality
Radius	Possible variation in sphere radius
x_specimen	Width of investigated specimen
y_specimen	Depth of investigated specimen
rows	Number of rows of spheres
angle	Angle of sphere impact (initially 90°)
number_spheres	Number of spheres (per defined rows)
delta_x	Horizontal distance between each sphere
delta_y	Vertical distance between each sphere
row_offset	Offset between different rows
step_time_shot	Step time related to the impact phase
dens_mat; YM; pois;	Density and elastic behavior of investigated material
A; B; n;	JC material parameters for the investigated material
C; eps_dot_0	Strain hardening parameters according to the JC model
damping_time	Additional step time for stress oscillation analysis
friction_coefficient	Defined friction state between specimens and impacting spheres
field frames	Number of field output frames within each step
v_shot	Shot velocity of spheres
mat	Density of spheres (depending on the material)
fine_mesh_region	Mesh size of direct impact zone
ground_mesh_region	Mesh size of the remaining geometry
RS_node	Node set definition for the residual stress analysis

In order to keep the number of degrees of freedom (dof) for the upstream data analysis reasonable, only the variables v_shot, radius, mat, elastic, and JC parameters of the investigated material (Section 3) were changed. For a further extending of simulation dof, a link between the Python input script and the overlaying automation layer is prepared. The fundamental FEA is defined as dynamically explicit, with widely used element type CPS4R (mesh size 0.01 mm) and a steady friction coefficient of 0.3. To achieve a high shot peening coverage rate on the specimen's surface, 90 spheres within three different rows were created, with a horizontal and vertical distance of 0.025 mm and a vertical offset between each row of 0.02 mm. The specimen's length as well as width was defined with 1.0 mm. Additionally, the impact angle was set to 90° and not changed in this study. To avoid contact definition dependent errors, a loop within the script automatically defined a surface-to-surface contact between each sphere and the target. Table 5 shows the resulting parameters varied within this paper.

Table 5. Varied variables within this case study.

Varied Input Variable	Range (Step)
mat	Mat 1.0 (steel spheres)/Mat 2.0 (glass beads)
Radius	0.1–0.5 mm (0.05)
v_shot	30–200 m/s (10)
A; *B*; *n*; *C*; eps_dot_0	Literature value (Table 2, [53]) and values obtained (Table 3)

Figure 3 shows the visualization of an exemplary setup for one defined sphere radius. Depending on the varying radii of the respective spheres, the resulting point mass of each sphere changes. To reduce computational time for the required simulations, the spheres were defined as rigid. For the automated data generation, the Abaqus GUI was excluded from the solver operation.

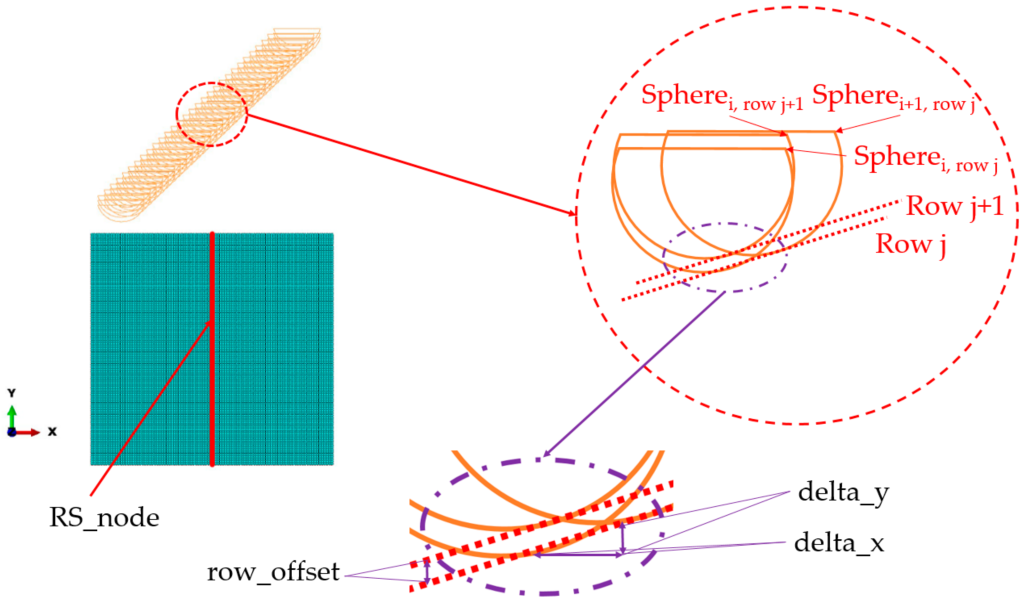

Figure 3. Visualization of the experimental setup and definition of geometric variables.

For the development of the white-box model, an initial database with all resulting residual stresses for each node included in the RS_node node set has to be created. This database also includes the different impact velocities and sphere diameters and serves as a basis for the initial GUI. In order to receive the steady-state residual stresses, the resulting amplitude at each respective node within the node set was analyzed. To consider a residual stress value for a node within RS_node as steady, the residual stress amplitude $\Delta\sigma$ for this node at a specific time increment has to be underneath 10 MPa (Figure 4). The fulfillment of this condition is checked within the initial Python algorithm. In this case, for a step time of 10^{-3} s, the condition is valid for each node within all performed simulations. The steady-state residual stress was returned and stored in the master database. As a result, one stress value for every 10 µm in each simulation is obtained.

Figure 5 visualizes the programming logic for the creation of this database, starting by the initial input script.

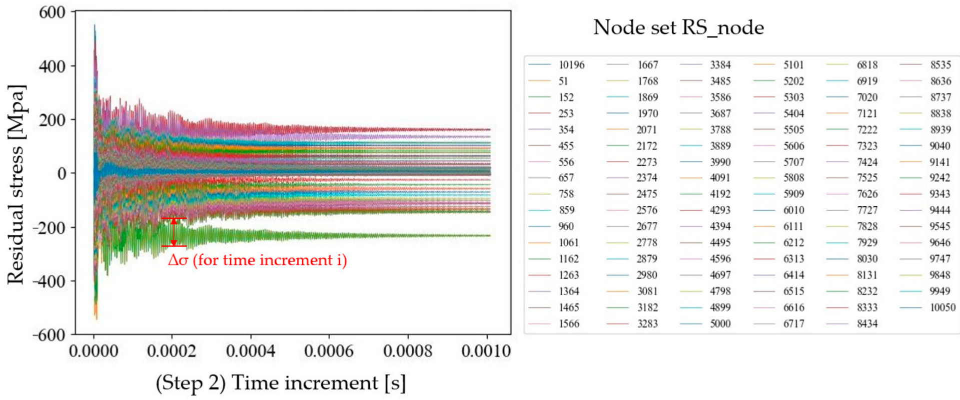

Figure 4. Exemplary residual stress amplitudes over step time with included nodes in RS_node.

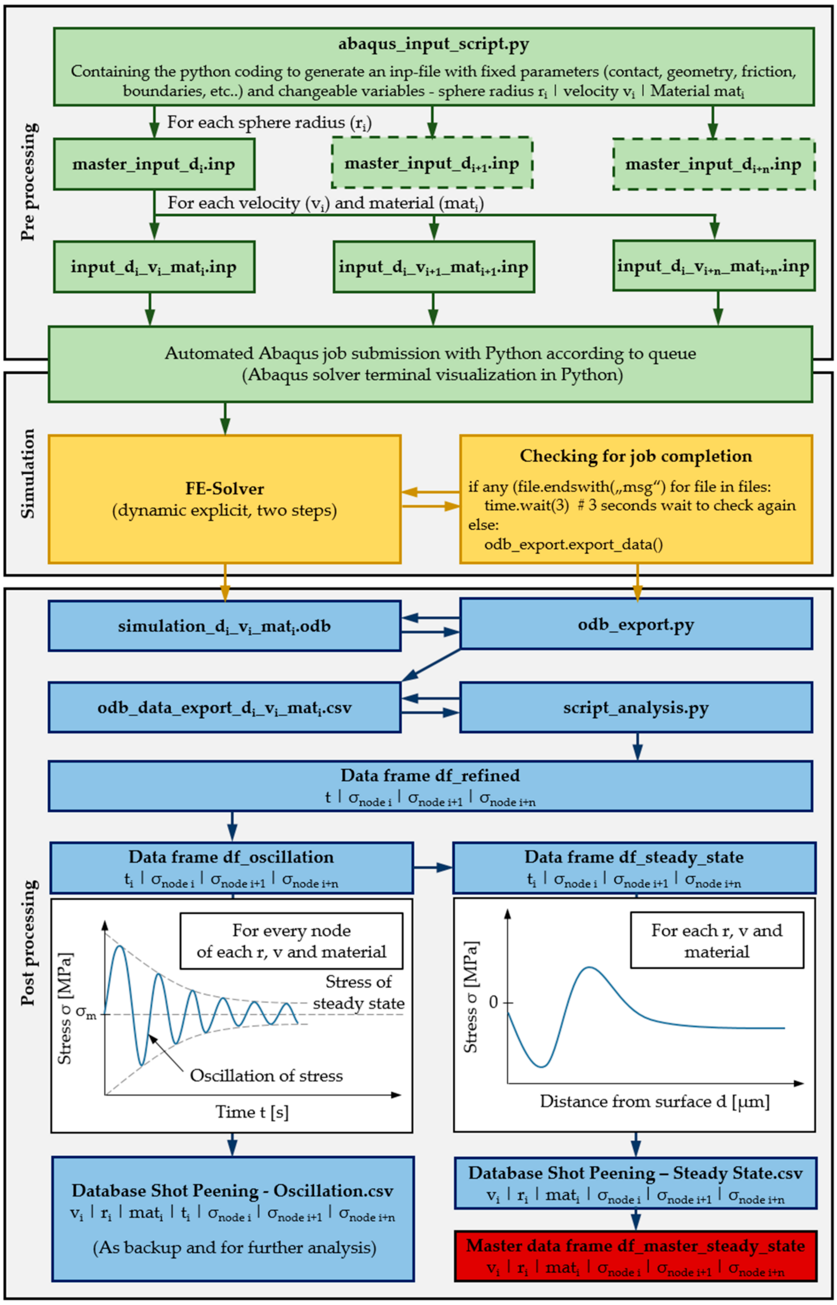

Figure 5. Programming logic for the obtainment of the database and master data frame from FEA data.

The master data frame extracted from the steady-state database contains all necessary information for further analysis and implementing the initial white-box-model-based logic. Figure 6 shows the comparison between different velocities for one exemplary sphere diameter (0.4 mm), whereas both investigated sphere materials (steel (red) and glass beads (blue)) are visualized. Additionally, the results for the JC material parameters from [53] are shown (steel spheres (green) and glass beads (orange)).

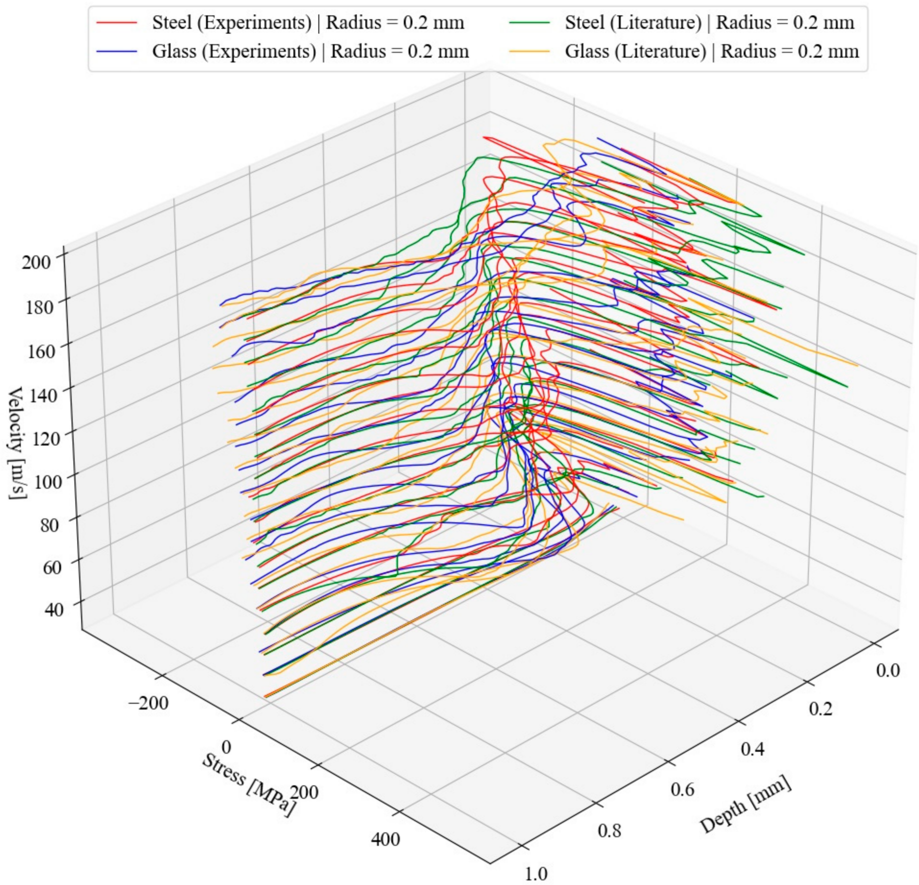

Figure 6. Resulting residual stress profile for a defined sphere diameter (0.4 mm) for the JC parameters obtained experimentally (steel spheres (red), glass beads (blue)) and alternative parameters derived from [53] (steel spheres (green), glass beads (orange)).

As demonstrated in Figure 6, a significant difference between the JC parameters determined from literature and own experiments can be seen, for the reasons explained previously in Section 4. In general, the impact of steel spheres results in higher residual stresses within comparable velocities and diameters. This effect can be explained by the higher resulting momentum of the iron-based sphere material, as the density is 3.1 times higher than the density of glass. The observed tensile stresses at the surface are a result of the material flow through adjacent impacts. This effect can be enhanced by the rigid definition of the spheres as well as the chosen mesh size. As the main objective of this framework is to obtain valid residual stress minima under reasonable computational time, this divergence was not considered any further [54].

Figure 7 shows the same sphere material and material parameter variation for a steady velocity (100 m/s) with varying sphere diameters (0.2–1.0 mm). The increase in maximum negative residual stresses with bigger sphere diameter can be explained again by the higher resulting momentum for a steady velocity [28].

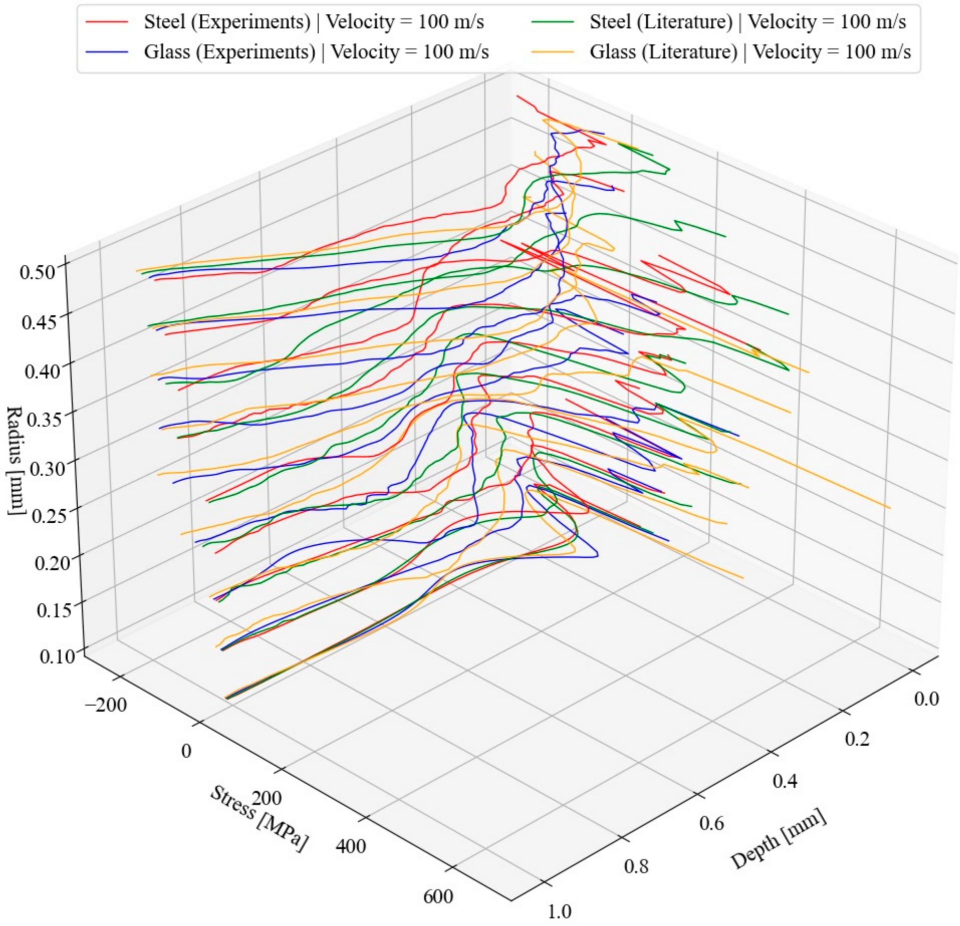

Figure 7. Resulting residual stress profiles for a defined velocity (100 m/s) for the same variations defined within Figure 7.

Figure 8 illustrates the difference between literature values and the data obtained from the experiment exemplarily.

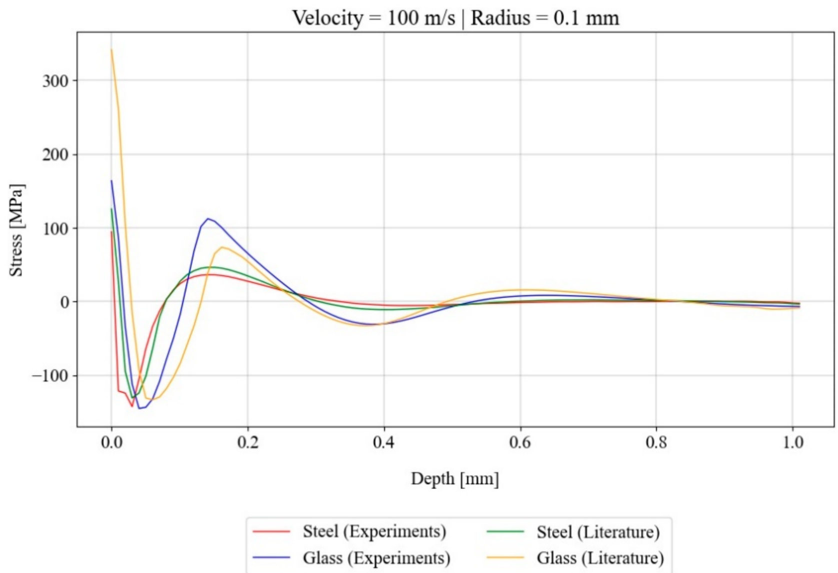

Figure 8. Resulting residual stress profiles for velocity = 60 m/s and a sphere diameter of 0.4 mm for literature and experimental data.

7. Development of the Initial White-Box Model for the Residual Stress Prediction

Figure 9 visualizes the initial white-box logic, beginning with the input parameters defined by the respective user to the final values returned from the algorithm.

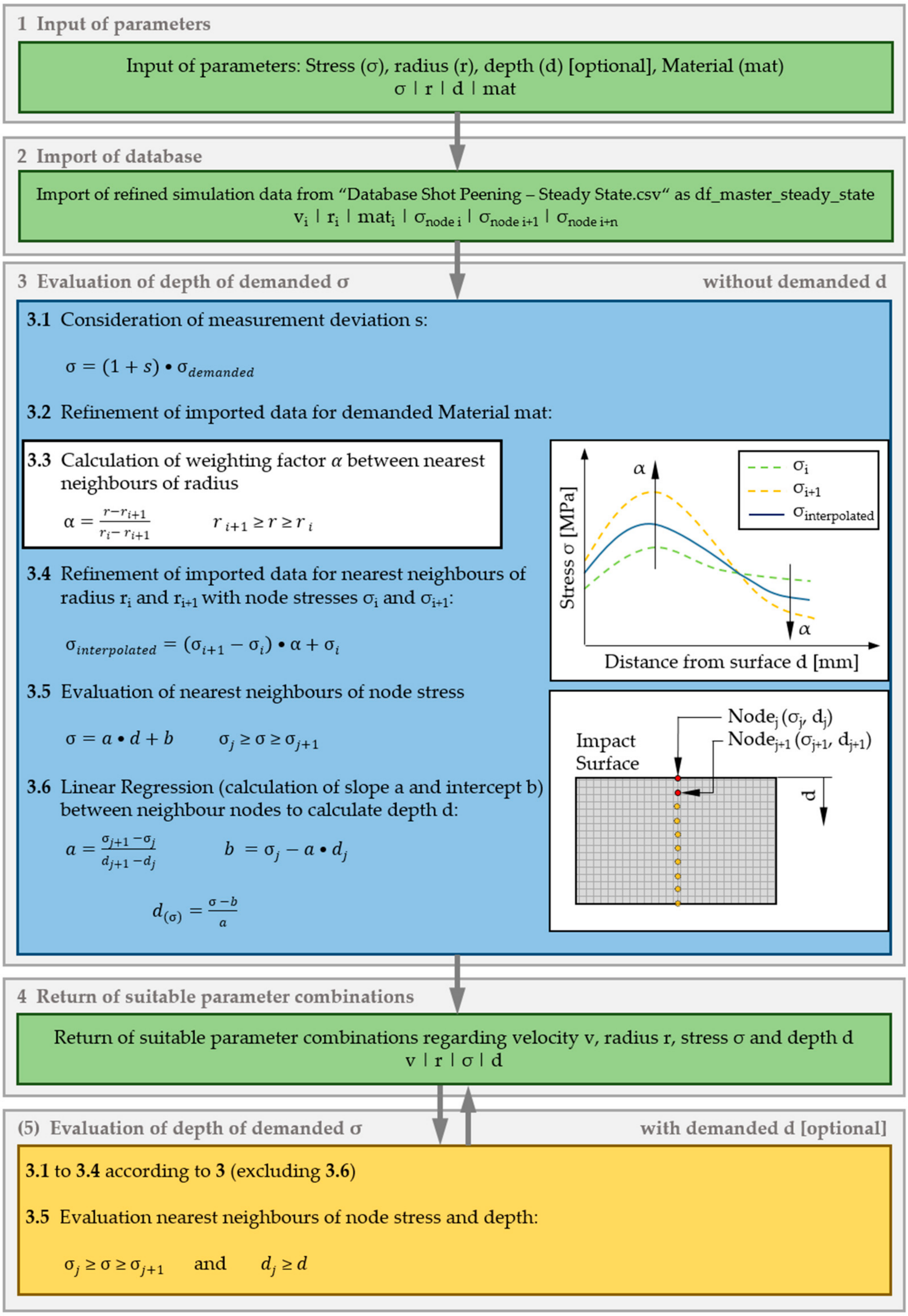

Figure 9. Algorithm for the transformation of user input data (real sphere diameter and desired residual stress, optionally required depth) into shot peening parameters (velocity options suitable for the defined input) by using the master data frame defined in Figure 6.

For the user to be able to adapt the initial sphere diameter to the real value, the model has to be capable of interpolating within the given data set. To achieve this, an interpolation scheme, including a linear weighting factor α which interpolates between given boundaries of the initial (FEA-based) data set, was defined. For the practical usage, the respective user is able to define the desired residual stress required for the individual case. Additionally, it is possible to define the desired depth in which the specified stress value should be obtained. If no depth is defined, the user gets a data frame which includes all shot velocities fulfilling the defined input value, including the depth in which the residual stress is reached first. To ensure that the calculated value will be reached in practice, a security factor s was set in the back end, which multiplies the input stress value with the factor 0.2.

8. Experimental Data-Driven Machine Learning Algorithm

As within every simulation, a deviation between the calculated results and experimentally determined data occurs. To close this gap in an efficient and sustainable way, the possibility of including actual test data in the model is considered, whereas the actual test data can be gained from different experiments (e.g., XRD measurements). In general, these results contain a few data points for each experiment carried out. To be able to adapt the initial FEA-based data cloud within the master data frame, at least four experiments have to be executed, analyzed, and transferred into the Python environment. These experiments have to be within a defined range of velocities ($\Delta v <= 30$ m/s) and sphere radii ($\Delta r <= 0.2$ mm). Based on this data set, non-linear functions with a sufficient amount of respective supporting grid points (initially 100 per three original data points) are created. For more complicated residual stress profiles, this range must be decreased to ensure accuracy. Based on this additional data, the curves received from the FEA within the range of the experimental data sets are overruled and excluded from the master data frame and steady-state database. Furthermore, interpolations that include experimentally obtained curves change significantly. This procedure is carried out automatically within a Python algorithm, which leads to a steady increase of data-driven analytics. This data is not directly connected to real-physics, which includes black-box approaches within the initially white-box model, resulting in a grey-box model. Figure 10 demonstrates this paradigm change over increasing experimental data infeed.

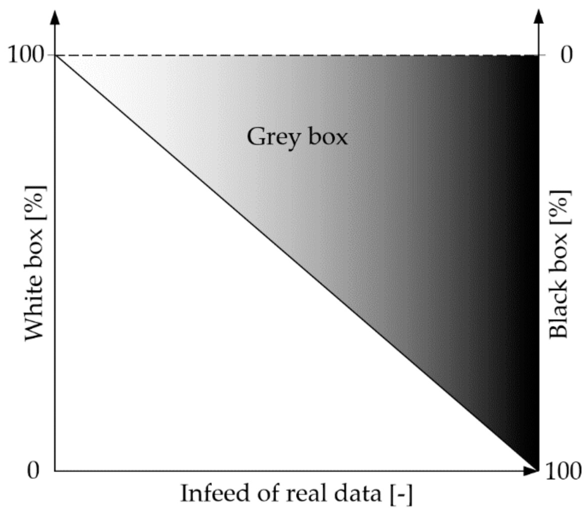

Figure 10. Change of model characteristics with increase of infeed data: the original FEA and real-physics-based model is overruled with more data from practical experiments.

Figure 11 shows the logic behind this machine learning approach, programmed within the same Python environment. To smoothen the resulting experimental data points without producing overfitting and therefore unrealistic behavior, a non-linear, second-order fitting approach between experimental data points was chosen. For the same purpose, a mean value between two overlapping functions for the same data point was used. The resulting second order functions serve as boundaries for the creation of support data points, to be able to interpolate between the new resulting data sets with the same algorithm as for the initial white-box model.

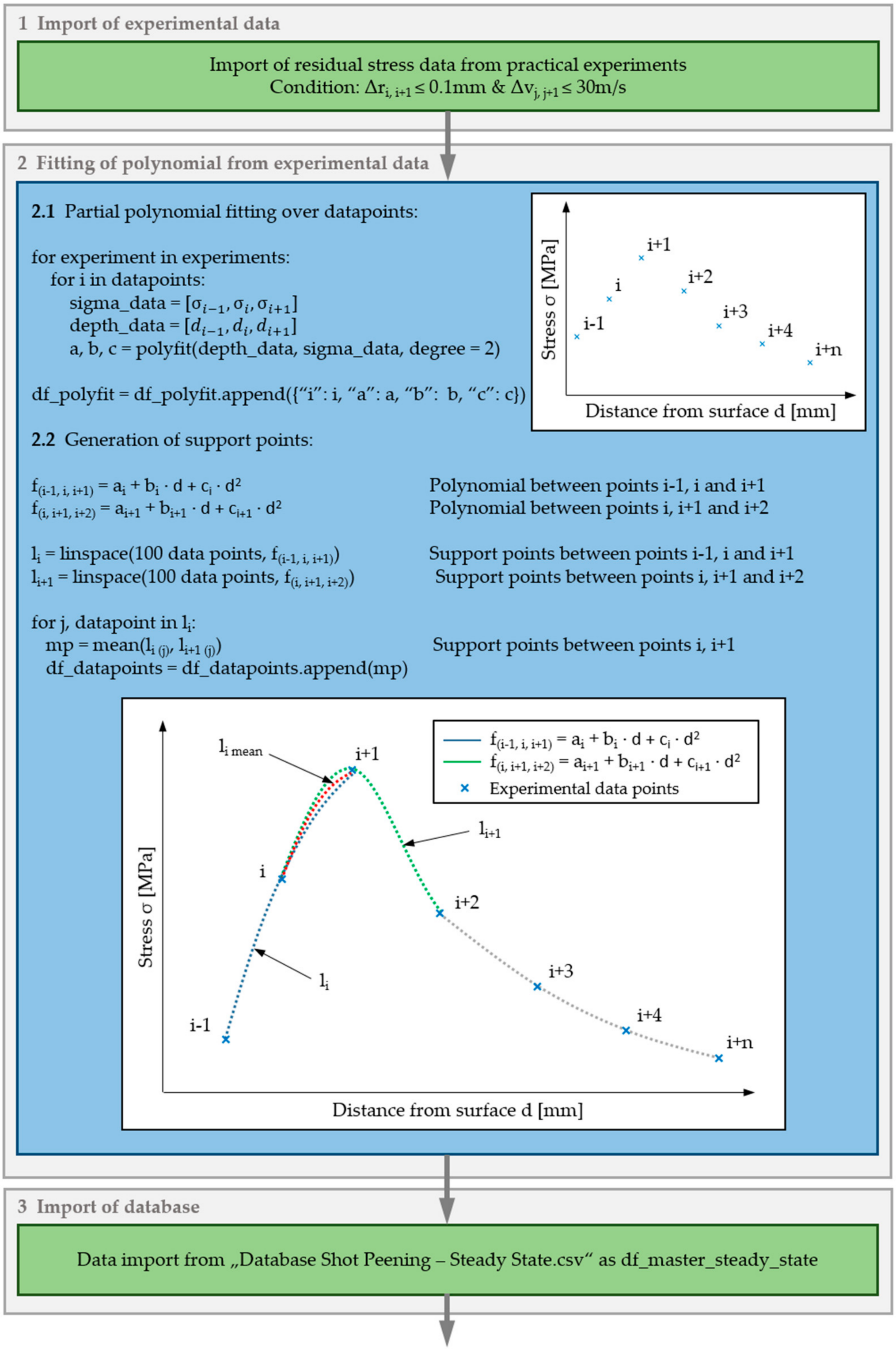

Figure 11. *Cont.*

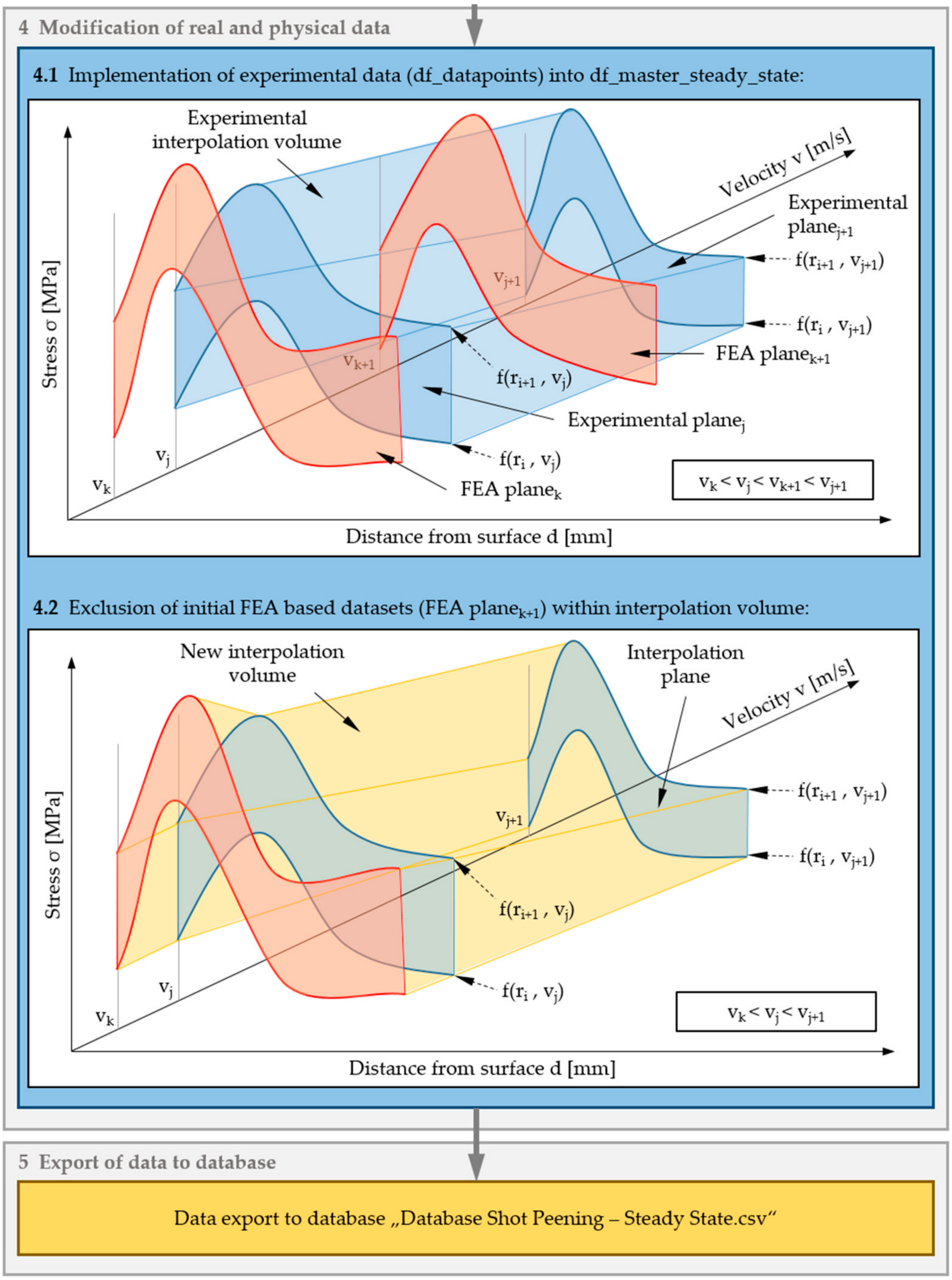

Figure 11. Python logic implemented to adapt the initial FEA based white-box model by adding data from residual stress experiments. 1: Import data; 2: generation of support data points from experimental data and storage in a new data frame; 3: loading master data frame; 4: import data points from 2 and overrule data points of the master data frame to increase prediction efficiency; 5: overwrite master database with new data points.

9. Graphical User Interface

Based on the logic explained in Sections 7 and 8, a simple and user-friendly GUI was developed, using a C++ based open-source visualization environment. Due to an included library package within the Python environment, a direct programming within the same environment is possible. Figure 12 visualizes the automatic interaction between the resulting GUI and the algorithm developed.

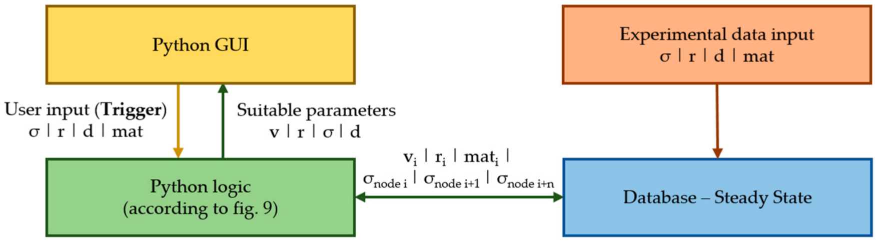

Figure 12. Interaction between the developed residual stress algorithm and GUI. To avoid confusion of respective users, the input of experimental data from practical experiments is excluded from this visualization.

Figure 13 shows the implemented GUI without optional definition of desired depth.

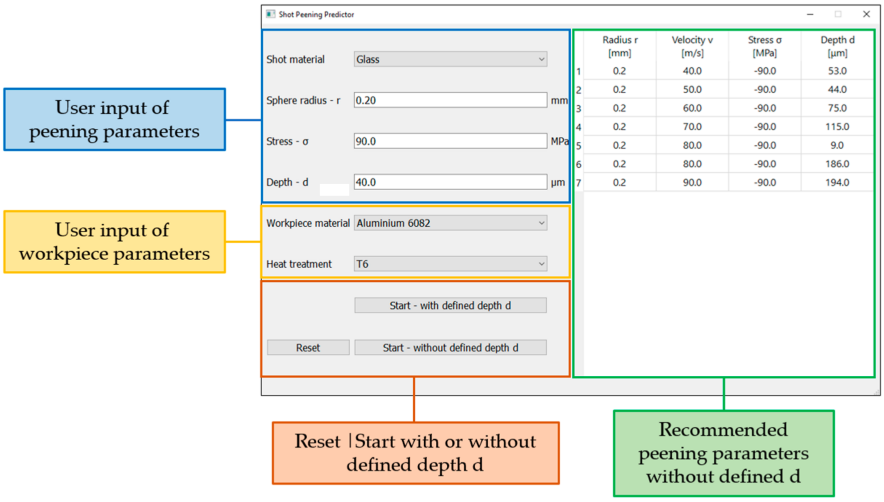

Figure 13. GUI with exemplary values for the prediction of residual stresses (without user-defined stress-corresponding depth).

As can be seen in Figure 13, a range of different velocities for the user-required residual stress is returned. If the stress value is necessary within a certain depth, the back-end algorithm changes, resulting in a recommendation for only those shot peening parameters, which result in a smaller depth while fulfilling the required stress (according to Figure 9). Figure 14 demonstrates this by using the same exemplary variables as in Figure 13.

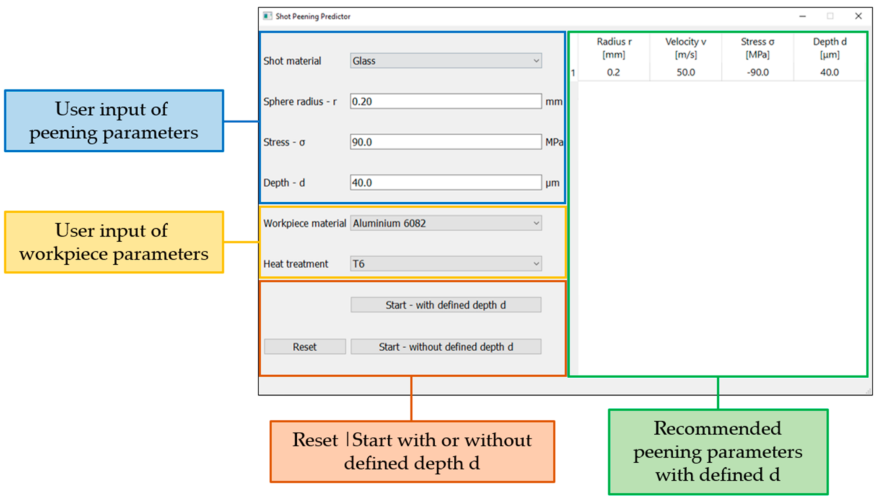

Figure 14. GUI with exemplary values for the prediction of residual stresses (with user-defined stress-corresponding depth).

10. Results

This paper describes the development of a residual stress prediction module for the shot peening process. In order to demonstrate the logic implemented, an EN-AW 6082 T6 alloy was examined to obtain valid input parameters for the FEA simulation. This FEA model is set up according to literature [26,32,54–56], whereas the reduction of computational time without losing required accuracy was focused on. As a result, over 350 simulations with varying input parameters were automatically executed, resulting in residual stress profiles within common shot peening process ranges for two different sphere materials, 18 different velocities, and ten different sphere sizes. These simulations serve as a basis for the data mining algorithm introduced in Section 7. To enhance the predictor's accuracy, an algorithm for the implementation of experimental data from residual stress tests was additionally implemented. This algorithm is capable of overwriting the initial database within a defined range. For the usage in a production environment and for demonstration to interested parties, a user-friendly, front-end GUI was created, using the same open-source environment as for the logic introduced by the authors.

11. Discussion

Due to the ongoing fourth industrial revolution, the technologies implemented in the metal processing and manufacturing environment change significantly. Recent developments in automatic data exchange between production systems do not just increase the productivity within the production operation. The implementation of standardized interfaces additionally offers new possibilities to include other technologies into the process chain with reasonable effort. Numerical simulation, especially FEA, is a common tool in research and development, whereas the direct integration into the process chain is not state-of-the-art in practice. Nevertheless, the possibilities and potential advantages of FEA are pointed out recently in current literature [57,58]. The framework developed by the authors offers the possibility to be implemented into a digitalized production network. The algorithms introduced are programmed completely open-source, which allows interested companies the implementation without high economic barriers. Furthermore, the FEA solver used can be exchanged with every other software package suitable, as long as an interface to an open-source programming language is available. Despite the advantages of the ongoing digitalization and data-driven modeling, real-physics-based engineering has to be included to a certain extent. For the shot peening process, the relationship between workpiece and shot peening material as well as process parameters is complex. Using only black-box approaches would result in an unreasonable amount of required data from practical experiments to be obtained. On the other hand, using only real-physics-driven models often do not consider influences occurring in the manufacturing environment (e.g., sensor offset of respective aggregates, deviations from executed experiments due to different users). The combination of both techniques, although, can reduce the effort as well as deviations, offering an efficient and effective possibility to enhance the production process. Another advantage of the framework introduced in this work is the possibility of extension for all kinds of materials as well as according varieties in heat treatments, as already implemented in the respective GUI. Due to the possibility of changing the interpolation range within the machine learning algorithm, more complex residual stress profiles can be predicted with similar accuracy. However, it is important to note that smaller interpolation ranges result in a higher amount of required input data.

The GUI is designed under special consideration of user-friendliness, giving respective technicians the possibility to choose between two different initial options. Furthermore, the back-end programming carried out in Python ensures fast understanding and can therefore be used for educational purposes. The high connectivity provided within the Python environment allows easy coupling to superordinate networks, enabling users to connect the process simulation easily into a digitalized production system. For this purpose, the two-dimensional setup of the described FEA model should be the optimal compromise between accuracy and efficiency. Nevertheless, for more complex geometry (e.g., bevel, material steps), a three-dimensional approach is recommended, as the difference between experiments and simulations for more complex geometries cannot be neglected. As the simulation model is based on Python, the implementation of such variations as well as the transformation to a 3-D model can be done shortly. Furthermore, by slightly adapting the initial post-processing, the resulting three-dimensional stress state can be easily obtained.

12. Conclusions and Outlook

In this article, a white-box-based framework for the prediction of residual stress profiles after shot peening treatments based on FEA simulations is presented. To include decisive influencing factors, the shot velocity, the sphere's diameter, and the material parameters were varied. According to this framework, a GUI was developed that enables the user in industrial environments to insert preferred residual stresses that should be obtained, receiving the optimal process conditions for this case. Due to the reduction of the simulation setup by using a two-dimensional FEA simulation that is based on the JC material model, the underlying algorithm presents a reasonable fit between efficiency and accuracy. The entries of the JC model can be extended for different materials based on a few practical experiments. The possibility to enhance accuracy of the predictions is given by the ability of the user to insert experimentally investigated resulting stress profiles, which the model adopts while cancelling imprecise entries.

