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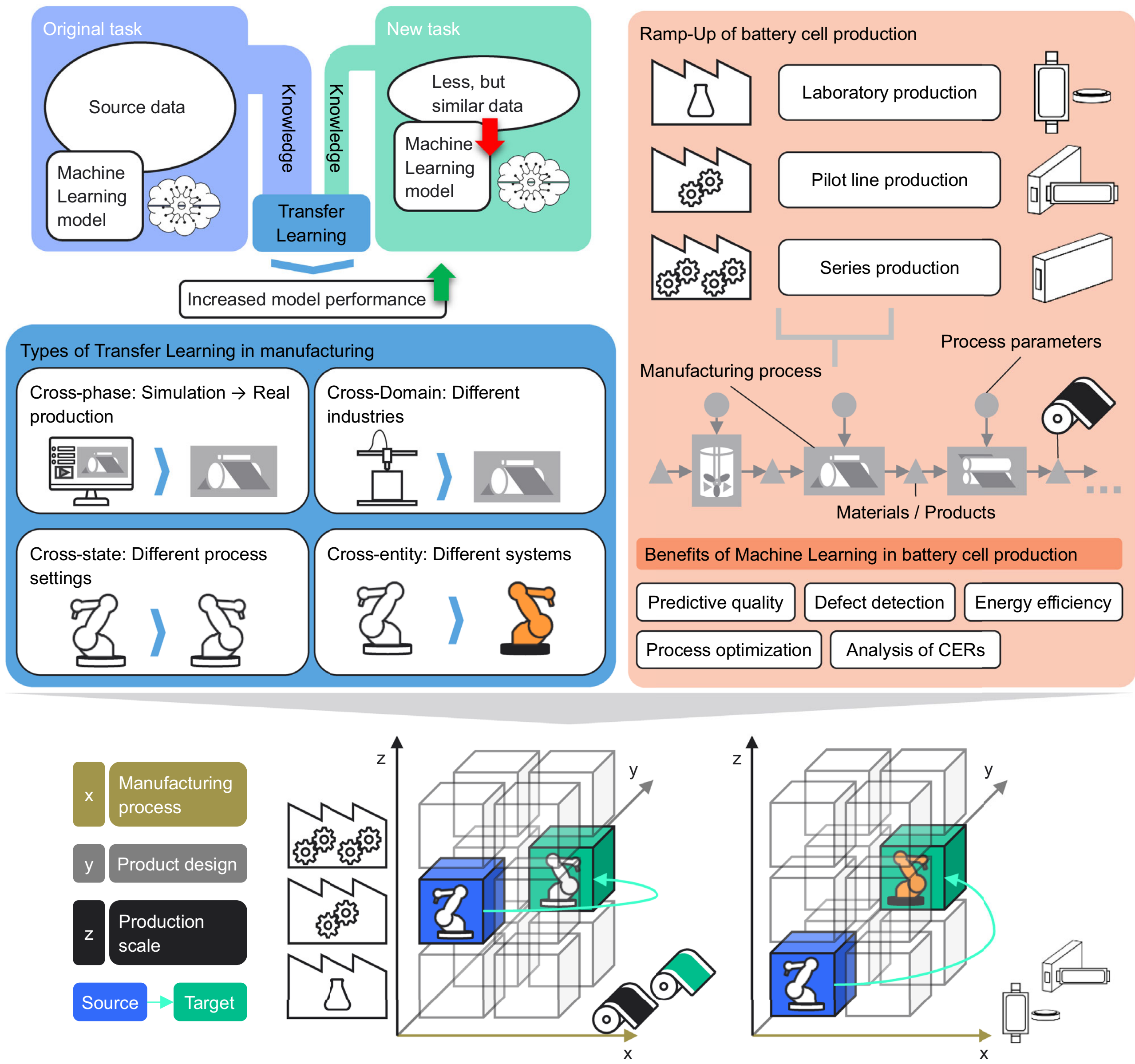
Transfer Learning for Battery Cell Manufacturing: Review On Applications, Challenges, and Benefits

Marten Klenner,* Yijin Wang, Marija Lindner, Sebastian Thiede,* Christoph Herrmann, and Artem Turetskyy



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The increasing demand for battery cells in the automotive sector forces battery cell manufacturers to accelerate product development and scale-up of their production processes. To achieve this, digitalization expands data acquisition and enables the use of machine learning methods. These methods can be utilized for quality assurance, process optimization, and more. However, the application of machine learning requires a large amount of data, which is especially difficult to acquire in the pre-series production due to the vast number of parameter variations, the complex process chain and the small production quantities. Additionally, these obstacles lead to high costs in pre-series production of battery cells. Therefore, there is a need for methods, which are able to train machine learning models on small datasets and increase their generalization abilities. A possible method for this is transfer learning which can use parts of previous models on a new, but similar problem. This method has scarcely been applied in the context of battery cell manufacturing and motivates a structured literature review about its applicability, challenges, and benefits. This study compares transfer learning methods applied to other industries with machine learning approaches of battery cell manufacturing to identify and evaluate potential use cases.

1. Introduction

The demand for lithium-ion batteries (LIBs) is continuously increasing, not only in the automotive sector but also across various industries.[1] It is expected that the global demand reaches 2–3 TWh in 2030.[2] The reasons for this increasing demand include the technological advantages of LIBs over other battery variants and the focus of electromobility on LIBs.[3] For example, LIBs can have a higher specific energy and specific power combined with a longer lifetime than other battery types.[2] To meet the demand, new LIB chemistries must be developed, and series production needs to be ramped up. To achieve this, machine learning (ML) has been employed to address three main challenges in battery production: 1) increasing throughput to reduce costs; 2) enhancing quality through improved process stability, cell performance, and cell safety; and 3) boosting sustainability through higher energy efficiency and usage of resources.[4]