To enhance the usage of the introduced algorithm, additional experiments to obtain valid input parameters from different materials are planned. Based on this additional data, other materials of interest will be inserted into the database. Further results from XRD-based residual stress experiments will also be included for the investigated material as well as additional materials, resulting in a significant increase of accuracy of the algorithm.

The model presented will be implemented within the Smart Forming Lab at the Chair of Metal Forming, connected with different types of Cyber Physical Production Systems by an open-source based MES. The main objective for this specific algorithm is to calculate accurate process parameters for processed workpieces, in order to increase the effectiveness and efficiency of the value chain, from casting to recycling. A possibility to extend this model is the incorporation of the resulting topology. This can be achieved by using the approach of Zeng et al. through comparative measurements, calculations, and adapted simulations [59]. Including the resulting mechanical properties and the expected hardness after shot peening would improve the model considerably. Due to the easy-to-implement logic of this framework, it is possible to apply this model to further mechanical surface treatments. Uprising technologies that are currently heavily investigated such as laser shock peening could be considered. A comparison of the three-dimensional FEA carried out by Li et al., also using the JC model to the two-dimensional model, will be considered [60]. Recent work from Dong et al. describes the development of a FEA for machining operations [61]. In this work, the effect on residual (tensile) stresses combined with a bimodal Gaussian function is used to predict existing stresses after machining and before mechanical surface treatment. This approach can be used to integrate the initial stress state of components to be shot peened. As a result, the accuracy of the initial white-box model presented in this work can be increased. Based on this combination, the number of practical experiments for the calibration of the algorithm can be further reduced. Recent work from Bock et al. [62] can additionally serve as a basis for the training of a physical data-driven artificial neural network.

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A 5 Publication 5

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3. B. Schödinger: software

4. H.-J. Schmölzer: software

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6. M. Stockinger: resources, supervision

sensors

Case Report

Implementation of a Six-Layer Smart Factory Architecture with Special Focus on Transdisciplinary Engineering Education

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Abstract: Smart factories are an integral element of the manufacturing infrastructure in the context of the fourth industrial revolution. Nevertheless, there is frequently a deficiency of adequate training facilities for future engineering experts in the academic environment. For this reason, this paper describes the development and implementation of two different layer architectures for the metal processing environment. The first architecture is based on low-cost but resilient devices, allowing interested parties to work with mostly open-source interfaces and standard back-end programming environments. Additionally, one proprietary and two open-source graphical user interfaces (GUIs) were developed. Those interfaces can be adapted front-end as well as back-end, ensuring a holistic comprehension of their capabilities and limits. As a result, a six-layer architecture, from digitization to an interactive project management tool, was designed and implemented in the practical workflow at the academic institution. To take the complexity of thermo-mechanical processing in the metal processing field into account, an alternative layer, connected with the thermo-mechanical treatment simulator Gleeble 3800, was designed. This framework is capable of transferring sensor data with high frequency, enabling data collection for the numerical simulation of complex material behavior under high temperature processing. Finally, the possibility of connecting both systems by using open-source software packages is demonstrated.

Keywords: engineering education; smart factory; digitalization; industry 4.0; metal processing; layer architecture

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1. Introduction

Since the beginning of the fourth industrial revolution, a paradigm change within the manufacturing environment can be observed [1–6]. As an integral part of this revolution, the Reference Architecture Model Industry 4.0 (RAMI 4.0) was introduced [7]. RAMI 4.0 is an extension of the Smart Grid Architecture Model (SGAM) to meet the initial requirements of Industry 4.0 [8,9]. Within this model, information type, system hierarchy as well as asset lifecycle is considered within an administration shell, responsible for the communication between these sections [10]. The inclusion of these key factors is especially important for the development of a smart factory [8,11]. This kind of abstract reference model for layer architectures is not a new concept [12–14], but it has a superior advantage due to international standardization. The high amount of the current literature regarding layer architectures demonstrates the importance of this topic among different disciplines in the manufacturing environment, e.g., in [15], Zyrianoff et al. focused the implementation of layered internet of things (IoT) solutions for the development and further enhancement of smart agriculture and smart cities; in [16], Ungurean and Gaitan describe a further concretization of the reference model with a special focus on industrial internet of things (IIoT) solutions; in [17], Gonzalez et al. present the utilization of Modbus TCP to overcome proprietary automation solutions for smart microgrids in the photovoltaic sector. Despite the high academic as well as industrial research activities within the last years [1,2,18], numerous new concepts and developments are not suitable for small and medium sized enterprises (SMEs) operating in the manufacturing environment [19,20]. High investment costs, a high level of standardization in conducted processes (e.g., by lean management approaches) as well as advanced internal IT and data management/digitalization know-how is required for a majority of solutions recommended in the literature [21–27]. The vast majority of high specialized SMEs do not fulfill these requirements because they have a huge variety as well as low volumes within the production plans. Another characteristic of these businesses is a lower degree of process automation, combined with generally less standardized process management [28,29]. Nevertheless, the economic contribution of SMEs in this sector is not negligible and provides employment opportunities for many current and future graduates of academic institutions [30–32]. To ensure sustainable economic development in these companies, variable low-cost digitalization solutions can add major advantages [33,34]. Therefore, interdisciplinary expertise from current and future employees is required in order to achieve this objective [35–37]. For this reason, an academic smart factory environment [38] was developed, which serves students and therefore future experts as a practical learning environment to deepen their knowledge in digitalization technologies. In comparison to similar learning factories [39–44], the framework discussed in this paper has the advantage of consideration of real physical processes and material parameters (e.g., the possibility of integrating numerical simulation, prediction of microstructure of examined specimens). Furthermore, it supports SMEs by demonstrating low-cost possibilities of digitization and digitalization approaches within the metal processing industry. Despite the hardware solutions, the usage of open source and, more importantly, highly integrative software solutions is of crucial significance. Furthermore, the effort of learning, implementing and updating of such a programming environment must be reasonable. For this reason, Python (Version 3.8) was chosen for the majority of data processing operations described in this case study, using the open source PyCharm Integrated Development Environment (IDE). Python's increasing popularity in the manufacturing as well as academic world was an additional driver for this decision [45,46]. In addition to the free availability as an open-source product, the increasing popularity is due to the multitude and diversity of the frameworks and their continuous improvement and expansion. Popular frameworks such as pandas enable the preprocessing and manipulation of data [47], Matplotlib visualizes the data [48], and Numpy as well as Scipy allow the elaboration of mathematical operations and machine learning algorithms [49]. Additional frameworks permit the fast assembly of versatile GUIs, e.g., PyQt [50].

For the development of a smart factory layer architecture, efficient and effective data management is key. Digital data storage allows a more efficient, secure and accessible data administration and preservation. Databases are practical for storing and managing data and facilitating the retrieval of specific information. In addition, many databases determine which people or programs can access data depending on the respective permissions. In order to facilitate such a permission system, a database management system (DBMS) is used. For this case, the Structured Query Language (SQL)-based relational DBMS MySQL (Version 8.0.23) was chosen because it is an open source product exhibiting a high compatibility with Python and is simple to learn for engineering students [51]. Furthermore, it provides a straightforward connection to Hypertext Preprocessor (PHP), another widely used open source language for the development of advanced Web applications [52]. Additionally, the hosting can be outsourced to an external server provider or done on in-house servers.

Because there is no all-encompassing solution available for the implementation, suitable for the majority of entrepreneurs, two different layer architectures were developed, depending on the existing IT-infrastructure as well as degree of automation within the respective machine systems. Despite retrofitting approaches, which involve a major proportion of old machine systems with a poor degree of automation, the integration of state of the art machines that already possess a specific digital interface into a not-proprietary IT-framework is of utmost importance [34]. A lot of these systems do not exhibit a standardized open source interface, leading to highly functional, but in most cases isolated, applications [53]. Because the full potential of digitalization and digital transformation lies in the integration of these stand-alone solutions, machine manufacturers commonly offer high cost solutions for the coupling of their individual data acquisition (DAQ) system with other foreign applications [54]. Especially for small and medium-sized enterprises, it is common to avoid these cost-intensive solutions by independently developing efficient solutions.

The following work shows two possibilities of methods capable of gathering and processing necessary data for condition monitoring, maintenance interval optimization and machine learning approaches for engineering education purposes. A special focus lies on the integration of different heterogeneous interfaces as well as easy-to-use human machine interfaces (HMIs) [55–57]. Another important attribute of the presented layer architectures is the resilience regarding a harsh manufacturing environment, achieved with the inclusion of data mirroring and strict access right policy [58]. The possibility of adding new layers, e.g., real time numerical simulation as well as a possible interface to an enterprise resource planning (ERP) system was additionally considered.

2. Transdisciplinary Engineering Education 4.0: Target Groups and Learning Outcomes

As a result of the fourth industrial revolution and corresponding digitalization and digital transformation in the metal processing environment, required competencies and skills for engineers in this field have changed significantly [59–61]. The increase in inter- and transdisciplinary skills necessary to work within this digitalized manufacturing environment must substantially affect the curricula of traditional secondary and tertiary engineering education in order to ensure long-term employability [62–64]. For this reason, a new transdisciplinary lecture at the Montanuniversität Leoben was designed. This lecture aims to introduce engineering students of different disciplines into the fundamentals of digitalization and digital transformation in the metal processing environment. Table 1 gives a general overview about affected disciplines at the academic institution.

Table 1. Main target engineering disciplines at the Montanuniversität Leoben.

Engineering Focus	Associated Programs at the Montanuniversität Leoben
Energy	Industrial Energy Technology
Materials	Materials Science
Process and Product	Metallurgy; Mechanical Engineering; Industrial Logistics
Recycling	Industrial Environmental Protection and Process Technology; Recycling

Students of industrial energy technology, mechanical engineering, industrial logistics, recycling and process technology are heavily affected by the changes in the process and production environment. Therefore, fundamentals of smart-factory-related layer architectures are mandatory for their future careers. Material scientists additionally need to be aware of digitalization in the research and development field. This especially includes know-how about technology-enabled advances in material testing and how this discipline can profit from recent Industry 4.0 related technologies and corresponding advances in sensor technologies. Metallurgists and materials-science-interested mechanical engineers should be aware of developments in both sectors mentioned.

As an integral part to fulfill these requirements, two different layer architectures were developed. The first development focuses on the fundamentals of digitization and digitalization and is based on a low-cost layer architecture, often used in an SME environment (Section 3). Additionally, to point out the importance of such a framework for material scientists, mechanical engineers and metallurgists, the possibilities of including complex FEA into this architecture is elaborated in Section 5. To also demonstrate the potentials and advantages of higher frequency measurement methods for material testing and characterization, a second layer system including fiber optic measurement technologies is implemented on a state-of-the-art thermomechanical treatment simulator. Both architectures transmit data by the Modbus TCP/IP protocol widely used in industrial practice to the internal server system.

3. Digitalization and Low-Cost Layer Architecture: Structure and CNC-Lathe Integration

The DAQ is performed by a Wago PFC200 G2 2ETH RS controller, which executes PLC control tasks and internally processes analog and digital signals supplied by input/output (I/O) modules. The I/O modules used are analog input modules that receive analog signals from the CNC-lathe and forward them to the controller in order to convert these analog signals into digital ones that are required for further computer-aided processing (Figure 1).

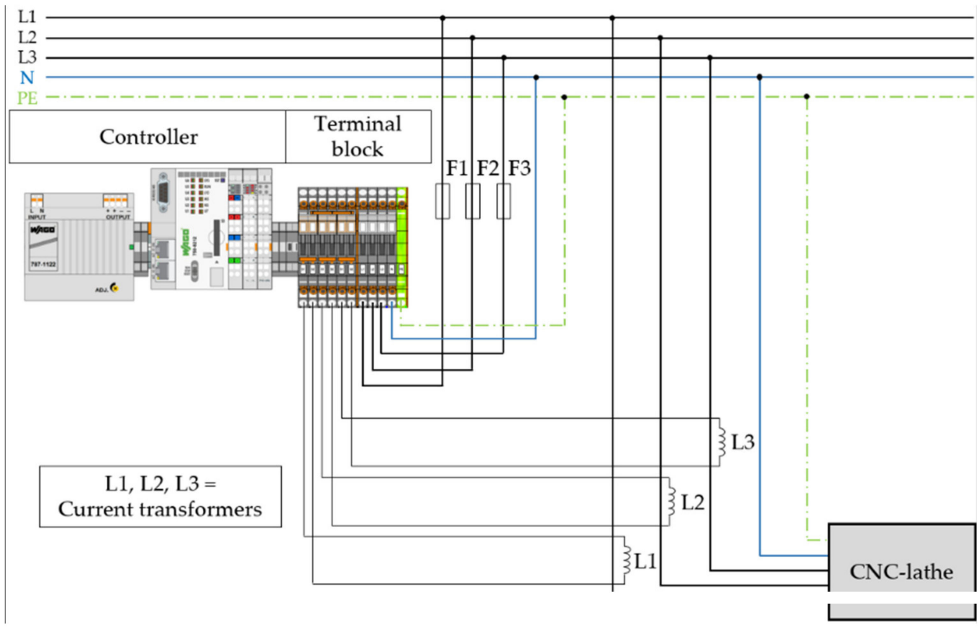


Figure 1. Circuit diagram for the connection of the CNC-lathe to the superordinate system.

By connecting three-phase currents measured by a current transformer as well as voltages, the Wago 750-494 analog input module, a three-phase power measurement module, enables real-time measurement of reactive power, apparent power, active power, energy consumption, power factor, phase angle and frequency. The corresponding circuit diagram from the power module point of view is visualized in Figure 2.

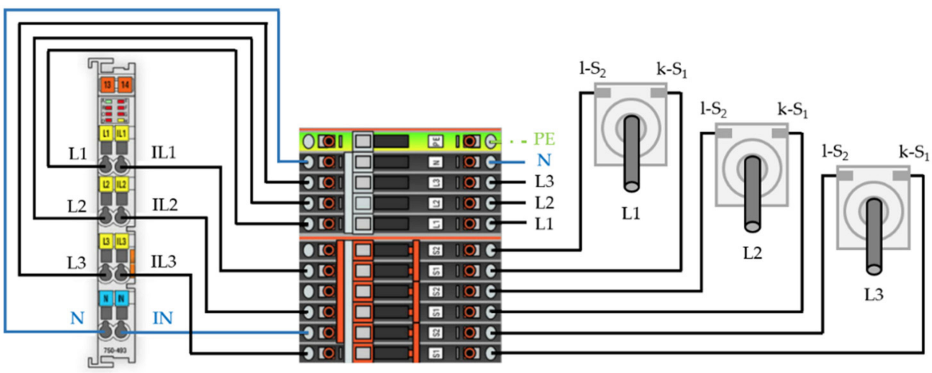


Figure 2. Circuit diagram: power module side.

Figure 3 shows the implemented measurement and DAQ module. The selected controller is further capable of storing data directly on a SDHC device, serving as an additional security layer. If network transfer would fail, e.g., due to a server maintenance or other, nonplanned downtimes, the processing data is still automatically stored within the memory device.

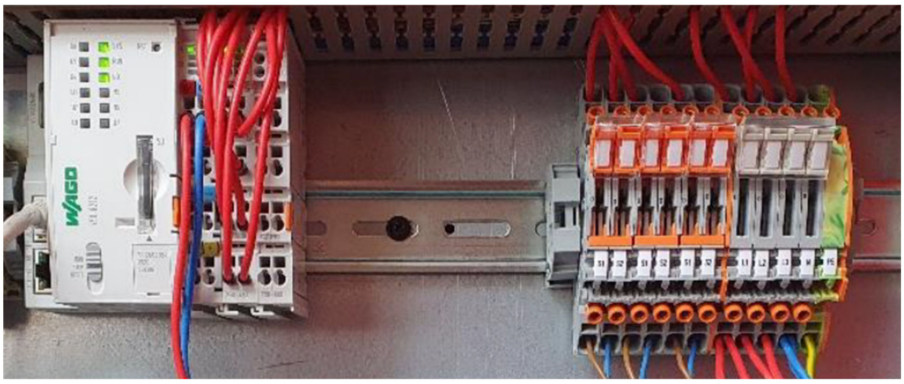


Figure 3. Controller (left) and terminal block (right) with wiring.

While the analog module automatically stores the measurement data, additional measurements can be manually added for the purpose of calibration or further specific analysis of defined indicators (e.g., with higher frequency). These measurements can be started and stopped with a graphical user interface (GUI), (Figure 4, dash button 'Electrical Measurement'), created with the Wago e!Cockpit software suite, which, moreover, allows real-time monitoring of the system parameters.

To apply various data processing programs to acquired data and minimize storage space to a reasonable size, all signals are converted and saved as pre-sorted text-files by an automatically working data transfer protocol, running simultaneously on two local computers. The SD-memory is checked for differences between its storage and the server storage every 24 h. If a deviation is detected (more/different data on the SDHC in comparison to the local raw data file storage), the raw data will be overwritten. In order to avoid a malfunction in the SDHC device, the stored raw data on the server is automatically mirrored, enabling the administrator to investigate potential errors after their occurrence. Because space on the memory card is limited to 32 GB, the card is automatically cleared after exceeding of 80% internal memory space. To guarantee no loss of data, the server storage is mirrored within each 24 h and stored to a SQL database, which operates on a different server partition.

The recorded data set contains the timestamp, active, reactive and apparent powers, currents, voltages, power factors and the quadrants of the three phases (Figure 4, yellow frame). The automatic measurement data recording is realized with a sampling frequency of 2 Hz, which was found to be sufficient from previous evaluations. A preprocessing algorithm also calculates the resulting machine costs according to the consumed apparent power (Figure 4, red frame), serving as a basis for the project management tool.

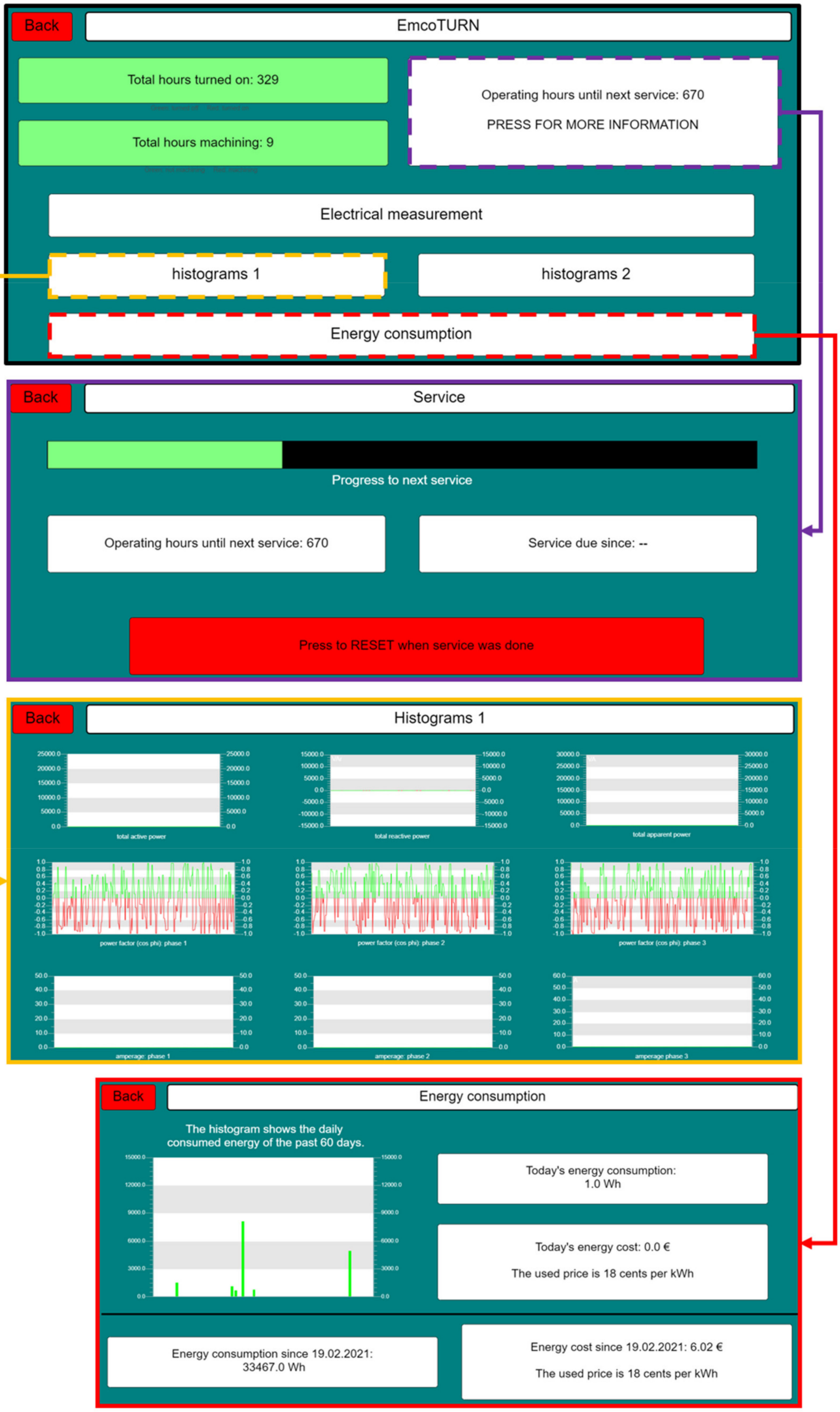
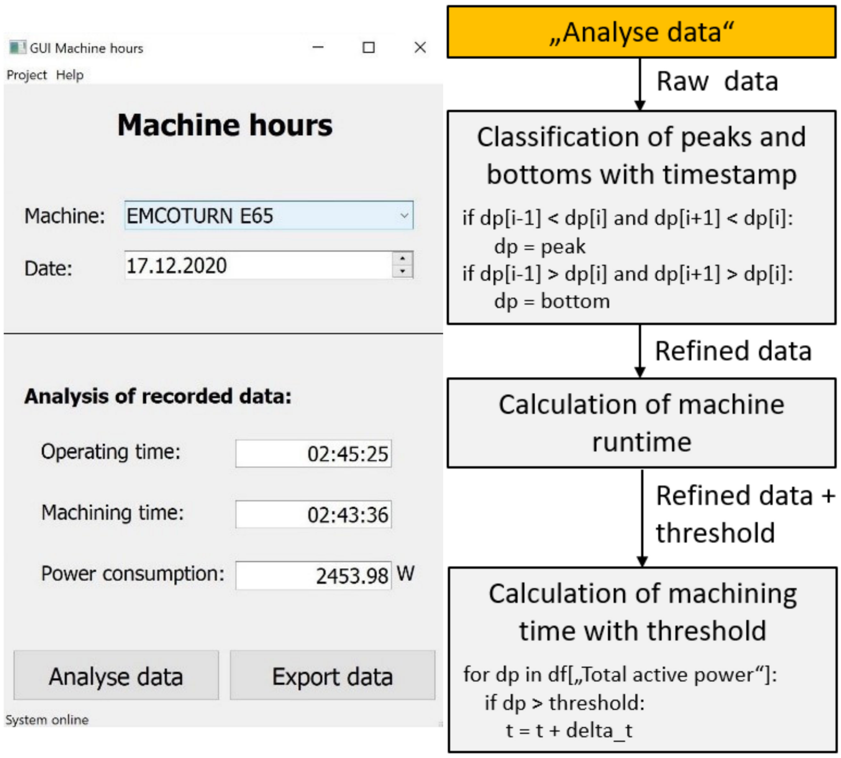


Figure 4. Wago GUI for measurement control (CNC-lathe).

Figure 5 shows the main GUI for the Python processing layer, which visualizes the non-idle machine hours from the recorded data, analyzed by the embedded programming algorithm [65]. In order to minimize data access time, previously refined data is stored for accounting and general project management purposes in the network within a second mySQL database, and it is made available to technicians and students.



(**a**) (**b**)

Figure 5. Python logic for machine hour counting: (**a**) visualization, programmed in QtPy; (**b**) back end logic for the GUI.

Figure 6 summarizes the first four layers of the low-cost layer architecture for the CNC-lathe, from implemented sensors to the main processing layer.

Table 2 shows the implemented roles and corresponding rights regarding viewing and changing settings within the PHP GUI for an exemplary project. The second SQL database, including the refined data as a result of the main processing layer, serves as an underlying fundamental for this GUI. Within the Python programming environment, input data from the PHP GUI (e.g., new projects or involved coworkers within a specific project) is stored automatically within the refined SQL-database. For the education of engineering students, the developed PHP GUI was duplicated and set up with realistic values to enable a comprehensive experimental setup without disturbing the workflow of respective employees. For this replica, students receive logins for every role, thus enabling them to work with existing roles and corresponding rights. This approach also enables the possibility to change the underlying logic in the back-end of the project management tool, giving deeper insights into PHP-based programming.

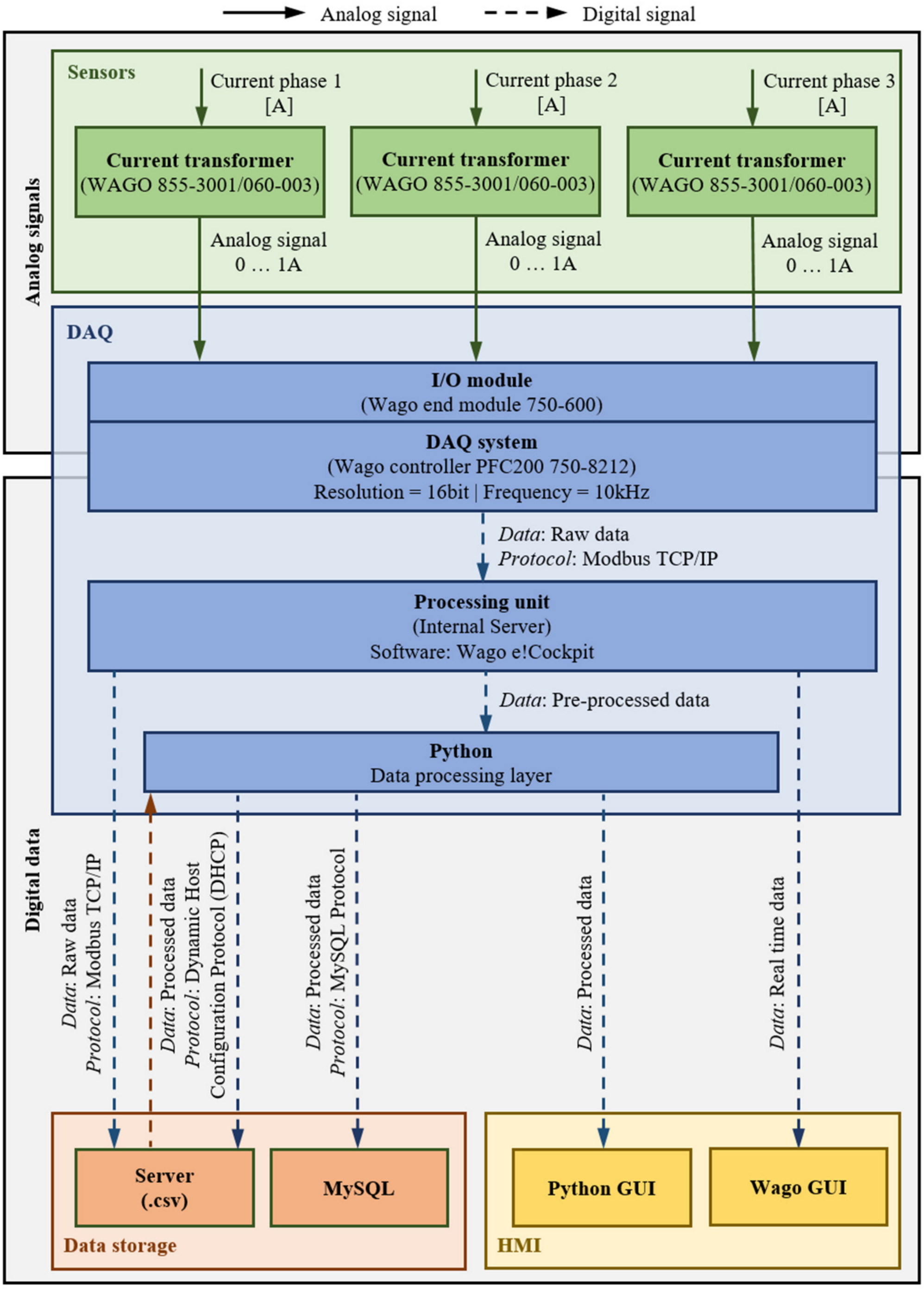


Figure 6. Data flowchart for the integration of the CNC-lathe into the low-cost layer architecture.

Table 2. Project management GUI: implemented roles and corresponding rights (E = employees/M = machines/P = project).

Role	Admin	Project Leader	Project Member	Technician	Other Personnel
Overview	X	X	X	X	X
Detail view	E/M/P	E/M/P	M/P	M	-
Set new project activities	X	X	-	-	-
Budget & cost details	X	X	-	-	-
Employee details	X	X	-	-	-
Change milestones	X	X	-	-	-
Change budget	X	-	-	-	-

The visualization and publishing of refined data for the interactive project management tool is done within the internal network using PHP programming, with a special focus on IT security due to the implementation of different roles with different rights within the PHP GUI (Figure 7).

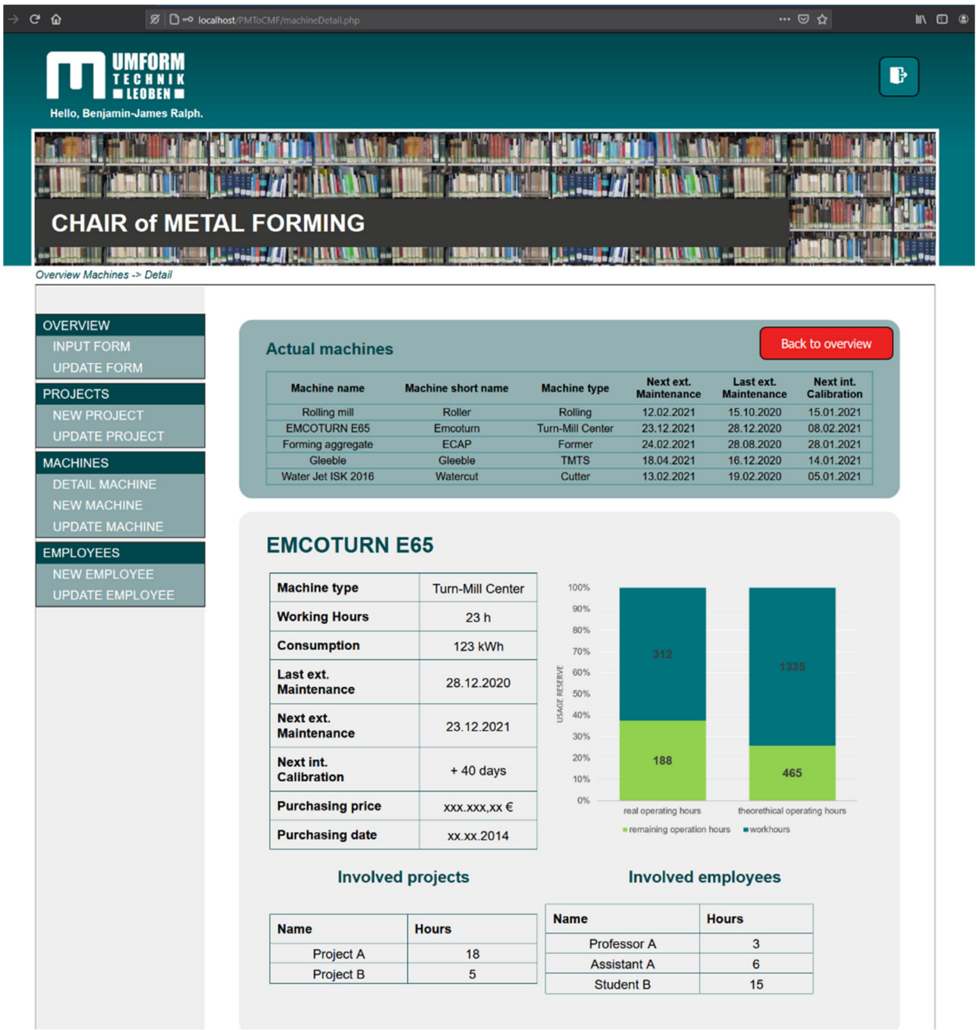


Figure 7. Interactive project management tool, programmed in PHP and directly coupled to an underlying MySQL database. The SQL database is coupled within the Python logic presented in this work.

Figure 8 illustrates the resulting six-layer architecture. To sustain a resilient, adaptive and smooth working system, the machine park and corresponding machine sensors are divided into different nodes. The number of machines coupled to one node is depending on the number of sensors and therefore data transferred, as well as the frequency required. For node 1, two heterogeneous aggregates are coupled to controller 1, whereas the CNC-lathe transfers 25 different indicators with a frequency of 2 Hz, running continuously. This results in a low and steady CPU usage on the respective controller. The second aggregate submitting data through node 1 is a retrofitted cold rolling mill, which transfers data from four different sensors with a frequency of over 500 Hz when operating. This frequency is only achievable through writing data directly on the RAM of the controlling device, resulting in a temporary additional CPU load of more than 80% on the controlling unit. This load peak must be considered when planning digitalization solutions because an overload cannot be avoided persistently in most of low cost controllers. In this case, the necessary algorithm, programmed in structured text format, must also be implemented separately as the used controller initially merely provides up to 1 Hz of acquisition frequency.

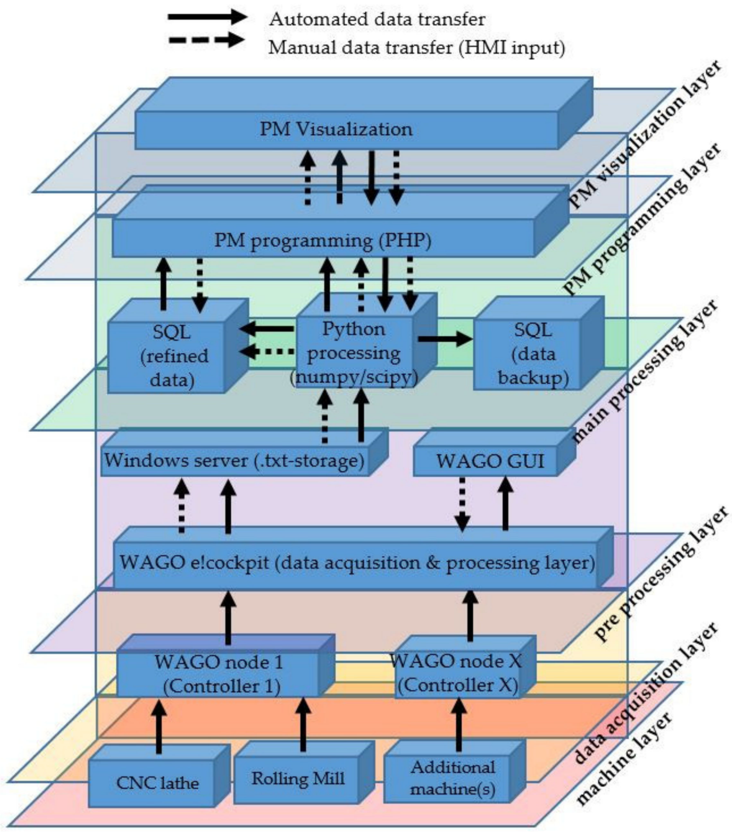


Figure 8. Resulting low-cost six-layer architecture.

4. Data Gathering for Initial Condition Monitoring and Further Analysis: A Case Study

As data science fundamentals become more important for future manufacturing experts, a simple case for the reproducible DAQ was defined and carried out. The objective of this approach was to collect data sets which can be easily edited by students on a basic level. Additionally, a simple state-of-the-art logic was implemented, serving as a basis for more sophisticated programming efforts within a supportive learning environment. The respective logic is initially able to distinguish between three states of the lathe system:

- Off;
- On but not working (idle time);
- Working (real machining time).

To be able to differentiate between real machining time (the CNC-lathe operates on a workpiece) and idle machine time (e.g., calibration, adjustment between two machining steps, set-up times), a pretest was carried out. In this pretest, idle mode, tool changer movements and main spindle rotations with different rpm without actually operating on a work piece were performed and analyzed to gain knowledge about the behavior of all recorded electrical parameters. This pretest exhibits the advantage of a low time consumption, allowing lecturers to demonstrate the data collection quickly and therefore enhance awareness of the comprehensive matter. Table 3 shows the 15 different settings investigated.

Table 3. Testing program for the identification of idle related change in electrical indicators.

Test No.	Type of Testing
1	X− transition of tool turret
2	X+ transition of tool turret
3	Z− transition of tool turret
4	Z+ transition of tool turret
5	Z− transition of tailstock
6	Z+ transition of tailstock
7	Counterclockwise rotation with 1000 rpm of main spindle
8	Clockwise rotation with 1000 rpm of main spindle
9	Counterclockwise rotation with 2000 rpm of main spindle
10	Clockwise rotation with 2000 rpm of main spindle
11	Counterclockwise rotation with 3000 rpm of main spindle
12	Clockwise rotation with 3000 rpm of main spindle
13	Counterclockwise rotation with 4200 rpm of main spindle
14	Clockwise rotation with 4200 rpm of main spindle
15	Full 360°rotation of tool turret

To analyze real machining time, a cylindrical workpiece (alloy steel, type 708M40) with a length of 250 mm and an initial diameter of 68 mm was axially turned at constant speed using a new cutting blade XMGC30 with an infeed of 0.5 mm per process step. An additional testing plan was created, consisting of constant machining parameters and using axial machining operations to reduce the base material in diameter (Table 4). In order to evaluate the influence of cooling on the power consumption of the machine, tests number 20 and 21 were carried out without the usage of the internal cooling system.

Table 4. Calibration plan and parameters for machining.

Test No.	Initial Diameter (mm)	End Diameter (mm)	Cooling	Rotational Speed (1/s)	Feed in (mm)	Cutting Speed (mm/s)
16	68.0	62.0	Yes	10	0.5	1.5
17	62.0	55.0	Yes	10	0.5	1.5
18	55.0	45.0	Yes	10	0.5	1.5
19	45.0	35.0	Yes	10	0.5	1.5
20	35.0	25.0	No	10	0.5	1.5
21	25.0	18.0	No	10	0.5	1.5
22	18.0	10.0	Yes	10	0.5	1.5

During the entire machining process, the measured sensor data was likewise recorded to identify the corresponding test data faster and figure out correlations between the machining time and the measured values. Another advantage of the control scheme is the opportunity to increase the frequency (simultaneously) while processing without interrupting the continuous DAQ process.

The analysis of all different types of electrical indicators shows that the total active power is the best suited indicator to distinguish between idle time and actual working time. Figure 9 shows the performed testing program according to Table 4, visualized using the Python matplotlib.py extension package.

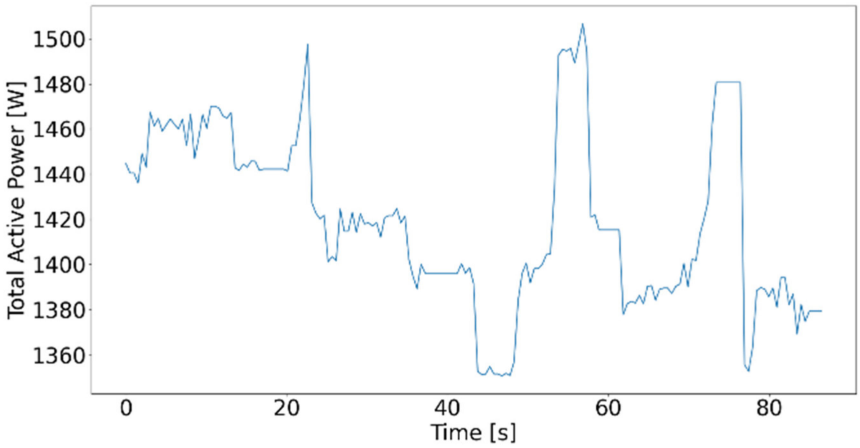


Figure 9. Total active power of idle tests carried out.

Figure 10 illustrates the total active power of test 13 and 14, a rotation of the main spindle with 4200 rpm. The power consumption does not significantly deviate for clockwise and counterclockwise rotation. For these tests, the average active power consumptions sum up to about 5100 W. This trend is also consistent with the results of paired tests at other speeds, i.e., test 7 and 8, 9 and 10, 11 and 12.

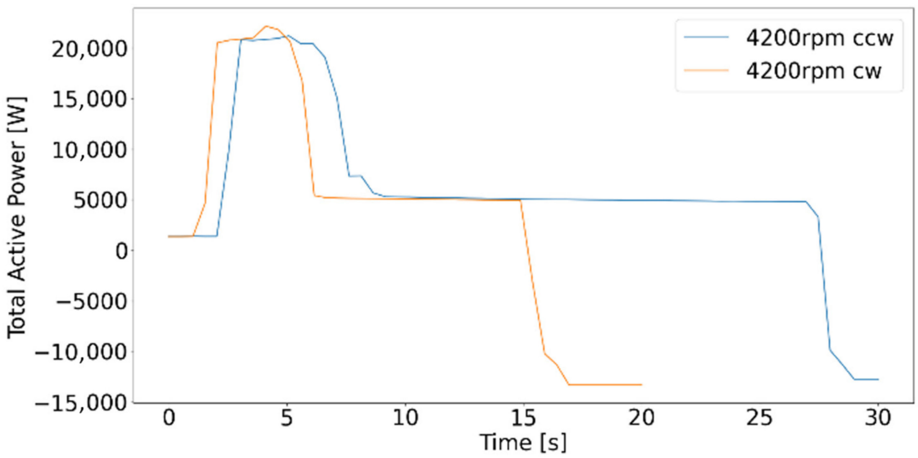


Figure 10. Total active power of tests 13 and 14.

Figure 11 shows the results of the tests with counterclockwise rotation at different speeds. As already shown in Figure 10, the power consumption remains constant after an initial peak. These plateaus increase in magnitude with speed. By analyzing the measurement data with Python, no trivial correlations or patterns were determined by reactive power, apparent power, phase current, phase voltage, power factor or phase angle. Through the visualization of the total active power, a comprehensible relationship can be established between the machining operation and the evaluated parameters.