Battery cell production consists of three main steps namely electrode production, cell assembly and cell finishing.[5] The specific manufacturing processes within each step vary depending on the production scale, cell format, and cell chemistry. **Figure 1** provides an overview of the most common processes involved in producing prismatic cells at pilot line scale. The electrode production starts with mixing active material, additives, solvent, and binder to form a viscose paste called slurry, for either anode or cathode. This slurry is then coated onto a metal foil that is continuously unwound from a coil. After coating, the foil undergoes a drying process to remove the solvent and is rolled up again. Next, the dried foil passes through a calendaring process, where it is compressed between rotating rollers to reduce the coating thickness and improve material density. Electrode production ends with slitting, where the coil is divided into narrower daughter coils using rotary knifes. The first step to assembly a battery cell is to cut sheets from a daughter coil using a laser. These electrode sheets are then stacked, and a separator is placed after every electrode. A welding process is first used to join the contacts of anodes or cathodes and to close the metallic housing in which the cell stack is inserted afterward. The housing is filled with electrolyte and initially charged and discharged to enable the formation, which activates the cell's electrochemical functionality. Aging is used to assess whether the cell meets the performance requirements. An end-of-line test applies a standardized test procedure as final quality check.

An example of the application of ML in battery cell manufacturing is modeling the coating process to investigate the interrelationships between material properties, process parameters, and product properties.[6] This analysis of interrelationships in the manufacturing process chain is enhanced by improving the interpretability of the applied ML model, which can set electrode properties in relation to cell properties.[7] Another use case for ML models is the prediction of the product quality to enable continuous improvement and decision support during production of battery cells.[8] Also, ML can be used to improve the energy efficiency of a production line.[9] In combination with simulation data an ML model can be utilized for multiobjective optimization of electrode properties of LIBs.[10] Additionally, one goal could be to optimize a continuous manufacturing process based on times series data of process parameters.[11]

Nevertheless, the application of ML in battery cell production continues to face several challenges, particularly in areas such as data specifications,[12] data acquisition, and model deployment.[13,14] A main challenge is data scarcity, which is especially pronounced in laboratory production.[13] Laboratory and pilot line production are part of the pre-series production, which is the first phase in the ramp of battery cell production, as pictured in **Figure 2**. The amount of data in this phase is scarce because

M. Klenner, A. Turetskyy
Prototyping
PowerCo SE
Industriestraße Nord, 38239 Salzgitter, Germany
E-mail: marten.klenner1@powerco.de

M. Klenner, M. Lindner, C. Herrmann
Institute of Machine Tools and Production Technology (IWF)
Technische Universität Braunschweig
Langer Kamp 19b, 38106 Braunschweig, Germany

Y. Wang, S. Thiede
Department of Design Production and Management (DPM)
University of Twente
Drienerlolaan 5, 7522 NB Enschede, Netherlands
E-mail: s.thiede@utwente.nl

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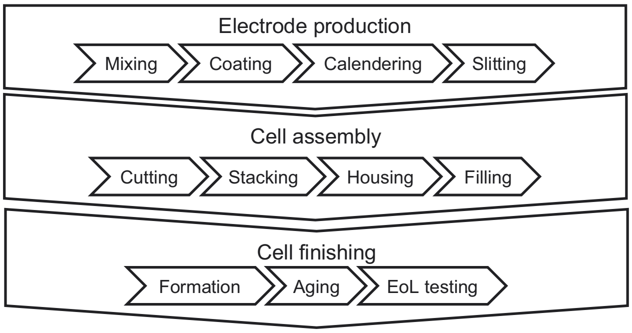

Figure 1. Main process steps for producing prismatic battery cells based on Heimer et al.[5]

of lower quantities compared to sample and series production. Additionally, the data in pre-series production is more heterogenous because of three main changes occurring during upscaling. First, the amount of different materials and manufactured products is high in early phases of product development, as pre-series production aims to continuously enhance battery cell performances.[15–17] For instance, the cell format can change during upscaling from small-format cells like coin cells or single-layer pouch cells in laboratory production to near-series formats like multilayer prismatic cells in pilot line production. Second, different tools and machines are used to achieve higher material throughput and manufacture larger battery cells. This leads, for example, to the use of doctor blade coating in laboratory production and slot die coating in pilot line production.[17] Third, the experimentation with various material combinations and the scaling of machinery leads to changes in process parameters and varying degrees of manual operation. For example, increasing the drying rate is necessary to boost throughput during coating. Furthermore, while electrode stacking may be performed manually in laboratory production, it is typically automated in pilot line production. These three changes during upscaling complicate the reproducibility of desired product properties at subsequent scaling levels. As a result, a large number of experiments is required, and the duration of machine ramp-ups is extended. Although data scarcity is less of an issue in series production, machine wear and maintenance can still introduce data heterogeneity.

The heterogeneity of the data can also be described as data or concept drift, as shown in Figure 2. A data drift is characterized through values outlying the learned parameter space. A concept drift describes a situation in which the learned relation between input and output has changed due to parameters not included in the model. In both cases, the performance of an ML model will be reduced.

Marten Klenner is a Ph.D. candidate at PowerCo SE and TU Braunschweig, specializing in the integration of machine learning techniques into industrial battery cell production. He earned a bachelor's degree from the TU Braunschweig and a master's degree from the University of Stuttgart in Mechanical Engineering focusing on production and material engineering.

Yijin Wang is a Ph.D. candidate of manufacturing systems at the University of Twente (the Netherlands). She is interested in transfer learning and its deployment in real industrial applications. Battery manufacturing is one of her main application fields.

Marija Lindner is a research associate and group leader in digital production at the Institute of Machine Tools and Production Technology, Technische Universität Braunschweig. Her research investigates data-driven strategies to improve the sustainability of manufacturing process chains, particularly in electroplating and foundry, across machine, process, and product levels, with a focus on energy and resource efficiency.

Sebastian Thiede is a fulltime professor of manufacturing systems at the University of Twente (the Netherlands). Prof. Thiede is interested in innovative technologies, methods, and tools for the planning and operation of manufacturing systems and whole factories. Battery manufacturing is one of his main application fields in this context.

Christoph Herrmann is university professor for Sustainable Manufacturing and Life Cycle Engineering and co-director of IWF, Institute of Machine Tools and Production Technology, Technische Universität Braunschweig as well as director of the Fraunhofer Institute for Surface Engineering and Thin Films IST. He has conducted various industry and research projects in the context of life cycle engineering and sustainable manufacturing. He has published more than 300 papers and book publications as author, co-author and editor. Prof. Herrmann is member of the German Academic Association for Production Technology (WGP) and of the International Academy for Production Engineering (CIRP).

Artem Turetskyy is a production data scientist at PowerCo SE, focusing on the digitalization of battery cell prototyping. He obtained his Ph.D. from the Institute of Machine Tools and Production Technology (IWF), Technische Universität Braunschweig, where he specialized in data analytics for battery production systems. His research interests center on the digitalization of battery manufacturing, particularly in the areas of data acquisition, manufacturing operations, and the integration of data-driven models.

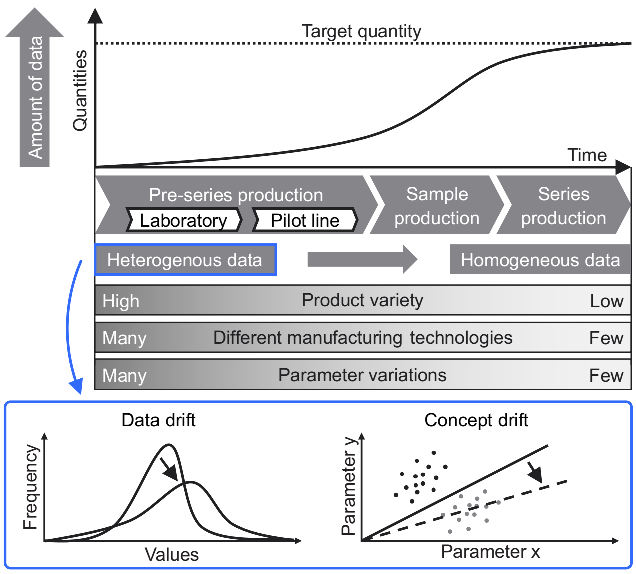

Figure 2. Heterogeneity of production data in the ramp-up of battery cell production leads to data and concept drifts (production ramp-up curve based on Kornas[154]).

Therefore, if an approach aims for applying ML in pre-series production, there is a need for methods and concepts that can train ML models on smaller datasets and react to data and concept drifts to ensure the accuracy of an ML model. In those early ramp-up phases, ML could be used to accelerate the launch of a new battery cell design by enabling the process developers to adjust the manufacturing processes faster. These adjustments are necessary for conducting experiments or quality control. An ML model trained on input and output features of a manufacturing process could be used to predict battery cell characteristics and thereby for finding the right machine settings. The first approach to develop an ML model in pre-series production would be to use ML algorithms that are suitable for smaller data sets, such as support vector machines. However, artificial neural networks, which require a larger amount of data, are particularly suitable for describing the complex interrelationships in the process chain of battery cell manufacturing, as demonstrated in Turetskyy et al.[8] Another method to react to data scarcity, also mentioned by Lombardo et al.,[13] is transfer learning (TL). TL utilizes ML models on similar problems to save the effort of retraining and to achieve a transfer of knowledge. Therefore, the required amount of training data can be reduced. TL has already been successfully applied to manufacturing processes, such as injection molding[18] or additive manufacturing.[19] However, TL has hardly been studied in the context of battery cell manufacturing. In an initial literature search for TL in battery cell production, only a few studies were found in context with manufacturing processes of LIB production.[20–23] Among these, there are more studies focusing on defect detection of welded parts[20–22] than modeling specific manufacturing processes.[23] This focus of TL on defect detection based on image processing will be confirmed in a broader assessment in the result sections. More approaches were found applying TL to already manufactured battery cells predicting state of health,[24] state of charge,[25] or capacity.[26] For that reason, a structured literature research is conducted to find out, which TL approaches have been applied on manufacturing processes and assess potential use cases of TL for battery cell manufacturing.

The remaining paper is structured as follows. In Section 2, the basics of TL are described in the context of battery cell manufacturing. Section 3 explains the study methodology, which is based on two separate literature researches. One research is conducted for TL in different production settings and the other for the application of ML in battery cell manufacturing. The results of this research are first presented separately in Section 4 and 5, before comparing ML in battery cell production with TL in other industries. The aim of this comparison is to assess the applicability of TL and to find out possible application scenarios.

2. Transfer Learning

As introduced in the previous section, TL is a method for improving model performance in case of data or concept drifts. To enhance model performance, TL aims to transfer knowledge embedded in the underlying data or learned within the structure of the ML model. **Figure 3** explains the key terms of TL. The source describes the data on which a model is trained before a data or concept drift occurs, while the target describes the data on which the source model would have less performance when not adjusted. The source as well as the target consist of domain and task. The domain itself is composed of a feature space and a marginal probability distribution. The feature space includes all data points without label information. The marginal probability distribution describes the distribution of values for every single feature. The other component of source and target is the task, which includes a label space and an objective predictive function. The label space holds the information about the target variables when applying a supervised ML model. The predictive function is learned by evaluating pairs of feature vectors and labels.[27]

In the context of battery cell manufacturing, the coating process can serve as an example to illustrate the concept of TL (Figure 3). The source could be a dataset from a coating process in plant A and the target a dataset from a coating process in plant B. When modeling a coating process, properties of the paste like viscosity or solid content are critical. In addition, process parameters like the coating gap define the product properties, such as the mass loading. The feature space is constructed from solid content, viscosity, and coating gap. The target variable is the mass loading and could describe the product quality as a categorical variable (NOK/OK). Between the coating processes in plants A and B, various differences can occur leading to a data or concept drift. For example, the solid content and viscosity differ due to the different formulation of the slurry. Or the battery design changes, and a different thickness of the coating is required, causing a change in mass loading.