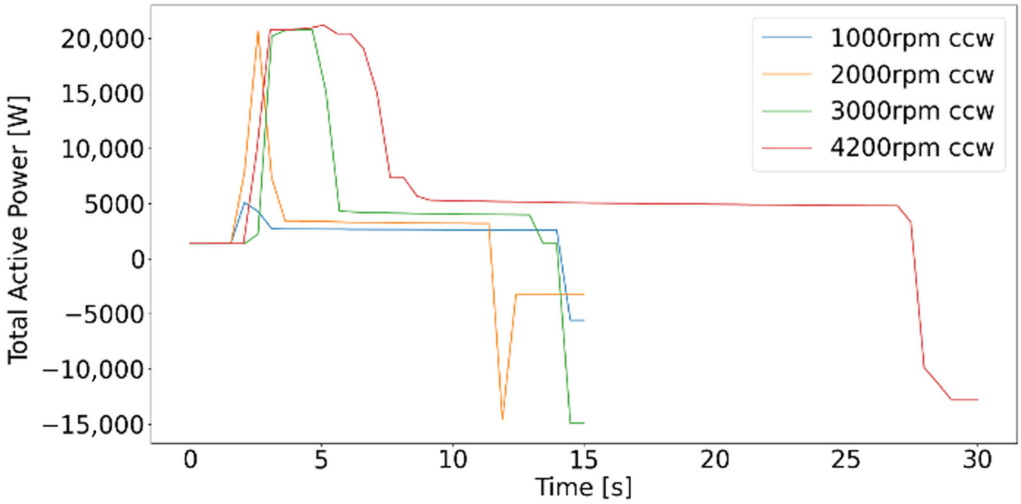


Figure 11. Total active power of tests 7, 9, 11 and 13.

As Figure 12 illustrates, a trend displayed by the dashed green line can be observed, which is a representative of the diameter and machined length. The negative measurement peaks, ranging from 50 to 550 W apart from the green trend line in terms of magnitude, represent the tool being set down from the workpiece and returned to the starting position to perform the next programmed process step.

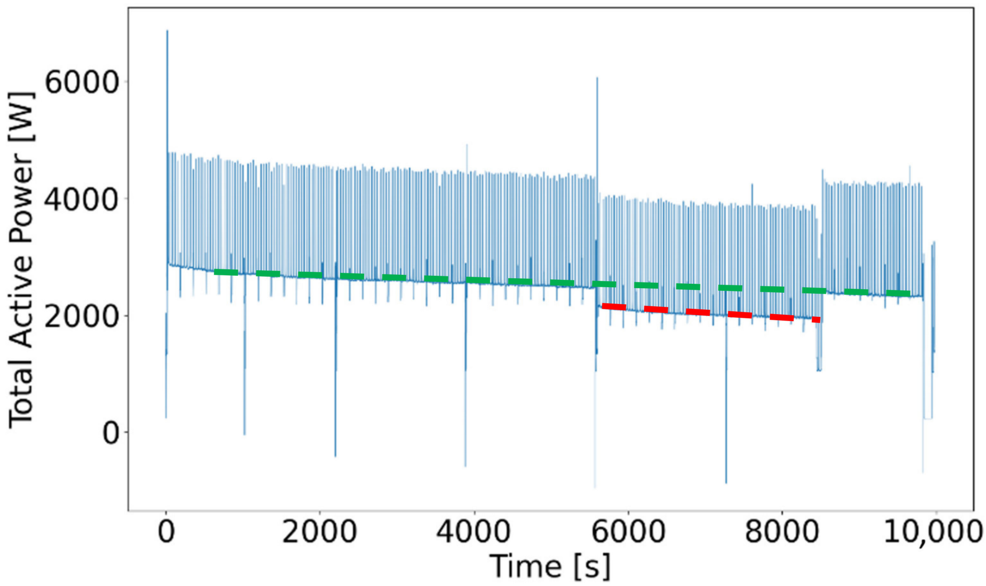


Figure 12. Total active power during axial machining.

To demonstrate the influence of adequate cooling, test numbers 20 and 21 were performed without cooling (Figure 12, red dashed line), resulting in a lower total active power in comparison to other test samples. The constant deviation from the green dashed trend line by an offset in magnitude can be explained as a result of decreasing power consumption due to unused aggregates for coolant supply. The number of negative peaks within Figure 12 is equivalent to the number of process steps for each test.

Figure 13 shows six of these smaller negative peaks that are equivalent to the number of processing steps of test number 16. If negative peaks fall below a total active power of 1500 W, the machinery is not operating—the time during which the total active power falls below this value does not contribute to machining and can be excluded from the machine-hours-counting algorithm.

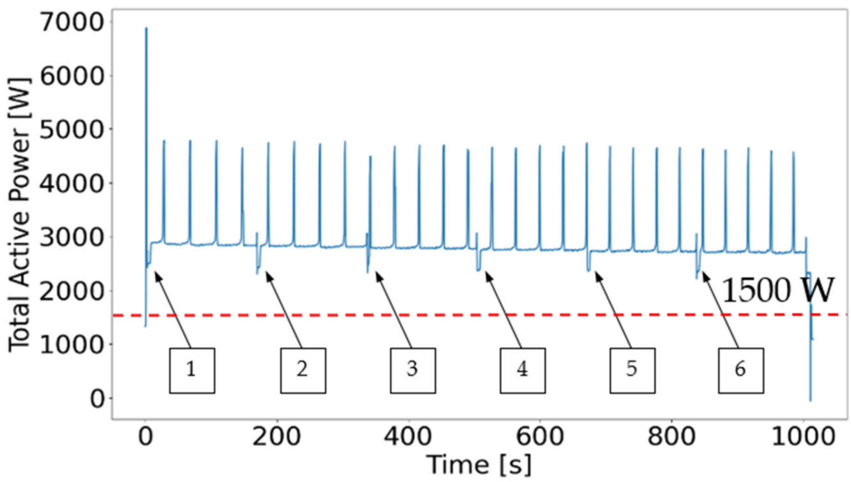


Figure 13. Total active power of test number 9.

Table 5 demonstrates the accuracy of the investigated behavior. A wrong classification of machining parameter data points is below 0.03%, which is not significant in terms of maintenance or machine hour calculations, and therefore, it is an activity-cost-based project management approach. If these tests were conducted more frequently, a higher number of heterogeneous datasets would be generated and simple machine learning algorithms for the classification of the respective data (e.g., Support Vector Machines, Decision Tree Analysis) can be instructed [66,67].

Table 5. Data point classification.

	Data Points Real Machining	Data Points Idle Machining
Sum	19,960	174
Right	19,440	173
Wrong	520	1
% Wrong	0.026	0.0057

Due to the relatively short recording time for test numbers 7 to 14 (20–30 s), higher mean values and standard deviations arise compared to machining tests 16 to 18. The shorter the recording time, the higher the influence of peaks at the beginning and the drop at the end of the data set (Figures 9 and 10), leading to the resulting deviation. This divergence also demonstrates the significance of encompassing statistics behind data-driven technology and the relationship between the amount of data and prediction accuracy.

Table 6 shows the calculated peak values, the mean values as well as the standard deviations of all test numbers listed in Tables 3 and 4. The precise identification of real machining and therefore actual wearing of the analyzed aggregate has several advantages. Before the development of the discussed architecture, ordinary maintenance was executed after specific time intervals, instead of considering the effective wear of the machine system. The implementation of this framework enables maintenance intervals to be determined on the basis of actual machine hours. This approach leads to lower maintenance costs because unnecessary servicing is minimized and additional necessary maintenance is recommended. As a result, periods with higher machine utilization are identified automatically and quantitatively. For a more efficient scheduling, the residual time until the next external service is calculated as a moving average. The exact predictability increases with the duration of the system's utilization. For a further cost reduction, a standardized internal calibration test was developed. After exceeding 25% of calculated machine hours until next external service, a standardized test, serving as an indicator for possible malfunctions within the aggregate will be executed. The machining time left until the next internal service is implemented within the project management GUI (PHP/Python) as well as programmed Wago GUI (structured text). After internal or external service, the calculation can be reset within the corresponding GUI.

Table 6. Analysis of peak values, mean values and standard deviation of all tests.

Test No.	Peak (W)	Mean (W)	Standard Deviation (W)
1	1400.52	1373.97	22.45
2	1506.73	14,447.17	41.40
3	1470.10	1453.34	11.17
4	1497.68	1417.77	23.17
5	1480.63	1416.03	39.87
6	1394.20	1379.81	11.69
7	5081.58	2053.05	2198.34
8	10,064.27	2586.07	1864.12
9	20,644.23	1979.91	5508.34
10	20,754.51	2997.70	6094.99
11	20,723.80	4685.71	8261.15
12	20,752.01	607.02	10,746.6
13	21,175.08	5664.18	7751.18
14	22,137.44	3658.69	11,133.24
15	3374.98	1949.28	864.02
16	6879.55	2840.18	403.78
17	4655.05	2731.31	406.98
18	4590.80	2676.75	405.01
19	4929.11	2599.64	423.23
12	6070.17	2140.74	409.52
21	4245.32	2035.68	449.24
22	4556.87	2270.27	717.81

A substantially more precise calculation can be achieved by the developed project management GUI. As the system provides the real power consumption of the aggregate, internal as well as external projects can be calculated on a more reality-based manner. While the PHP interface authorizes respective project leaders to set up new projects and enter personnel costs with or without the usage of machines, the system also substitutes different manual working hour recordings, which were carried out for internal projects individually and more qualitatively until the implementation.

To ensure a learning experience that is as close to reality as possible by a reasonable data set from machine systems as well as the developed project management tool, the initial framework is also used on a daily basis by the personnel at the institution. When implementing new IT infrastructures with a higher level of automation, it is essential to involve the staff and identify their preferences at an early stage of the introduction. Therefore, all co-workers were briefed and asked about their opinion towards a project management system and what it is supposed to contain to facilitate the daily workflow. As a result, the PHP GUI was adapted several times, considering the preferences of respective employees. Moreover, the Wago as well as PHP GUI is available on every computer device within the local network of the academic institution, which allows all involved personnel to start measurements, overview specific machines and create or update projects independently from their specific location (depending on individual rights). Through secured VPN access, a completely remote condition monitoring is possible. This degree of freedom also offers students the possibility to engage with and refine the system remotely if access is given by respective lecturers.

5. Integration of Numerical Simulation and Implementation of a High Frequency DAQ Architecture

Due to the rise in computational capacity and speed within the last decades, the possibility of integrating real-time numerical simulation within the actual production process becomes more and more suitable among the manufacturing environment [68].

Therefore, the presented framework can be extended to include numerical simulation (near) real time in a variety of production processes.

Figure 14 visualizes the additional integration of a finite element analysis (FEA) program within the developed framework. In this example the Python GUI adapts different rolling steps within one rolling operation based on the results of a FEA, calculated during the time required for the previous process within the production operation and under consideration of processing and material properties.

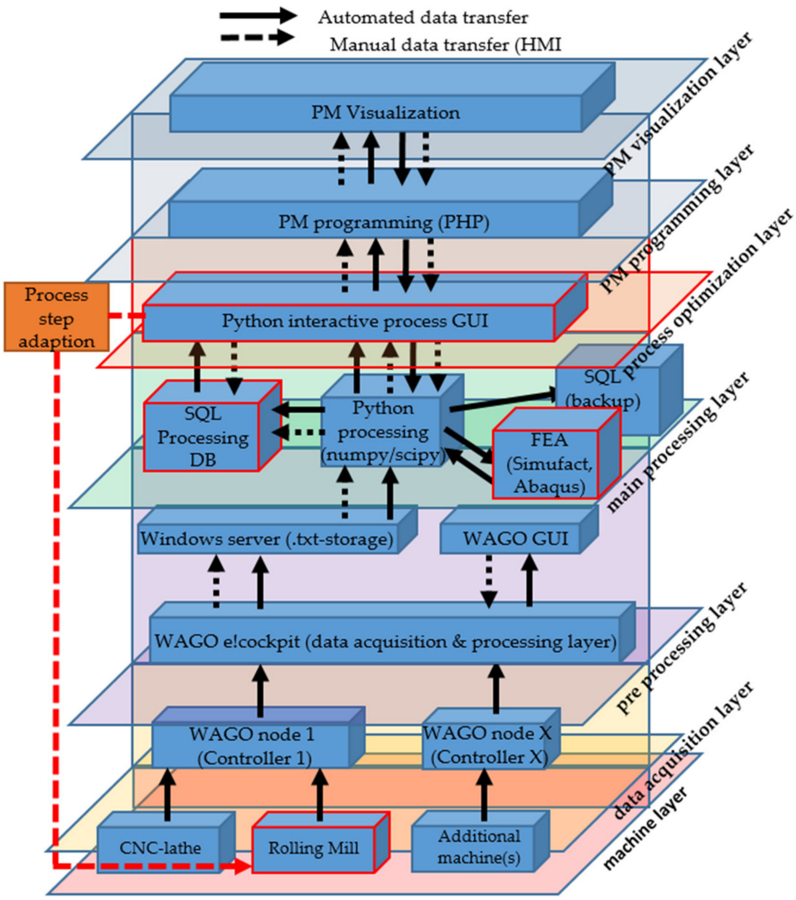


Figure 14. Six-layer architecture with integrated numerical simulation: FEA digital shadow for semi automatized process adaption (example rolling mill).

Based on the knowledge gained from the case study in Section 4, the integration of sophisticated numerical simulations into the framework derives in a broader understanding of the possible advantages of these technologies. Nevertheless, most material processing operations, especially high temperature forming processes, require constant surveillance of the material behavior under enhanced temperature and forming conditions. In order to be able to handle a forming process of a particular material, it is necessary to have a certain comprehension of microstructural changes. In general, extensive material parameter studies are indispensable for predicting the final microstructure resulting from the forming process, such as anisotropy and the resulting grain size or grain size distributions, as well as possible material damage influencing variables [69].

In an increasing number of cases, integrated microstructure models are used in the numerical simulation of a forming process as accompaniment, relating the occurring forming parameters (e.g., temperature gradient, strain rate) to the resulting microstructure changes such as static or (meta-) dynamic recrystallization as well as grain growth [70]. The required material parameters are commonly obtained in suitable thermomechanical simulators, that operate on a laboratory scale [71–75]. Since the processes proceed expeditiously, especially in the case of simultaneous forming at high strain rates, it is essential for material data acquisition to ensure a significantly higher sampling frequency of the system [76,77]. For this reason, an additional DAQ system provided by iba was implemented at the institution's thermo-mechanical treatment simulator (Type Gleeble 3800). This DAQ is widely used in industrial practice, offering different software packages and the possibility of significantly higher sensor sampling rates for further processing [78,79]. The connection between the sensors and the system is realized with a proprietary A/D converter, transferring digitized data by a fiber optic line with up to 100 kHz on four channels:

1. Temperature;
2. Dilation of the respective specimen;
3. Resulting Force;
4. Displacement.

The gathered data is preprocessed directly within the ibaAnalyzer software package and automatically submitted to a file system hosted by the internal server architecture of the institution.

The high sampling rate offers the possibility of investigating the influence of time-dependent changes in material behavior by measured values. The resulting data sets can be further used to develop and adapt numerical models to digital shadows and, in long instances, digital twins [80,81].

The Gleeble system, like a majority of highly specialized material testing aggregates, offers a proprietary software solution for resulting data analysis. By recording a hot tensile test of bainitic steel and comparing the results of both data sets, previous work of the authors revealed a significant difference in the gathered temperature data, which indicates an internal data preprocessing and correction of the proprietary software unit [38]. Due to the low output voltage signal of thermocouples used, a voltage fluctuation within 10^{-3} V results in a temperature deviation of 250 K. Figure 15 illustrates this deviation. These examples can be used to raise awareness about these kinds of potential inaccuracies.

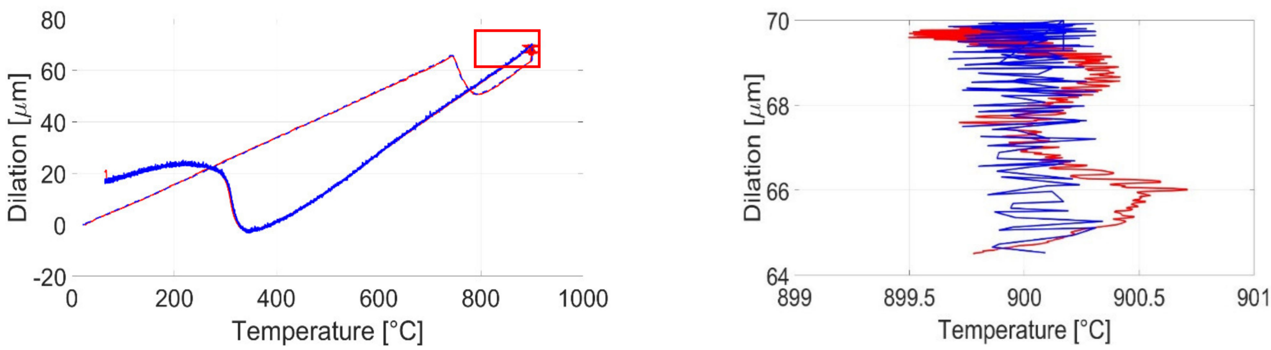


Figure 15. Dilation curve for a tensile test of bainitic steel, carried out with the Gleeble system [38]: (**a**) temperature change with respect to dilation, blue line: Gleeble data set, red line: iba data set; (**b**) cutout area of deviation between both data sets from (**a**).

Figure 16 visualizes the resulting architecture, from the applied sensors to the (refined) data storage at the internal server.

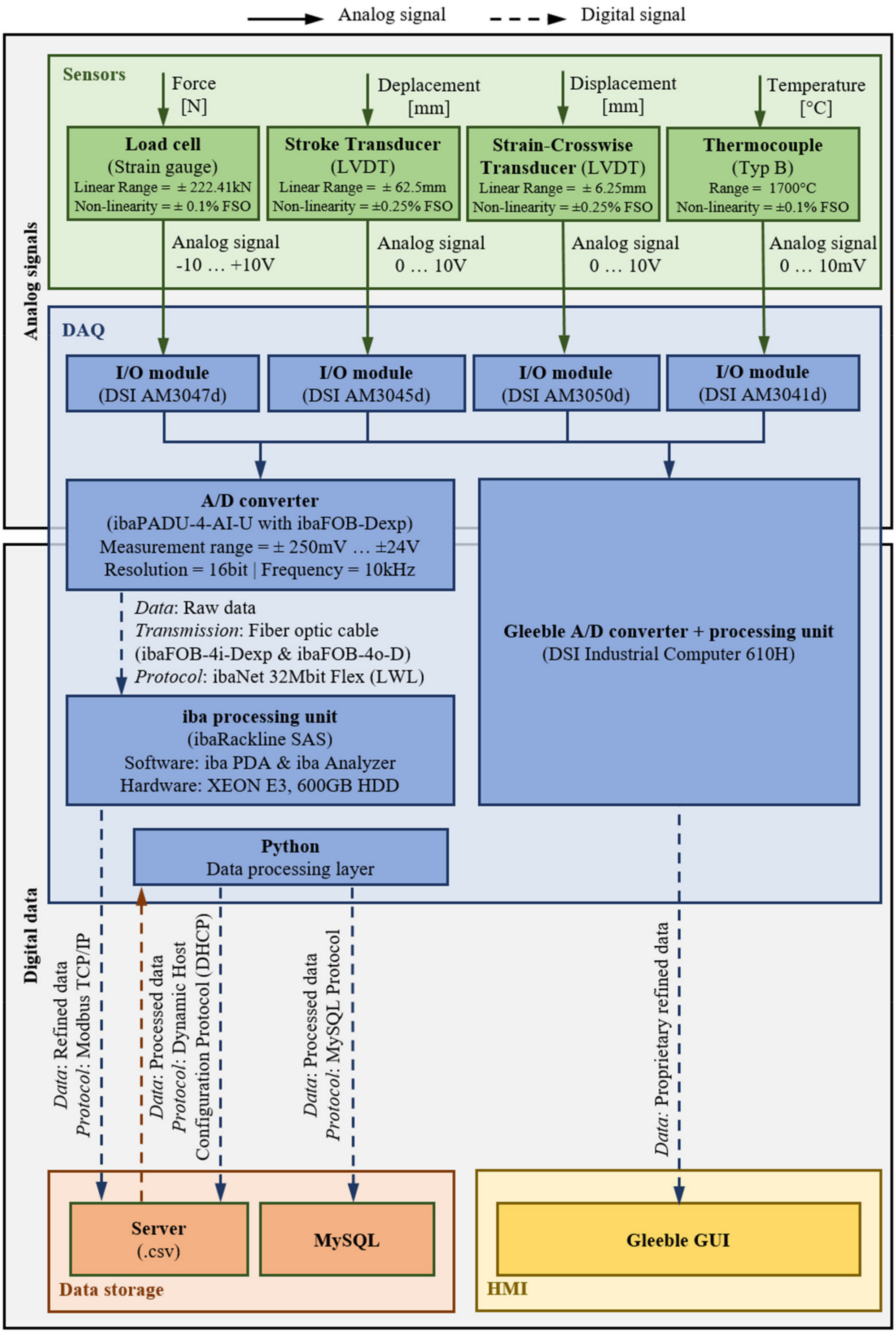


Figure 16. High frequency DAQ and data storage.

6. Results and Discussion

As a result of this work, a six-layer architecture was designed, concentrating deliberately on the use of a few selected products (open source if possible) in order to make application and modification by interested parties as simple as possible. Additionally, a second DAQ system was developed to give this group the opportunity to gain data for real physics-based numerical simulations. Besides, the most important objective was to create a smart factory layout that enables students and practitioners from the metal processing field to engage with different levels of digitization and digitalization, reaching from analog signal to numerical simulation integration. The resulting layer architecture is highly adaptable in terms of the used programming languages (e.g., Python can be substituted with C++ or Java if preferred; mySQL can be substituted with flux). This architecture fulfills three purposes. First, a technical fundament for teaching students in manufacturing related disciplines was created, which allows the following:

- To gain an overview about the most important fundamentals of networking technologies and corresponding protocols in the manufacturing environment;
- To deepen knowledge on manufacturing related data science by working with different amounts and homogeneous as well as heterogeneous data sets;
- To be able to work with different types of DAQ systems used in industrial practice;
- To optimize interfaces and investigate interface-related efficiency and effectivity concerns in-person or remotely;
- To enhance knowledge about common programming languages and machine learning technologies in manufacturing by working with real data from machining processes;
- To obtain an overview of interactive project management and how (near) real-time adaption of required parameters (e.g., cost changes) can affect project outcomes;
- To raise awareness about the importance of transdisciplinary communication and education in the manufacturing field.

The second operational area of the implemented framework is the research and development of state-of-the-art digitalization technologies, based on this initial work by the following:

- Extending the framework with other, more complex machine systems (e.g., hydraulic presses, ovens);
- Extending the framework with more complex machine systems by developing predicting algorithms including thermo-mechanical properties of materials;
- Using this algorithms for the transformation of existing machine systems to Cyber Physical Production Systems (CPPS) based on the brownfield approach [82,83];
- Integrating further open-source-based logic between these CPPS, resulting in a superordinate Cyber Physical Logistic System [84–86].

The third purpose is the collaboration with interested parties from the industry, especially SMEs, who can use this framework within interdisciplinary projects. This approach has the main advantage of giving industrial experts the opportunity to deepen their knowledge or perform highly experimental tests. Additionally, engineering students are given the possibility to collaborate with these companies from an early stage, gaining additional practice and establishing networks already during their studies.

The presented architecture in Section 3 is an efficient and effective way of taking advantage of current information and communication technologies within a small volume and high-variety production environment. The tools and programs used are either low-cost or even completely free-of-charge, therefore providing an ideal basis for digitalization of small production facilities from scratch. To build up such a low-cost, resilient system, the following points must be considered:

1. How many different channels (different values from sensors, e.g., pressure, force, dilation, temperature) are needed for each respective machine system? (specification of needed input modules);
2. Which frequency is needed for each channel? (avoidance of aliasing, dependent on the process and respective material characteristics);
3. What kind of database is applicable within the respective company? (considering internal know-how and experience);
4. How resilient does the physical hardware and software have to be? (dirt, dust, temperature, accessibility, space);
5. What IT-infrastructure serves as a basis for the framework? (Windows, Linux, other server—OS);

6. What kind of GUI/HMI do respective employees favor?

The individual answer to (1) implies knowledge about all respective machine systems. In general, one can recommend starting with one system where all (from a present point of view) required sensors are already applied and the resulting data is understood.

Answering (2) seems more complex because the required frequency depends on the purpose. In the case of the rolling mill at the academic institution, a medium frequency is needed. In case of the discussed CNC lathe, a much lower frequency is applicable because the process itself is highly standardized trough the internal machine control unit. For high temperature or high-speed forming processes, a significantly higher sampling rate has to be ensured. In general, if the material behavior itself should be analyzed, higher frequencies are mandatory (e.g., considering microstructural changes due to applied or internal forces or as a function of the temperature gradient in case of an involved heat treatment).

Question (3) is dependent on the internal knowledge. If no specific database system is used, open-source programs can be recommended.

Question (4) is heavily dependent on the specific environment. If existing sensors are working within the environment, the sole important point to consider in this case is the resilience of the respective controller. Most Supervisory Control and Data Acquisition (SCADA) suppliers offer specific, more robust solutions (e.g., Wago XTR series).

Regarding (5), an efficient and stable interface between the resulting storage solution (server or PC) must be programmed. In this study, a regular windows system was used. One of the advantages that Python and its various extension packages offer is the very broad possibility of interface programming. There are different types of extensions for the coupling of different IT-systems to the controller system available. The controller system itself in this case produces txt-files, which then were automatically implemented in the SQL based database system as well as stored parallel on the used windows server system.

The answer to (6) is crucial for a successful implementation. Without considering the experience and preferences of involved employees on the shop floor, a well-planned digitalization solution is likely to fail. Including respective workers in the development of user interfaces at the earliest possible stage helps to successfully implement and sustain the change in working environment.

The second architecture should serve as an additional expansion to higher frequency DAQ technologies with a special focus on data gathering for numerical simulations. From a network technology and data science point of view, the most essential questions to answer, additionally, are as follows:

7. What sampling rate is sufficient to obtain enough data for an accurate material behavior prediction? (e.g., recrystallization behavior of the investigated material under defined process parameters)
8. How accurate are implemented DAQ systems? Is it possible to confirm resulting data?

These points should be considered intrinsic by each engineering student who strives for a career in a digitalized metal processing environment. This work should therefore give an experimental basis to concretize the answers given by the author for specific cases.

7. Conclusions and Outlook

This paper describes the development of a six-layer smart manufacturing architecture for the transdisciplinary engineering education. For this purpose, two DAQ systems—one to demonstrate fundamentals and possibilities of open-source low-cost digitalization solutions and a second for high frequency measurement applications—were developed and implemented. For both architectures, case studies were provided to enhance comprehensible teaching in a digitalized manufacturing environment. A major advantage of the proposed structure is the open-source components used wherever possible. The selected technologies are already common in industrial practice, due to the high degree of connectivity, cost efficiency and practicability in the metal processing environment.

As measurement results of the high frequency architecture are stored within the same server architecture as the Wago DAQ system, respective data can be analyzed and further processed in the same Python environment. The Gleeble system coupled in this network is also a widely used simulators in the industrial practice, especially in the research and development field. By including this system into the layer architecture and coupling this architecture with a superordinate MES, the horizontal integration of different departments in the manufacturing environment can be simulated. Because the complexity in the academic institution's learning factory (14 heterogeneous machine systems with different initial degree of automation) can be defined as similar to those in SMEs, a low-cost open-source solution can be programmed and implemented to serve as MES. By using Python for this purpose, already-existing extensions for the coupling with an ERP program can be realized efficiently, allowing students and future manufacturing experts to use this framework for the simulation of manufacturing processes from initial digitization to the coupling with, e.g., corporate accounting or procurement. The Montanuniversität Leoben additionally launched the new bachelor's program Industrial Data Science, focusing on the transdisciplinary engineering education with special emphasis on data gathering and processing within the material processing environment. As additional machine systems are integrated within the frameworks, machine learning algorithms can be further implemented and optimized by interested engineers for data monitoring applications. The monitoring and malfunction detection as well as related IT-security issues, highly discussed in the current literature [87–89], can further be used for the deeper education of future industrial data scientists.

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A 6 Publication 6

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Conceptualization of the Lecture 'Digitalization and Digital Transformation in Metal Forming' based on Implications from Contemporary Teaching and Learning Theories

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Abstract

In the modern world, the economy and society are affected by ongoing changes triggered by a multitude of influencing factors, e.g., digitalization, (g)localization, and global pandemics. Therefore, industrial engineering education needs to focus on the ongoing evaluation and the continuous development of new, respectively adapted, teaching and learning approaches to contribute to the continuous development of abilities, skills, and competences of the human workforce. Based on the implications of current teaching and learning theories, this paper focuses on the conceptualization of the lecture 'digitalization and digital transformation in metal forming'. As a result, the authors present a module-based structure that includes theoretical lectures, practical demonstrations, group discussions, and industrial case studies. The developed teaching and learning concept can be used as a reference guideline to contribute to professionalization and lifelong learning for the industrial engineering profession.

1 Introduction

Industry 4.0 approaches offer a multitude of new concepts and technologies to increase the competitiveness of manufacturing enterprises by relying on the basic principles of digital interconnectivity, autonomization, self-control of systems, and big-data analysis (Bosch et al., 2017; Woschank and Zsifkovits, 2021). Thereby, the usage of new technologies like artificial intelligence, machine learning, deep learning, as well as other IT-related innovations, will have a significant impact on the many fields of action within a manufacturing enterprise, e.g., on the strategic and tactical process optimization, cyber-physical systems, predictive maintenance, hybrid decision support systems, production planning and control systems, and the improvement of operational processes (Woschank et al., 2020).

In this context, the systematic evaluation of potential barriers and necessary requirements for a successful implementation of Industry 4.0 initiatives indicates a tremendous need for the realignment of current learning and teaching approaches in industrial engineering education (Dallasega et al., 2019; 2020; Woschank and Pacher, 2020).

Up to now, only a few studies have dealt with the design of new lectures based on empirically validated success factors for the further development of human skills and competences in the modern industrial environment. Additionally, current initiatives regarding the development of teaching and learning in industrial engineering education seem to ignore a multitude of potential exogenous and endogenous influencing factors in professionalization processes, leading to low efficiency in the proposed achievement of the established learning outcomes.

Therefore, this paper reflects current teaching and learning approaches that are applied to the new conception of the lecture ‘digitalization and digital transformation in metal forming’. The lecture will be further divided into four modules, ‘Module I: Digitalization – Theoretical Part’, ‘Module II: Digitalization – Practical Part’, ‘Module III: Digital Transformation – Theoretical Part’, ‘Module IV: Digital Transformation – Practical Part’ and contains a balanced mixture of theoretical lectures, practical demonstrations, group discussions, and industrial case studies by using a hybrid approach of both online and offline settings supported by state-of-the-art technology. Finally, the concept lecture can be seen as a starting point for the systematic development of competences regarding the areas of digitalization and digital transformation in metal-forming-related production systems.

2 Teaching and learning theory approaches

Learning can be defined as a lifelong process that is based on continuous reflection and change processes in confrontation with oneself and with the environment. Thereby, exemplary learning environments are work, education, leisure, further education, family, and friends. Learning takes place any in these learning environments or within the framework of transitions between them. In this context, the concept of lifelong learning (LLL) describes the necessity to learn during the entire life based on structured educational and learning processes, due to the ongoing changes in the knowledge society (keywords: industrialization 4.0, the half-life of knowledge, etc.) and the associated need for action. These targeted learning activities aim at the continuous improvement of subjective abilities, skills, and competences. The approach of LLL leads to a delimitation of learning and, thus, to massive changes at the institutional level. Accordingly, the pedagogical focus should not only be placed on the design of appropriate learning environments, but also on the creation of appropriate institutional frameworks. Thereby, the modularization of educational offerings can be regarded as one way to create flexibility and achieve the goals of LLL initiatives. In any case, networking and cooperation are essential on all levels. Educational institutions on various educational levels must be more closely coordinated to develop the so-called transversal competences. Also, the forms of learning must be expanded to include informal and non-formal learning processes. Thus, previous learning experiences must be interlinked with subsequent individual and organizational learning experiences. This should influence not only the micro-level, but also the meso- and macro-level of LLL (Hof, 2013). Moreover, the perception of transitions must be more strongly focused on both the individual and the institutional side. A precise framework of educational needs and educational necessities must be defined and, therefore, operationalized, on the institutional level, as well.

2.1 Teaching and learning processes in transitions

Due to the current characteristics of modern societies, the decoupling of standardized curricula vitae, flexibilization, and the focus on learning within the curriculum vitae becomes necessary. However, lifelong learning activities are not linear and continuous, thus they are determined by transitions, i.e., situations of upheaval or transitions with challenges for new- or re-learning. Transitions can be defined as social processes that enable changes in habits, patterns of action, and behavior (Felden, 2014). Particularly, in the current situation of social upheaval, every transition triggers subjective learning experiences and learning processes that transform the unknown into the known, and vice versa. In these transformations, not only is new knowledge acquired but also a new perception of the world is generated. In this context, Marotzki and Koller refer to the framework of ‘transformative educational processes’ (Hof, 2013). Mezirow further argues that, in line with the theoretical considerations of Habermas, learning always takes place through interaction and that, in the context of transformative learning processes, a reflexive discourse is needed as an essential dimension for achieving a mutual understanding and a change in subjective attitudes (Zeuner, 2014). Moreover, challenges in transitions require a closer look at learning and educational processes. In the sense of a phenomenological or socio-constructive view of learning, this can be generated by experiences, for example in the daily life. The social constructivist theory of learning assumes that learning interlinks new and existing experiences and then creates a subjective perception of the world that is determined by cultural, normative, and social interpretations. Accordingly, learning starts from the individual and subjective human experience within their ‘worlds of learning’ (Felden, 2014). The goal of the transformative learning approach is the individual as well as the collective development of the ability to act in the respective living environments, both from a social and a political perspective. This implies an ongoing change and/or further development of changes in all life situations.

Therefore, the current teaching and learning theory approaches and frameworks must be modified and/or extended according to the current trends described above to generate new strategies for action. For students and future experts, it is essential that the learning processes during the selected curricula are to be regarded as 'useful'. Accordingly, learning as a societal requirement further involves the removal of boundaries at all levels (e.g., forms of learning, places of learning, learning media, and learning times) (Maier-Gutheil, 2015). In this context, the implications of Woschank and Pacher (2020) will be used for the professional planning and monitoring of teaching and learning processes in the context of ILEE by developing a new conception of a lecture in the following chapter.

3 Lecture 'Digitalization and Digital Transformation in Metal Forming'

This lecture deals with the fundamentals of the fourth industrial revolution, under special consideration of issues regarding the metal forming industry. Especially in metal forming, which can mainly be divided into forging and sheet forming, specific issues arise when state-of-the-art holistic digitalization frameworks are applied. Complex processes, and, in general, a low degree of automation make it difficult to apply real-physical decoupled, data-driven digitalization solutions to this industry field. During research carried out at the Chair of Metal Forming at the Montanuniversitaet Leoben in 2019, the following concepts and key technologies were identified as an enabler for a successful digitalization and digital transformation in this industry segment: 1) Cyber Physical Production Systems (CPPS) with special focus on their Human Machine Interface (HMI) on the shop floor; 2) Industrial Internet of Things (IIoT), related transfer protocol technologies and corresponding IT-security approaches; 3) Finite Element based Digital Shadows (DS), Digital Twins (DT), and their connection to Artificial Intelligence (AI) and Big Data Applications; 4) Change Management, especially bottom-up commitment (Ralph and Stockinger, 2020; Zsifkovits and Woschank, 2019; Rauch et al., 2020).

3.1 Objectives

This lecture aims to get to know the potentials and challenges of the fourth industrial revolution in the field of metal forming. The theory learned is demonstrated using practical developments at the Chair of Metal Forming.

After successful completion of this lecture, students should be able:

- to create and evaluate concepts for the digitalization in metal-forming-related production systems
- to apply the theoretical concepts in the case study
- to apply and implement them together with experts from different disciplines
- to understand and implement the applied procedures in practice based on the theoretical and practical knowledge acquired

3.2 Main schedule and assessment

The lecture is characterized as an integrated lecture (IL) and will be supported by Moodle in a flipped classroom style. During the attendance times, the respective valid hygiene measures and guidelines are included in the execution. The lecture will be implemented in summer semester 2021 with a workload of 2.5 ECTS within the following timeline of the modules:

- Module I: February-March
- Module II: April
- Module III: May
- Module IV: May-June

3.3 Assessment criteria

Due to the focus on measurable and comparable learning outcomes, the 'learning outcome approach' was applied. According to Adam (2004), this approach includes "[…] what a learner is expected to know, understand and/or able to demonstrate at the end of a period of learning. They are usually defined in terms of a mixture of knowledge, skills, abilities, and understanding, that an individual will attain as a result of his or her successful engagement in a particular set of higher education experiences." The learning outcome orientation should aim at the quality development of educational measures as well as make learning outcomes visible and above all comparable. The challenge is "how learning outcomes can be systematically achieved, described, recorded, and compared" (Schlögl, 2012). According to this, however, learning outcomes can only be determined 'pragmatically', since both the learners and the teachers and the entire teaching and learning process influence the 'learning outcome' (Pacher, 2019). The more accurately these learning outcomes reflect real learning achievements, the greater the success (Zürcher, 2012).

Different measurement methods are used to evaluate the students' performance and are shown with percentages, as the following overview shows:

- Module I: Written exam, 60% of grade
- Module II: Cooperation during the practical demonstration, 5% of grade
- Module III: Contribution during the discussion, 5% of grade
- Module IV: Presentation, 30% of grade

The first module concludes with a written test to assess the students' theoretical knowledge. This basic knowledge is an essential prerequisite for the following modules and practical training. In further modules, the focus is also on cooperation and active participation in various practical training courses. Accordingly, the respective cooperation is documented by the lecturer throughout the lecture and then included in the overall evaluation. At the end of the lecture, the theoretical and practical contents worked out in the modules are presented to the plenum. The students have the task to present a strategy and an operational approach for a digitalization project.

3.4 Grading

The grading follows the following 5-part scale:

- Not sufficient (5); < 50%
- Sufficient (4); ≥50 - <62.5%
- Satisfactory (3); ≥62.5 % - <75%
- Good (2); ≥75% - <87.5%
- Excellent (1); ≥87.5%

3.5 A generic overview of the structure

This lecture will be mainly divided into four parts: 1) Theory of fundamentals in digitalization: A face-to-face introduction in the lecture structure followed by Moodle supported self-study of the theory; 2) Practical demonstration on digitization and digitalization technologies at the Smart Forming Lab at the Chair of Metal Forming (Ralph et al., 2020); 3) Digital transformation in metal forming: Face-to-face discussion of practical issues regarding implementation of digitalization technologies in the metal forming industry (Change Management); 4) Case study about a typical digitalization project in the industrial environment.

3.5.1 Module I: Digitalization – Theoretical Part

As depicted in Table 1, the first part of this lecture will mainly be taught via e-learning powered by Moodle. The most important approaches and key technologies of digitalization in the metal forming sector are included and will be provided via four digital chapters. Students can learn independently. To give all participants an appropriate framework, each sector of this module starts with the learning objectives, which should be achieved after the complete elaboration of the provided course material. Due to the lack of homogeneity in academic literature, prepared scripts for content (2), (4), and (5) will be provided. Furthermore, the most important state-of-the-art academic research papers will be accessible. For students who want to deepen their knowledge in specific areas of module I, additional book chapters will be provided. At the end of each section, possible exam questions related to the scope of the specific part will be visible, which should support every student in their exam preparation and avoid misunderstandings regarding the scope of the exam. Additionally, at least two questioning hours will be provided to support students during the preparation process.
At the end of module I, a written exam will take place. This exam is crucial, as a minimum of knowledge in theory and nomenclature is necessary to be able to understand the upcoming modules of this lecture and contributes 60% to the final grade.

Table 1. Module I: Digitalization – Theoretical Part.

<table>
<tr><td colspan="2">Module I: Digitalization –Theoretical Part:
Face-to-face and online</td><td colspan="2">Timeframe: 4x1h, 2x2h, 1x3h, 1x6h, 1x15h</td></tr>
<tr><td colspan="4">Topic(s): Introduction and arising of awareness for chances and issues of digitalization in the metal forming industry (1); Fundamentals of automation in the metal processing industry, including retrofitting and digitization (2); Fundamentals of networking technologies: state-of-the-art protocols and data management, including retrofitting and IT-security (3); CPPS and HMI in the metal forming environment (4); DT and DS in metal forming related operations, including AI and big data (5)</td></tr>
<tr><td colspan="4">Objective(s): Knowing the most important definitions and differences in metal forming related digitalization key technologies; Raising the ability to communicate with IT-domain experts in the manufacturing environment; Understand the possible advantages of digitalization technologies</td></tr>
<tr><td>Content:</td><td>Methods:</td><td>Material:</td><td>Duration:</td></tr>
<tr><td>(1)</td><td>Face-to-face lecture;
group discussion</td><td>PPT; handouts; videos</td><td>1h</td></tr>
<tr><td>(2)</td><td>Moodle-based e-learning; online script; actual research papers; videos</td><td>PDFs; videos</td><td>2h</td></tr>
<tr><td>(3)</td><td>Moodle-based e-learning; actual research papers; videos; practical tutorials</td><td>Online tutorials; PDFs; videos</td><td>2h</td></tr>
<tr><td>(4)</td><td>Moodle-based e-learning; online script; actual research papers; videos</td><td>PDFs; videos</td><td>1h</td></tr>
<tr><td>(5)</td><td>Moodle-based e-learning; online script; actual research papers; videos</td><td>PDFs; Handouts; videos</td><td>3h</td></tr>
<tr><td colspan="4">Remarks: Additional case studies for deepening of gained knowledge provided at Moodle, including additional book (chapter) recommendations (6h); Exam preparation: Predefined possible exam questions for elaboration, published via Moodle (15 h); Written exam to demonstrate necessary knowledge for the upcoming practical part (1h); Total 60% of the final grade</td></tr>
</table>

3.5.2 Module II: Digitalization – Practical Part

Table 2 displays the concept of the second module which is used to deepen the theoretical knowledge gained in module I. A division in an equally sized group of eight will be carried out in the first instance. Every group will then attend three practical units at the Smart Forming Lab at the Chair of Metal Forming. Parts (1) and (3) will include face-to-face lectures and rely heavily on interest-driven group discussion. In part (2) of this module, every group will additionally program its methods in Python, which then will be transferred into the four-layer digitalization architecture at the lab. The cooperation of each participant during the parts will contribute five percent to the final grade of this lecture. The contribution will be measured inversely. Initially, every student will start with a full five percent, students who show no effort in contributing productively or disturb the workflow or group discussion inappropriately will be graded with zero percent for this module.