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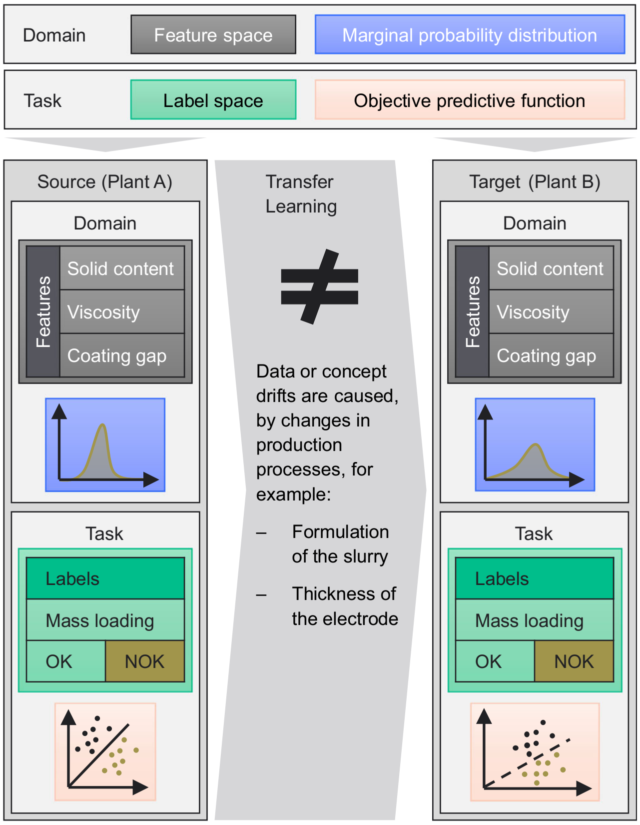

Figure 3. Definition of TL in context of battery cell manufacturing.

Moreover, Fernandez et al.[23] demonstrate the practical feasibility of TL for a coating process in LIB production. The authors show that a TL approach can improve prediction performances by transferring parts of a ML model to electrodes manufactured with different active materials. In their work, the source is a larger dataset coming from the production of negative electrodes with graphite as active material. The target domain consists of smaller datasets based on the production of silicon-graphite and NMC electrodes. The feature space includes different manufacturing parameters like solid content, comma gap, and coating speed. The output variables represent product properties like density and mass loading.[23]

The implementation of TL can be categorized into four methodical approaches as shown in **Figure 4**: 1) instance-based, 2) feature-based, 3) parameter-based, and 4) relational-based.[27] These categories specify what elements are transferred from source domain to target domain.

The main idea behind **instance-based** TL is that certain parts of the labeled data points from the source domain can be reused together with labeled data points from the target domain.[27] In order to determine, which parts of the source data can be applied to the target task, their interdependence and similarity with the target data must be evaluated.

Feature-based TL focuses on learning new features based on source domain and target domain to create a feature representation which improves performance of the ML model on the target task. The goal is to minimize the difference between the source features of the source domain and the features of the target domain or between their new feature representations in the common feature space.[27] In addition, two more subcategories can be identified for feature-based transfer learning approaches, that is, asymmetric and symmetric approaches. The former aims to align the source features to match the target ones. As for the symmetric approaches, a common feature representation is created, where the difference between the source and target features tends to be smaller.[27]

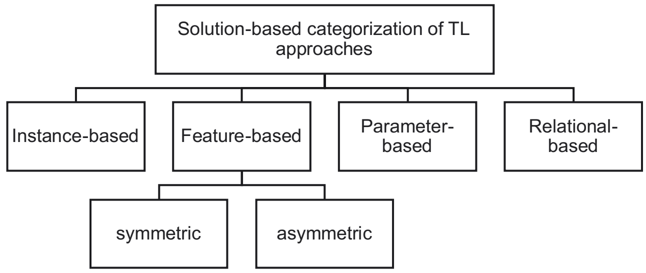

Figure 4. Solution-based categorization of TL approaches.

Unlike feature-based TL approaches which encode the transferred knowledge in features, **parameter-based** TL aims to construct the target model by using some preshared parameters or prior distributions of hyperparameters from the source model.[28] This parameter-based approach is linked to the widespread use of deep learning in combination with transfer learning, as artificial neural networks (ANN) offer the possibility of transferring knowledge by adapting only certain layers to the new task. This is referred to as freezing and fine-tuning the layers.

Unlike the previous three categories, the **relational-based** approach assumes that it deals with data points that are interrelated or non-independent and identically distributed (non-i.i.d.).[27] Instead of merely transferring individual features or labels from a source domain to a target domain, this approach focuses on transferring the relationships between these data points.[27] This can be particularly useful in situations where the interrelationships or structure between data points (like graph-based relationships, social network, etc.) carry more generalizable information than the data points themselves.[27]

Maschler and Weyrich[29] describe the application of TL in the context of production and manufacturing as industrial TL. Industrial TL can be classified into four categories: 1) cross-phase, 2) cross-state, 3) cross-entity, and 4) cross-domain.[29] Each category describes the use case and the motivation behind TL based on changes related to production. **Table 1** presents an overview of the different categories. First, cross-phase transfer happens between different life cycle stages,[29] which could apply when transferring a model learned on simulation data during product development to production data. Giving an example in context of battery cell production, the influence of intermediate product properties on final product properties could have been simulated, before utilizing the model in production. Second, cross-state relates to a transfer caused by dynamically changing parameters

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Table 1. Categories of industrial TL based on Maschler and Weyrich (2021).[29]

Type	Description/example
Cross-phase	Data sources from different life cycle phases
Cross-state	Same machine/production line, but different settings
Cross-entity	Different machine/production line with different settings
Cross-domain	Images from steel production and electrode production

within an entity.[29] For example, if in pre-series production of electrodes, a new battery cell design is introduced, which leads to changed process and product parameters and possibly to a data or concept drift. The third category cross-entity is interpreted in this review as transfer between different machines or plants, which includes cross-state transfer. This could mean the transfer of a model describing the energy demand of a dry room in plant A to a dry room in plant B. Finally, cross-domain refers to a transfer between the production of different products.[29] Applying this description is difficult, because it is not defined when a product is different. In this review, cross-domain defines a transfer between different types of manufacturing processes or model purposes. A different model purpose exists when, for example, one model evaluates images of animals and the other images of the electrode surface.

3. Study Methodology

To point out and evaluate use cases for TL in battery cell production, a literature search regarding TL approaches in the manufacturing industry is conducted. The corresponding procedure is explained in Section 3.1. Afterward, a second literature search is conducted concerning ML in battery cell production, which is described in Section 3.2. Both literature searches are based on the Scopus database. To derive results from the literature search, the studies are characterized by categories clarified in Section 3.3. Most of the categories are applied to TL approaches as well as to ML approaches in battery cell production enabling a direct comparison between these fields. The comparison is conducted according to the procedure presented in Section 3.4 and has the goal to find use cases for TL in battery cell production.

3.1. Literature Search for Transfer Learning in Manufacturing

The first literature search aims for TL approaches applied in production and manufacturing. An overview of the search process can be found in **Figure 5**. The first step in this process is an initial query searching for a combination of transfer learning and production or manufacturing in title, abstract, and keywords: (TITLE-ABS-KEY ("transfer learning" AND (manufacturing OR production)). Besides, only literature written in English is included. The search resulted in a total number of 2304 studies.

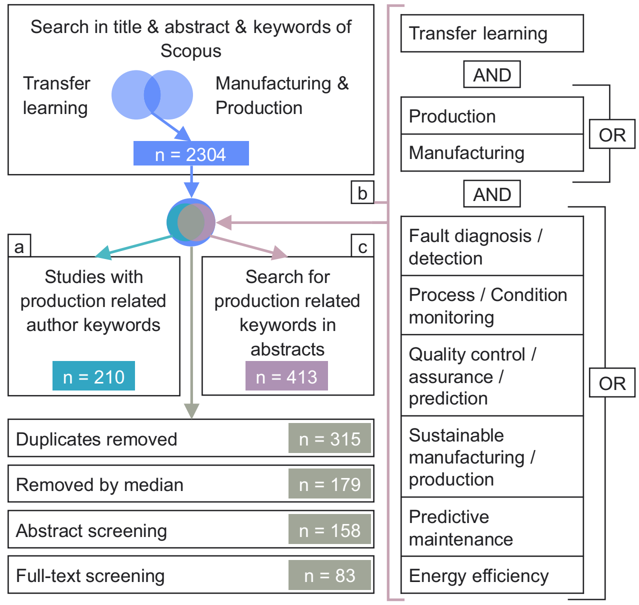

Figure 5. Overview of the screening process for TL in manufacturing: a) analysis of keywords, b) identified keywords/Production targets, and c) search based on identified keywords.

To reduce the number of publications found in the initial search, only studies with the goal of improving a production process were included. To achieve this, in a first step, keywords defined by the author were checked and the corresponding studies included, if the keyword was related to a method or a purpose to increase quality or efficiency of the production. This procedure led to 210 results as illustrated in Figure 5a and to a list of keywords related to improving production. From this list, overarching production targets were derived, which are stated in Figure 5b. These production targets are utilized for another search query to ensure that the abstract is included in the literature search. This new search query was applied to the title, keywords, and abstract and resulted in 413 hits, as illustrated in Figure 5c. After removing duplicates between studies identified by production-related author keywords and studies with production-related keywords in the abstract, it became clear that there are too many studies for full-text screening and categorization. As a result, the median of citations for every year was calculated, and only studies above the median were included in the abstract screening (179 studies). During the abstract screening, only publications are considered that: develop, implement, or evaluate a TL approach regarding a production process; are not a review, survey, or mapping study; and are accessible to us. This resulted in 158 studies for full-text screening. The full-text screening utilizes the same inclusion criteria and leads to 83 studies.

3.2. Literature Search for ML in Battery Cell Manufacturing

The second literature search was conducted to find ML approaches in battery cell manufacturing. **Figure 6** shows an

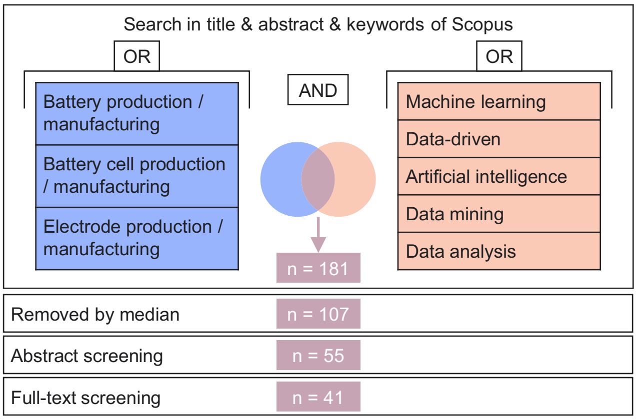

Figure 6. Overview of the screening process for ML in battery cell manufacturing.

overview of the procedure. The search query consisted of the terms shown in Figure 6 and was applied to title, abstract and keywords. Only literature written in English was included. This resulted in 181 studies, and to reach a reasonable number of studies for full-text screening and categorization, the median of citations for every year was calculated. Based on that, only studies above this median were included in abstract screening except for the years 2024 and 2025 where all journal papers were included. This led to 107 studies for abstract screening. During abstract screening, only publications are included which: develop, implement, or evaluate a ML approach regarding a production process; are not a review, survey, or mapping study; and are accessible to us. This resulted in 55 studies for full-text screening in which the same inclusion criteria were utilized. Leading to 41 studies for the review.

3.3. Setting Up Categories

An overview of the categories applied to the literature is given in **Table 2**. To enable a comparison between approaches for TL in manufacturing and ML in battery cell manufacturing, specific categories were chosen, which are applicable to both fields. The comparison categories are used to identify similar approaches that suggest that the TL approach could be transferable to the production of battery cells. Additionally, there are specific categories for both fields, which are needed to describe them in more detail.