Table 2. Module II: Digitalization – Practical Part.

Module II: Digitalization – Practical Part: Face-to-face		Timeframe: 1x1h, 1x2h, 1x3h	
Topic(s): Explanation and practical demonstration of the fundamentals of automation and networking technologies via a four-layer digitalization approach, including DS, DT, and AI (1); Practical demonstration of a suitable implementation approach for CPPS and HMI, demonstrated by the Chairs retrofitted experimental cold rolling mill, using a variety of different software (2); Showing practical open-source IIoT solutions, demonstrated on operating machine hour counters and related project management implementations at different forming aggregates (3)			
Objective(s): Knowledge transaction from theory into practical implementation; Deepening the understanding to know the fundamentals of digitalization as a future domain expert			
Content:	Methods:	Material:	Duration:
(1)	Face-to-face lecture; group discussion	Different forming aggregates and infrastructure at the Smart Forming Lab	3h
(2)	Face-to-face lecture; group work; group discussion	Demonstrating the digitalization environment of the Smart Forming Lab, including cold milling aggregate and different software	2h
(3)	Face-to-face lecture; group discussion	Showing the four-layer architecture and the advantages in digitalized project management by using the Smart Forming Lab	1h
Remarks: Total 5% of the final grade			

3.5.3 Module III: Digital Transformation – Theoretical Part

As outlined in Table 3, the third module deals with the specific issues related to the implementation of digitalization technologies as part of a digital transformation framework in the metal forming environment. During a two-hour face-to-face meeting, the participants should realize the importance of corporate culture and human coworkers as part of the digital transformation process. This knowledge will be gained through practical case studies related to change management and metal forming related companies. To be able to use the gained knowledge through the practical examples given in part (2) and (3), in the first instance, a theoretical background about the fundamentals of corporate culture and change management will be provided. This part will contribute five percent to the final grade and grading will be underlying the same restrictions as in module II.

Table 3. Module III: Digital Transformation – Theoretical Part.

Module III: Digital Transformation – Theoretical Part: Face-to-face		Timeframe: 1x2h	
Topics: Major issues regarding the implementation of digitalization technologies in the metal forming environment (1); The importance of top-down and bottom-up change management (2); Practical change management approaches in the metal forming industry (3)			
Objective(s): Understanding the fundamentals and purpose of change management in metal processing manufacturing; Generating awareness for the most important challenges arising with digital transformation on the different layers of management; Knowledge about practical approaches to overcome the most common resistance in a sustainable way			
Content:	Methods:	Material:	Duration:
(1)	Face-to-face lecture;	PPT; board	1h
(2)	Interactive face-to-face lecture; group discussion	PPT; board	0.5h
(3)	Interactive face-to-face lecture; group discussion	Board	0.5h
Remarks:			

3.5.4 Module IV: Digital transformation – practical part

Table 4 provides information about the fourth and final module of this lecture. This module will summarize the theoretical and practical inputs participants acquired during the lecture. Each group, as defined in module II, has to elaborate on a different case study. The scope of the studies will be the implementation of a specific digitalization technology in a fictive metal forming company, under special consideration of issues regarding the digital transformation strategy to achieve the primary goal. The variation of at least one factor (e.g., company size, budget, degree of automation) will be carried out to avoid the same results from more than one group. The individual solution of each group will then be assessed by a short presentation (maximum 10 minutes), considering the solution provided as well as the presentation style. This module has an estimated workload of 22.5 hours and contributes to the final grade with 30 percent.

Table 4. Module IV: Digital Transformation – Practical Part.

Module IV: Digital Transformation – Practical Part: Face-to-face		Timeframe: 1x20h, 1x2.5h	
Topics: Developing a strategy and operational approach to successfully run a digitalization project (1); Summarizing and presenting the elaborated solution in an appropriate way (2)			
Objective(s): Participants can run a digitalization project in the metal forming industry successful			
Content:	Methods:	Material:	Duration:
(1)	E-learning, group work	Lecture material	20h
(2)	Presentation	PPT; board; video	2.5h
Remarks:			

4 Conclusion

In summary, it can be stated that, in the future, a major focus in the formal education and training sector should be placed on improving quality assurance and on professionalization processes. Hereby, the main goal is to strengthen the individual position and competence to contribute to the professionalization of the entire sector and to establish the engineering profession as an essentially necessary component in the sense of the demand for lifelong learning (LLL). In addition to the development of individual professionalism, collective professionalism development must also be promoted by implementing standardized frameworks and pre-defined procedures.

Based on current teaching and learning theories, this paper has introduced a module-based concept for the lecture ‘digitalization and digital transformation in metal forming’ as an example for modern industrial engineering education. Thereby, the authors placed a special emphasis on current Industry 4.0-requirements of manufacturing companies by focusing on the usage of modern technologies such as cyber-physical production systems, the Industrial Internet of Things, human-machine interfaces, and augmented reality. To guarantee an efficient knowledge transfer, the students will be actively involved during the lecture through participant-based teaching and learning methods, e.g., group discussions or industrial case studies.

Future research should further focus on the systematic evaluation regarding the impact of potential success factors of modern teaching and learning methods on learning outcomes by using multivariate statistical procedures. Moreover, the gap between offered and required educational services should be further reduced by incorporating recent scientific findings as well as company-orientated requirements into the educational programs of future industrial engineering education.

5 Acknowledgments

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7 Biographies

Benjamin Ralph holds a master’s degree in metallurgy from the Montanuinversitaet Leoben, Austria and a master’s degree in international industrial management from the University of Applied Sciences, FH Joanneum, Kapfenberg. He currently works as a University Assistant and PhD. candidate at the Chair of Metal Forming at the Montanuniversitaet Leoben, Austria. He is also an MBA candidate at the Warwick Business School, Coventry, England. Before his academic career, he served four years in the Austrian Armed Forces and was part of the United Nations Interim Forces in Lebanon (UNIFIL). His research interests include the areas of digitalization and digital transformation, materials science, numerical modelling, and management, mainly but not exclusively in the area of metal forming.

Manuel Woschank received a diploma degree in industrial management and a master’s degree in international supply management from the University of Applied Sciences, FH JOANNEUM, Graz, Austria, and a Ph.D. degree in management sciences with summa cum laude from the University of Latvia, Riga, Latvia. He is currently a Senior Researcher, Senior Lecturer, and the Deputy Head of the Chair of Industrial Logistics at the Montanuniversitaet Leoben and an Adjunct Associate Professor at the Faculty of Business, Management and Economics at the University of Latvia. He was a visiting scholar at the Technical University of Kosice (Slovakia), and at the Chiang Mai University (Thailand). His research interests include the areas of logistics system engineering, production planning and control systems, logistics 4.0 concepts and technologies, behavioral decision making, and industrial logistics engineering education.

Corina Pacher is an Education Project Manager at the Resources Innovation Center in Leoben. She studied pedagogical and educational science at the University of Klagenfurt with a specialization on social and inclusive education as well as on professional education. During and after her studies, she gained work experience, e.g., as the head of educational programs and in different social public service enterprises as social education worker. Currently, she is mainly focusing on raising the awareness for a resource-orientated handling of raw materials by connecting research, education, and society, e.g., by building and expanding skills and competences of students through training initiatives.

A 7 Publication 7

B. J. Ralph, M. Woschank, C. Pacher, M. Murphy: Evidence-based Redesign of Engineering Education Lectures: Theoretical Framework and Preliminary Empirical Evidence, under review (20.04.2021) in: *European Journal of Engineering Education.*

Author contributions

1. B. J. Ralph: conceptualization, formal analysis, data curation, methodology, writing – original draft preparation, writing – review and editing, visualization, project administration

2. M. Woschank: conceptualization, formal analysis data curation, writing – original draft preparation, writing – review and editing, supervision

3. C. Pacher: conceptualization, methodology, formal analysis, writing – original draft preparation, writing – review and editing,

4. M. Murphy: writing – review and editing, supervision

Evidence-based Redesign of Engineering Education Lectures: Theoretical Framework and Preliminary Empirical Evidence

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Abstract

While the fourth industrial revolution continues to change manufacturing facilities all over the world, not all enabling key technologies are taught sufficiently at universities. As engineering disciplines have further diverged in different specializations over time, digitalization strives for the opposite: transdisciplinary education in the fundamentals of digital transformation is necessary to remain competitive. In specialized European technical universities, the manufacturing industry became the pacemaker when it comes to technical innovations. To provide engineering students with knowledge to succeed in a modern manufacturing environment, it is mandatory to know the state-of-the-art requirements of the industry. For this purpose, a new lecture was designed, teaching engineering students the fundamentals of digital transformation. To elevate the requirements for employability, a statistically representative part of Austrians' metal forming companies were asked about their degree of maturity regarding digital transformation. For the sake of teaching efficiency, a survey revealing students' knowledge of digital transformation and preferred learning methods was carried out. As a result, a stakeholder-oriented lecture was developed. Furthermore, a general framework on how innovative transdisciplinary academic courses in the engineering environment can be developed in an effective and practical way was derived, closing the gap between modern engineering education and required practical skills.

1 Introduction

Since the official introduction of Industry 4.0 in 2011 from the German government, thousands of publications regarding the corresponding key technologies, as well as necessary changes in the working environment were carried out (Kaur et al., 2020; Oztemel and Gursev, 2020; Zheng et al., 2020). While a majority of this literature indicates that key components (e.g., Cyber Physical Production Systems (CPPS), Industrial Internet of Things (IIoT), Big Data, Human Machine Interfaces (HMI)) are implemented in parts of the European manufacturing environment (Grzybowska et al., 2020), the degree of integration of those technologies significantly varies within different sectors of this industry. As a result, highly standardized sectors, characterized through high volume and repetitive robust processes within the manufacturing operation, can be described as leaders in the digitalization and digital transformation process, while segments that don't fulfil these requirements remain behind (Matt et al., 2020; Peukert et al., 2020). Another important development to consider is the increasing backshoring trend of high-quality manufacturers from low-wage countries to Europe and the U.S. (Ancarani and Di Mauro, 2018; Foerstl et al., 2016; Gray et al., 2017; Johansson and Olhager, 2018a, 2018b). This trend contradicts the Industry 4.0 related relative (fear of) job rationalization in manufacturing companies from an employee's point of view (Fomunyam, 2019; Kovacs, 2018; Müller, 2019).

As a result, the future human workforce role, especially on shopfloor level, is not completely clear. While a majority of current literature implies the importance of human factors in an Industry 4.0 environment (Kadir et al., 2019), there are often empirical based studies that indicate that current decision makers in industrial practice decline this hypothesis (Vuksanović Herceg et al., 2020). Nevertheless, a significant change in future worker's requirements cannot be neglected (Kiel et al., 2017; Sony, 2018), whereas the majority of current research states that a general shift to more complex and less repetitive work evolves (Kadir et al., 2018; Müller et al., 2018; Pfeiffer, 2016, 2018). This paradigm shift not only affects basic shopfloor activities but also results in a change in skill requirements for engineering academics in the manufacturing sector. Before the start of the fourth industrial revolution, specialized engineers from different sectors (e.g., mechanical engineering, materials science, automation technologies, IT) mainly operated within small, specialized groups. As one of the main advantages of the digitalization and digital transformation in manufacturing is the interoperability between different manufacturing, as well as, business intelligence layers, these experts are forced to work in a much more interdisciplinary way (Brougham and Haar, 2018; Ghobakhloo, 2020). Responsibilities and resulting boundaries between different disciplines dilute. As a result, engineering experts have to be able more than ever to communicate outside these socio-cultural boundaries. Manufacturing companies acknowledge these developments by creating new jobs (e.g., Chief Digitalization Officer) or extending existing job roles (e.g., IT-managers are additionally responsible for parts of the digital transformation efforts within the company) (Culot et al., 2019; Horlacher and Hess, 12016; Tumbas et al., 2017, 2018). Some concerns even extend their organizational structure by creating new companies that focus on the digital transformation of the whole concern (Rotter and Eder, 2017).

Regarding job perspective for engineering students, these developments result in mainly two contradicting effects: i.) there are effectively less jobs in the classic manufacturing environment; ii.) new jobs in specialized engineering fields that include digitalization related knowledge are created (Adam et al., 2019; Vermeulen et al., 2018). To prepare potential engineering experts for their future in the field of ii.), it is crucial for their educating universities to ensure that adequate knowledge tailored to the industries requirements for a successful job entrance phase is provided. While recent literature suggests that continuous adaptions in respective curricula are made, the basis of these adaptions is, to a major extent, only related to specific requirements from a few industry partners (Andersen et al., 2019; Büth et al., 2018; Jeganathan et al., 112018; Umeda et al., 2019). Furthermore, the initial knowledge of respective students is often not considered, leading to adaptions mainly based on the experience of responsible lecturers and respective external partners.

For this reason, this paper describes the development and adaption of a lecture for the transdisciplinary education of engineering students. The respective academic course focusses on the Austrian metal forming environment, giving students of various manufacturing related engineering disciplines the opportunity to learn the fundaments of digitalization and digital transformation in the metal forming industry. Beginning with section 2, the teaching and learning methodology for this development is explained. In section 3, the first concept of the lecture, based on recent literature, industry expert interviews and practical experiences of the authors is defined. Derived from this initial concept, section 4 describes the adaption of the literature, as well as, internal and external knowledge-based drafted by a descriptive statistics-based analysis of requirements of Austrian's metal forming industry (section 4.1). Furthermore, actual knowledge of potential participants from different disciplines was analyzed, based on a quantitative survey (section 4.2). Derived from results from previous subsections, section 4.3 examines the identified gap between the learning objectives of the first concept and the required skills from the respective industry. Based on this gap, the initial objectives are shifted in order to enable a practice-orientated education. Furthermore, as a result of the statistical analysis of initial student knowledge, the workload per topic is additionally changed to ensure comprehensibility and avoid participants from being overchallenged or underchallenged. Section 5 additionally includes adaptions to the initial pedagogical approaches with respect to actual developments of the educational engineering 4.0 approach resulting in a content and state-of-the-art engineering education experience.

2 Realignment of engineering education concepts towards Engineering Education 4.0

The advancing technology and digitalization thrusts, enhanced by the global COVID-19 pandemic restrictions, have not only led to new markets and also challenges in industry but also, and especially in, the entire education system. The transformative educational processes triggered by the pandemic across all societal sectors, institutions, as well as, life spans, now requires long-term inclusion. The explosive adaptation of learning and educational processes to the micro, meso, and macro levels of human learning in terms of the use of digital media and tools opens up unprecedented learning spaces and opportunities. These transformation processes are flowing into all areas of social life and are being massively advanced by the rapidly progressing implementation of Industry 4.0 concepts. These new approaches require not only a transformation of teaching and learning methods but also a new conceptualization of learning content and imparted competencies, especially in higher education for the experts of tomorrow. The new technologies resulting, require new and extended qualifications, knowledge and competences of future engineers. Above all, it also requires an adapted mindset with regard to the willingness and necessity to flexibly engage with new things (e.g., approaches, programs, work steps) and to continue learning throughout one's life and to further educate oneself both professionally and privately. Thus, two major transformation processes and implications for engineering education in the tertiary sector can be derived from the current trends. On the one hand, the expansion of the understanding of education to the entire lifespan and the focus on the individual educational trajectories, which forces the resulting participant-centeredness, is mandatory. Accordingly, the increasing shift from teacher-centeredness to participant-centeredness must be made, especially in the higher education sector. On the other hand, with regard to innovations through the implementation of new (digital) concepts in industry, the increasing value of the human capital of a company and the entire industry can be observed. As a result, the education and training of employees is increasingly seen as an innovative force and thus constitutes a key competitive criterion (Zsifkovits et al., 2021).

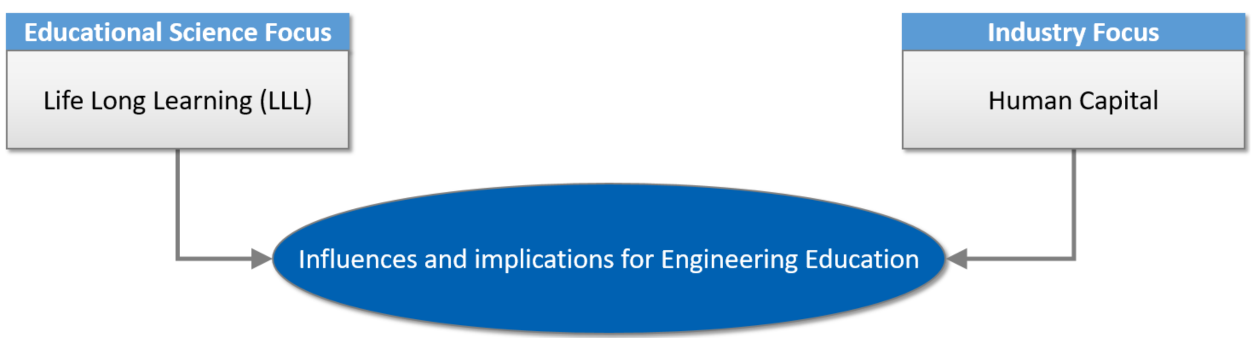

Figure 1. Influences on Engineering Education.

Figure 1 illustrates the factors influencing the engineering education of tomorrow. The universities are now challenged to successfully implement the tendencies/demands and thus to ensure the ability to work, the understanding of the role of engineers and the competitiveness of future generations (Ramirez-Mendoza et al., 42018). This transformation requires a new conceptualization or adaptation in a holistic way, i.e. both on the institutional level and with regard to transdisciplinary cooperation with industry, as well as, a push towards national and international cooperation (Fomunyam, 2019).

Education can be considered as a central investment in the future, especially in, what (Schäffter, 1998, 2001) defines as today's transformation society. Thereby, one of the essential goals is the ongoing development and necessity of lifelong learning (LLL) to ensure skills development, employability and long-term competitiveness .

The teaching of relevant and up-to-date skills is indispensable and represents a central element of the European pillar of social rights. Thus, transnational high-quality education should be made available to all people, so that they can actively and self-confidently make a significant contribution as citizens to further development and ongoing innovation. The European Competence Agenda of the European Parliament (Soldi et al., 2016) clarifies that Europe needs to narrow the gap in this respect since around 70 million people are neither able to read and write properly, nor do arithmetic, nor do they have digital skills and are, therefore, at risk of poverty, unemployment or social exclusion. The demand here lies in fundamental reforms of European education systems and their positioning towards future-oriented knowledge, skills, and competencies 'adapted to the digital age' (European Council, 2017). Since technological progress - keywords: artificial intelligence, robotics, IoT - is developing rapidly, lifelong investment in key skills and above all, digital skills are required. The tertiary sector is particularly called upon to push ahead with sustainable reforms in terms of skills development and the incorporation of labor market trends to ensure the availability of next-generation professionals. Practical experience, new learning instruments and materials, the use of digital technologies and a lifeworld orientation must be incorporated into modern curricula (European Commission, 2018). Under the postulate 'Industry 4.0', the permanently and rapidly developing digitalization of the working world through the penetration of new technologies such as Augmented Reality, Virtual Reality, Cyber Physical Systems, Digital Twins, etc. requires the implementation of new methodological-didactic teaching and learning settings, so to speak, 'Education 4.0'.

The aforementioned demands on individuals and society as a whole, require the continuous acquisition of new knowledge, qualifications and competencies over the entire lifespan. Ergo, learning over the entire lifespan has a double meaning. On the one hand, LLL means for the educational subjects the chance for personal and professional development and change over the entire life span. On the other hand, the necessity of LLL implies the permanent challenge for subjects, but also for society as a whole, to maintain and further develop work and competitiveness. LLL thus influences both the individual and the societal dimension and consequently leads to the dissolution of learning boundaries in terms of time, space and content. Thus, engagement with learning and educational processes must be considered across the lifespan and therefore, permeate through all phases and domains of life. In other words, learning is implicated in the biography of each individual (Hof et al., 2014; Schröer et al., 2013). To ensure the necessity of implementing the LLL approach, the following concept of circular education will be used to divide the life-span into 4 main dimensions (Figure 2).

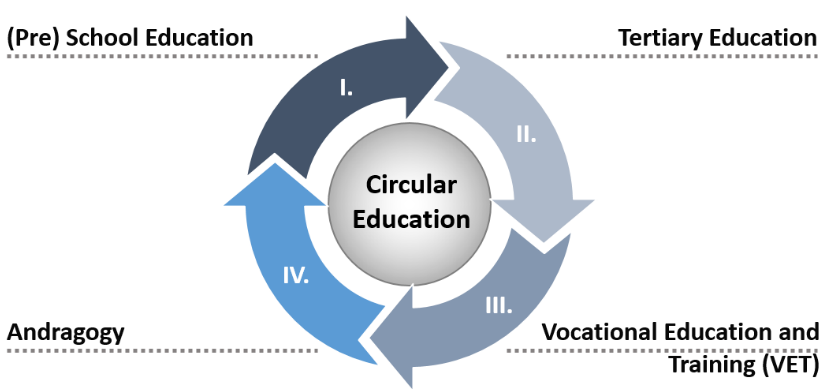

Figure 2. The circular education model.

According to the circular education approach, the lifespan is divided into a total of 4 dimensions and ranges from earliest childhood to high adulthood. Due to the increasingly blurred boundaries between life stages and ages, these 4 areas are to be understood as dimensions with fluid transitions and not every person passes through each dimension, these can also be skipped or dealt with at a later point in time. The first dimension covers the period from early childhood to the end of basic education. In the second dimension, higher education and all related educational formats are included. Gainful employment and its educational activities are located in the third dimension (VET). The fourth dimension includes all adult education activities, whether formally, non-formally or informally acquired.

A professional and successful design of educational activities requires the inclusion of essential core aspects in planning, implementation and evaluation phases. Transferred to pedagogical practice in higher education, this implies a reorientation to the entire institutional level. First, the concept of LLL and the accompanying de-standardization of learning and life phases and topics necessitates the adaptation of institutional frameworks. Ergo, the learning dimensions must be expanded to include informal and non-formal aspects, which in turn affects the macro, meso and micro levels of learning. Thus, the focus of learning efforts also shifts to the individual level and must be adapted to the situation. This means the participant and their respective life context must be considered when planning educational measures. Through the concept of LLL and the accompanying shifts in learning and educational processes, the following didactic guiding principles for pedagogical practice in adult education can be derived:

- Participant-orientation;
- Case reference;
- Practical relevance;
- Group dynamics;
- Orientation to everyday life;
- Self-determination;
- Biography orientation.

To offer high-quality courses at the Montanuniversität Leoben, the aspects described above must be included in the program planning in advance and current contexts such as practical requirements must be considered to guarantee educational success. According to (Tietgens, 1992), expectations, needs or wishes of all key stakeholders involved in the learning process in the respective discipline can be emphasized as an essential success factor. Only in this way it is possible to respond to current trends and challenges in practice and to equip future engineers with the necessary knowledge, qualifications and competencies. These must then in turn be fed back into the didactic guiding principles and maxims of higher education, in order to be able to guarantee professional methodological-didactic training programs.

Furthermore, (Pacher et al., 2020) investigated the educational needs in the extractive sector on the basis of an extensive study within the framework of an EU project and concluded that the focus of higher education should be on the training of transversal competencies such as soft skills, decision-making skills, or digital competencies. In addition, practical testing of the technical competencies acquired during studies is essential for future careers. (Bauer et al., 2014) also state the need to develop language skills, especially with regard to the English language, due to the advancing internationalization efforts.

Accordingly, an expansion of the essential transversal key competencies is required to prepare the future experts of tomorrow for the challenges in their daily private and professional lives. The educational systems at universities should include new learning materials, systems, instruments and resources that strengthen (online) cooperation on the one hand and include the lifeworld-orientation of the learners on the other hand, thus levelling supposed socio-economic performance differences. Additionally, this approach can increase equal opportunities, as well as, learning efficiency through a subjective reference to the motives and interests of the target group (European Commission, 2020).

In order to ascertain further requirements and expectations of the course, the authors of this article carried out an additional extensive study in addition to the literature research, to be able to further advance the

professionalism development of teaching at the Montanuniversität Leoben and thus, guarantee an essential contribution to competitiveness in the metal forming sector on the one hand and the employability of future experts on the other. The course was already designed in advance, according to the principle of constructive alignment (Biggs and Tang, 2011) and will now be adapted based on the research results from the study and the implications of the COVID-19 pandemic. The authors follow the PDSA- circle (Deming, 1998; Shewhart, 1986) and adapt the course planning based on feedback loops.
As a result, the final lecture described in this work should consider all points illustrated in Figure 3 and therefore, serve as a pilot project for upcoming lectures and curricular adaptions at the Montanuniversität Leoben, following the Transdisciplinary Engineering Education approach.

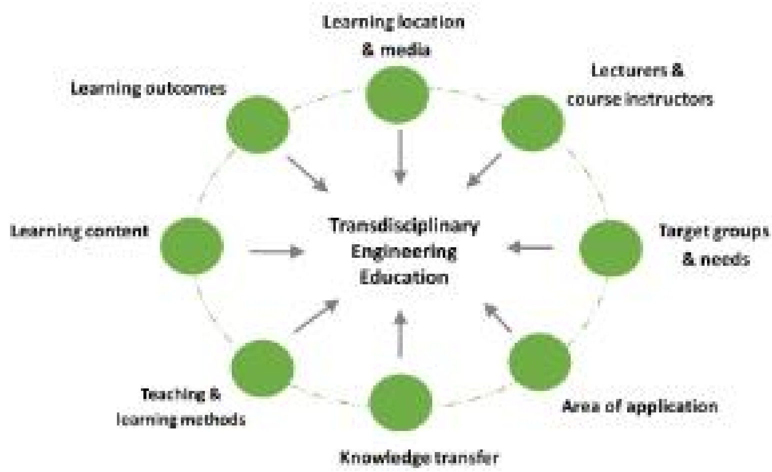

Figure 3. Transdisciplinary Engineering Education Approach: the inclusion of all parties and methods is mandatory for the development, planning and implementation of an Industry 4.0 related lecture.

3 First concept development

To be able to include students', as well as, industries' preferences and requirements during the developing phase, a first concept including the core technologies and frameworks of digital transformation was designed (Ralph et al., 2020). This concept is based on state-of-the-art learning techniques and was initially designed without Covid-19 based restrictions. In the sense of "constructive alignment" according to (Biggs and Tang, 2011), the teaching and learning concept is aligned with the learning outcomes, the teaching and learning activities and the final assessment. The focus of the concept is participant orientation by using the method of (Cohn, 1989) (topic-centered interaction is used to place topics, questions or ideas in the center elaborated on by the participants in mutual exchange). Accordingly, all teaching and learning materials are designed to meet the needs of the target group.
Through the experience and competence of the lecturers, the integrated course conveys fundamentals and in-depth knowledge that are essential for understanding and assessing current digitization processes in industrial practice. Fundamentals and theory are illustrated and reflected by concrete practical examples (Coşkun et al., 2019; Edward, 2002).

The course is built up modular in a blended-learning format. In modules I to III, the teaching content is essentially conveyed through compact lectures with the help of multimedia support, as well as, interactive phases (workshops, question rounds, etc.). The four modules are coupled and are each held in the summer semester and over a period of one month. Blocks 2 and 4 are held as classroom sessions and blocks 1 and 3 as online learning via the platform CISCO WEBEX. In addition, the theory blocks are supported by synchronous and asynchronous teaching methods. This supports the more flexible scheduling of the learning content for students. Derived from current literature, as well as, the authors' experience, after successful completion of the lecture the students should be able to:

- create and evaluate concepts for digitalization in metal forming related production systems;
- apply the theoretical concepts in a case study;
- implement them together with experts from different disciplines;
- understand and implement the applied procedures in practice based on the theoretical and practical knowledge acquired.

Figure 4 illustrates the fundamental scope and module dependent learning objectives of the lecture.

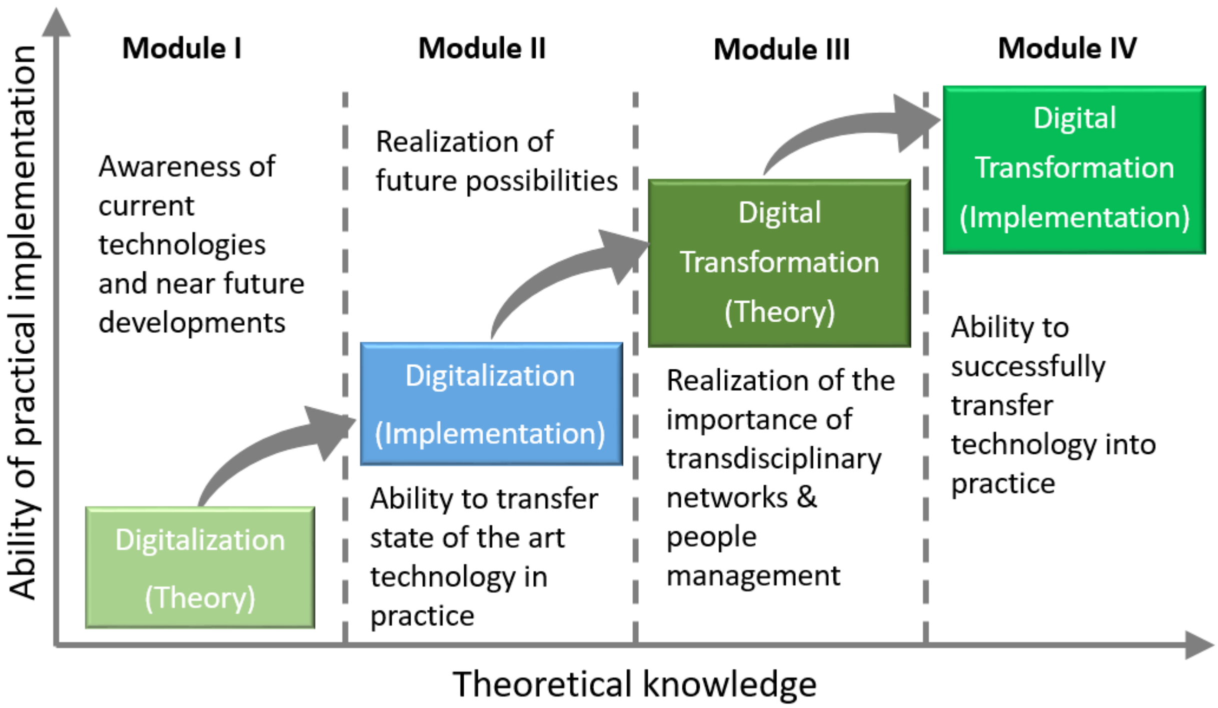

Figure 4. Module definition and corresponding learning outcomes for the lecture.

Another restriction to consider is the strategic fit within the curricula of potential participants. For the first implementation, a workload of 2.5 European Credit Transfer System (ECTS) credit points (CP) was set up, resulting in a maximum overall workload of 75 hours (Directorate-General for Education and Culture, 2005; European Commission, 2008; Grosges and Barchiesi, 2007). Based on all mentioned requirements and restrictions, the following tables summarize the initial module definitions.

Table 1. Initial lecture definition for the first module, adapted from (Ralph et al., 2020)

Module I: Scope and duration (h)	**Applied methods**	**Used materials**	**Learning objectives**
Introduction into opportunities and issues of digitalization technologies in the metal forming environment (2)	Icebreaker and subsequent presentation; Group discussion	PPT; Handouts; Videos	Awareness of the potential impact of key technologies of the fourth industrial revolution
Fundamentals of digitization, including sensor and actuator technologies (7)	Self-study using e-learning platform	Online script; State of the art research papers;	Knowledge about the basics of state-of-the-art digitization technologies in the metal forming environment

		videos	
Fundamentals of digitalization, including networking technologies, state of the art protocols, interfaces, data management and IT-security (7)	Self-study using e-learning platform and external tutorials	Script; State of the art research papers; Videos; Prepared scripting examples	Understanding the potential of sophisticated and non-proprietary networking solutions; Ability to connect requirements of digitization to a digitalization framework
The importance of CPPS and corresponding HMI in the metal forming environment (7)	Self-study using e-learning platform and external tutorials	Script; State of the art research papers; Case study videos from the SFL	Ability to define and understand CPPS in the metal forming environment; Realization of the importance of accurate HMI options
Definition of Big Data, AI, DT and DS within the metal forming industry (7)	Self-study using e-learning platform	Script; State of the art research papers; Case study videos from the SFL	Accurate definition of DT, DS, AI and Big Data; Awareness of the connection between simulation engineering, digitalization and data management

Table 2. Initial lecture definition for the second module, including practical exercises, adapted from (Ralph et al., 2020).

Module II: Scope and duration (h)	**Applied methods**	**Used materials**	**Learning objectives**
Practical demonstration of the fundamentals of networking technologies, state of the art programming languages and resulting layer architecture at the SFL (2)	Face to face lecture; group discussion	Digitalized forming machine systems at the SFL; corresponding IT-infrastructure	Knowledge transfer from theory to practice on a holistic basis
Practical demonstration of a developed CPPS and corresponding HMI at the SFL (2)	Face to face lecture; group discussion	Digitalized and retrofitted rolling mill aggregate at the SFL	Knowledge transfer of CPPS and HMI and underlying technologies from theory to practice
Demonstration of different possibilities of interface design and layer architectures at the SFL (2)	Face to face lecture; group discussion	SFL infrastructure; Case study of digitalized CNC-lathe	Awareness of benefits and downsides of different commonly used interfaces within a manufacturing digitalization environment in practice

Table 3. Initial lecture definition for the third module, adapted from (Ralph et al., 2020).

Module III: Scope and duration (h)	**Applied methods**	**Used materials**	**Learning objectives**
Recap block (0.5)	World Café (break out session)	Miro material (MIRO)	Stepping up and deepening the learning process for information provided in module I and II
Discussion of major issues arising within the implementation of digitalization approaches within an industrial environment (0.5)	Face to face lecture; group discussion	PPT; Board	Realization of importance of social-cultural aspects within a digitalization project
Introduction in appropriate frameworks to overcome social-cultural tensions within the manufacturing environment (0.5)	Face to face lecture; group discussion	PPT; Board	Awareness of the most common frameworks of change management
Possibilities of implementation of change approaches in the manufacturing environment (0.75)	Face to face lecture; group discussion	PPT; Board	Deepened theoretical knowhow regarding overcoming of change based resistance

Table 4. Initial lecture definition for the fourth module, including final examination, adapted from (Ralph et al., 2020).

Module IV: Scope and duration (h)	Applied methods	Used materials	Learning objectives
Handing out and guidance for elaborating on prepared case study (1)	Face to face lecture; Self-study using e-learning platform	Prepared case studies	Know how to elaborate a given project (case study)
Preparation for final group presentation (20)	Individual group lectures;	Prepared case studies; Script and external sources	Know how to transfer gained knowledge into a practical case
Final group presentation (1)	Presentation; feedback loop	PPT; Board; Other available media sources	Know how to present results as a project leader within a presentation to superiors in a clear and professional way

The workload determined by the scope of the module blocks sums up to a total of 61 work hours. Leaving an additional 14 work hours for self-study activities, where the scope of this activity is not exactly defined. Furthermore, recommended comprehensive literature is made available to all participants by the used online platform Moodle, giving students the opportunity to elaborate on a specific topic of interest more deeply.

4 Stakeholder analysis and knowledge gap identification

To provide the most efficient and effective educational experience, it is necessary to know the main stakeholders and their needs as to involve them in the development. Table 5 shows a comprehensive overview of the identified stakeholders, derived from (Meyer and Bushney, 2009).

Table 5. Identified stakeholders for the lecture (re-)design (Meyer and Bushney, 2009).

Stakeholders	Reason for inclusion	Way of inclusion in the lecture development
Participating engineering students	The most important stakeholders are at the center of attention	Representative survey; adaption of initial teaching methods scope
Employers	Provide jobs for graduated students; know what skills are important to become successful	Representative survey; adaption of weighting of different module parts within the lecture
Alumni and experts (have worked, or are currently working, in the metal forming environment with an engineering or IT background)	Know which skills are important in industrial practice for their specific engineering discipline	Personal interviews; recommendations were included in the development of the first structure
Local universities	Possibility of using external knowhow and lessons learned from their local initiatives	Personal interviews with academic staff from other technical universities within Austria; gathered information was included in the development of the first structure of the lecture
International universities	Comparing of other international curricula to the planned initiative	Research about similar engineering programs and how they included digital transformation in their curricula; gathered information was included in the development of the first structure
Government departments	Legal basis; special consideration of restrictions due to ongoing Covid-19 crisis (e.g., limitation of students; mandatory distance learning)	Including a variety of different teaching techniques for each part of a module to sustain a proper educational experience for all participating students regardless of actual restrictions (from face-to-face to completely online)

Lecturers	Mainly responsible for creating a stimulating environment for the best possible knowledge transfer to lectures' participants	Did the development of the first structure and carried out the research, personal interviews and surveys; adapt the first structure of the lecture based on the results of the gathered information

The main objective of the empirical study is to develop evidence-based implications for the redesign of engineering education lectures which are focused on the topics of digitization and digital transformation. Therefore, two independent surveys were conducted to increase understanding regarding the systematic development of the competencies for the engineers of tomorrow. For the data collection, the authors used a triangulated approach whereby random sampling was used within the student's survey and theoretical sampling was applied to the company´s survey in the timeframe between September 2020 and November 2020. Within this combined approach, theoretical sampling is applied to decrease potential difficulties in obtaining relevant data, to avoid misunderstandings of the survey items by the target population, and to isolate confounding variables, while random sampling was chosen to compensate potential shortcomings in terms of validity and generalizability from the theoretical sampling approach (Zhu et al., 2008).

4.1 Research methodology and results: Questioning companies from Austrian's metal forming industry

To adapt the learning outcomes to fit to the requirements of the industry, a total of 200 companies from Austrian's metal forming industry segment were surveyed. From the total number contacted, 64 questionnaires (32.00 %) were completed, valid, and therefore, usable for the subsequent statistical procedures. Again, a non-response bias test (Armstrong and Overton, 1977) did not show any significant differences between early and late respondents, which additionally indicates a high degree of transferability, respectively representatively, of the established research results (Lippe, 2011). All items were operationalized by using 5-point LIKERT scale from 1 (e.g., not agree) to 5 (e.g., fully agree).
The resulting questionnaire contains three major theme blocks: i.) DIG: asking for the digital maturity of the respective company; ii.) DAT: evaluating the gathering and processing of internal data; iii.) ATT: analyzing the attitude of the respective companies regarding the fourth industrial revolution and corresponding organizational changes. The questions were derived from the authors' experience, as well as, expert interviews carried out in advance, to ensure comprehensibility of potential participants.
The scope and results of the survey are illustrated in Table 6.

Table 6. The Austrian metal forming industry: Survey scope and results from valid responses.

Item	Text	N	Min.	Max.	Mean	Std.Dev.
DIG_1	All production processes that occur are recorded by a higher-level ERP system.	64	1	5	3.33	1.574
DIG_2	All production processes that occur are controlled and timed automatically using an MES system, PPS, or ERP system with similar functionality.	64	1	5	2.69	1.457
DIG_3	The machines used all have at least one interface to higher-level systems (SCADA on MES/ERP).	64	1	5	2.72	1.397
DIG_4	Captured processes and general production data are stored and processed via cloud solutions.	64	1	5	1.97	1.403
DIG_5	Data can be made fully available through an interface for external use by other applications such as business intelligence.	64	1	5	2.47	1.345
DIG_6	Internet of Things solutions are used on a large scale in production (e.g., IIoT gateways, transmission using IoT protocols such as MQTT).	64	1	5	1.81	1.296
DIG_7	Collected data is analyzed using big data technologies.	64	1	5	1.81	1.332
DIG_8	Important production processes are modeled with simulation programs (e.g., finite element simulation).	64	1	5	2.36	1.396
DIG_9	The visual representation of production data is structured and user-friendly.	64	1	5	2.64	1.289
DIG_10	All production processes are fully described by means of standards.	64	1	5	3.25	1.297
DIG_11	Finite element simulations are used for troubleshooting as well as process optimization.	64	1	5	2.23	1.488

DIG_12	Simulations interact directly with a higher-level production system (e.g., SCADA, MES, ERP)	64	1	5	1.80	1.311
DAT_1	Process data is archived completely digitally.	64	1	5	3.45	1.126
DAT_2	All production processes include controls and auditing bodies to ensure conformity with internal and external requirements.	64	1	5	3.56	1.320
DAT_3	Quality controls are fully digitized and archived.	64	1	5	3.17	1.279
DAT_4	(Short-term) changes in the production plan are fully and transparently integrated into the existing control systems.	64	1	5	2.97	1.357
DAT_5	Process data is collected completely automatically.	64	1	5	2.42	1.206
DAT_6	In the event of a failure of the production control system, production can be carried out completely manually if necessary (until repairs are made).	64	1	5	3.78	1.362
DAT_7	The provision of data for internal purposes is completely digital.	64	1	5	3.25	1.113
DAT_8	The data collected is transparent and used for analysis and comparison.	64	1	5	3.00	1.141
DAT_9	The value chain (purchasing, logistics, production, sales, after-sales service) is fully digitized and can be viewed transparently by all areas of the company.	64	1	5	2.83	1.121
DAT_10	Data is always the basis for improving the business process.	64	1	5	3.31	1.220
DAT_11	Sufficient IT security is ensured at all digital levels (data security and protection of all systems).	64	1	5	3.84	1.224
ATT_1	There is a clearly defined digitization strategy in the company.	64	1	5	2.83	1.077
ATT_2	There is a dedicated person responsible for digitization issues (internal or external).	64	1	5	2.86	1.435
ATT_3	The management level promotes the digital transformation in the company in a credible manner and believes that progressive digitization will ensure the company's success in the long term.	64	1	5	3.33	1.235
ATT_4	Digitization solutions that have already been implemented make an important contribution to business success, especially during the ongoing Corona crisis.	64	1	5	3.36	1.302
ATT_5	Digitization solutions that have already been implemented have increasingly led to redundancies in your company in the past.	64	1	5	2.09	1.519
ATT_6	Workers and employees in the company fully welcome digitization and digital transformation in the company.	64	1	5	3.13	.968
ATT_7	The productivity of your company is much higher than that of your competitors.	64	1	5	2.95	.785
ATT_8	The economic success of your company (profit) is significantly higher than that of your competitors.	64	1	5	2.92	.841
DIG	Mean from DIG_1 to DIG_12	64	1	5	2.42	.898
DAT	Mean from DAT_1 to DAT_11	64	1	5	3.24	.792
ATT	Mean from ATT_1 to ATT_8	64	1	5	2.93	.735

In the next step, the variables DIG, DAT, and ATT were computed as an amalgamation of the underlying indicators. The resulting Cronbach´s alpha values (CBA_DIG=.875; CBA_DAT=.860; CBA_ATT=.779) are above the recommended threshold of 0.600 and therefore, ensure the internal consistency of the respective scales (Hair Jr. et al., 2014; Heath and Jean, 1997).

Table 7 shows the result of the correlation analysis. Thereby, the results showed no significant correlations between DIG and DAT (.212), highly significant correlations between DIG and ATT (.435**), and highly significant correlations between DAT and ATT (.583**).

Table 7. The Austrian metal forming industry: Correlations between DIG, DAT and ATT.

		DIG	**DATA**	**ATT**
DIG	Correlations (Pearson)	1	.212	.435**
	Significance (2-tailed)		.093	.000
	N	64	64	64
DAT	Correlations (Pearson)	.212	1	.583**
	Significance (2-tailed)	.093		.000
	N	64	64	64
ATT	Correlations (Pearson)	.435**	.583**	1
	Significance (2-tailed)	.000	.000	
	N	64	64	64

The statistical analysis of the conducted survey demonstrates the differences between theoretical and practical state-of-the-art in this specific industry segment. Reviewing the degree of automation and digitalization (DIG), a majority of participating companies did not fulfill the requirements for the implementation of Industry 4.0 technologies according to the literature (e.g., CPPS, DT). This hypothesis is supported by the results of the DAT block, which reveals a lack of effective data gathering and, as a result, intransparency of a majority of production process outside the main domain. Despite this, data visualization and user-friendly HMIs are already standard. In contrary, commitment and therefore, willingness to change from involved staff on different levels can be observed. For the adaption of the first lecture concept, the following main outcomes can be stated:

- Basic knowledge about ERP/MES/PPS systems are mandatory;
- Knowhow about SCADA related technologies and tools are a requirement to work in this industry segment;
- Enhancing valid data gathering can add significant value to a majority of participating companies, although the importance of this skill is not recognized by most of them;
- Numerical simulation of production processes, IIoT, Big Data solutions, as well as, the ability to integrate (numerical) simulations into the production network are a distinguishing factor for potential employees and can therefore, be seen as an asset for applicants that are capable of using these tools.

4.2 Research methodology and results: Questioning participating engineering students

For the design of the respective survey for students, the third block (for companies ATT) was changed to LEC (lecture: what requirements students actually have on a transdisciplinary lecture?). Additionally, questions within the item blocks DIG and DAT were adapted according to more accurate scientific definitions and extended with upcoming technologies that have the potential to become future standards in the metal forming industry segment. This approach should ensure that future engineering experts also have the fundamental knowledge to execute independent LLL in this field of interest if necessary. For an upcoming analysis of potential deviations between students from different engineering disciplines and study progress, the enrolled field of study, as well as, study progress (bachelor, master or PhD) were additionally surveyed.
In order to gain a valid overview about student's actual knowledge and abilities, a total of 3495 students from the Montanuniversität Leoben in Austria were surveyed. From the total number contacted, 234 questionnaires (6.70%) were completed, valid, and therefore, usable for the subsequent statistical procedures. Following the same tests for representativeness as in section 4.1, the results can be seen as valid. For the operationalization, the same LIKERT scale as for the company survey was used (Armstrong and Overton, 1977; Lippe, 2011).

Table 8. Engineering students at the Montanuniversität Leoben: Survey scope and results from valid responses.

Item	Text	N	Min.	Max.	Mean	Std.Dev.
DIG_1	Can you distinguish between the terms 'digitization' and 'digital transformation'?	233	1	5	2.41	1.122
DIG_2	Can you define the term 'digitization"?	232	1	5	2.91	1.155
DIG_3	Are you familiar with the term 'internet of things' or 'industrial internet of things' and can you define it?	232	1	5	2.88	1.429
DIG_4	Are you familiar with and able to define the term 'cyber physical systems' or 'cyber physical production systems'?	233	1	5	2.23	1.335
DIG_5	Can you define the term 'human machine interface' and do you know what is meant by it in industrial practice?	230	1	5	2.56	1.296
DIG_6	Are they familiar with the definition and distinction of 'big data' in an industrial context?	234	1	5	3.13	1.243
DIG_7	Can you define the term 'digital twin'?	231	1	5	2.64	1.465
DIG_8	Do you know the difference between a 'digital model', 'digital shadow' and 'digital twin'?	232	1	5	1.76	1.196
DIG_9	Do you know what exactly is meant by 'retrofitting' in the context of digitization?	232	1	5	1.69	1.205

DIG_10	Can you define the terms 'vertical and horizontal integration' in production?	234	1	5	2.31	1.462
DIG_11	Are you familiar with the basic concepts of IT security in an industrial context?	232	1	5	2.27	1.252
DIG_12	Do you know the 'OSI reference model'?	233	1	5	1.58	1.150
DIG_13	Are you familiar with the term 'cloud computing' and do you know what it means?	231	1	5	3.06	1.360
DIG_14	Are you familiar with the concepts of change management in the industry?	231	1	5	2.44	1.422
DIG_15	Are you familiar with the basics of data and database management?	232	1	5	3.04	1.383
DAT_1	Are you familiar with the different levels of the automation pyramid?	234	1	5	2.11	1.203
DAT_2	Do you know one or more of the following programming languages: Python, R, C, C++, Java?	234	1	5	3.44	1.479
DAT_3	Can you define the term 'MES'?	232	1	5	1.76	1.299
DAT_4	Can you define the term 'ERP System'?	233	1	5	2.21	1.572
DAT_5	Can you define the term 'SCADA' in the context of production?	232	1	5	1.62	1.106
DAT_6	Do you know the most common protocol formats in the context of production planning and control?	232	1	5	1.65	1.062
LEC_1	In general, would you be interested in your own course on the fundamentals of digitization and digital transformation in industrial practice?	226	1	5	4.43	.837
LEC_2	Would you like to see most of the required theory taught via the Moodle platform (anytime access, text, image and video material)?	225	1	5	4.31	1.000
LEC_3	Would you like a significant portion of the course to include practical components (demonstration of various technologies in a digital factory)?	227	1	5	4.57	.786
LEC_4	Would you welcome the opportunity to work on a case based on reality as a project manager? (Management of a digitalization project)?	226	1	5	3.96	1.082
LEC_5	Would you welcome the opportunity to briefly present such a project as part of the course? (Presentation technique in practice)?	227	1	5	3.60	1.220
LEC_6	Do you feel able to take over project management or assistance in a digitization project in industrial practice?	223	1	5	2.78	1.299
DIG	Mean from DIG_1 to DIG_15	234	1	5	2.46	.837
DAT	Mean from DAT_1 to DAT_6	234	1	5	2.14	.927
LEC	Mean from LEC_1 to LEC_6	227	1	5	3.94	.655

As with the company survey, the variables DIG, DAT, and LEC were computed as an amalgamation of the underlying indicators. Similarly, the resulting Cronbach´s alpha values (CBA_DIG=.899; CBA_DAT=.811; CBA_LEC=.688) are above the recommended threshold of .600 and therefore, ensure the internal consistency (Hair Jr. et al., 2014; Heath and Jean, 1997). Table 9 shows the results of the correlation analysis. Thereby, highly significant correlations were found between DIG and DAT (.788**) and DIG and LEC (.222**). However, the results showed no significant correlations between DAT and LEC (.106).

Table 9. Participating engineering students at the Montanuniversität Leoben: Correlations between DIG, DAT and LEC.

		DIG	**DAT**	**LEC**
DIG	Correlations (Pearson)	1	.778**	.222**
	Significance (2-tailed)		.000	.001
	N	234	234	227
DAT	Correlations (Pearson)	.778**	1	.106
	Significance (2-tailed)	.000		.110
	N	234	234	227
LEC	Correlations (Pearson)	.222**	.106	1
	Significance (2-tailed)	.001	.110	
	N	227	227	227

The analysis of the questionnaire's results reveals a very low degree of knowledge regarding Industry 4.0 enabling and corresponding technologies. Furthermore, knowhow defined as mandatory from the industry's point of view is specifically lacking within the majority of the participants. This evaluation indicates a fundamental change in the scope of the first concept of the lecture, changing the weighting of the topics of module I to more fundamental technologies topics (e.g., automation technologies, SCADA, MES).

Additionally, the authors used an ANOVA to calculate significant differences in the variables DIG, DAT, and LEC between the bachelor, master, and PhD students (Figure 5). The results showed highly significant differences in the variable DIG (F=4.248; Sign.=.001), significant differences in the variable DAT (F=4.248; Sign.=.015), but no significant differences in the variable LEC (F=.393; Sign.=.676).
These results implicate that the lecture can be executed similarly for all students, without considering their academic study progress. Furthermore, this study reveals that in the past, no educational efforts at the university, independent from the degree level, were able to successfully build up knowledge in a majority of Industry 4.0-related topics, especially data management, to engineering students.

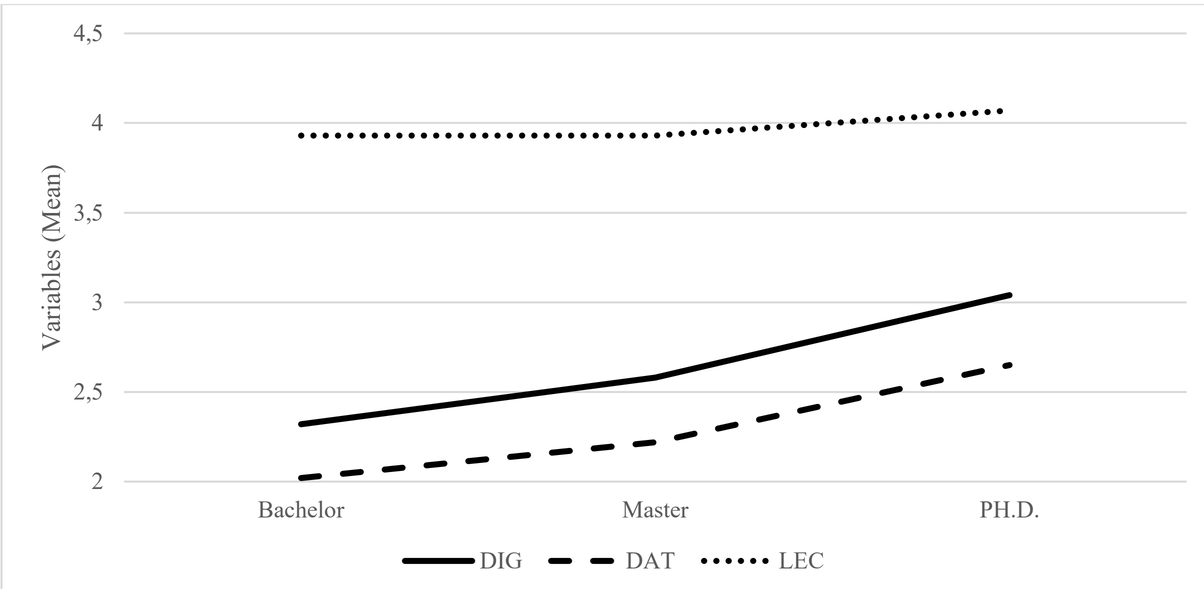

Figure 5. Differences in the mean value of the defined item blocks: comparison between bachelor, master and PhD students.

To identify potential differences in initial knowledge about the lecture's topics, students were grouped according to two summary disciplines:

- Core manufacturing disciplines (CMD): engineering disciplines that have a direct connection to manufacturing processes (e.g., mechanical engineering, metallurgy and materials science, industrial logistics, industrial energy technology)
- Supportive manufacturing disciplines (SMD): engineering disciplines that are indirectly related to manufacturing processes or the metal forming environment (e.g., raw materials engineering, recycling)

In this case, the results showed no significant differences in the variable DIG (T-value=-.715; p-value=.475), no significant differences in the variable DAT (T-value=-.203; p-value=.839), and no significant differences in the variable LEC (T-value=-.249; p-value=.804) between the CMD and SMD groups. Therefore, additional analysis of single disciplines was not executed. The results of this analysis are illustrated in Table 10.

Table 10. Correlation between CMD and SMD.

	Sample	N	Mean	Std.Dev.	Std.Err.
DIG	CMD	189	2.401	.790	.058
	SMD	26	2.522	.917	.180
DAT	CMD	189	2.090	.872	.064
	SMD	26	2.128	1.117	.219
LEC	CMD	185	3.927	.646	.048
	SMD	23	3.964	.782	.163

The feedback from participating students regarding the lecture design leads to the conclusion that the general scope, as well as, proposed learning methodologies are reasonable and will result in proper engagement from participating students. The relatively low score regarding question LEC_6, as well as, within the DIG and DAT item block implies that the learning objectives initially defined (section 3) are suitable.

4.3 Identified knowledge gap: engineering students vs. Austrian's metal forming industry

The authors evaluated significant differences between the student sample and the company sample in the variables DIG and DAT. The results showed no significant differences in the variable DIG (T-value=.296; p-value=.768) but highly significant differences in the variable DAT (T-value=-8.668; p-value=.000) between the student sample and the company sample. The descriptive results are displayed in Table 11.

Table 11. T-Test – Descriptive Statistics: correlation between industry segment and engineering students.

	N	Minimum	Maximum	Mean	Std.Dev.
DIG	298	1	5	2.451	.849
DAT	298	1	5	2.372	1.006

	Sample	N	Mean	Std.Dev.	Std.Err.
DIG	Students	234	2.459	.837	.055
	Companies	64	2.423	.898	.112
DAT	Students	234	2.135	.927	.061
	Companies	64	3.236	.792	.099

Especially in the data segment, a significant gap between actual knowledge of engineering students and requirements from potential employers can be seen. This result is particularly interesting, as companies from the Austrian's metal forming sector are already behind in terms of effective and efficient data management for Industry 4.0 purposes compared to literature. This context will be considered in the final lecture redesign, to be able to prepare future experts in the metal forming field for their career and thus enhance respective companies' performance in a digitalized working environment.

5 Result based lecture redesign – didactical concept

For the sake of comprehensibility, the result section is divided into three parts. In subsection 5.1, the adaptions regarding scope based on results from 4.1 and 4.2 for the initial concept (section 3) are demonstrated. In 5.2, the changes in learning methods as a result of the adaptions made are described. In 5.3, the further improvement of the initial lecture based on the PDSA cycle is defined, ensuring competitiveness and ergo, enable the University to use this didactical framework and corresponding lecture as a basis for the successful transformation or creation of other transdisciplinary lectures.
Figure 6 shows the resulting redesign approach, based on the implications from sections 2, 3 and 4.

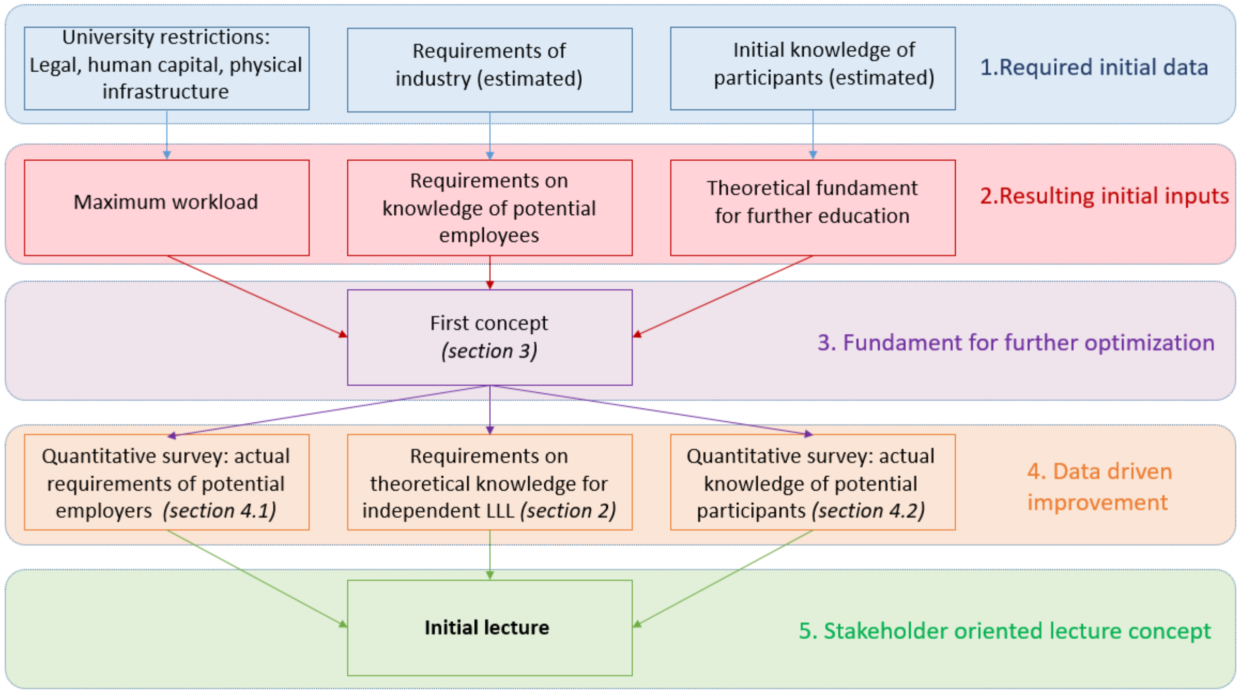

Figure 6. (Re)design approach of a state-of-the-art digitalization and digital transformation lecture: a stakeholder-oriented approach.

5.1 Lecture redesign: Adaptions in scope

The technical fundamentals of the fourth industrial revolution are mainly the scope of the first two modules of the initial lecture design (Figure 4, Table 1, Table 2). Based on the analysis of participated engineering students and metal forming companies, adaptions in scope and scope weighting within these two modules were conducted, as illustrated in Table 12 (module I) and Table 13 (module II).

Table 12. Adaptions made in module I based on results of the executed stakeholder analysis

Module I: Initial scope	**Initial duration (h)**	**Adapted scope**	**Adopted duration (h)**
Introduction into opportunities and issues of digitalization technologies in the metal forming environment	2	Introduction into fundamentals of automation and networking technologies and the correlation with digitalization technologies in the metal forming environment	3 (+1)
Fundamentals of digitization, including sensor and actuator technologies	7	No adaption	7 (-)
Fundamentals of digitalization, including networking technologies, state of the art protocols, interfaces, data management and IT-security	7	Additional fundamentals of Computer Integrated Manufacturing (CIM), MES and ERP	15 (+8)
The importance of CPPS and corresponding HMI in the metal forming environment	7	Fundamentals of CPPS and HMI	5 (-2)
Definition of Big Data, AI, DT and DS within the metal forming industry	7	No adaption	7 (-)

Table 13. Adaptions made in module II based on results of the executed stakeholder analysis

Module I: Initial scope	**Initial duration (h)**	**Adapted scope**	**Adopted duration (h)**
Practical demonstration of the fundamentals of networking technologies, state of the art programming languages and resulting layer architecture at the SFL	2	No adaption	4 (+2)
Practical demonstration of a developed CPPS and corresponding HMI at the SFL	2	No adaption	2 (-)

The identified lack of knowledge about fundamentals in production technologies, as well as, industry requirements on knowledge about SCADA systems lead the authors to the conclusion to increase the workload on the fundamentals of these technologies, in theory (Table 12) and practice (Table 13). As CPPS are not focus of the industry and due to the lack of required knowledge from potential participants point of view, a decrease in focus on this Industry 4.0 concept was defined.
As a result of the higher amount of required workload (9 hours), the preparation time for the final examination (initially 20 hours), based on a group presentation (Table 4) will be adapted. To ensure fair grading, a new concept for the performance examination was developed.

5.2 Lecture redesign: Adapted didactical concept

<u>Prerequisites & Admission</u>
The language of instruction is English. The selection procedure is based, on the one hand, on submitted qualification certificates (diploma, work certificate) and on the other hand, on the respective positions in the curriculum.
Prerequisite for admission to the course is the fulfillment of one of the following qualifications:

- Completed bachelor's degree or degree from a university of applied sciences in a relevant field of study
- Prerequisites and position of the course in the respective curriculum
- Freely accessible for all enrolled students at the Montanuniversität Leoben

The decision on admission is made by the scientific management on the basis of the submitted qualifications.

<u>Number of participants</u>
The maximum number of participants is 100. Two lecturers take turns in the practical part, due to COVID-19 divided into groups of 5 students each, i.e. 10 groups per lecturer in the practical, 2 hours each, divided into 3 days per unit (currently one practical unit per group is planned). Depending on the current pandemic restrictions, the delivery of the practical sessions will be adapted to ensure the safety and health of all participants.

<u>Target group</u>
This compact course is aimed at students from all fields of study who are interested in digitization concepts and their practical implementation. In addition, a certain affinity for the development of innovative solution approaches with regard to the challenges in the digital transformation is essential.

<u>Learning outcomes</u>
After successful completion of this lecture, students should be able to:

(i) create and evaluate concepts for the digitalization in metal-forming-related production systems
(ii) apply the theoretical concepts in a case study

(iii) apply and implement them together with experts from different disciplines
(iv) understand and implement the applied procedures in practice based on the theoretical and practical knowledge acquired.

Teaching and learning concept

In the sense of "constructive alignment" according to Biggs, the teaching and learning concept is aligned with the learning outcomes, the teaching and learning activities and the final assessment. The focus of the concept is participant orientation and for this the method of Ruth Cohn of topic-centered interaction is used to place topics, questions or ideas in the center and these are worked on by the participants in mutual exchange. Accordingly, all teaching and learning materials are designed to meet the needs of the target group. The selection of the main topics was made by means of an extensive survey of potential students and industry needs. The conceptual design, implementation and results of the surveys are described in Chapter 4.

Through the experience and competence of the lecturer, the integrated course conveys, on the one hand, fundamentals and in-depth knowledge that are essential for understanding and assessing current digitization processes in industrial practice. Fundamentals and theory are illustrated and reflected by concrete practical examples.

The course is modular in a blended-learning format. In modules I to III, the teaching content is essentially conveyed through compact lectures with the help of multimedia support, as well as, in interactive phases (workshops, question rounds, etc.). The four modules are coupled and are each held in the summer semester over a period of 2 months. Blocks 2 and 4 are held as classroom sessions and blocks 1 and 3 as online learning via the platform CISCO WEBEX. In addition, the theory blocks are supported by synchronous and asynchronous teaching methods. This supports the more flexible scheduling of the learning content for students.

For the conclusion, a presentation "Elevator Pitch" (Module IV), as well as, a final discussion on the chosen methods and theories will be held, to ensure the highest possible practical relevance.

Duration, structure and scope

The university course consists of a total of 4 blocks and includes 2 semester hours of 50 contact hours and 25 hours of self-study, for a total of 2.5 ECTS credits.

Assessment

The assessment includes the active participation in the course, as well as, the contribution and presentation of the case study and a short final discussion on the chosen methods and theories in the case study. To reduce the workload for the final examination and further enhance fairness and transparency in final grading, the group presentation initially developed is replaced by a short stand-alone version. Within this presentation, which should not exceed five minutes (‘Elevator Pitch’ (EP)), participants should demonstrate a possible solution to a case study previously handed out within module III. The prepared case study will include different aspects from all previous modules, whereas the given information within ensures that a suitable outcome can be realized within the calculated (reduced) preparation time of 11 hours. The case studies prepared are slightly different for each participant, ensuring comparable but not identical solutions are proposed. The style, as well as, media mix used for the presentation is not restricted in any direction, allowing each candidate to choose what fits best to her/his needs. In order to actively involve the participants in the evaluation process and the results, each student is asked to evaluate his or her fellow for the performance in the EP scenario according to the criteria listed in Figure 7 (Peer assessment). Consequently, both technical and soft skills knowledge should be deepened and reflected upon by following this approach.

Lecture - Final Pitch	Overal proposed solution			Unique Value Proposition		Pitch / Q&A		Results	Comment	
	Quality of service	Coherence problem/solution	Adapted to the target group	Benefit for the target group	Utilisation	Pitch performance (clear, understandable,	Quality of Q/A		Pros	Cons
	1= weak; 5=strong	1= weak; 5=strong	1= weak; 5=strong	1= weak; 5=strong	1= weak; 5=strong	1= weak; 5=strong	1= weak; 5=strong	(SUM of all attributes)		
Person 1								0		
Person 2								0		
Person 3								0		
Person 4								0		
Person 5								0		
Person 6								0		
Person 7								0		
Person 8								0		
Person 9								0		
Person 10								0		
Person 11								0		
Person 12								0		

Figure 7. Fellow evaluation of a student's performance on the final elevator pitch.

Assessment regulations

This presentation contributes to 75 % of the final grade. After the presentation, a short discussion with the respective teacher is carried out, in which related theory to the presented topic is discussed. The students´ performance within this discussion is also part of the peer review process. Additionally, the performance of the candidate within this discussion contributes to an additional 25 % and is the only contribution to the final grade awarded by the corresponding teacher.

Students are required to work independently on a case study (beginning of module 3) from an industrial context. The example will be handed out to the students by the instructor. In the final presentation, the results, including reflection and subsequent discussion, must be presented in the form of a so-called "elevator pitch" of max. five minutes. The presentation of the case study, as well as, the presentation itself, will be written down in advance and submitted to the course instructor. The medium of the presentation is open, different forms are desired (e.g., film, PowerPoint presentation, cards, ...). The form of presentation must be agreed upon in advance with the instructor.

The following explanations of the elevator pitch method should be presented to the students during the introduction in the first module (Denning and Dew, 2012):

- What is an elevator pitch?
  An elevator pitch is a short speech (verbal presentation) that is typically carried out within 1-5 minutes. The pitch outlines the most pertinent information and was devised around the concept that you could sell your idea in the time that it took for an elevator to reach its' designated floor. So how much could be said in a typical elevator journey could depend on how many floors the elevator needs to travel, but in most cases, it is not too long and ergo, not too much can be said. So, you need to make what you say count!
- What are the typical components of an elevator pitch?
  - Introduction: Who are you and what do you do?
  - Services: What can you offer?
  - Target audience: Who is your target audience?
  - Unique Value Proposition: How can you help your target audience and why?
  - And now (next steps): What are you going to / How can you help them and what do you need from them?

Afterwards, the applied theories and methods, as well as, their fundamentals will be summarized and briefly reflected upon in a short final discussion.

5.3 Continuous improvement and further generalizability

According to the PDSA circle (Deming, 1998; Shewhart, 1986), a continuous improvement of the lectures scope and teaching methods is planned. Figure 8 illustrates the methodology, where one adaptation phase per semester will be executed.

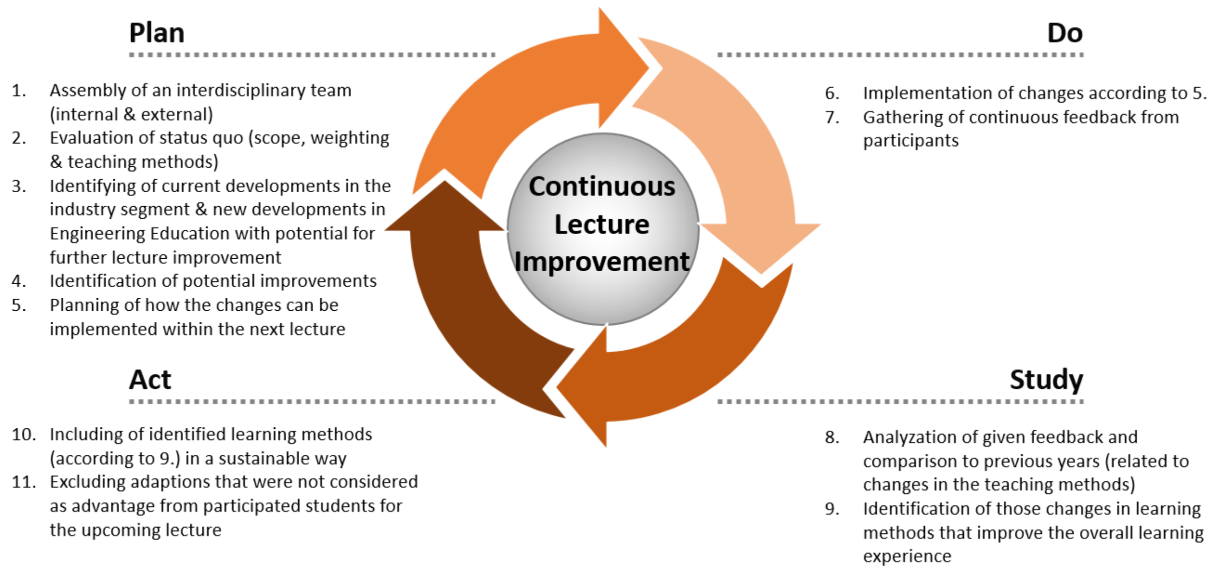

Figure 8. Developed 11 steps PDSA circle for the continuous improvement process of the developed lecture.

The frameworks visualized in Figure 6 and 8 can also be used for a general concept of adapting transdisciplinary lectures. If a new lecture has to be developed, both frameworks should be applied. If an existing lecture should be adapted in terms of scope or teaching methods, the developed framework shown in Figure 8 can be used.

6 Conclusion and discussion

The approach demonstrated in this paper has several advantages. As it was derived from a practical case, the usability of the framework for a transdisciplinary engineering education approach with focus on one specific industry segment can already be validated. However, the success of this stakeholder-oriented approach depends on the quality of resulting data from potential employers (the respective industry segment) and their potential employees (the potential participants). If no valid information gathering from these groups can be maintained, the resulting (re)design can be inefficient or not in scope, especially when data from the respective industry field is not valid. For this reason, it is mandatory for responsible lecturers to know their stakeholders before starting with the proposed (re)design. If this requirement is fulfilled, a suitable method for data gathering must be defined, where suitability depends on the target group within identified stakeholders (e.g., which industry segment replies to which data gathering instruments, how must a questionnaire be designed to reach target auditorium in the practical field, which engineering disciplines should participate in the academic course). Additionally, the learning methods must be aligned to the respective scope (e.g., grade of practical experiments within the course, estimated course size, available human and physical resources).
Another advantage of the developed framework is the consideration of further improvements by an adapted PDSA circle, which frequently carried out allows a proactive reaction of involved teaching personnel on changes in the stakeholder environment. Furthermore, by requiring continuous feedback from participants

during the different modules of the course, it is possible to rapidly implement changes. This approach ensures a higher satisfaction of participating engineering students, as their contribution to enhancing the quality of the lecture is clearly visible to them. As a result, a 'PDSA-light' is developed, beginning with the fourth step (Figure 8; Plan - 4.) based on given recommendations from students during the lecture(s).
Based on the methods and framework introduced in this paper, a state-of-the-art approach for the development of a transdisciplinary engineering lecture, including modern teaching methods, was developed and by the example of a digitalization and digital transformation lecture for engineers in the metal forming field, successfully implemented.

7 Outlook and Implications

In today's globalised world the topic of digital education in higher engineering education can no longer be detached from the idea of teaching students in a classroom, as a blended/hybrid or fully online format. It opens up a whole new world of comprehension and methodological flexibility. This is the reason for the realignment of this lecture at the Montanuniversität Leoben, to take initiative and enhance teaching standards in Europe to a digital and much needed level. Only through the integration of digital concepts into teaching can lasting solutions for the industry be created. It can thus, provide the required expertise to create a new digital top-notch education system for the Montanuniversität Leoben, as well as, a noteworthy contribution for the European Higher Education Area.
Moreover, there is a need for uniform learning analytics in Europe and at a national level as well for collecting, evaluating, and making use of data based on the development of skills and knowledge in a targeted manner so that education systems and content can be adapted to subjective educational needs. In many cases, however, this approach is only in a pilot phase and for this reason, further approaches and holistic reforms at the university level are essential (European Commission, 2020).
To be adequately trained for the future and to be able to design appropriate Engineering curricula, the educational needs and key-competencies for future Engineers must first be defined. In this regard, targeted, up-to-date skills intelligence (European Commission, 2020) is needed, which must be embedded in national competence strategies and educational systems. This will ensure that future experts have the essential skills and expertise to develop and implement measures for everyday challenges, such as climate change or resource-saving initiatives, in a sustainable world. In addition, a significant contribution can thus be made to cross-regional exchange to counteract the brain-drain phenomenon and to legal migration.

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A 8 Publication 8

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Transformation of a rolling mill aggregate to a Cyber Physical Production System: from sensor retrofitting to machine learning

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Abstract:

This paper describes the transformation of a rolling mill aggregate from a stand-alone solution to a fully integrated cyber physical production system. Within this process, already existing load cells were substituted and additional inductive and magnetic displacement sensors were applied. After calibration, those were fully integrated into a six-layer digitalization architecture at the Smart Forming Lab at the Chair of Metal Forming (Montanuniversitaet Leoben). Within this framework, two front end human machine interfaces were designed, where the first one serves as a condition monitoring system during the rolling process. The second user interface visualizes the result of a resilient machine learning algorithm, which was designed using Python and is not just able to predict and adapt the resulting rolling schedule of a defined metal sheet, but also to learn from additional rolling mill schedules carried out. This algorithm was created on the basis of a black box approach, using data from more than 1900 milling steps with varying roll gap height, sheet width and friction conditions. As a result, the developed program is able to interpolate and extrapolate between these parameters as well as different initial sheet thicknesses, serving as a digital twin for data-based recommendations on schedule changes between different rolling process steps. Furthermore, via the second user interface, it is possible to visualize the influence of this parameters on the result of the milling process. As the whole layer system runs on an internal server at the university, students and other interested parties are able to access the visualization and can therefore use the environment to deepen their knowledge within the characteristics and influence of the sheet metal rolling process as well as data science and especially fundamentals of machine learning. This algorithm also serves as a basis for further integration of materials science based data for the prediction of the influence of different materials on the rolling result. To do so, the rolled specimens were also analyzed regarding the influence of the plastic strain path on their mechanical properties, including anisotropy and materials' strength.

KEYWORDS: Cyber Physical Production System; Retrofitting; Digitalization; Digital Twin; Machine Learning; Smart Forming Lab; Industry 4.0;

1 Introduction

The ongoing fourth industrial revolution forces manufacturers around the globe to face significant changes in their possibilities to plan and steer production processes and overlying operations (Zhong et al. 2017). Despite all the advantages the connection and network technologies offer (e.g. digital value chain, one-piece flow concept), there are crucial thresholds to overcome in order to implement digitalization technologies in a successful and sustainable way. These thresholds can be divided into investment (economic related) and socio-cultural (management and psychology related) challenges. Regarding investment issues, especially SMEs face a serious problem, as most digitalization approaches are highly scalable, making the amortization time for necessary investments much longer for this kind of businesses (Müller et al. 2018). This also includes the required human capital to implement infrastructural changes within a company. To sustain the digital change in the manufacturing environment, responsible managers must be aware of potentials and possible threats on the technical as well as working environment layer (Akkaya 2019).

To contribute to the solution of this issues, this paper focusses on two main objectives:

a. Reducing the investment costs for smaller companies by using mainly open source software (SW) and cost-effective but suitable hardware (HW),
b. Development of a resilient Cyber Physical Production System (CPPS), which can be used to

educate engineering students and therefore future production managers as well as other interested parties from the manufacturing industry segment in the topic of digitalization and associated technologies.

In order to create a case study which fulfills the requirements of (a) and (b), an already existing metal forming aggregate at the Smart Forming Lab (SFL) at the Chair of Metal Forming (CMF) of the Montanuniversitaet Leoben was chosen (Ralph et al. 2020). For this purpose, the CMFs rolling mill aggregate was used, as it can serve as an ideal example of how retrofitting from sensor application up to implemented machine learning algorithms can be integrated successfully in a low cost (LC) resilient digitalization layer architecture (Ralph, Woschank et al. 2021). This brownfield approach is also a common initial state within the metal forming and metallurgical environment, as the production asset life span tends to be significantly higher than in other industry segments (Ball et al. 2020; Elkins et al. 2004). Especially considering SMEs and their lower investment budget, brownfield approaches dominate when it comes to digitalization approaches in comparison to corresponding greenfield investments (Sorensen et al. 2019).

2 Fundamentals of the rolling process and CPPS

Within this chapter, the most important characteristics of the rolling process as well as a common definition of a CPPS is introduced. Based on these definitions, the case study will be elaborated, beginning with the initial state (3), followed by digitization (4) and digitalization (5) and the developed data driven (black box) digital twin setup (6) (Ralph and Stockinger 2020).

2.1 The rolling process

According to DIN 8580, rolling belongs to the manufacturing processes of forming under compressive loads and to the group of direct forming processes. During the process, a sheet material is formed through the roll gap between at least two rotating rolls, leading to a reduction in the cross-section of the rolled material (fig.1) (German Institute for Standardization).

During the rolling process, a force flow occurs through the roll stand as a result of the load applied to the processed material. All parts of the roll stand, that are directly or indirectly affected from the force flow, undergo an elastic deformation (Wang et al. 2017). Affected parts are the rolls, roll bearings, load cells, adjusting elements and the roll stand itself. This elastic deformation causes the roll gap to increase, from the initial (set) gap s_0 to s_1, whereas the difference between is defined as Δs (fig. 1).

$$\Delta s = s_1 - s_0 \qquad (1)$$

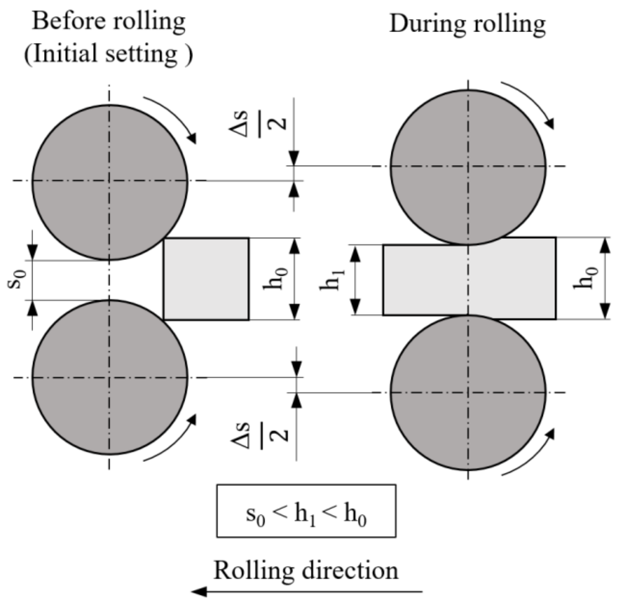


Fig. 1 Geometry change during rolling

The end thickness of the rolled sheet h_1 can be calculated according to the Gage-meter equation (Lee and Lee 1999). The Gage-meter equation specifies the expected exit thickness of the rolled material h_1 depending on the initial roll gap height s_0 and the elastic deformation, which depends on the rolling force F_R and the stand modulus C. The elastic deformation of the aggregate is characterized by C and corresponds to the slope of the roll stand module in the rolling gap diagram.

$$h_1 = s_0 + \frac{F_R}{C} \qquad (2)$$

The rolling gap diagram shows the rolling force F_R over s_0 and initial material thickness h_0 (fig. 2). The point of intersection between the roll stand characteristic curve, defined by slope C, and the materials characteristic curve, the material module in the rolling gap diagram is called the working point (A). A provides information on the exit height of the rolled sheet h_1 as a function of F_R (Fig 2).
It is important to note that the influence of sheet metal width is not considered as influencing factor of C, but included in the material module. One hypothesis of this paper is, that the friction state and resulting rolling force differences mainly depend on the sheet geometry. Therefore, the contact surface in the roll gap increases the resulting rolling force significantly more than the effect of a rougher surface topology. In addition, the approximated linear behavior of C is given for one s_0. The second hypothesis stated and to be elaborate more deeply in section 6 is the non-linear behavior of C with different s_0 and overall difference between h_0 and h_1, Δh.

$$\Delta h = h_0 - h_1 \qquad (3)$$

Similar to hypothesis 1, an influence on the material behavior (e.g. due to work hardening) can be observed, although the authors state that the force flow through the machine system also contributes significantly to the change in h_1, which as a consequence results in a dependency of C on Δh.

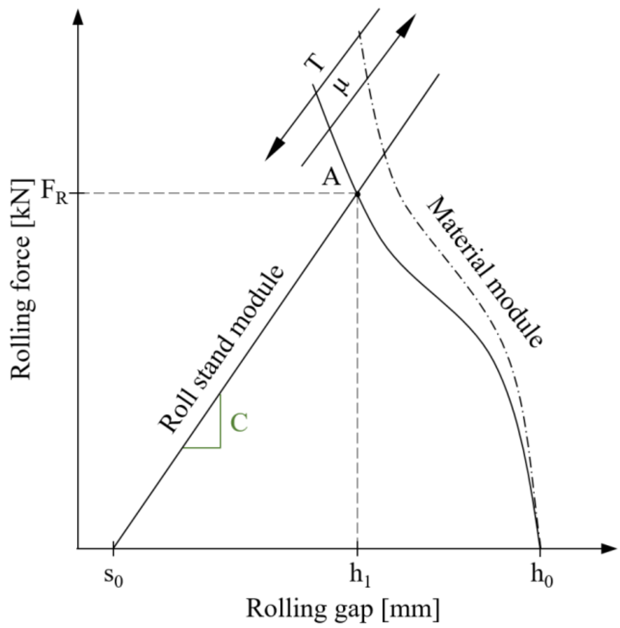


Fig. 2 Work diagram for rolling for a defined s_0.

2.2 Cyber Physical Production Systems (CPPS)

CPPS can be defined as a derivative from Cyber Physical Systems (CPS), especially tailored to the production segment. Although CPS and CPPS are heavily researched in the past years, there is still no standardized definition for this technology framework (Wu et al. 2020).
According to Wu et al. (2020), the most accepted definition can be derived from the work of Cardin (2019) who extended a previous definition from Monostori et al. (2016) to the following statements:

i. CPPS are superordinate systems within systems.

ii. CPPS consist of cooperative elements, those connect with each other situationally appropriate, on and between all different levels within the production environment, from the processes itself, through involved machines up to overlaying networks, e.g. MES or ERP-systems.

iii. CPPS enhance decision making processes in real-time in a resilient and robust way, with respect to time as well as foreseen and unforeseen events (Wu et al. 2020).

The fulfillment of i.), ii.) and iii.) for the case study presented in this paper will be demonstrated in the following chapters. In order to do so, these very broad conditions have to be concretized. Despite this requirements, the practicability for learning purposes as well as financial restrictions (e.g. for the implementation in a SME or academic learning environment) were considered. Most important, the user friendliness of a CPPS will also be in focus of this study. Therefore, the development of shop-floor friendly, intuitive Human Machine Interfaces (HMIs) are a central point in this work. Additionally, low-cost solutions to avoid expensive maintenance and update plans were used wherever possible. Table 1 summarizes the specifications of the LC user centered CPPS developed within this paper.