The first category is "**field of application**" and describes the main purpose of the approach regarding production. The individual purposes of the studies differ between the two literature researches and were determined during paper screening. A study can imply multiple fields of application, but only the main benefit was categorized. For TL five subcategories were identified describing the field of application: 1) detection of product defects, 2) energy efficiency, 3) fault state detection and diagnosis, 4) predictive quality, and 5) tool condition monitoring. The first category is mainly about detecting surface defects on various products. Energy efficiency describes approaches, which aim for optimizing the energy consumption of production processes. Included in the category fault state detection and diagnosis are studies about finding a faulty state in machines or production lines. These studies are mainly based on process parameters and may extend their approach by predicting possible causes. Studies about predicting quality-relevant product properties or identifying a suitable set of process parameters are summarized under the category predictive quality. Tool condition monitoring describes approaches about the prediction of tool wear.

Table 2. Categories to characterize studies about TL in manufacturing and ML in battery cell production.

Domain	Category	Description
Categories for comparison	Field of application	TL: detection of product defects, energy efficiency, fault state detection and diagnosis, predictive quality and tool condition monitoring
		ML: analysis of cause–effect relationships (CERs), defect detection, energy efficiency, manufacturing process optimization and predictive quality
	Scope	Extent to which production parameters are included in the ML model (product, process, process chain, factory)
	Data source	Phase of product development: simulation, experimental, running production
	Data type	Categorical, numerical, time series, image
	Number of datapoints	Divided into four classes: <100, <1000, <10,000, <100,000, above
	Type of ML	Regression, classification, clustering, anomaly detection, dimensional reduction
	ML algorithm	Random forest (RF), support vector machine (SVM), artificial neural network (ANN), etc.
	Interpretability	Approach considers interpretability and explainability of the ML model
TL specific	Manufacturing process	Primary shaping, material forming, cutting, joining, coating and modifying material properties, none, not specified, production line, process engineering
	Type of TL for manufacturing	Cross-phase, cross-state, cross-entity, cross-domain
	Transfer principle	Instance-based, feature-based, parameter-based or relational-based
ML specific	Included process steps	Steps in the process chain of battery cell manufacturing
	Cell format	Coin, pouch, prismatic, cylindric

For ML in battery cell production, five subcategories for the **field of application** were determined: 1) analysis of cause–effect relationships (CERs), 2) defect detection, 3) energy efficiency, 4) manufacturing process optimization, and 5) predictive quality. The analysis of CERs describes approaches which focus on evaluating the influence of process parameters and intermediate product properties on final product properties, often through interpretable ML models. Defect detection is for example about finding particles between electrodes or faults in welding seams for joining the tabs of electrodes. Studies about optimizing the energy demand are categorized into energy efficiency, whereas studies about optimizing process parameters to improve product properties are labeled with process optimization. The field of application "predictive quality" applies for studies predicting quality relevant product properties based on inputs of a manufacturing process like material properties or process parameters.

To complement the category field of application and further characterize the use of an approach in production, the category "**scope**" is introduced. The scope is described by four categories: product, process, process chain, and factory. The subcategory product is fulfilled when the ML model is built on product properties coming from a single manufacturing process, e.g., detection of surface defects in images. A scope of process is achieved by including input and output parameters of a manufacturing process into the model development. When the model takes parameters from multiple process steps into account, the scale process chain is reached. The final scale is applied when the model describes relations on factory level. At this level, aggregated parameters are used, which are made up of the individual process steps of the production process, for example, the energy consumption or the scrap rate of a production line.

Another option to find similarities between TL and ML in battery cell manufacturing is to characterize the used data through source, type, and size. In this review, **data sources** originate from different phases of product development: simulation, experimental, and running production. Regarding battery cell production, experimental refers to laboratory as well as pilot line production. The **data type** is subclassified into categorical, numerical, time series and image data. For describing the size of the datasets used for modeling, the **number of datapoints** is divided into five classes: <100, <1000, $<10{,}000$, $<100{,}000$, and above.

To determine the comparability in a more direct way, the **type of ML** and the name of a specific **ML algorithm** are useful. The former is subdivided into regression, classification, clustering, anomaly detection, and dimensional reduction. The latter contains algorithms like artificial neural network (ANN) or random forest (RF).

One aspect of TL is the transfer of knowledge stored in the data and the trained ML model. To make this knowledge accessible, the model needs to be interpretable. Therefore, a TL approach should consider the **interpretability** of the ML model in the context of its use in production. Interpretability can be improved by selecting a more interpretable model or by applying a specific method like Shapley values. During the paper screening, studies that consider interpretability will be marked.

A category specifically used for reviewing TL approaches is the **manufacturing process**. This category determines the addressed manufacturing process according to DIN 8580. In DIN 8580, manufacturing processes are classified based on the underlying procedure. The 6 main groups are: 1) primary shaping, 2) material forming, 3) cutting, 4) joining, 5) coating, and 6) modifying material properties. If the evaluated data is not related to a manufacturing process, the category "none" is marked. There are studies which use images without stating the corresponding manufacturing process. These studies are categorized with "not specified." When data from multiple processes is used, the category "production line" is selected. Additionally, there are studies analyzing processes from the field of process engineering.

To further distinguish between different TL approaches, the **type of TL for manufacturing** (cross-phase, cross-state, cross-entity, cross-domain) as introduced in Section 2 is classified. A TL approach can fulfill multiple types of transfer as well as utilize multiple TL principles (instance-based, feature-based, parameter-based, and relational-based).

For a more comprehensive clustering of ML in battery cell manufacturing, the categories "Included process steps" and "cell format" are used. Marking the process steps, which are included in the ML model, supports the description of the scale of the model. To access the transferability of an ML approach to a new production and testing environment, information about the cell format is required. The applied cell formats are coin, pouch, prismatic and cylindric.