Table 1 LC user centered CPPS: further adaption and concretization (Wu et al. 2020)

	Criteria	Concretization
I.	System in a system	Data exchange and process adaptions on other upcoming process steps based on gathered data from the rolling mill through a unified network layer
II.	Situationally appropriate connection and data transfer on different layers	Change in data storage frequency based on actual machine status (on/off) and state dependent data publishing route within the layer system
III.	Enhance decision making process in real time and state dependent	Implementation of a machine learning algorithm that predicts results of the actual process step and upcoming process steps in near real time including the capability of adaption of the prediction due to foreseen and unforeseen events
IV.	User centered GUI	Two user friendly front end and two (IT-skilled) user friendly back end interfaces
V.	Low-cost and resilient design	Finding the optimum of cost-effective HW and SW solutions under the restriction of resilient, robust and easy to use solutions

3 Initial machine and digitalization set up

This chapter describes the initial state of the existing infrastructure at the SFL, whereas (3.1) focusses on the IT-layer structure and (3.2) shows the initial state of the rolling mill system to integrate into the layer architecture.

3.1 The six-layer architecture at the SFL

Figure 3 shows the initial layer system implemented at the SFL. Before the integration of the milling system, a CNC lathe (type EMCOTURN E65) was connected with a

power measurement unit into a condition monitoring system, powered by a WAGO controller with integrated warm memory storage (type PFC200 G2 2ETH RS). The unrefined data (e.g. phase currents, voltages) is pre-processed, agglomerated and uploaded on the internal server structure at the SFL, using the structured text (STS) based WAGO e-cockpit SW, after A/D transmission via additional modules (type WAGO 750-494). Within the STS environment, an additional condition monitoring system and corresponding GUI was programmed. The server-stored data is extracted autonomously with a Python based script, running on the same server environment. This script extracts and transforms the data into a set up SQL database, from which most important project management (PM) data is published near real time on a PHP based PM tool (Ralph, Sorger et al. 2021).
The layer architecture was initially created with the purpose of connecting different machine systems at the SFL step by step, including not only condition monitoring and PM-related data, but also process data and, as final objective, resulting in different LC user centered CPPS. Therefore, the five criteria defined in table 1 were already considered within the planning and development of this structure.

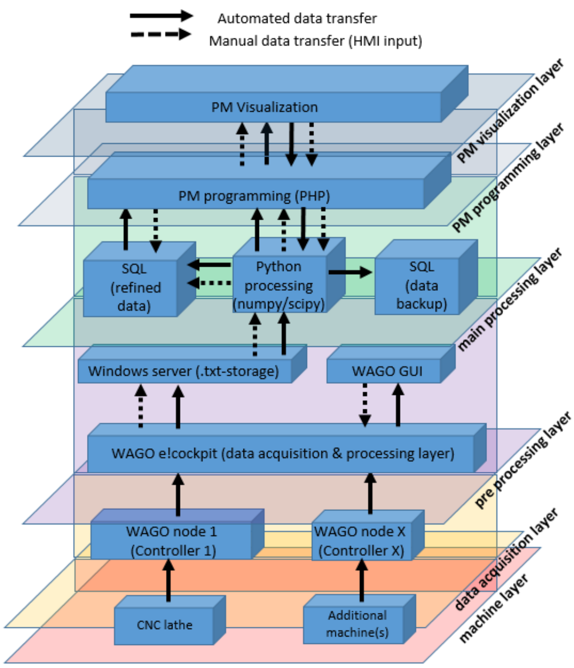


Fig. 3 Initial state of the six-layer architecture at the SFL (Ralph, Sorger et al. 2021)

3.2 The rolling mill system

The rolling mill system at the SFL at the CMF is a duo rolling mill and was built and put into operation in 1954. The hand wheel at the top of the rolling mill is used to adjust the height of the roll gap (fig. 4) and rotates the guide spindle via gears, which increases or decreases the height of the rolling gap depending on the direction of rotation. An adjustment of 0.07 mm per gear tooth was used as a parameter for adjusting the roll gap height.

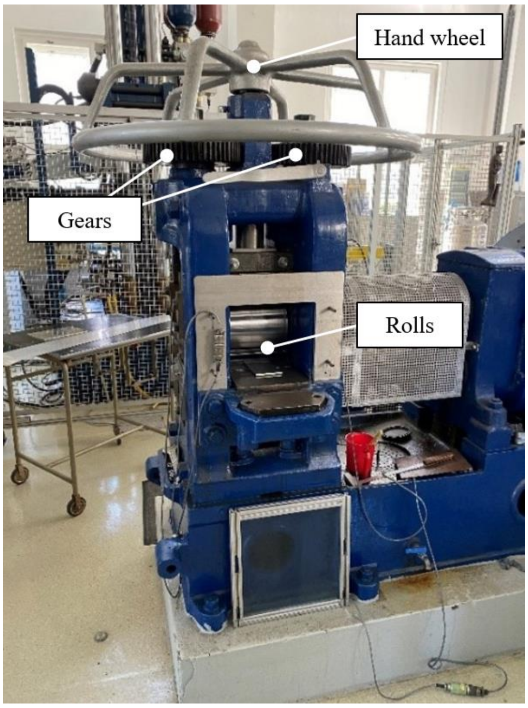


Fig. 4 Rolling mill system: initial state

More than a decade ago, the machine was equipped with two load cells to measure the rolling force on the left and right guide spindle. Figure 5 shows the initial load cell mounted between the left guide spindle and the roll chock. The data acquisition during a milling process, in order to obtain the actual F_R with corresponding time increments, was done with a proprietary Windows XP based DAQ system, with a maximum data transmission frequency of 22.5 Hz.

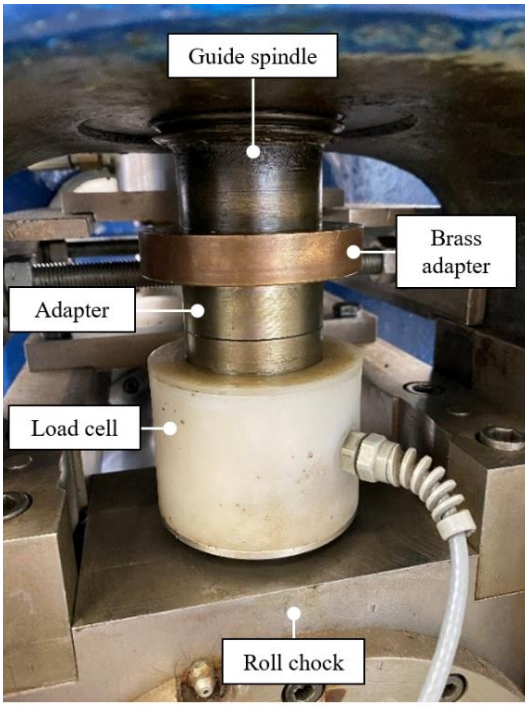


Fig. 5 Load cell of the left guide spindle: initial state

4 Retrofitting and Digitization

The following subchapters describe the sensor retrofitting (4.1) as well as corresponding digitization (4.2) and therefore coupling of the calibrated sensors to the SFLs six-layer architecture.

4.1 Sensor retrofitting

In order to choose appropriate sensors to meet the criteria of a LC user centered CPPS, the required specifications were defined in first instance. Based on these requirements, the sensor technology was selected. In addition to the required magnitude of the sensors, parameters such as linearity and resolution play a major role in the resulting quality of the recorded data and in the selection of suitable sensor technologies. Furthermore, the maximum resolution of the DAQ system must be taken into account, as in most terms the bottleneck is not the measurement of an analog signal or the signal transfer through an A/D converter but the buffering and writing of gathered data on the controlling unit (fig. 3, data acquisition layer). In order to implement a machine learning algorithm based on eq. 1 and eq. 2, table 2 shows the minimum quantities to be measured to achieve such a system. The measurement range is a result of the rolling mill systems specifications.

Table 2 Necessary quantities and corresponding range to be measured

System Parameter	Measurement range
F_R	0-400 kN
s_0	0-20 mm

For the measurement of F_R, the already existing load cells had to be replaced, as the maximum measurement range of each cell was defined with 150 kN. Furthermore, after calibration and analysis of the resulting data, a significant deviation between both cells and high non-linearity in each measurement system was detected, indicating a malfunction within at least one of them.
For the new load cell measurement system, despite the specified range, the following requirements had to be fulfilled:

a) The measuring system must be able to withstand an overload to avoid measuring errors and shortened lifespan.
b) The load cells must have a high linearity in order to be able to resolve the rolling force to a sufficient degree during the rolling process.

Additionally, the initial roll gap s_0 and with it, the change of the gap during the rolling process had to be measured with sufficient linearity and within the defined range. Based on heuristic knowledge and basic calculations, the deflection of the roll gap could be defined in the range of tenths of a millimeter, while the maximum height of the roll gap is constricted by the machines' geometry to 20 mm. Since the linearity of a sensor is specified as a percentage of the measuring range, two conditions must be met:

c) The sensor must be able to measure a distance greater than the maximum adjustable roll gap and
d) must have a high linearity in order to be able to resolve the deflection of the roll gap to a sufficient degree during rolling.

To meet the requirements of c), d), and the defined measurement range in a cost-effective manner, a linear variable differential transformer (LVDT) sensor was chosen. In addition, an angle sensor was attached to the gear of the hand wheel for demonstration purposes to students and other interested parties at the SFL.
Table 3 shows the finally selected sensors and their specifications.

Table 3 Selected sensors and their specifications

Sensor	Type	Range	Linearity	Output signal
Kern CR 20000-1Q1	Load cell	0-200kN	0,1%	2mV/V
Waycon LV-S-25-300-KA05-L10	LVDT	0-25mm	0,1%	n/a
ASM PH36	Magnetic multiturn encoder	31x360°	± (2°+ 0.015 %)	4-20mA

Table 4 defines the external electronics used to transfer the sensor signals into a suitable analog signal for the DAQ system. For the LVDT sensor, the external electronics from the same manufacturer was used. External electronics from a third-party supplier were installed for the load cells. These mV transmitters can be individually configured to the specifications and requirements of the load cell and can therefore also be used if the load cells are replaced.

Table 4 External electronics and specifications

External electronics	Type	Sensor	Output
PR Electronics 2261	mV transmitter	Load cell	0-20mA
Waycon LV-S-25-300-KA05-L10	integrated electronic (n/a)	LVDT	4-20mA

In order to mount the selected sensors on the rolling mill, mechanical adaptions had to be made. Since the diameter of the new load cells is larger than the width of the roller supports, the entire contact surface at the bottom of the load cell cannot be supported. This could lead to a falsification of the measurement results. In order to be able to use the entire contact surface of the new load cell, an intermediate plate was installed between the roll chock and the load cell. To connect the guide spindle with the load cell, an additional adaptor was designed to transmit the rolling force coaxially (fig. 6, fig. 7).

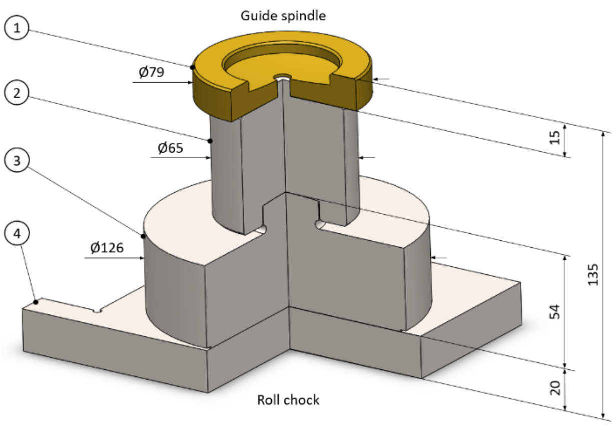


Fig. 6 Construction scheme of the new designed load measurement unit

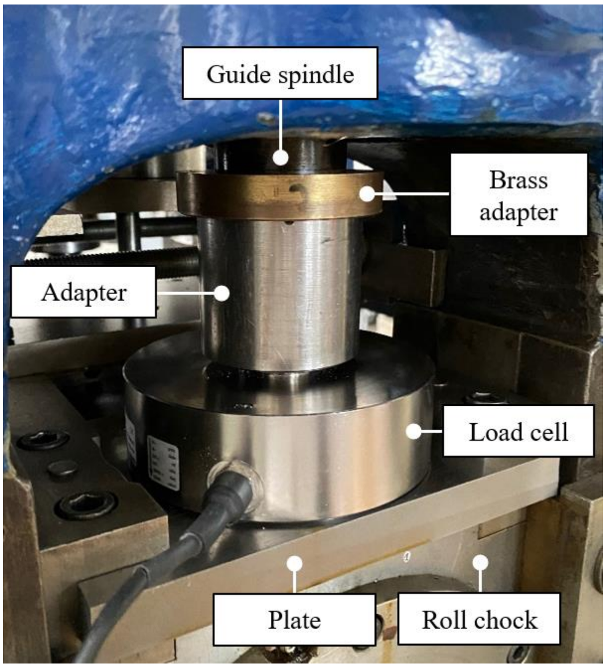


Fig. 7 Resulting implementation of the new designed load measurement unit

The LVDT sensor was mounted between the two roll chocks. In order to prevent interferences with the inductive measuring principle, the sensor holder is made of non-magnetic material (fig 8).

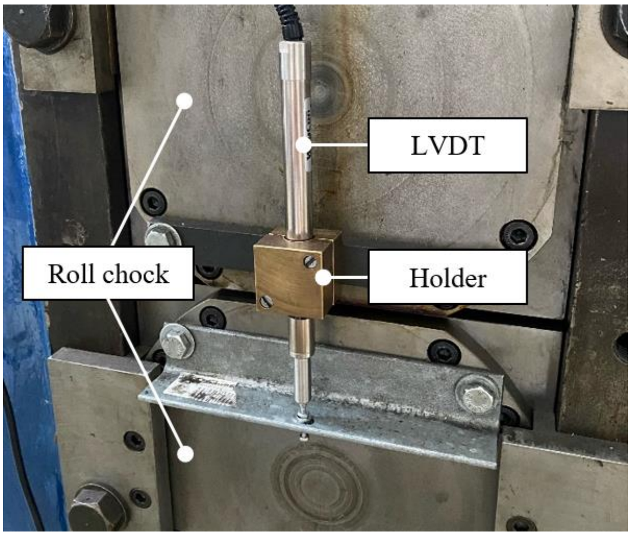


Fig. 8 Mounted LVDT sensor

The multiturn encoder was mounted directly on the machine rack. The resulting angle after manual roll gap changing is derived via the connection of the sensor with one of the two main gears at the mill, which are connected to the hand wheel via a defined gear transmission ratio. To consider the surface roughness of the gear and therefore ensure contact between the sensor and the gear, a pre-stressed spring is applied to ensure continuous contact (fig. 9).

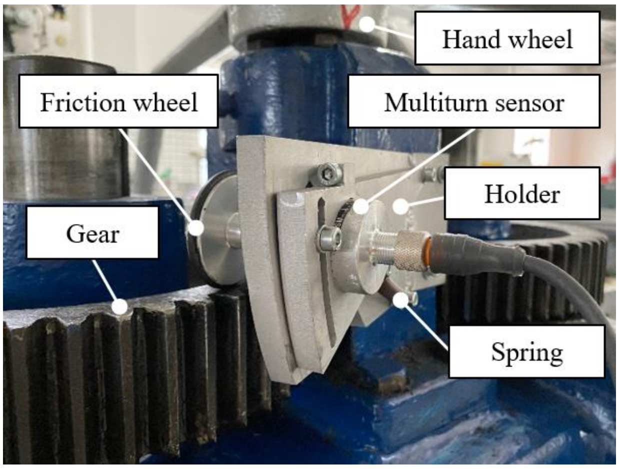


Fig. 9 Mounted multiturn encoder

4.2 Digitization

In order to convert the analog signals from the external electronics (table 4) into signals suitable for computer-aided processing, the devices were connected to the already existing WAGO node 1 (fig. 3, data acquisition layer). This node consists of a WAGO PFC200 G2 2ETH RS controller coupled with I/O modules (fig. 10). The I/O modules used are from the same supplier (type 750-453) and are designed for transforming analog signals in the range of 0 to 20 mA. As already mentioned, the resolution depends on the DAQ, which can resolve the analog signals of the sensors in 15 bit, therefore the analog signal of each sensor can be resolved in 2^{15} equivalent steps.

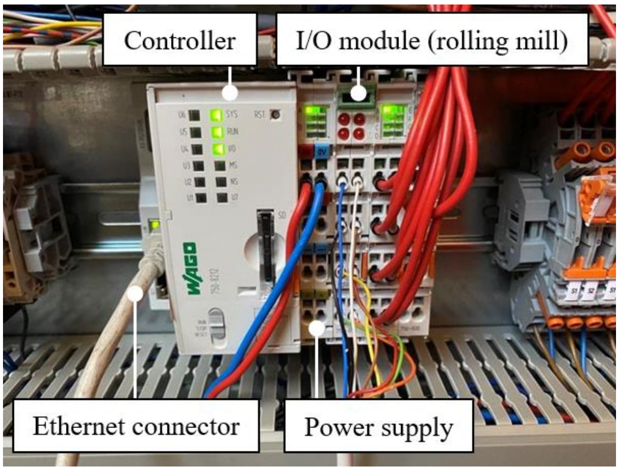


Fig. 10 Controller and I/O modules

Figure 11 shows the corresponding connections of the three mill sensors with the used I/O module.

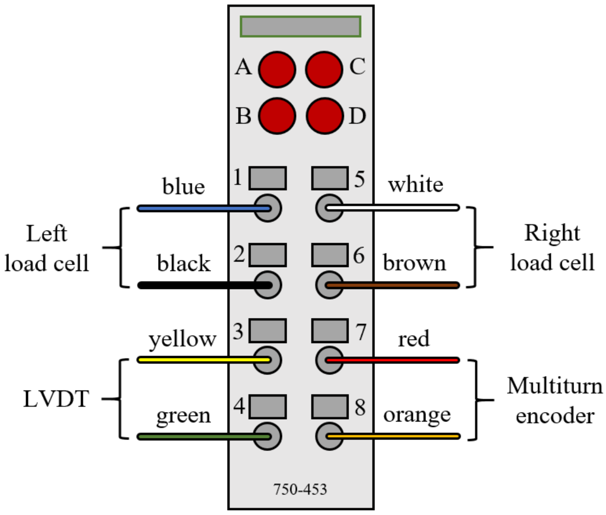


Fig. 11 Circuit diagram of the connection rolling mill sensors/DAQ

Figure 12 shows the final digitization framework for all three sensor types, from the physical measurement entity to the implementation into the layer framework. It is important to note that the used WAGO DAQ system isn't the most cost efficient possibility to connect the machine within such a system (e.g. Arduino based microcontroller would have been a more low-cost alternative). Under consideration of practicability and longtime maintainability, the use of a standardized framework which operates on industrial standards like the WAGO system or other comparable solutions was chosen. Another reason for this decision is the user friendly back end GUI, that comes within the SW and that allows non IT-personnel to supervise and even extend programmed functionalities with basic IT knowledge (e.g. the usage of predefined module blocks within the SW instead of STS coding). This advantages also apply for the first developed front end GUI, which is also based on the same framework.

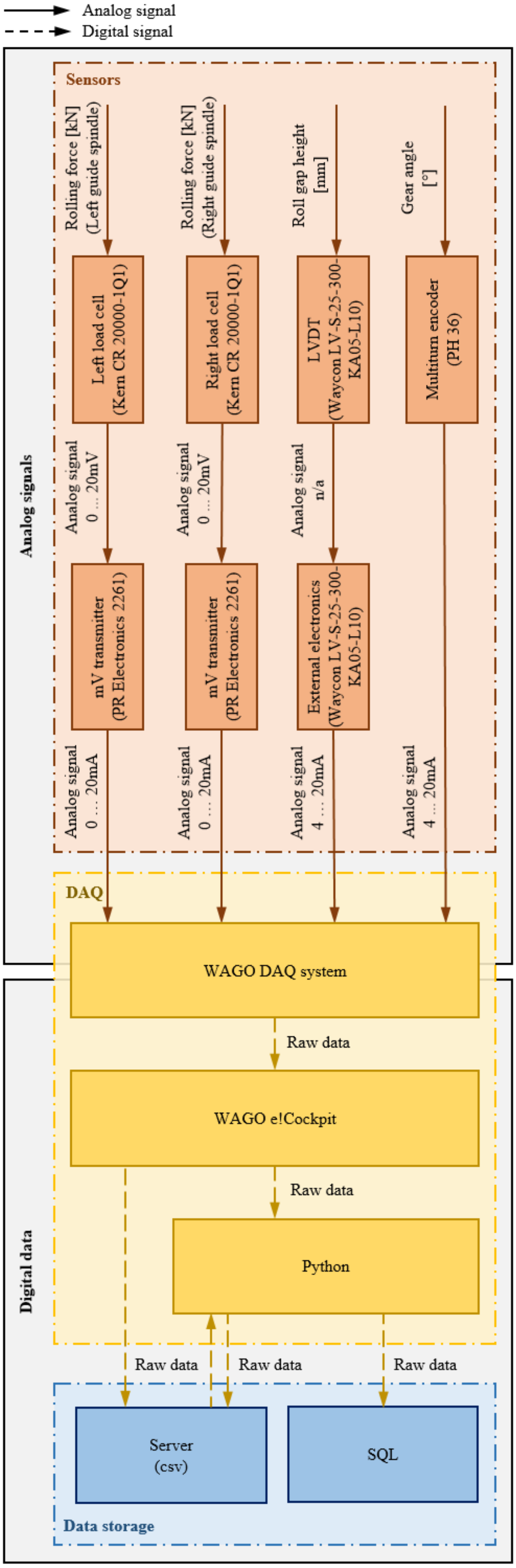


Fig. 12 Sensor connection and A/D conversion

5 Digitalization

This chapter describes the transformation of digitalized sensor data within the layer architecture. After A/D conversion, resulting digital signals have to be transformed into real physical quantities. This is done within the data preprocessing layer (fig. 3) using STS based programming and an additional Python script. Additionally, state dependent data gathering frequency is set within this layer (subsection 5.1). Subsection 5.2 describes the adaption of the first front-end GUI for the rolling mill setup.

5.1 Data pre-processing layer

Before working with the digitized signal data is possible, transformation of the resulting data into corresponding physical quantities has to be done. This operation is carried out within the data pre-processing layer (fig. 3) using the STS environment provided by the WAGO SW. All three sensor types can be calibrated linearly under consideration of their characteristic linearity (table 3). As a result, a linear equation was programmed for each input channel, whereas the two individual coefficients were derived as a result of the range restriction of the specific device.

$$f(physical\ quantity) = a + b * bit\_value \qquad (4)$$

Figure 13 visualizes the transformation of the current signal into its physical value on the example of the load cells used schematically.

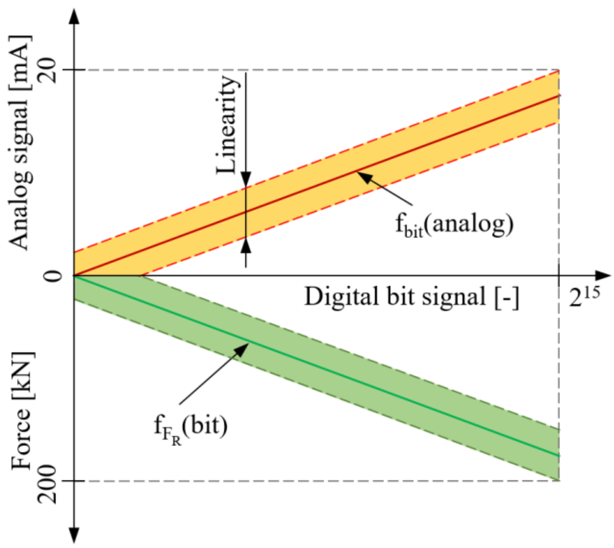


Fig. 13 A/D input signal to physical quantity transformation: example rolling mill

Table 5 displays the resulting coefficients for all three sensor types on the basis of eq. (4).

Table 5 Coefficients for the linear characteristic curve of implemented sensors

Physical quantity	a	b	Range
F_R [kN]	0.0	6.104E-3	0-200 kN
s_0, s_1 [mm]	6.5536E+3	9.537E-4	0-25 mm
deg [°]	6.5536E+3	4.257E-1	0-31x360°

The resulting F_R is then obtained summarizing the values from both load cells within the STS environment. This approach also ensures that eccentric sheet insertion can be measured and do not result in a higher measurement error. To fulfill requirement II. (table 1), two different sampling rates for all rolling mill channels were defined. The first one is enabled continuously. In this case, 1 Hz was set within the STS. This low frequency is used to work as a simple condition monitoring system, giving warnings over the WAGO GUI (section 5.2) whenever sensor values are out of calibrated range. For the actual processing, via a trigger that can be manually turned on within the GUI, a sampling frequency of 500 Hz was determined. In this case a Boolean variable is turned TRUE, which activates the higher rate, whereas the lower frequency stays enabled. After the actual process, the user can end the measurement again manually through the GUI, which sets the Boolean equal FALSE again. The major advantage through the manual activation is the possibility of measuring unconventional processes or trials, which would not be measured if the higher sampling rate would be activated by a force or dilation triggered algorithm (e.g. very thin sheets with low resulting F_R, very soft material with low Δs).While the continuous data gathered is directly stored on the CMFs' internal server, the actual 500Hz measurements have to be refined additionally before data science and machine learning algorithms can be used on it. This refinement algorithm is carried out within a simple Python script, which deletes numerical artefacts and duplicates from the given raw data. Numerical artefacts are lines that may occur due to buffering issues on the used controller unit. As the controller is initially not able to obtain frequency rates above 100Hz, a script that uses the controllers' RAM instead of warm memory was written and implemented in the STS environment. Nevertheless, the buffering operation stores data points until a defined extend, before submitting these data points to be actually written on the controllers' internal memory. During the writing process, doubled data points within the same time stamp occur. Additionally, lines with zeros or NaN values are a result of this procedure. To avoid errors at upcoming mathematical operations (6.2, 6.3), these data points and corresponding rows have to be filtered first.

5.2 WAGO based GUI

The already existing WAGO GUI was extended with an additional layer for the rolling mill system, taking into account the preferences of involved technicians on the shop-floor level. The GUI runs on the controlling unit and is available through the corresponding IPv4 address with all computing devices within the SFL network. Figure 14 shows the STS programmed rolling mill layer within the GUI. Additional to the two resulting loading force values and sum of both, another variable is visualized, which is named “max load until reset”. This variable returns the maximum value stored at a current measurement. If the “Max Reset” button is pressed, the variable is set to 0. The same function is given for the variable “max roll gap until reset”, to be able to see the maximum height and force within a measurement, whereas all other variables defined return the real time value from the respective sensors. Depending on the status of the Boolean “Run Measurement”, the sampling rate is whether 1 Hz (Boolean = FALSE, button=GREEN (fig. 14) or 500 Hz (Boolean = TRUE, button = RED). The parenthesized integer next is coupled with a counter in the STS, which counts up for each measurement executed within the same day. If the day within the timestamp changes, the counter is reset to 0. As the automatic export of high frequency measurement data is done in single files, named “YEAR-MONTH-TRIAL-NR”, the Python filter algorithm can easily distinguish between appending files within the defined folder. In order to prevent overloading of the rolling stand and power train, the visualization of force only contains a range of 0-300 kN. This ensures that the aggregate is not permanently operated at its load limit.

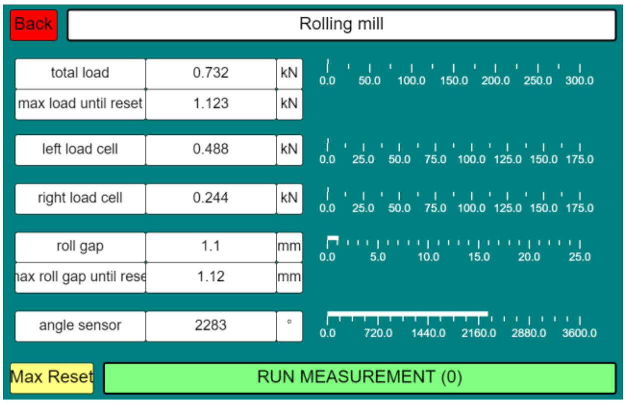


Fig. 14 Rolling mill layer of the WAGO GUI

As mentioned in 5.2, the data storage from the I/O module is executed directly in the hot memory of the controller. Therefore, another layer was developed, which shows the actual CPU load of the respective controller. If this load exceeds 60 %, writing and therefore accurate data gathering from connected sensors cannot be guaranteed. This value is reached within this setup if both connected aggregates are activated and the sampling frequency of the rolling mill exceeds about 0.560 kHz. If 60 % are reached, another Boolean in the STS is set TRUE and a warning signal is shown at the main display. Figure 15 shows the CPU load GUI both connected machines disabled.

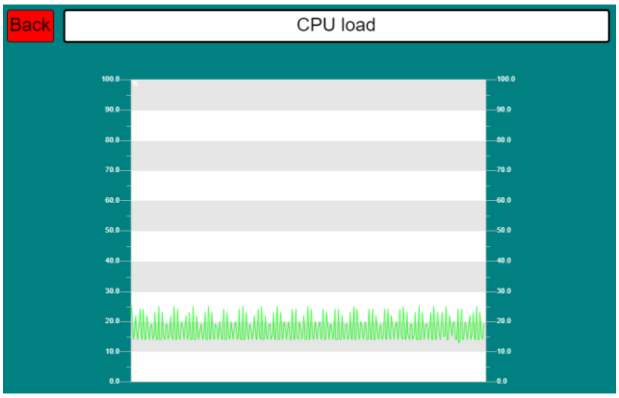


Fig. 15 CPU load layer of Node 1: connected machines turned off

6 Machine learning algorithm and decision enhancing digital twin

After successful digitization (section 4) and digitalization (section 5), requirement III. (table 1) has to be implemented. For this purpose, the connected rolling mill system had to be equipped with a suitable and efficient algorithm to support decision making within the milling process. As the correlation between the most important variables (section 2.1) is rather complex in practice, a data driven modelling approach was chosen in first instance. This data driven model should be resilient, robust and easy to understand. Therefore, the complex and non-linear real-physical interrelationships between the machine system and processed material were discretized and transformed into a system of interdependent linear equations, calculated within the Python environment (section 6.4). To avoid unrealistic or unreproducible results, a statistical approach was chosen (section 6.1). Additionally, as the focus in this work lies on the calibration of the stand module C with all relevant dependencies, a well characterized material (section 6.2) was chosen for the first setup. As a result, the second front-end GUI mentioned initially in this paper is presented and explained (section 6.5).

6.1 Experimental setup

According to hypothesis 1 and 2 (section 2.1), the stand module C is a function of the processed sheet width b as well as Δh and s_0. Despite this statement, another important influencing factor in practice is the usage of an appropriate lubricant. Therefore, the following dependencies have been investigated within this experiment:

$$C = C(s_0, b, \Delta h, \mu_{lubricant}) \qquad (5)$$

For the initial calibration, $\mu_{lubricant}$ describes the change between sufficient lubrication and no lubrication. To be able to develop a data driven prediction model for the rolling process, three different rolling schedules (V_1, V_2 and V_3) were defined (table 6). The main objective of this setup was to get a broad set of data points for different $s_0(\Delta h)$, to investigate the influence of different combinations of these variables. To ensure comparability, an initial thickness of 6mm and a final s_0 of 0.5mm was defined for each rolling schedule.

Table 6 Defined rolling schedules for data gathering

Nr.	$s_0(V_1)$ [mm]	$s_0(V_2)$ [mm]	$s_0(V_3)$ [mm]
1	4.50	5.00	5.00
2	3.50	4.00	4.50
3	2.75	3.50	4.00
4	1.75	2.50	3.50
5	1.00	1.50	3.00
6	0.75	1.00	2.50
7	0.50	0.50	2.00
8	-	-	1.50
9	-	-	1.00
10	-	-	0.50

By varying the rolling schedules according to table 6, it is possible to investigate if different cumulated strain paths (eq. 6) have an influence on the elastic behaviour of the mill stand and therefore C.

$$C\,(\Delta h_{ij}, s_{0_k}) = !\,C\,(\Delta h_{lm}, s_{0_n}) \qquad (6)$$

For the investigation of the influence of b, three widths for the initial test and calibration data setup were chosen. For the validation of the resulting equation system, two additional widths were defined, one between the three first and one out of initial range, to be able to proof interpolation as well as extrapolation capabilities of the system (table 7). For this validation experiments, rolling steps 1-4 from V_1 were used, followed by a direct height reduction from 1.75 to 0.75 mm (table 6, $s_0(V_1)$). The fifth step was spared out to be able to see if the interpolation between known s_0 would obtain valid results within the developed machine learning algorithm.

Table 7 Defined rolling schedules for data gathering

Nr	Width [mm]	Test/ Calibration	Validation
B_1	150.00	X	
B_2	100.00	X	
B_3	50.00	X	
B_4	74.50		interpolation
B_5	30.10		extrapolation

To investigate the influence of lubrication on C, two different test series were defined, whereas test and calibration data sets were mirrored for both process friction states (table 8).

Table 8 Defined rolling schedules for data gathering

Test series	Description
T_1	full lubrication
T_2	no lubrication

The sheet specimen for the rolling process has to be entered manually (fig. 4). To avoid measuring errors due to deviations in the reproducibility of single process steps within the rolling schedule, a statistical approach has been chosen. For this experiment, twelve sheets for each tested rolling schedule, test series and width were cut out of two identical raw sheets. In sum, 216 sheets for the creation of test and calibration data were used, split into three different rolling schedules, three different widths and to different test series (table 9). To ensure a smooth transition into the milling system, the initial length of each specimen was set to 135 mm. Additionally, each sheet was deburred and cleaned before treatment.

Table 9 Specimen classification: test/calibration data

Test series	Specimen nr.	Rolling schedule	Sheet width
T_1	1-12	V_2	B_1
	13-24	V_3	B_1
	25-36	V_2	B_2
	37-48	V_3	B_2
	49-60	V_2	B_3
	61-72	V_3	B_3
	73-84	V_1	B_1
	85-96	V_1	B_2
	97-108	V_1	B_3
T_2	1-12	V_2	B_1
	13-24	V_3	B_1
	25-36	V_2	B_2
	37-48	V_3	B_2
	49-60	V_2	B_3
	61-72	V_3	B_3
	73-84	V_1	B_1
	85-96	V_1	B_2
	97-108	V_1	B_3

The configuration shown in table 9 for each test series ensures a continuous reduction of s_0. In sum, 1736 milling process steps were carried out to gather the required test and calibration data. Figure 16 shows the processed specimens before and after rolling.

Fig. 16 Processed sheet specimens: rolled (T1, top); initial (T2, bottom)

Table 10 shows the setup for the gathering of validation data. For this purpose, only 36 additional specimens were used and processed within T_1 (no lubrication) and rolling schedule V_1, whereas back up material was kept if the validation attempt in the resulting algorithm would fail. Including all process steps, a total of 1904 milling operations delivered output for the data driven modelling of the corresponding machine learning algorithm (section 6.4).

Table 10 Specimen classification: validation data

Test series	Specimen nr.	Rolling schedule	Sheet width
T_2	109-124	V_1	B_4
(validation)	125-144	V_1	B_5

6.2 Deformation behavior of used material under rolling conditions

The material used in this study is EN AW-1050A, also referred to as Al 99.5, which is considered as technically pure aluminum due to its low content of constituents. Pure aluminum shows excellent ductility, exhibiting exceptionally good deformation behavior even after severe cold working. The hardening of the material introduced by forming can be attributed to the introduction and the multiplication of dislocations during their migration. For deformations such as in a cold rolling process, the face-centered cubic (fcc) crystal structure determines the slip systems: primarily, slip is observed on {111} <110>-slip systems since the Peierl's stress is lowest in this direction. The stacking fault energy of about 170 mJm^{-2} in pure aluminum, which is comparatively high for fcc-structured metals, determines the predominant deformation mechanism of slip, rather than developing deformation twins (J P Simon 1979).
The increase in strength introduced by cold working can be described in terms of increasing dislocation density. As a rough estimate, the dislocation density can be approximated by the increase in strength using eq. 7.

$$\sigma = 0.5Gb\rho^{\frac{1}{2}} \tag{7}$$

In eq. 7, σ is referred to as the strength, G is the shear modulus of the respective material, b is the burgers vector and ρ is the dislocation density. The higher the dislocation density, the lower the mean free path between the dislocations. As a result of their interaction, strength increases due to reduced mobility. The dislocation increase depends on the selected forming degrees, which are introduced into the material at certain height reductions Δh due to the rolling schedule. This increase in dislocations is opposed by certain softening processes since the condition including a high dislocation density is thermodynamically unstable. The most essential softening mechanisms represent recrystallization and recovery, the latter being crucial for aluminum due to the high stacking fault energy. For recrystallization to occur, both a critical degree of deformation and an elevated temperature of about 40% of the melting temperature are required, whereas both conditions are not met within this experimental setup (Gottstein 2004).
During the rolling of a pure aluminum sheet, part of the applied forming energy is stored as deformation energy, the other, much larger part, dissipates in heat, driven by two phenomena: i.) the plastic deformation itself and resulting internal friction and ii.) caused by tribological effects at the interface between the rolls and the sheet metal or the lubricant. These conditions favor the recovery processes which are characterized by facilitated cross-slipping of screw dislocations and climbing of step dislocations, thus causing annihilation of dislocations and therefore decreasing the dislocation density and the effect of cold working. These softening processes are diffusion-dependent, which occur at an accelerated rate under temperature increase, although room temperature is already sufficient to continue these processes to equilibrium when considering pure aluminum (Hasegawa and Kocks 1979).
Therefore, strengthening due to cold working is already reduced at short time periods, leading to the conclusion that these processes do not have an effect on the corresponding strength values. Despite the recovery effect, the heat transfer within the tribology system is of utmost importance for the rolling process within this case study.
Aluminum is furthermore characterized by its high thermal conductivity, which at approximately 220 $W(mK)^{-1}$ exceeds that of conventional steel grades by a factor of three. For this reason, the dissipated forming heat and heat generated by friction between the rolls and the sheet surface spreads rapidly over the entire specimen. As a result, the heat is more easily transferred to the lubricant and dissipated in this fluid. This phenomenon can have a substantial influence on the resulting behavior of the rolled specimen, especially considering different friction states (Ostermann 2014).

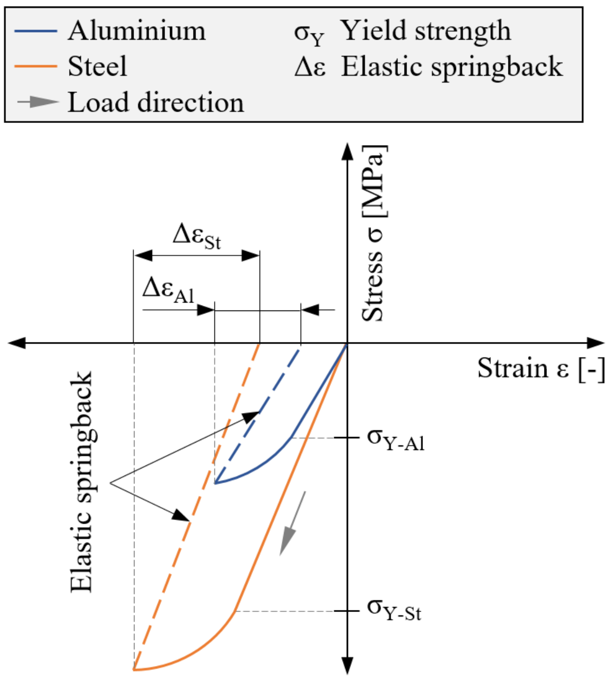


Fig. 17 Elastic stiffness and corresponding effect on h_1 during rolling

Despite cold work hardening and thermal expansion, the elastic properties of the used material significantly contribute to the resulting process parameters in rolling. After the force is locally removed from the processed specimen, the elastic component of the strain applied results in an increase of the thickness h_l. As a result, materials with a lower Young's Modulus (YM) are increasing height after rolling significantly more than stiffer materials (fig. 17).

6.3 Resulting experimental data

As expected from plastic deformation fundamentals, the resulting geometry changes of the tested specimens after rolling varies. The maximum bearable local plastic deformation wasn't exceeded at any specimen within the experiment, therefore the law of constant volume (eq. 8) applies.

$$\ln\frac{l_1}{l_0} + \ln\frac{b_1}{b_0} + \ln\frac{h_1}{h_0} = \varphi_l + \varphi_b + \varphi_h = 1 \qquad (8)$$

According to eq. 8, l_l can be obtained if b_l and h_l as well as the initial geometry is known. Before the resulting test and calibration data is analyzed from a black box point of view, a first indication about whether there is a difference between the two data series can be made after measuring the resulting sheet width of each specimen. This was made on three reproducible locations at each specimen, according to figure 18. Table 11 shows the mean value at each measured point for each calibration and validation series, additionally divided into test series T_1 and T_2.

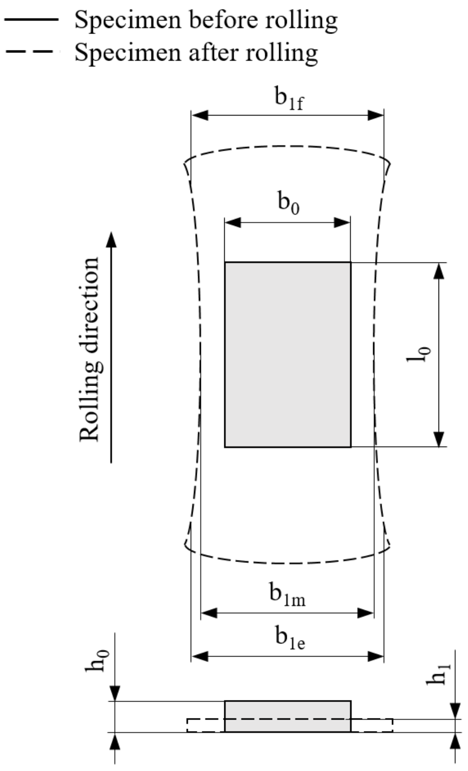


Fig. 18 Sheet width measurement after rolling

Table 11 Specimen classification: Calibration and validation data

T_1	Specimen nr.	b_{1f} [mm]	b_{1m} [mm]	b_{1e} [mm]
test data	1-6	150.93	150.82	150.95
calibr. data	7-12	151.10	150.84	151.13
dev. [%]		0.11	0.01	0.12
test data	13-18	151.02	150.90	151.02
calibr. data	19-24	151.08	150.90	151.15
dev. [%]		0.04	0.00	0.09
test data	25-30	101.06	100.86	100.76
calibr. data	31-36	100.98	100.93	101.15
dev. [%]		0.08	0.07	0.39
test data	37-42	101.27	100.99	101.23
calibr. data	43-48	101.11	100.90	101.09
dev. [%]		0.16	0.08	0.14
test data	49-54	51.71	51.35	51.68
calibr. data	55-60	51.56	51.34	51.56
dev. [%]		0.29	0.02	0.24
test data	61-66	51.19	51.00	51.22
calibr. data	67-72	51.29	51.07	51.25
dev. [%]		0.19	0.13	0.07
test data	73-78	151.00	150.84	151.06
calibr. data	79-84	151.00	150.8	150.97
dev. [%]		0.00	0.02	0.06
test data	85-90	101.10	100.89	101.11
calibr. data	91-96	101.06	100.80	101.11
dev. [%]		0.04	0.09	0.00
test data	97-102	51.33	51.27	51.46
calibr. data	103-108	51.33	51.27	51.59
dev. [%]		0.00	0.01	0.24
T_2				
test data	1-6	151.42	151.14	151.51
calibr. data	7-12	151.26	151.11	151.36
dev. [%]		0.11	0.02	0.10
test data	13-18	151.47	151.14	151.44
calibr. data	19-24	151.45	151.10	151.53
dev. [%]		0.01	0.03	0.06
test data	25-30	101.08	100.79	101.24
calibr. data	31-36	101.35	100.84	101.36
dev. [%]		0.27	0.06	0.12
test data	37-42	101.17	100.88	101.11
calibr. data	43-48	101.25	100.97	101.18
dev. [%]		0.08	0.09	0.07
test data	49-54	51.55	51.11	51.45
calibr. data	55-60	51.56	51.17	51.45
dev. [%]		0.03	0.12	0.01
test data	61-66	51.06	50.83	51.03
calibr. data	67-72	51.15	50.79	51.01
dev. [%]		0.17	0.07	0.03
test data	73-78	151.54	151.14	151.53
calibr. data	79-84	151.50	151.10	151.46
dev. [%]		0.03	0.03	0.05
test data	85-90	101.18	100.85	101.07
calibr. data	91-96	101.28	100.95	101.16
dev. [%]		0.11	0.10	0.09
test data	97-102	51.70	51.25	51.65
calibr. data	103-108	51.88	51.37	51.68
dev. [%]		0.36	0.24	0.05

As visualized in table 11, the highest deviation in sheet width is 0.36 %, which leads the authors to the statement that no differentiation between test and calibration data can be made. This also supports the theory, that the population of investigated specimens is valid. According to section 6.2 and from a materials science point of view, there should also be no significant difference between sheets of same initial width that were rolled in different rolling schedules. Table 12 shows the standard deviation of all widths within a test series (V_1, V_2 and V_3).

Table 12 Standard deviation of width for T1 and T2

Test Series	$Dev(b_{1f})$ [mm]	$Dev(b_{1m})$ [mm]	$Dev(b_{1e})$ [mm]
T_1			
B_1	0.17	0.16	0.22
B_2	0.22	0.14	0.25
B_3	0.23	0.19	0.23
T_2			
B_1	0.14	0.13	0.15
B_2	0.14	0.12	0.27
B_3	0.31	0.26	0.29
B_4	0.22	0.14	0.30
B_5	0.15	0.15	0.09
$Dev(T_1/T_2)$			
B_1	0.26	0.20	0.28
B_2	0.19	0.13	0.26
B_3	0.28	0.24	0.26

6.4 Additional material related tests

The higher deviation between T_1 and T_2 within the same width indicates differences between the two test series, which, according to the authors, is the result of a changed tribology system. To investigate if this change significantly contributes to the resulting material behavior, tensile tests were carried out additionally. In order to characterize the mechanical anisotropy of the rolled sheets properly, a small but normed geometry was chosen to obtain stress-strain curves with 0°, 45° and 90° to the rolling direction for B_1 and B_2. For B_3, only 0° specimens could be realized with scientific validity. It is important to note that the resulting h_1 of each specimen varies as the final s_0 was kept constant but the resulting cumulated force diverges significantly and therefore, the elastic spring back behavior as well as work hardening and force related heat expansion of the used Aluminum alloy contributes to the final thickness to different extends (fig. 19). Table 13 shows the initial properties of each specimen used for additional tensile tests. For each sheet, three tensile tests specimens for each examined direction were produced, one sheet per corresponding test data series for T_1 and T_2. Figure 19 shows the normed specimen geometry, according to DIN EN 10002-1 (German Institute for Standardization), for the performed tensile tests.

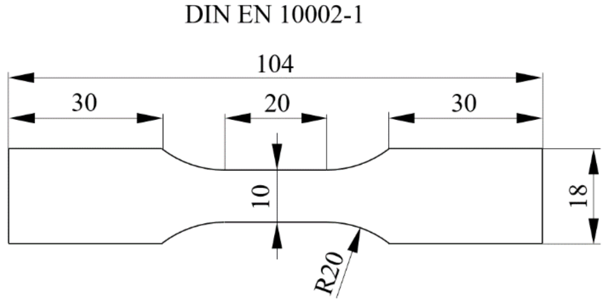


Fig. 19 Tensile test: initial geometry (German Institute for Standardization)

Table 13 Statistical comparison of h_1 and resulting cross section for all tensile test specimens

Specimen nr./ Schedule	Test Series	Initial Width [mm]	Thickness h_1 [mm]	Cross Section [mm^2]
2 / V_2	T_1	B_1	1.34 ±0.01	13.52 ±0.12
2 / V_2	T_2	B_1	1.50 ±0.01	15.25 ±0.15
14 / V_3	T_1	B_1	1.33 ±0.01	13.39 ±0.09
14 / V_3	T_2	B_1	1.46 ±0.01	14.82 ±0.13
26 / V_2	T_1	B_2	1.20 ±0.01	12.10 ±0.10
26 / V_2	T_2	B_2	1.37 ±0.01	13.89 ±0.21
38 / V_3	T_1	B_2	1.20 ±0.01	12.14 ±0.18
38 / V_3	T_2	B_2	1.35 ±0.01	13.56 ±0.16
50 / V_2	T_1	B_3	1.01 ±0.00	10.23 ±0.06
50 / V_2	T_2	B_3	1.17 ±0.00	11.87 ±0.04
62 / V_3	T_1	B_3	1.01 ±0.01	10.24 ±0.10
62 / V_3	T_2	B_3	1.13 ±0.00	11.41 ±0.02
74 / V_1	T_1	B_1	1.22 ±0.00	12.30 ±0.12
74 / V_1	T_2	B_1	1.33 ±0.01	13.33 ±0.13
86 / V_1	T_1	B_2	1.10 ±0.00	11.05 ±0.11
86 / V_1	T_2	B_2	1.21 ±0.01	12.14 ±0.20
98 / V_1	T_1	B_3	0.95 ±0.01	9.58 ±0.16
98 / V_1	T_2	B_3	1.03 ±0.00	10.34 ±0.03

The higher deviation in the cross section is a result of the sample production, which were cut out with a water jet cutter at the CMF. More important, it can be stated that the resulting h_1 for sheets that undergo the same treatment, except friction state (T_1, T_2) vary significantly. For each state, the height of rolled sheets without lubrication is effectively higher than with. As a result of the higher F_R applied, the sum of elastic suspension of stand parts involved in the force flow during the rolling process is significantly higher. Therefore, the same degree of forming is not achieved as with the T_1 series, and the plate thickness of the T_2 series does not reach the same h_1 as that with lubrication, especially when large height reductions within the process were set. Figures 20 and 21 show the comparison of a specimen with B_1 (fig. 20) and B_2 (fig. 21) for both friction states. A small but reproducible effect on strength due to anisotropy can be observed.

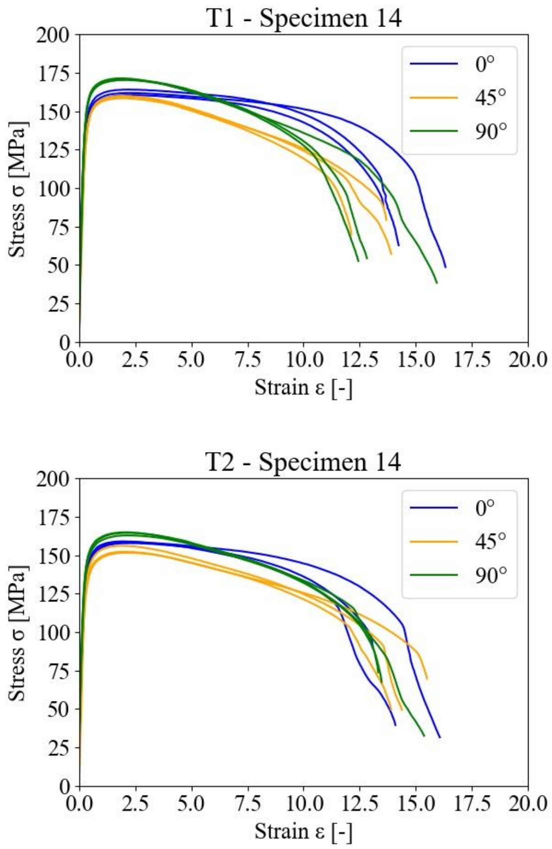


Fig. 20 Specimen nr. 14: mechanical anisotropy T1/T2

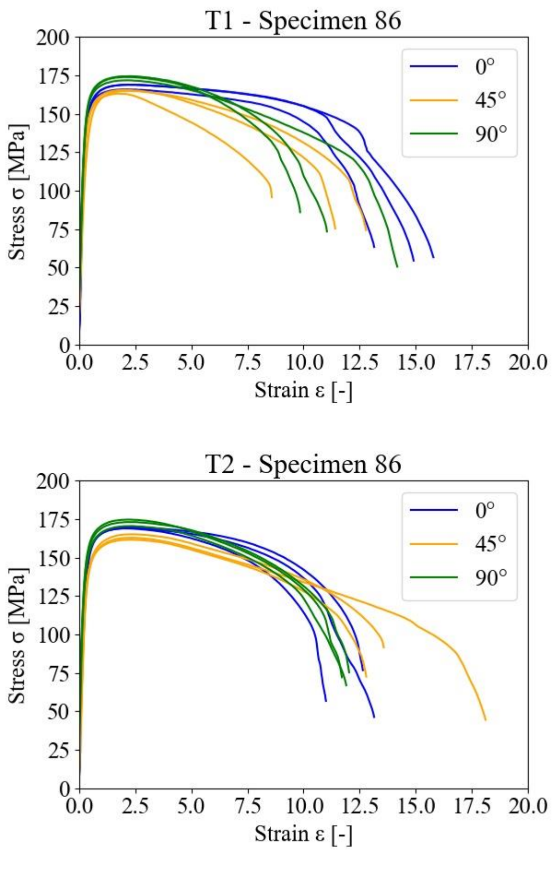


Fig. 21 Specimen nr. 86: mechanical anisotropy T1/T2

To investigate the influence of friction, the following figures 22 – 24 show the direct comparison between a specific rolling direction and both investigated test series. Figure 22 compares different tensile test specimens for 0°, 45° and 90° to rolling direction, for specimen nr. 14 (B_1). The same comparison was made in figure 23 for specimen nr. 86 (B_2). In figure 24, the smallest width within the test and calibration series (specimen nr. 98, B_3) is compared in rolling direction.

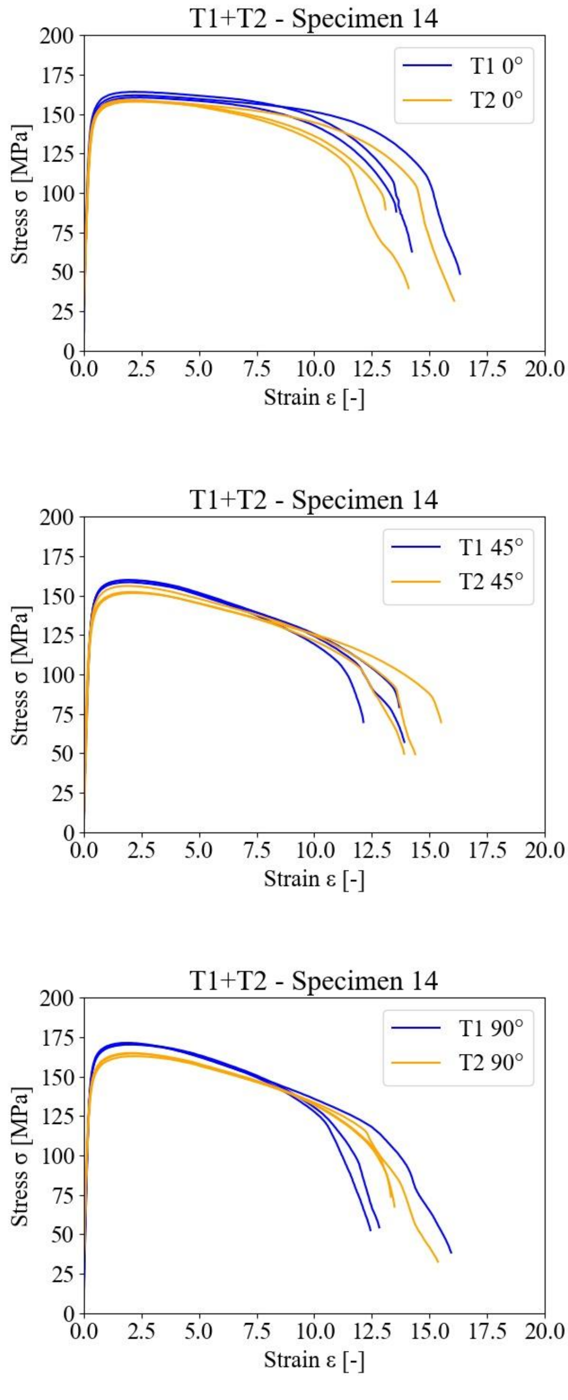


Fig. 22 Direct comparison: specimen nr. 14

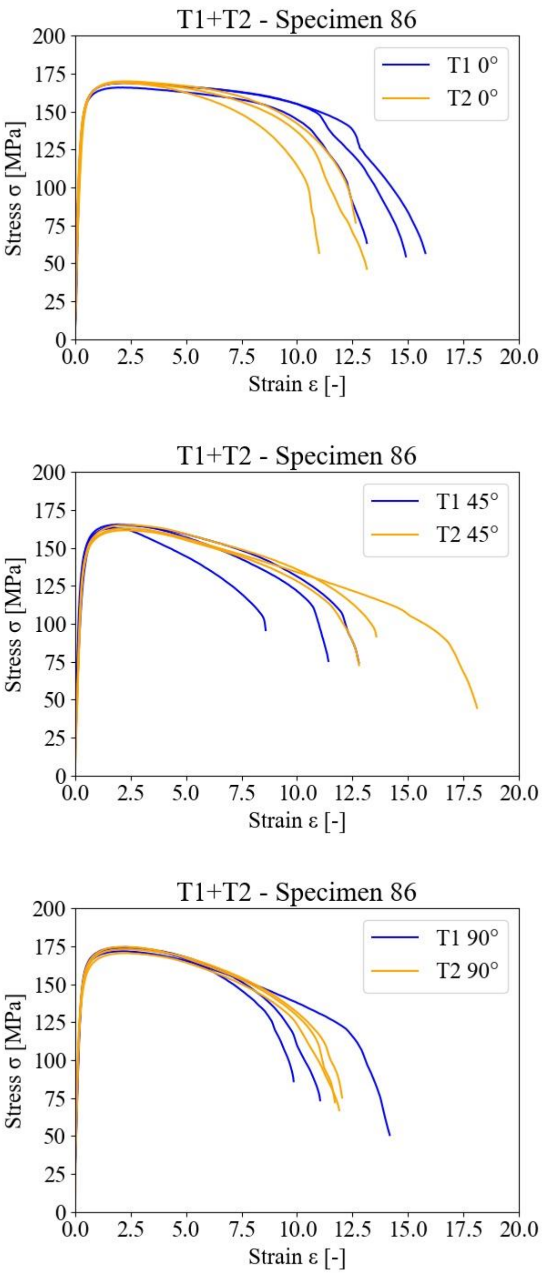


Fig. 23 Direct comparison: specimen nr. 86

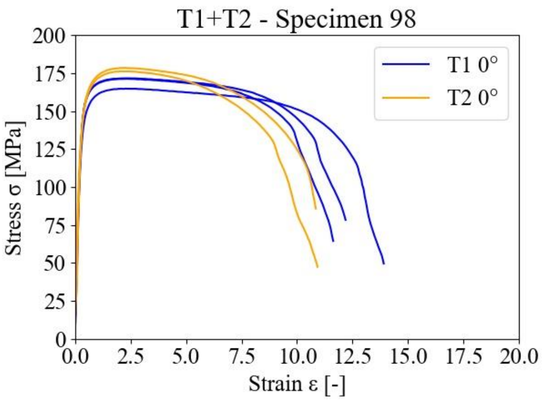


Fig. 24 Direct comparison: specimen nr. 98

The initial strip is commonly produced by hot rolling. This treatment already elongates the grains in the rolling direction, therefore the grains align themselves along a preferred orientation. The resulting microstructure exhibits a so-called rolling texture, as visualized in figure 25. The resulting anisotropy of the grain orientation also commonly affects the mechanical properties. The considerably larger number of grain boundaries to be overcome 90° to the rolling direction generally leads to an obstruction of the sliding processes. To determine the extent of anisotropy on sheet materials, tensile specimens are therefore regularly extracted and tested at 0°, 45° and 90° to the rolling direction. The recovery discussed in section 6.2, however, leads to another phenomenon that is essential in explaining the low influence of anisotropy on macromechanical properties (fig. 20 and 21), namely the polygonization of small-angle grain boundaries. This effect results in a substructure that forms globular sub grains. In optical microscopy images (OMI), this rearrangement is difficult to detect. In this case, the Barker electrolytic etching was used to visualize the microstructure (figures 25-28), only showing the superposed deformation structure. It can be assumed that the progressed recovery stage in the pure aluminum used in this experimental setup is most likely responsible for the similar deformation properties between the directions in the tensile test (Humphreys and Hatherly 2007).

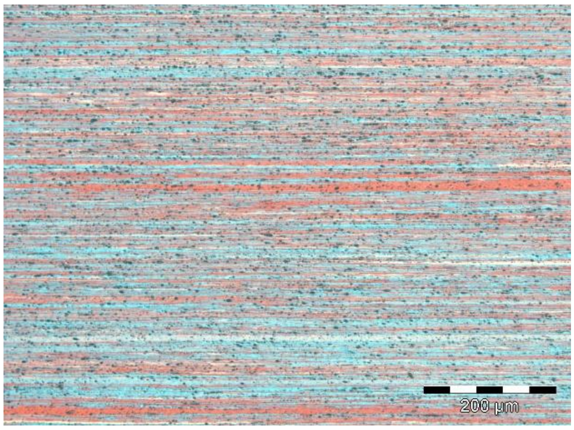


Fig. 25 Exemplary OMI: initial microstructure in rolling direction (T_1 /specimen nr. 86, 0°)

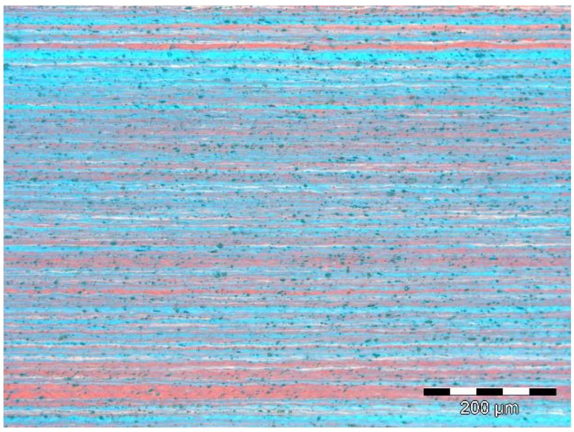


Fig. 26 Exemplary OMI: microstructure after the rolling process (T_1 /specimen nr. 86, 0°)

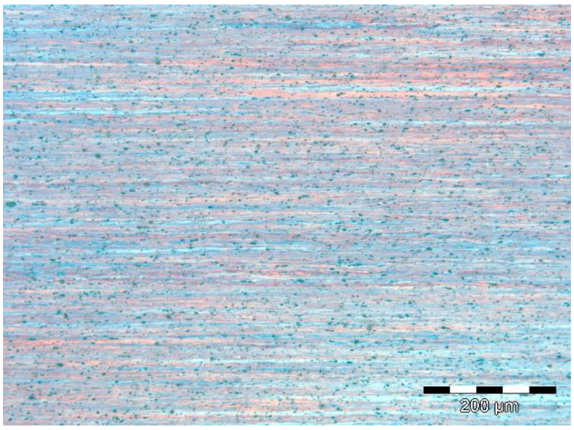


Fig. 27 Exemplary OMI: microstructure after the rolling process (T_1 /specimen nr. 86, 45°)

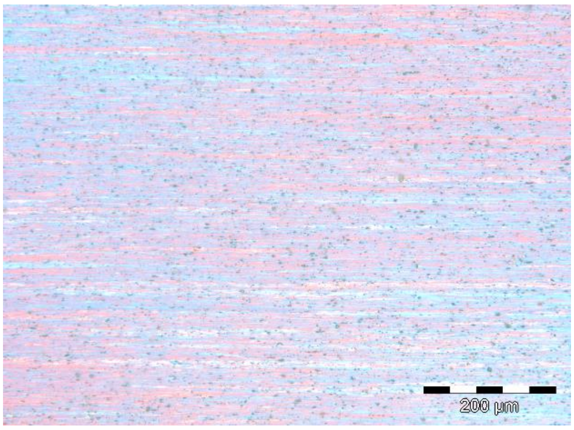


Fig. 28 Exemplary OMI: microstructure after the rolling process (T_1 /specimen nr. 86, 90°)

Table 14 summarizes the resulting ultimate tensile strength (UTS) of each tested specimen under consideration of tested degree to rolling direction.

Table 14 Statistical comparison of UTS for tensile test specimens

Nr./ Test Series	UTS (0°) [MPa]	UTS (45 °) [MPa]	UTS (90°) [MPa]
2 / T_1	166.54 ±1.82	160.98 ±0.86	171.27 ±1.23
2 / T_2	162.35 ±1.26	156.40 ±0.46	164.10 ±1.46
14 / T_1	162.21 ±1.48	159.41 ±0.64	170.82 ±0.45
14 / T_2	158.53 ±0.45	153.37 ±1.97	164.18 ±0.87
26 / T_1	165.22 ±1.28	162.41 ±1.26	172.05 ±0.56
26 / T_2	163.94 ±1.28	160.67 ±1.80	167.75 ±1.24
38 / T_1	167.75 ±1.02	160.28 ±1.22	171.86 ±0.41
38 / T_2	162.29 ±1.68	157.19 ±2.30	167.47 ±1.04
50 / T_1	167.56 ±0.64	-	-
50 / T_2	170.85 ±1.11	-	-
62 / T_1	169.02 ±1.24	-	-
62 / T_2	169.76 ±0.42	-	-
74 / T_1	165.02 ±0.93	163.23 ±0.53	172.00 ±0.72
74 / T_2	169.76 ±0.42	156.65 ±2.08	164.96 ±1.89
86 / T_1	167.95 ±1.45	164.54 ±1.00	173.38 ±1.13
86 / T_2	169.39 ±0.45	163.29 ±1.43	172.80 ±1.72
98 / T_1	169.32 ±2.15	-	-
98 / T_2	177.61 ±0.98	-	-

The low but significant differences in UTS between different measured directions of one specimen can be explained as stated previously. The reproducible deviations in UTS between different specimens are a result of geometric differences, as specimens with different h_1 and therefore initial cross sections have different damage mechanisms dominating. The thinner the respective specimen, the more the plane stress state dominates, which results in higher resistance against damage and therefore slightly higher UTS values.

6.5 Data based experimental results

As stated in section 6.4, the higher resulting friction within the tribological system of test series T_2 result in a higher elastic suspension of the stand components of the rolling aggregate. This phenomenon leads to a higher increase of h_0 as well as h_1 in T_2 compared to T_1. Despite the resulting higher h_1, the rolling mill and especially the mill stand has to apply higher forces than in the tribologic system with adequate lubrication. Figure 29 demonstrates this effect on the resulting F_R on an exemplary rolling force hysteresis, where the same specimen from T_1 is compared with T_2. The effect of higher F_R for T_2 occurs in all different widths, as figure 30 (B_2) and 31 (B_3) demonstrate.

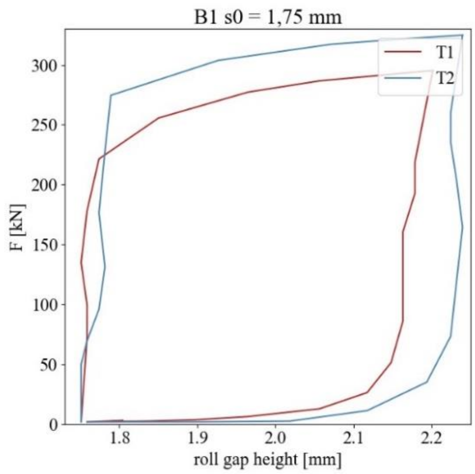


Fig. 29 Example of a rolling hysteresis: B_1 for s_0 = 1.75mm

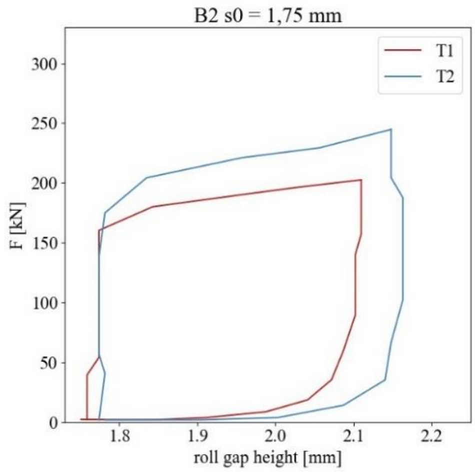


Fig. 30 Example of a rolling hysteresis: B_2 for s_0 = 1.75mm

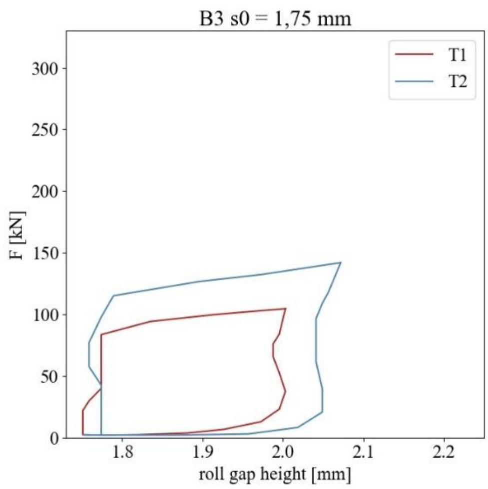


Fig. 31 Example of a rolling hysteresis: B_3 for s_0 = 1.75mm

Figure 32 shows a direct comparison between B_1, B_2 andB_3 from the same rolling schedule and s_0, for T_1 (fig. 32, top) and T_2 (fig. 32, bottom).

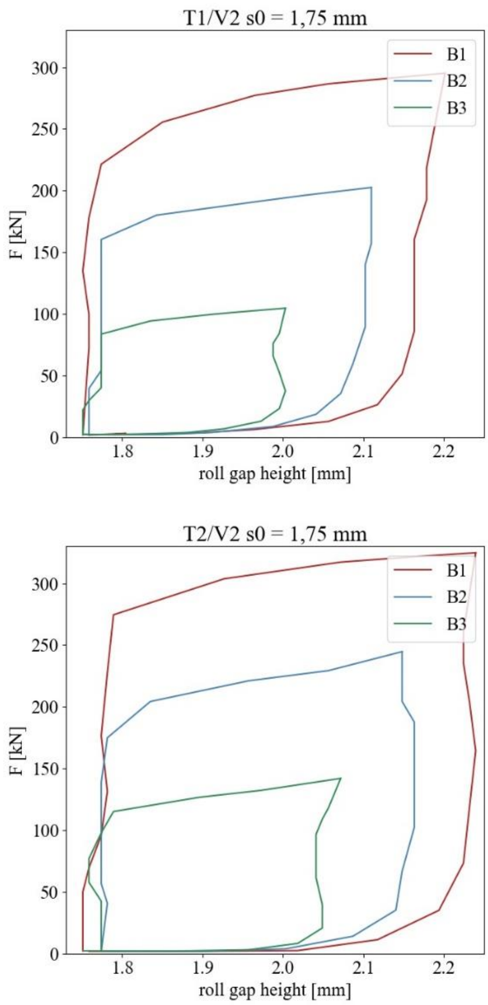


Fig. 32 Rolling hysteresis: resulting F_R as a function of initial sheet width: comparison between T_1 (top) and T_2 (bottom)

The unnatural angular curve progression is a result of the sample rate during rolling (500 Hz). To obtain smoother results, a controlling unit (section 4.2, fig. 10) capable of higher frequency would have to be implemented. As this plot only serves as a complementary visualization and the maximum valid sample rate is sufficient for the development of the machine learning algorithm (section 6.6), the controlling unit is not changed within this case study.

For the development of the algorithm described in this paper, the maximum rolling force F_R is of importance, whereas the curve progression is not relevant for the resulting digital twin. The usage of the maximum resulting force as F_R can be seen as valid, as the deviation between this value and corresponding data points within the rolling process doesn`t exceed 0.05 %. Figure 33 shows an exemplary F_R(time) curve from a rolling process carried out.

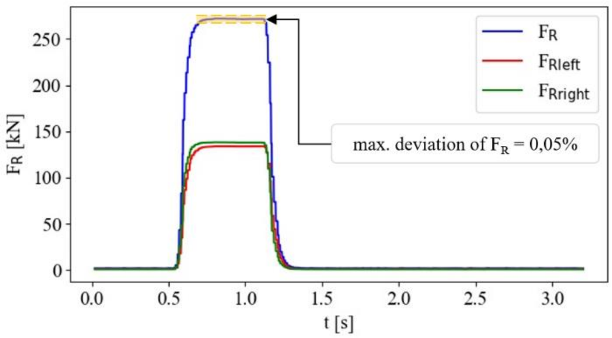


Fig. 33 Exemplary rolling force-time curve

Figure 34 shows the resulting data points for each process step within the test and calibration data setup, divided in test series and initial widths. In this diagram, a clear correlation between F_R, $\Delta h(s_0)$, B_i and T_i can be identified. As expected, test and validation data points for the same B, V and T cannot be separated. Therefore, no difference between those sets will be made in the following visualizations.

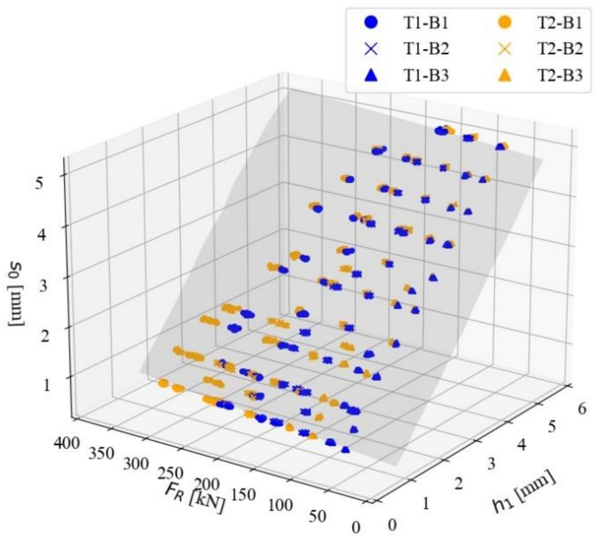


Fig. 34 Resulting data points (1736) from the test and calibration data series

As described in section 6.4, a difference between the maximum roll gap (s) and the resulting h_1 of a specimen occurs. This effect can be demonstrated by plotting the same data points as a function of the maximum s (fig. 35 and 36, yellow surface) and h_1 (fig. 35 and 36, blue surface). As visualized in figure 34, the difference between T_1 (fig. 35) and T_2 (fig. 36) can be seen due the offset of data points to higher F_R with T_2. The dependencies described in eq. 6 (section 6.1) and the effect of cold working (section 6.2) result in higher rolling forces with increasing Δh and decreasing s_0. As expected, the difference in the tribological system results in significantly higher F_R in T_2 in comparison to T_1. Also, higher F_R correlates with increasing initial sheet width. These effects are cumulative, resulting in a maximum offset of F_R between B_1/T_2 and B_3/T_1 at maximum value of the product $\Delta h * s_0$.

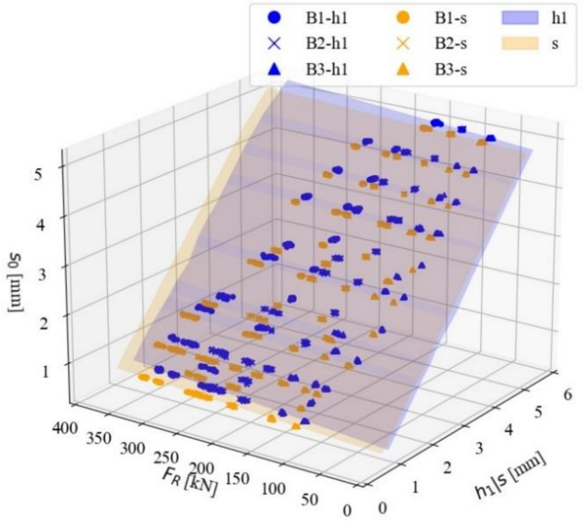


Fig. 35 Comparison between resulting s (yellow plane) and h_1 (blue plane) for B_1, B_2 and B_3 within test series T_1

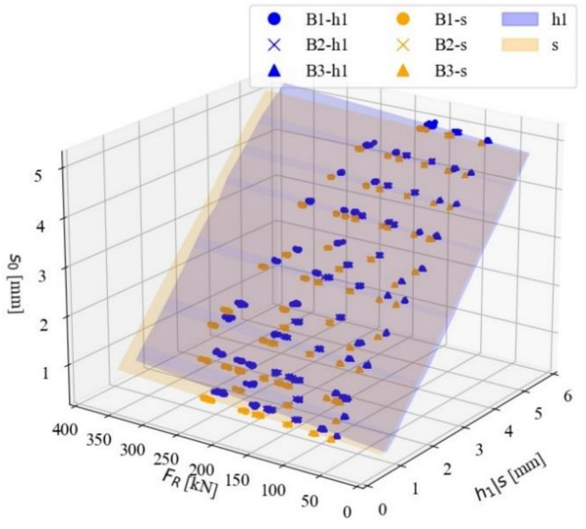


Fig. 36 Comparison between resulting s (yellow plane) and h_1 (blue plane) for B_1, B_2 and B_3 within test series T_2

In order to validate the stated hypotheses regarding the correlation of introduced variables, the validation data were implemented into the T_2 plane (fig. 37). For a better visualization, only the V_1 rolling schedule for each introduced B was plotted within. The resulting diagram shows a clear linear correlation between different widths and the corresponding s_0 of V_1. Furthermore, the modification of V_1 at $s_0 = 1.75$ mm (with a following s_0 of 0.75 mm instead of 1.00 mm) also supports the correlations stated by the authors within this paper.

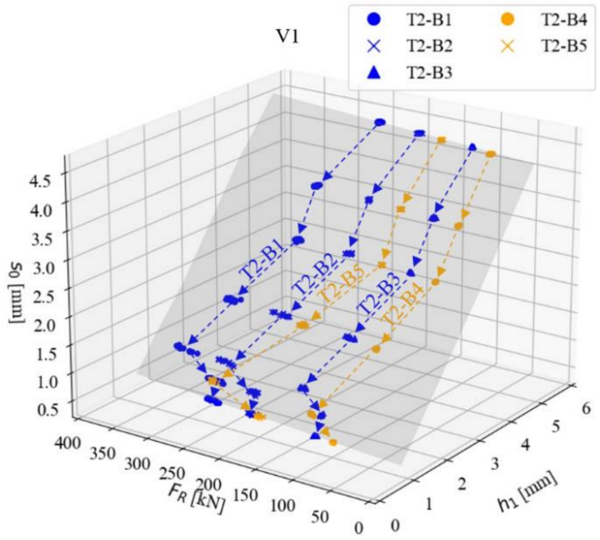


Fig. 37 Implementation of validation data: comparison with V_1 of test and calibration data sets

6.6 Result based machine learning algorithm

According to the statements made in the last subsections of section 6, the developed machine learning algorithm operates on linear interpolation and extrapolation of given test, calibration and validation data (fig. 38). The first setup is based on the logic demonstrated in figure 2, whereas the material curve was also modeled linear. For each given F_R and corresponding h_1, the algorithm interpolates with linear weighting functions between the initial data to obtain the working point A. This results in a new h_1, which is used as new input h_1 within a loop. As a result, a complete rolling schedule is obtained and in situ adapted during a carried out rolling process. To develop this digital twin further and realize actual machine learning, final data of an executed rolling scheme is added to the respective initial data set (T_1 or T_2) resulting in an overall adaption of the linearized functions for the characteristic rolling mill and material curve. Although it would be possible to use predefined machine learning algorithms (e.g. using the sci.py kit available within the Python environment), this logic has the advantage of a simple adaptability for other materials. Furthermore, it is easy to understand and adapt for learning students and other interested parties within the SFL at the Montanuniversität Leoben.

1. Import of refined data

Import of refined data T_1 (with lubricant) and T_2 (without lubricant) from the database containing { Specimen nr. | V_i | B_i | $F_{R\,i}$ | $h_{1\,i}$ | $s_{0\,i}$ }

2. Linear Regression

Stand

For every specimen n:

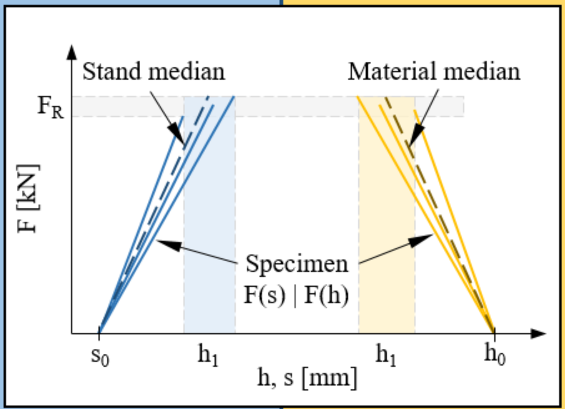
$$F(s) = a_{s\,n} \bullet s + b_{s\,n}$$

$$a_{s\,n} = \frac{F_R}{h_1 - s_0}$$

$$b_{s\,n} = -a_{s\,n} \bullet s_0$$

For each s_0 of every B:

$$a_{s\,median} \mid b_{s\,median}$$



Material

For every specimen n:

$$F(h) = a_{m\,n} \bullet h + b_{m\,n}$$

$$a_{m\,n} = \frac{F_R}{h_1 - h_0}$$

$$b_{m\,n} = -a_{m\,n} \bullet h_0$$

For each s_0 of every B:

$$a_{m\,median} \mid b_{m\,median}$$

3. Extrapolation of B

Stand

Linear Regression of $a_{s\,median}$ and $b_{s\,median}$ for 400mm > B1 and B5 > 10mm to obtain $B_{ex\,(i)} > B_1$ and $B_{ex\,(i+1),} < B_5$

Material

Linear Regression of $a_{m\,median}$, $b_{m\,median}$ and h_0 for 400mm > B1 and B5 > 10mm to obtain $B_{ex\,(i)} > B_1$ and $B_{ex\,(i+1),} < B_5$

4. Interpolation of demanded b

Stand | **Material**

Calculation of weighting factor α between nearest neighbours of given widths B_i

$$\alpha = \frac{b - B_i}{B_{i+1} - B_i} \qquad B_{i+1} \geq b \geq B_i$$

Stand

Interpolation of slope a_s, intercept b_s with weighting factor α for every s_0:

$$a_s = a_{s\,i+1} + \alpha \bullet (a_{s\,i} - a_{s\,i+1})$$
$$b_s = b_{s\,i+1} + \alpha \bullet (b_{s\,i} - b_{s\,i+1})$$

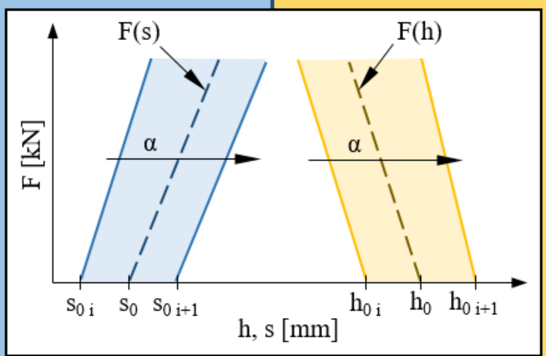
$$F(s) = a_s \bullet s + b_s$$

Material

Interpolation of slope a_m, intercept b_m and resulting h_0 with weighting factor α for every s_0:

$$a_m = a_{m\,i+1} + \alpha \bullet (a_{m\,i} - a_{m\,i+1})$$
$$b_m = b_{m\,i+1} + \alpha \bullet (b_{m\,i} - b_{m\,i+1})$$
$$h_0 = h_{0\,i+1} + \alpha \bullet (h_{0\,i} - h_{0\,i+1})$$

$$F(h) = a_m \bullet h + b_m$$



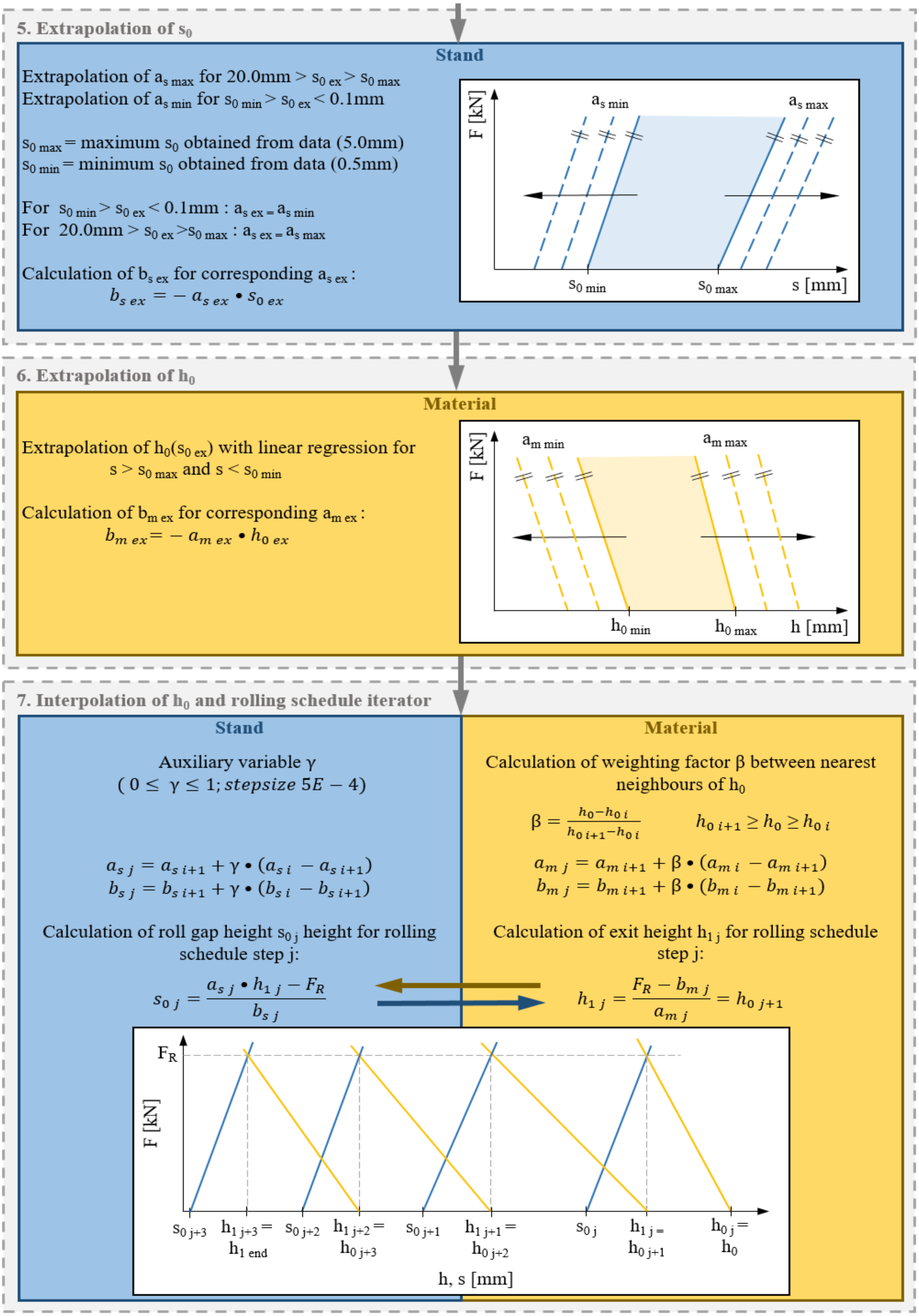


Fig. 38 Fundamental logic for the Python based rolling schedule iterator

6.7 Machine learning GUI

The logic visualized in figure 38 (section 6.6) serves as a basis for the second front end GUI. This GUI is also developed using the open source version of Qt Creator. The corresponding code was programmed using C++ and translated directly into Python within an appropriate translation framework (e.g. qtpy). As a result, the visualization can be started within the Python environment (e.g. using PyCharm or MS Visual Studio).