3.4. Identifying Use Cases

The procedure for identifying use cases for TL in battery cell production is illustrated in **Figure 7** and begins with a holistic description of TL for manufacturing in Section 5. After that, the fields of application found in the literature are described with examples in the subsections. The same approach is used in Section 6 to explain the application of ML in battery cell production. In Section 7, a comparison of TL and ML studies is conducted based on the comparison categories presented in Table 2. This comparison is continued in Section 7.1 for the representative studies which were used as examples in the subsections of Section 5 and 6. Section 7.1 identifies possible use cases of TL by calculating the number of same categories between a TL paper and a ML paper and thus measuring the similarity of the approaches. The categories that are included in the calculation are: field of application, scope, data source, data source, and type of ML and ML algorithm. Afterward, a utilization of TL in studies which show the most similarities is discussed. The resulting use cases are visualized using the TL cube described in the study of Wang et al.[30] According to this method, a TL use case in battery cell production can be characterized by three dimensions: manufacturing process, product design, and production scale. These dimensions represent changes or differences, which

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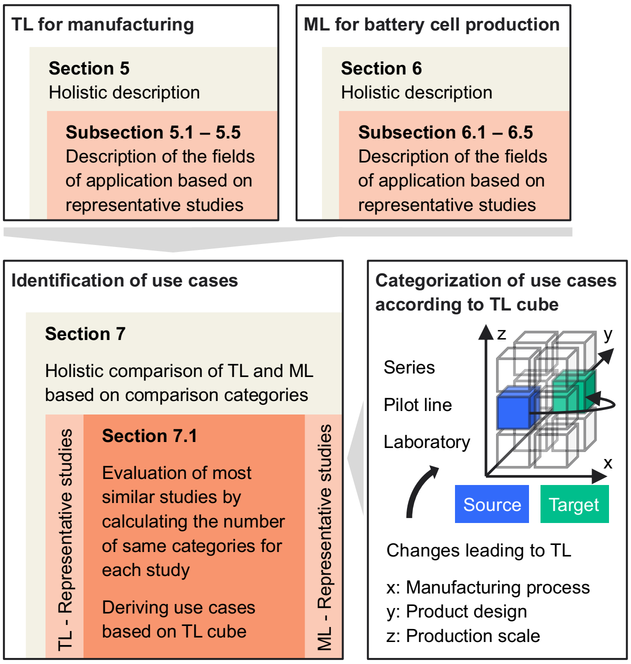

Figure 7. Overview of the screening process for ML in battery cell manufacturing.

motivate the application of TL. For instance, changes in the manufacturing process might involve different parameters, tools, or machines.

4. Existing Reviews

To identify promising TL approaches for the manufacturing of battery cells, it is essential to comprehensively survey the available literature on the subject. Therefore, an overview about similar reviews in the field of TL for manufacturing is given in Section 4.1 and for the field of ML in battery cell production in Section 4.2.

4.1. Reviews about TL for Manufacturing

Existing reviews about TL in manufacturing have focused on certain applications. A main application of TL is fault detection, fault diagnosis, and fault prognostic of machines, which is reviewed by Li et al.,[31] Li et al.,[32] Yao et al.,[33] Azari et al.,[34] Hakim et al.,[35] and Yan et al. (2024).[36] All these studies explain different TL approaches and discuss challenges as well as future directions. Li et al.[32] stands out by a detailed categorization of transfer settings in combination with the used TL method. Besides, in this study, the authors suggest a process flow for choosing an algorithm for deep TL and fault diagnosis. Deep transfer learning is also the focus of Li et al.[31] Yao et al.[33] present multiple open-source datasets more in detail. Concentrating on predictive maintenance Azari et al.[34] provide a detailed categorization of TL approaches. Hakim et al.[35] reviewed fault diagnosis based on deep learning and TL for rolling bearings. Also focusing on deep learning Yan et al.[36] discusses TL in context of analyzing time series data generated in different production environments. In the work of Tang et al.[37] TL approaches in additive manufacturing are reviewed and evaluated to give recommendations for their implementation. A more general review about industrial TL using deep learning is conducted in Maschler and Weyrich[29] by distinguishing between studies implementing anomaly detection, time series prediction, computer vision, fault diagnosis, fault prognostics, or quality management.

4.2. Reviews about ML in Battery Cell Production

In the field of battery cell manufacturing, there are a number of studies discussing the application of ML. Lombardo et al.[13] give an overview of the usage of ML Algorithms for different purposes in context of battery cell production: Searching for new battery materials, understanding and optimizing manufacturing processes, characterization of materials and electrodes, and diagnosis and prognosis of battery cell performance. In another work, Ayerbe et al. [14] review data-based as well as mechanistic modeling approaches studying how they can be integrated in a framework for developing a digital twin of battery cell production. Zanotto et al.[12] focus on evaluating the relevance of process parameters and product properties of each process step for the development of data-based and mechanistic models. Liu et al.[38] concentrate on battery health and partially described ML approaches based on production data by dividing into interpretable and non-interpretable algorithms. To give an overview of current approaches and to derive promising research directions, Haghi et al.[39] conduct a systematic mapping study of ML in LIB cell production. They categorized the literature by type of study, process steps, input/output variables, used algorithms, sample sizes, and more. Haghi et al.[39] conclude that pilot lines are necessary to bring fundamental research into industrialization. Furthermore, they state that the combination of simulations and ML models is required to optimize the complete process chain and to bring micro, meso, and macro levels into relation. Another conclusion was that a standardized documentation of the developing process of ML models would improve the validation and quality of these models.

5. Use of Transfer Learning in Manufacturing

In contrast to the reviews mentioned in Section 4.1, this study focuses on a holistic review of TL in manufacturing, without emphasizing a particular application. For this purpose, the categorization elucidated in Section 3.3 serves as basis for the results explained in the following. In this section, general results are presented based on **Figure 8** which shows the number of studies for every category in relation to the fields of application. The sub-sections then explain different TL approaches by giving more detailed information.