Figure 39 shows the resulting GUI for an exemplary rolling mill schedule. The possibility of including other materials is also considered.

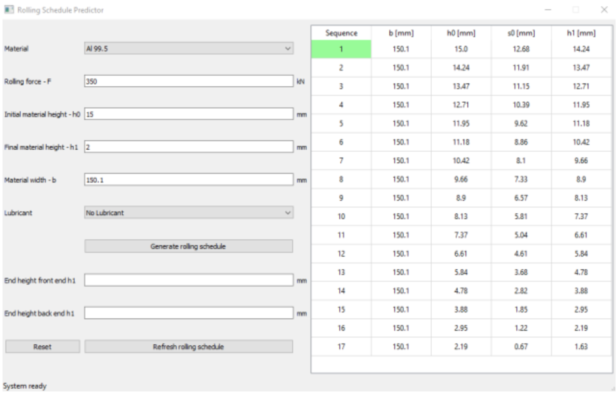


Fig. 39 Resulting front end GUI for the rolling scheme iterator

The highlighted sequence (fig. 39, green) indicates that no adaptions have been made and the generator calculated the complete scheme from the given input parameters (fig. 39: Material, Rolling Force, h_0, demanded final h_1 after schedule, T_1 or T_2). After a rolling step, the real h_1 can be measured on two points (fig. 39, End height front end h_1, End height back end h_1). Additionally, a change in width (according to eq. 8, section 6.3) or lubrication can be typed in, which also changes the result according to the fundamental logic (fig. 38). Figure 40 demonstrates the influence of varying these parameters after a rolling step.

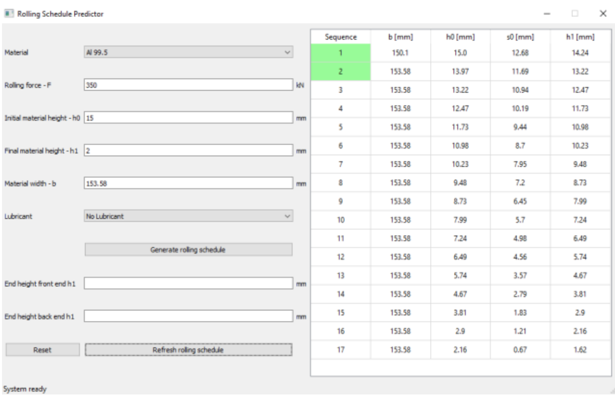


Fig. 40 Changed parameters based on fig. 38 after the first rolling step: increased width and deviation between measured and predicted h_1

The user-given input parameters are triggering the machine logic. Furthermore, these parameters were also written into the initial database, which serves as fundament for the whole logic. Based on this data base extension, the logic is able to shift the boundaries for the extrapolation (if a B, s_0 out of the initial widths is given) or generate new interpolation data points within the given boundaries. Regardless which condition is met, the algorithm changes its final interpolation logic by changing material and stand related slopes and intercepts. As this adaption is made via linear weighting functions between a small step increment, the influence on the change is rapidly decreasing with increasing distance from the generated data points. As the point cloud gets denser with every data input, the prediction gets more accurate with each rolling process carried out. Figure 41 shows an overview of this loop.

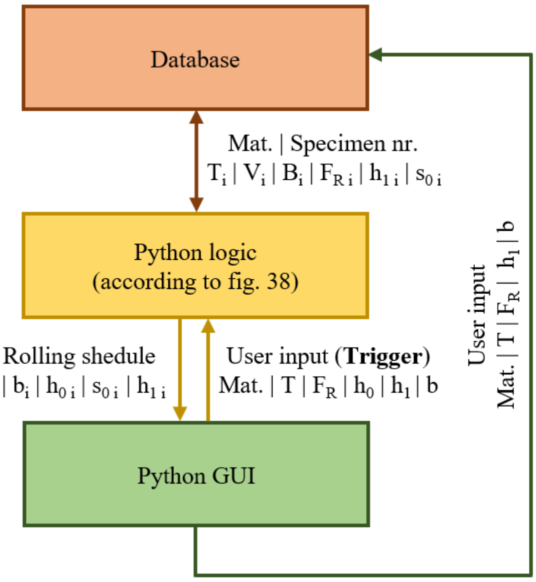


Fig. 41 Overview of the interaction between the database, the corresponding logic (back-end GUI) and visualization (front-end GUI)

7 Resulting LC user centered CPPS

For the development of a low-cost user centered CPPS, the chosen forming equipment, a rolling mill aggregate built in 1954, was digitized and digitalized from the implementation of state of the art sensor technology to the integration of a self-learning digital twin with corresponding GUI. For all necessary development steps, cost efficient but robust solutions were chosen, in order to be able to use this case study as a possible framework for SMEs and (academic) learning factories to develop CPPS based on similar technologies. Another focus within this paper, a wide and high usability for all interested parties of the developed solution was realized with two different front end and two easy to understand back end GUIs. The usage of low-cost and mostly open source software solutions is another advantage of this framework, as continuous updates are made in the open source community and expensive software maintenance is not necessary. Figure 42 shows the final data flow at the rolling mill, from analog sensor signals to the Python logic.

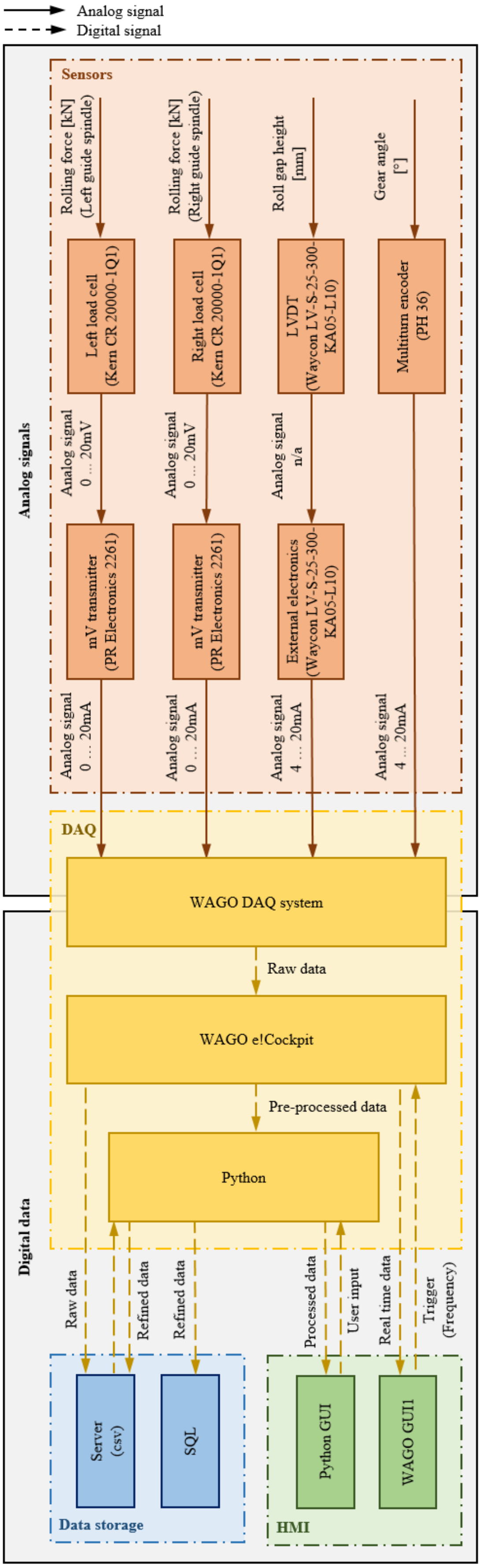


Fig. 42 Resulting data flow for the digitalized rolling mill

To demonstrate the fulfilment of all criteria for a LC user-centered CPPS according to table 1, figure 43 shows the final integration of the system in the layer architecture.

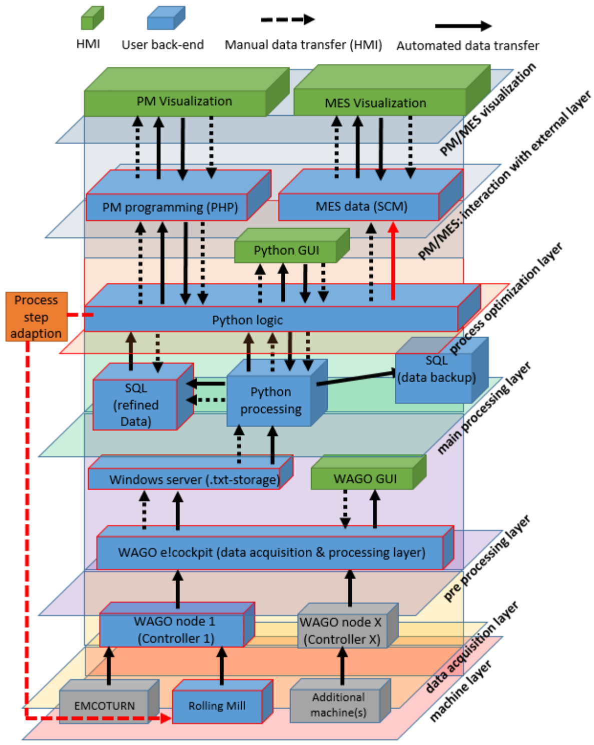


Fig. 43 Resulting layer architecture for the developed CPPS

Depending on the state of the machine (measurement on: 500 Hz; measurement off: 1Hz) a data flow into the MES is automatically enabled or not (fig. 43, red arrow).

8 Conclusion and Outlook

This paper describes the successful transformation from a proprietary machine system to a low-cost user centered CPPS. Although the resulting integrated machine learning algorithm is based on a purely data-driven modeling approach, the respective material has to be and was considered. Without complementary experiments, the number of possible dependencies between input parameters would result in a far more complex system. The usage of a e.g. neural network based algorithms could be an alternative. A huge disadvantage of a more complex logic, however, would be the missing link between real physical effects and resulting prediction. Especially when considering different, more complex materials then the technical pure aluminum used in this case study, an overfitting effect could be the result. In general, a strict separation between material and machine parameters is not possible, as the dependencies and interactions are too complex to distinguish without a significant error.

To extend the demonstrated framework for other material/process combinations, different alloys with different initial conditions will be implemented in the future. Furthermore, with the support of more advanced material characterization experiments (e.g. REM/EBSD), the prediction of grain size and corresponding anisotropy as a function of the thermomechanical treatment will be investigated. In general, the integration of temperature as an additional depended variable results in a far more complex equation system. To solve such a system in an adequate and reproducible way, the integration of finite element analysis connected to the framework within the Python logic will be investigated, whereas the reduction of computational time can be seen as most critical within such simulations. To decrease this parameter, direct coupling of Python based input and output files will be included. After successful coupling, the proposed extended algorithm will be able to predict micromechanical material properties as a function of the thermomechanical treatment. This information can be used to send recommendations into the MES-layer (fig. 43), which can optimize necessary upstream or downstream heat treatment processes based on this information.

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Author contributions

1. B. J. Ralph: conceptualization, formal analysis, data curation, methodology, software, writing – original draft preparation, writing – review and editing, visualization, project administration, supervision

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MUL 4.0: Systematic Digitalization of a Value Chain from Raw Material to Recycling

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Abstract

The digital revolution, also known as Industry 4.0, offers a variety of new technologies and technological concepts for the continuous optimization of production and logistics processes in manufacturing enterprises. Up to now, a multitude of scholars have investigated potential opportunities, barriers, threads, and necessary enablers of Industry 4.0 initiatives. However, most of the recent Industry 4.0 approaches can still not resist practical tests due to their limited view on a small range of relevant topics. This paper introduces the research project 'MUL4.0' which aims to digitalize an entire value chain, from raw material to recycling. Based on an action-research-orientated approach, the authors use a multi-case-study design to investigate the potential of digitalization approaches within production and logistics processes. Furthermore, the authors present future research activities and discuss the therefore necessary prerequisites, from a materials science, mechanical engineering, metallurgical, logistics engineering, and management perspective.

Keywords: Digitalization, Industry 4.0, Industrial Logistics, Engineering Education, Digital Twin, Finite Element Analysis, Metal Forming

1. Introduction

Industry 4.0, as the ongoing revolution of the manufacturing industry around the world, focuses on the integration of emerging information and communication technologies in traditional production and logistics processes [1]. Thereby, according to recent literature, current studies on digitalization in production and logistics can be divided into the clusters of 1) technologies and technologies concepts, 2) enablers of digitalization, 3) risks of digitalization, and 4) opportunities of digitalization. Thereby, cluster 1 listed data science, virtual environments, IoT devices, automatic identification, CPS, location (technologies), interfaces, and decentralized applications as the main technologies and technological concepts within the framework of Industry 4.0 [2]. However, from a methodological point of view, it must be noted that most studies can be assigned to the research type of conceptual studies, preliminary laboratory experiments, or single case studies leading to a limited external validity of the established research findings. Therefore, the authors conclude that, despite some fruitful insights, most studies provide only a limited view on the 'realistic' system behavior in economic practice.

To increase the generalizability and transferability of research results to manufacturing enterprises, the authors introduce the research project 'MUL 4.0' which aims to investigate an entire value chain, from raw material to recycling, based on a combination of quantitative and qualitative research methods. Moreover, this paper discusses the necessary prerequisites from a material science, mechanical engineering, metallurgical, logistics engineering and management point of view and concludes with a summary of potential future research initiatives.

2. Research methodology and concept overview: MUL 4.0

Based on the implications of relevant strategy papers from the European Commission, which are generally aiming at increasing the competitiveness of companies as micro-economic entities through the implementation of Industry 4.0 technologies, Austria's first digital learning factory is to be established in a cooperative project of four institutes or chairs of the Montanuniversitaet Leoben within the framework of a multitude of research projects. This learning factory represents an isomorphic representation of a fully digitalized value chain and should also be able to dynamically optimize processes based on the latest Industry 4.0 technologies. For the first time, in contrast to the mostly isolated basic concepts of Industry 4.0, holistic and sustainable measures of a digital learning factory derived from the fields of action 1) digitization and artificial intelligence, 2) resource-efficient production-oriented to concepts of the circular economy, and 3) human-machine interaction will be designed, implemented, and scientifically investigated. Therefore, Fig. 1 shows an overview of the production process and involved parties within this project.

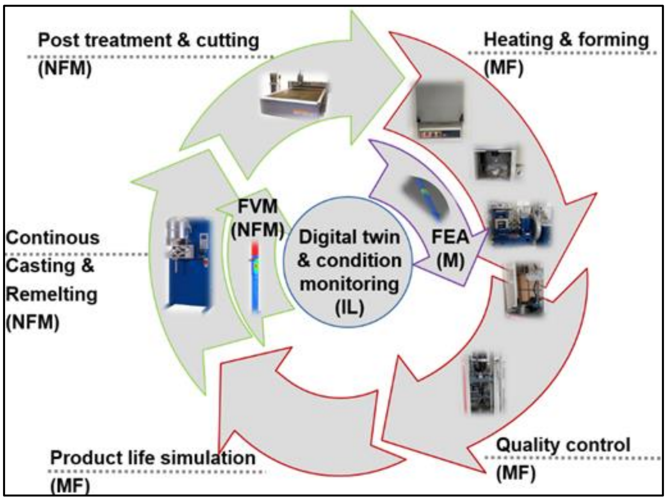

Fig. 1. Overview and responsibilities of respective process steps in the MUL 4.0 concept [3].

The starting point of the digital learning factory is the continuous casting plant at the Chair of Nonferrous Metallurgy (NFM). At the NFM, a previously specified aluminum alloy is casted with varying process parameters and geometries and prepared for subsequent process steps (Fig. 1, green). From the beginning of the casting process, continuous identification and automated data acquisition (DAQ) is performed by the higher-level tracking system, which processes the product, process, and logistics data (e.g., location, throughput time, etc.) and passes on information to the subsequent process steps. The processed workpiece is then transported from the NFM to the Chair of Metal Forming (MF), where it is first preheated and then formed into its final shape in two or more subsequent forming processes, with the possibility of reheating between each step. The transport itself from the NFM to the MF will be captured in real-time by the implemented tracking software. The most important process steps in terms of mechanical engineering, metallurgy, and materials science are mapped in real-time using finite element analysis (FEA) and finite volume analysis (FVA). Based on this FEA and FVA, real-time adaptations for active intervention in involved processes should then be possible. The Institute of Mechanics (M) (Fig. 1, violet) is mainly responsible for the development of the FEA-based digital twins based on real physical data together with the MF. Here, attention is also paid to the influence of thermo-kinetics, which leads to highly informative and accurate results about the current condition of the respective workpiece. The results of these simulations are validated and calibrated with the aid of appropriate quality management carried out at the NFM and MF. The adapted process data is fully automated and continuously transmitted to a Supervisory Control and Data Acquisition (SCADA) system already implemented at the MF, pre-processed, and then transferred to the higher-level tracking system. A similar suitable SCADA system is currently in development at the NFM.

After quality management has been carried out (on a statistical basis and as far as possible on a practical basis), the finished components can be put to further use. During almost all process steps, there is material waste, which is also fully tracked from the point of origin and systematically returned to the NFM. This closes the cycle of the (digitalized) value chain.

Besides the tracking system, additional simulations are carried out in logistics processes to be able to continuously optimize inventories, throughput times, adherence to schedules, and machine utilization. As a result, an ideal maintenance strategy can be systematically derived based on the system's behavior. The discrete event simulation used for this purpose can also be displayed three-dimensionally and, in combination with modern augmented reality technologies, is, thus, an important component of advanced teaching. The Chair of Industrial Logistics (IL) is mainly responsible for this image of the digital learning factory as well as the implementation, maintenance, and optimization of the tracking and condition monitoring system (Fig. 1, blue). The mainly used open-source and low-cost hardware and software also offers the possibility to educate a broad variety of engineering students of different disciplines as well as external parties under the premise of the transdisciplinary engineering education concept, which is displayed in Fig. 2 [4,5,6].

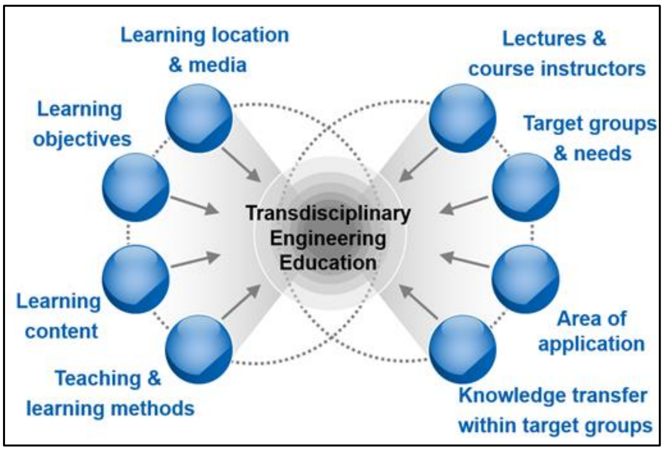

Fig. 2. Transdisciplinary Engineering Education concept [4,5,6].

Fig. 2 illustrates the variety of complex influencing factors that affect transdisciplinary learning processes. Different causal mechanisms intervene in teaching and learning processes, and, therefore, must be considered when planning, implementing, and evaluating it. On the one hand, endogenous factors, such as previous experience, expectations, or motivation of teachers and participants, affect the micro-level, as the respective learning unit. On the other hand, exogenous factors, such as legal foundations, living conditions, or higher-level goals at the meso- and macro-levels, further have a significant impact on the learning process. This transdisciplinary engineering concept will also be an integral part of a transdisciplinary engineering lecture, which mainly focuses on digitalization and its underlying technologies [4,5,6].

3. Process value chain: Holistic concept

In a prior analysis, several gaps in current research about digitization and digitalization in industrial logistics were found [1]:

- Many approaches to use new technologies or technological concepts in logistics processes do not go beyond a conceptual stage or theoretical validation and, thus, open up the demand for implementation and validation of the concepts in practice.
- A common method for examining the complex behavior of logistical processes is the usage of discrete event simulation. However, the literature review shows a lack of attention to the use of digital twins in the field of industrial logistics. The combination of real-time production data and a discrete event simulation can fill this gap. Nevertheless, the potential benefits of such systems, as well as development challenges, need to be addressed.
- The authors state that, even though current literature agrees on the positive impact of digitization on sustainability performance, research does not focus on the achievement of general objectives such as the Sustainable Development Goals (SDGs). In addition to this, small- and medium-sized enterprises (SMEs) face several barriers when implementing sustainability reporting (SR) in general [7]. Due to a lower market value, SMEs seem to have a lower SR quality. This circumstance is a result of an existing positive correlation between a company´s market value and the quality of SR [8].
- In physical as well as in digital processes, (IT-) security issues are a widely discussed topic [9]. Increased data sharing involves risks of cyber-attacks and the interest of certain parties to manipulate data.

The MUL 4.0 lab offers several opportunities to implement and assess newly developed models, frameworks, or technologies, which have only been theoretically approved in the examined literature. According to the authors, the main contribution to research is the development and implementation of a holistic near-real-time digital twin that extends material science and engineering-based simulations with simulation and visualization of the logistical processes.

Potentially, the above-mentioned research gaps can be closed due to practical implementation of the technologies in the laboratory to

- use real-time data to simulate logistics processes and forecast their output,
- use real-time data to evaluate different scenarios, based on the current status in the production, which enables the realization of decision support systems for logistical purposes,
- use real-time data to assess the environmental impacts of the process as well as the products and
- visualize real-time quality, sustainability, and process metrics in a production data cockpit.

Due to the laboratory character of the manufacturing system, the comparability and implementation of the gathered results into industrial environments with large-scale production and highly automated systems would lack of accuracy. Instead, the authors expect a similarity to environments of manufacturing SMEs, whose production resembles semi-automated workshop production.

The implementation of the near-real-time digital twin described above offers new possibilities to evaluate production plans and schedules on the fly, more precise forecasting, and faster exception handling during the manufacturing process, resulting in a more realistic factory planning. Furthermore, both a dynamic allocation of transport tasks and a dynamic routing through the production can be achieved. Due to the virtual environment of the production, reinforcement learning algorithms can be used.

An environment to assess and visualize sustainability and quality indicators of the production on the product-level in near real-time in workshop manufacturing could enable higher SR quality and shorter reaction times in case of an exceptional waste of energy or material. Furthermore, agent-based production planning and scheduling could be implemented, which focuses on the reduction of lead times of products with lower environmental impacts. Overall, material and energy efficiency could be increased due to new, realistic, and live insights in the production process and the creation of incentives to buy environmentally better products could be more feasible to potential customers due to reduced process-related costs.

Also, secure mechanisms to save and share recorded data across the supply chain could support efficient compliance with a potential supply chain act.

To enable the proposed logistics digital twin, the assessment and the implementation of several technologies are necessary:

- To create a valid 3D-simulation for simulating the material flow, a 3D-model of the laboratory setting must be generated. This could be achieved by new 3D-scanning methods such as LIDAR-sensors or smart cameras (e.g., Azure Kinect).
- Indoor Positioning Systems (IPS) have to be installed in the laboratory, including a continuous identification of the material flows by Auto-ID technologies. This should ensure the complete traceability of the material

flow and the localization of the means of transportation.

- A suitable integration of logistics applications into the proposed layer structure of the FEA and FVA must be defined. The establishment of interfaces is necessary for fast and reliable information exchange between the applications.
- The creation of a resilient software architecture for the integration of real-time data or a real-time initialization of discrete event simulations is crucial.
- The scope of the sustainability assessment has to be defined. According to this scope, valid input data, emissions factors, etc., must be available.
- Metrics that represent the environmental impact of the produced goods and IIoT-sensors to measure these metrics are to be found and implemented, e.g., GHG emissions during production, which arise because of energy usage. To capture this, electricity and gas meters have to be installed and integrated into the infrastructure.
- Security of information sharing has to be guaranteed to create unalterable data that are available to all necessary parties in near real-time.
- Recording production times for different products and their distributions, to create different production plans and for further investigations has to be carried out.

4. SCADA and numerical simulation integration

The following subchapters describe the data gathering at the most important aggregates within the digitalized supply chain. The focus lies on the interaction between the physical machining processes and resulting sensor data with near real-time integration of corresponding numerical simulations. Therefore, the main objective is the prediction of material behavior with upcoming process steps, which allows the superordinate logistics digital twin system to optimize the logistic chain in terms of lead time and general production planning. To achieve this efficiently and effectively, a variety of numerical simulations were designed. Based on the results of these simulations, process steps will be automatically adapted. Despite the positive effect on logistics, desired material quality can be optimized, and out coming parts that don't fulfill the quality requirements can be reduced [10].

4.1. Thermo-mechanical process route

The numerical process chain starts at the continuous casting unit, which produces slabs with defined geometry made from raw material, followed by a cutting operation on another aggregate. The resulting workpieces are heated to a defined temperature and pre-formed in a hydraulic press or alternatively rolling mill aggregate, which results in either bulk or sheet metal-based products.

Depending on the desired final shape and mechanical material properties, additional reheating steps can be performed and additional forming steps within the same aggregates can be taken. After quality control and simulated usage, the specimen is transported to the NFM, refined, and finally re-melted (Fig. 1). All machines are equipped with sensors matched to the measured parameters to be able to record the most important machine and process parameters qualitatively and quantitatively.

4.2. Aggregates with coupled numerical simulations

The Indutherm CC3000 continuous casting plant at the NFM is equipped ex works with a variety of different sensors (Fig. 3). These sensors record the crucible temperature, die temperature, draw path, time step of the draw path, reversing draw path, timestep of the reversing draw path, and resulting drawing force.

Fig. 3. Continuous casting aggregate at the NFM [10].

Two die shapes with dimensions 6x75mm and 30x110mm can be distinguished to produce specimens with different dimensions. These determine the width b and height h of the specimen. The casted slab is then separated into several specimens of length l. The temperature in the crucible and the mold temperature are measured with a thermocouple of Type K (NiCr-Ni) or Type S (PtRh-Pt) (Tab. 1).

Table 1. Sensors of the continuous casting plant [11].

Measurement	Sensor	Range
Crucible temperature [°C]	Thermocouple Type K or Type S	0-1200°C 0-1500°C
Die temperature [°C]	Thermocouple Type K or Type S	0-1200°C 0-1500°C
Draw path [mm]	N/A	N/A
Timestep of draw path [s]	N/A	N/A
Reversing draw path [mm]	N/A	N/A
Timestep of reversing draw path [s]	N/A	N/A
Draw force [N]	Load cell	N/A
Process time [s]	Processed by programming	Processed by programming

Due to the separate location of the continuous casting plant and the aggregates for the next process steps, which are carried out at the MF (approximately eight minutes transportation time), there is a significant drop in the temperature of the specimens during transport. To achieve desired material behavior, the specimens are reheated in a furnace at the MF in the next process step to set the specimen temperature required for the following forming operations. To determine the necessary temperature and time, a Type K thermocouple (NiCr-Ni) is added to the furnace by the retrofitting method, which has been adjusted to the maximum temperatures occurring in the furnace of up to 1200°C (Tab. 2).

Table 2. Sensors of the furnace.

Measured quantity	Sensor	Range
Temperature [°C]	Thermocouple Type K	0-1200°C
Process time [s]	Processed by programming	Processed by programming

The used main forming aggregate for bulk-forming, a hydraulic press, is placed next to the furnace to keep the transport distance and transport time and the associated temperature loss of the specimen as low as possible (Fig. 4). The sensor technology of this aggregate records the temperature of the specimen using a ratio pyrometer (also known as a comparison pyrometer) as well as the upsetting force applied during the upsetting process utilizing a load cell (Tab. 3).

A special advantage of the ratio pyrometer is its ability to measure correct temperatures at the surface of the specimen without having to know the emission of the underlying material. By measuring with two different spectra, the temperature of the measured object can be determined from their quotient, the radiation ratio [12]. This principle results in a further advantage, which is particularly relevant for harsh operating and environmental conditions - the insensitivity to interference, e.g., smoke and dirt between the measuring object and the ratio pyrometer [13].

Fig. 4. Hydraulic press with control unit (left), furnace (right).

Table 3. Sensors of the hydraulic press.

Measured quantity	Sensor	Range
Die force [N]	Load cell	0-1MN
Die position [mm]	LVDT	0-600mm
Temperature of specimen [°C]	Pyrometer	0-1200°C
Process time [s]	Processed by programming	Processed by programming

The rolling mill at the MF (Fig. 5) was equipped with suitable sensor technology to record the process parameters relevant to the rolling process (Tab. 4). As a result, the mill can be incorporated into the process chain to roll specimens and collect further information on texture or formability. Two load cells, one on each side of the work rolls, measure the resulting rolling force and sum to give the total force, which has the advantage of collect data regarding eccentricity directly in the roll gap. A Linear Variable Differential Transformer (LVDT) sensor, which has a very high resolution and low deviation from linearity, measures the height of the roll gap as well as the deflection of the roll gap during forming.

Fig. 5. Rolling mill system at the MF (300 kN).

Table 4. Sensors of the rolling mill.

Measured quantity	Sensor	Range
Rolling force [N] (left guide rail)	Load cell	0-150kN
Rolling force [N] (right guide rail)	Load cell	0-150kN
Roll gap [mm]	LVDT	0-25mm
Gear angle [°]	Magnetic multi turn encoder	0-360° x 32 turns
Process time [s]	Processed by programming	Processed by programming

4.3. IT-infrastructure and integration of numerical simulation

The DAQ of the sensors from the forming and heating aggregates is carried out within the CMs' internal network using the Wago controller of the XTR-series suited for harsh environmental conditions. Due to the usage of compatible I/O modules, the DAQ can be easily and flexibly adapted to a variety of analog and digital signals from the respective sensors, e.g., voltages, current, bits. The acquired signals are internally processed by the respective controller and converted into a digital signal that can be used for further computer-based processing and fed into a new set-up production network, which is accessible only for respective stakeholders of the MUL 4.0 project.

After initial calibration of all respective sensors, calibration curves varying between third and sixth-order were directly programmed into the corresponding controller in structured text, which results in the direct conversion of sensor signals into corresponding physical quantity.

For the connection of the aggregates used at the NFM, the proprietary software of the continuous caster will be used, resulting in txt files automatically stored at the MUL 4.0 production network.

The preparation and further processing of the process data from both chairs are carried out in an additional layer with the open-source programming language Python, which was chosen to prevent an isolated solution. Using suitable frameworks, the data in the network are collected, processed, and evaluated to make them available for analysis and automatic feeding into FVA and FEA-based simulations [14].

As soon as data are supplied from the continuous caster, the simulation of the upsetting forming process of the hydraulic press and/or rolling mill is automatically set up and started with Python. This provides the sample temperature to be set for the desired degree of forming. As a result, the temperature to be set as well as corresponding heating time will automatically be adapted. In the case of the bulk-forming processes, an additional thermal simulation of the temperature gradients within the specimen is carried out to ensure that all samples are heated thoroughly and homogeneously.

The process steps ‘reheating’ and ‘forming’ can be repeated several times, with each of these process steps being automatically simulated again. Furthermore, text (txt) files containing the relevant time steps, such as process start, and end, are stored in the network to provide the most important results of the simulation for further processing at the IL.

The obtained data are automatically fed into a SQL database using Python, which is shared between all cooperating chairs and institutes via the network.

The simulation of continuous casting and the associated implementation of a digital twin (DT) will be carried out by the NFM. The simulation of the continuous casting process will be performed using common FVA programs. If the required computational time cannot be achieved using FVA, a sophisticated abstraction using FDM will be designed.

The implementation of the three DTs and setup of the simulation using FEA for the furnace, rolling mill, and hydraulic press will be performed by the MF. Fig. 6 shows the resulting material and data flow within the numerical simulation optimized aggregates in the value chain.

All numerical simulations are supplied with input parameters and deliver output parameters, which are passed on to the simulation of the next process step according to the process chain (Fig. 1), to digitally represent the process chain in the best possible way. Tab. 5 shows an overview of the resulting input and output parameters.

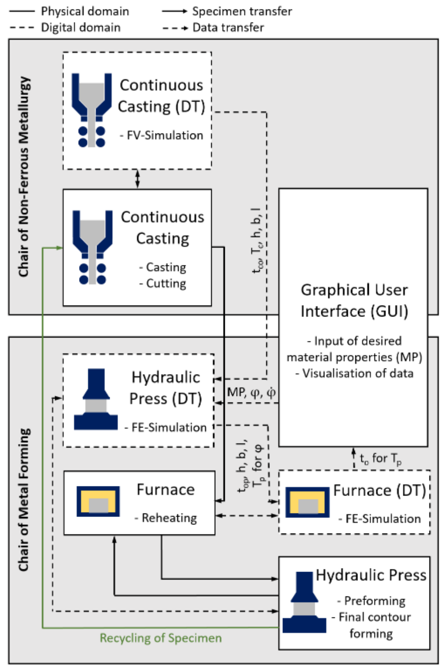

Fig. 6. Overview of the material and data flow corresponding to the numerical simulation-based DTs’.

Table 5. Input and output parameters of the coupled numerical simulations.

Machine	Type of Simulation	Input	Output
Continuous Casting	FVA (FDM)	CP, MP	t_{co}, T_c, h, b, l
Oven	FEA	CP, MP, t_{co}, T_c, h, b, l, φ, $\dot{\varphi}$	t_o for T_p
Press	FEA	t_{co}, T_c, h, b, l, MP, φ, $\dot{\varphi}$	t_{op}, h, b, l, T_p for ϕ

The automatic input data transfer and starting of the simulation is realized by Python (Fig. 7).

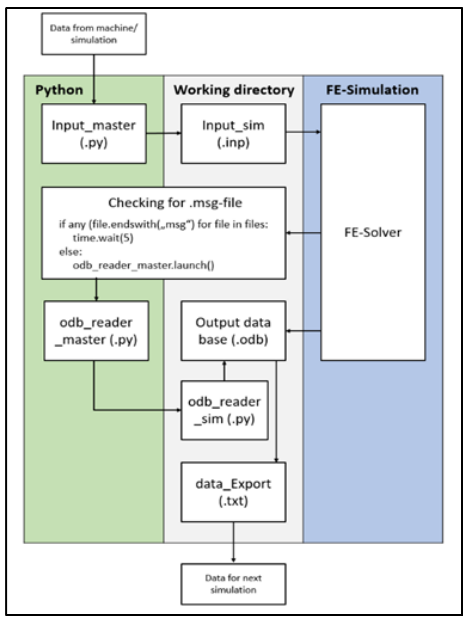

Fig. 7. Scheme of automated FE-Simulation with Python.

As demonstrated in Fig. 7, a python script is written, which serves as the basis for the automatic creation of an input (inp) file for the simulation with the FE program Abaqus (abq). This inp file contains all required information and data, e.g., CP, MP, geometries, to perform an FEA. The inp file also determines the characteristic values to be calculated, e.g., stresses, strains, displacements, temperatures, to streamline the scope of the simulation, resulting in a significantly shorter computation time. With Python, the input data from the previous process step is automatically transferred into the inp file and the simulation is started. During calculation, Python checks in defined time increments if certain files are present in the working directory, e.g., the message (msg) file, which is only present during and automatically deleted after completion of the respective simulation. If the script cannot find such an msg file, it automatically reads out the output database (odb) file using another Python (py) script.
It is important to note that the automated data extraction from the used FEA-program does not work within the used PyCharm IDE, as the extraction from the proprietary odb format must be carried out with a specific library only available within the abq environment. Therefore, the py Masterfile executes an abq-specific py file with the imported library and underlying methods directly in the abq environment using the abq command window.
The resulting abq odb file contains the output parameters defined in the inp file at all selected nodes, depending on the previous definition in the inp file. To make the resulting odb data usable for the simulation of the next process step, the master file transfers the odb data into a txt file and transfers it automatically into the next inp file, followed by the start of the upcoming simulation. A similar approach, depending on the decided FVA software will be carried out for the integration of FVA by the NFM.

5. Results and discussion

The cooperation between the involved chairs and institutes results in an interdisciplinary digitalization framework demonstrated in Fig. 8.

One advantage of the presented framework was the transdisciplinary development approach used, considering different points of view from automation, mechanical engineering, materials science, metallurgy, and industrial logistics perspectives. Furthermore, every party was involved, from the initial conception to the following adaption phases, allowing each different discipline to include specific knowledge from the very beginning.

Therefore, the resulting framework (Fig. 8) has the main advantage of being planned from scratch to create a low-cost open-source solution for the digitalization and digital transformation of low volume and high variety manufacturing environments. Proprietary solutions, resulting in heterogeneous data sources for the DAQ and functional domains, were avoided. The inclusion of numerical simulation domain experts from the beginning of this project avoided over-engineering in terms of (in practice not particularly needed) accuracy for the cost of higher computational times.

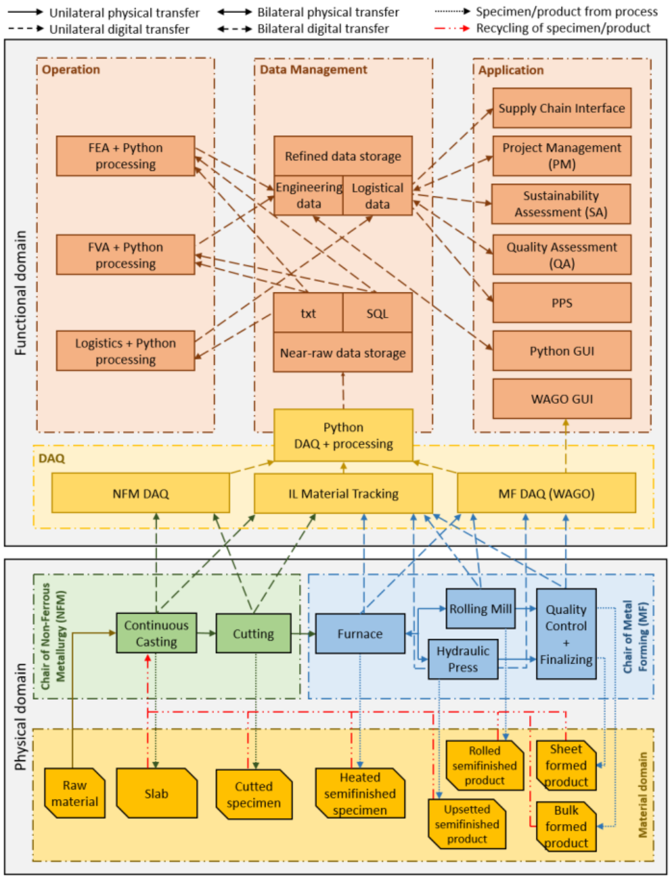

Fig. 8. MUL 4.0: physical and functional domain blueprint.

The exchange between logistics experts and involved process engineers leads to various adaptions in implemented sensor technology, as the integration of a logistics digital twin requires additional hardware, which to a significant extent must be implemented within the retrofitting process. The delocalized structure of the physical entities also made it necessary to include different IT-infrastructures from the beginning. Therefore, the implementation of a shared production network leading to a unified database structure was of utmost importance.

The MF and NFM also included their respective shop floor workers in the concept, giving regular updates on the project status to avoid refusal from coworkers who will have to work with the introduced framework regularly soon.

6. Conclusion and outlook

The framework presented in this paper is already in the implementation phase. The necessary retrofitting of involved aggregates is determined and will be completely implemented within this year. One of the main aggregates, the rolling mill at the MF is already fully integrated within the superordinate DAQ and Python layer and serves as a case study for further implementation in the Wago DAQ environment at the MF. The designed production network is planned, and necessary IT infrastructure is implemented. The first numerical digital twin is already in the final development phase and should be completed within mid of this year. The designed databases are defined, and corresponding python interfaces are programmed.

Until next year, the complete implementation of the framework is planned, whereas potential delays, e.g., due to delivery delays, are included in the defined time horizon.

To extend the transdisciplinary engineering education approach, an extension of the involved parties within the end of next year is planned. The main objective is to include further numerical simulation experts regarding FVA as well as ferrous metallurgists to be able to vary between nonferrous and ferrous input material for the upcoming forming processes, which adds more variety in the production planning and coupled numerical simulations. From a logistics point of view, the implementation of different materials also results in another location that must be tracked, as the production of casted steel grades, similar to the nonferrous counterpart, happens at a different location.

From a techno-economics perspective, on the long term, the introduced digitalization approach aims to serve future engineering experts as well as manufacturing SMEs as a practical case study, supporting knowledge and know-how transfer from the academic to the practical manufacturing environment [15].

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