Judging by the number of studies, TL for manufacturing mainly focuses on the fields of application detection of product

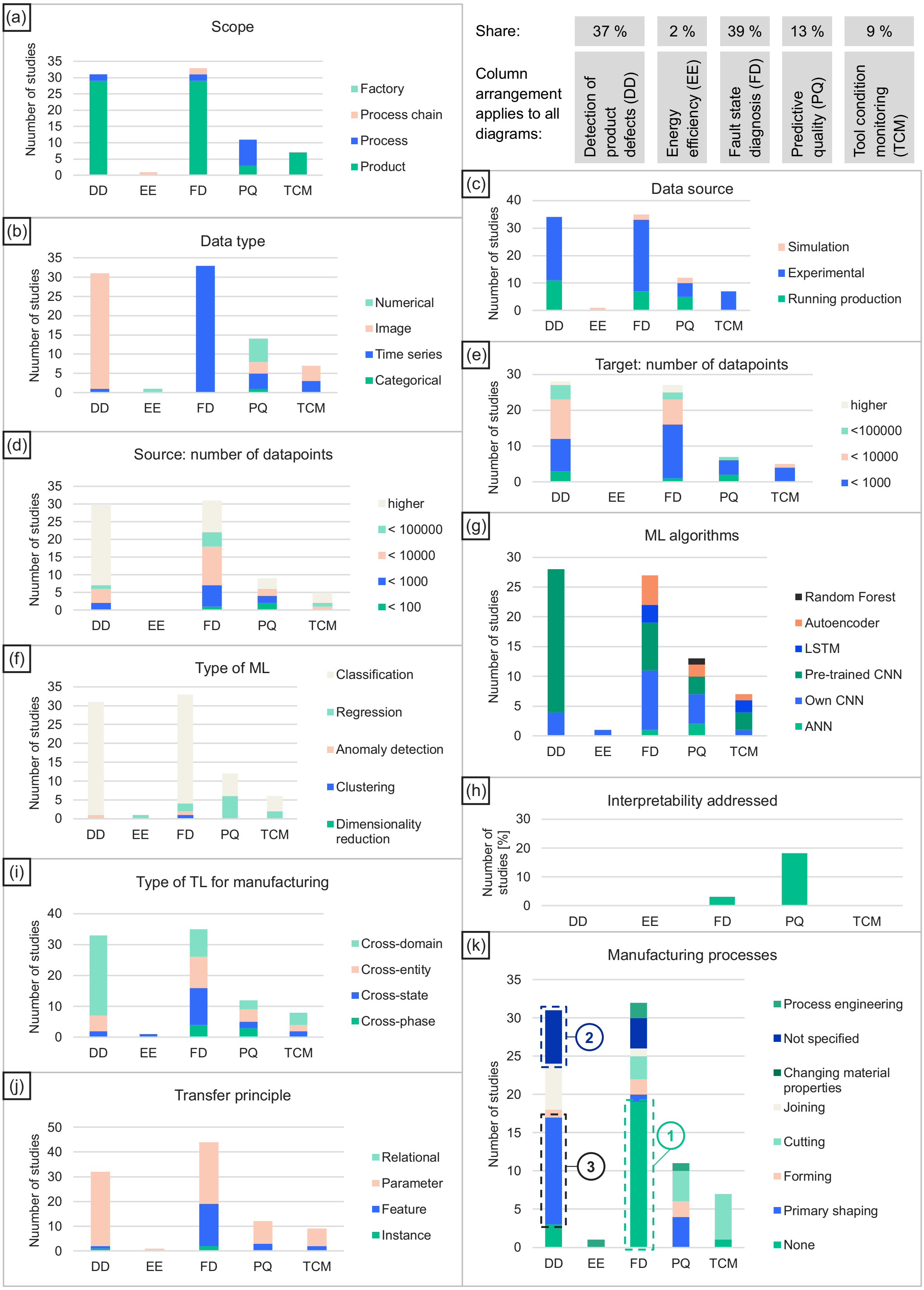

Figure 8. Fields of application in TL (DD: defect detection, EE: energy efficiency, FD: fault state diagnosis, PQ: predictive quality, TCM: tool condition monitoring) and the number of studies regarding: a) scope, b) data type, c) data source, and number of datapoints for d) source and e) target, f) type of ML, g) ML algorithms, h) interpretability addressed, i) type of TL, j) transfer principle, and k) manufacturing process.

defects (37%) and fault state diagnosis (39%) as stated in Figure 8. Some studies are categorized into predictive quality (13%) or tool condition monitoring (9%), but only a few develop an approach regarding energy efficiency (2%). The first graph in Figure 8a shows the number of studies for the different scopes. The graph makes clear that most studies develop an ML model for product properties. Only a few studies model relationships between process parameters and product properties. There is no approach in factory scale. Bringing the field of application in relation to the used data type in Figure 8b, only time series data is used for fault state diagnosis, whereas detection of product defects is mostly based on image data. In contrast, numerical or categorical data is rarely modeled. The evaluated data type is related to the type of ML in Figure 8f and the applied ML algorithm in Figure 8g. Figure 8f shows that classification is the most used type of ML especially for defect detection and fault state diagnosis. Defect detection relies in most cases on classifying images. Also, detection of faults in time series data mostly uses a classification algorithm. Regression tasks are only for predictive quality a prominent application. Unsupervised ML does not reach a mentionable number.

The most used ML algorithm, especially for detection of product defects, is a convolutional neural network (CNN), which indicates image processing. Regarding CNNs a distinction is made between own CNN and pretrained CNN. The former describes self-developed CNNs and the latter CNNs that are available as open source and have been trained and validated on a data set different from the manufacturing domain. Furthermore, CNNs are largely used for fault state diagnosis, although time series are the most prominent data type. The reason for this is that time series can be evaluated with CNNs or transformed into images.[40–48] In conclusion, image processing is a main application for TL in manufacturing. Another observation regarding ML algorithms is that the focus of TL is on neural networks, since the other applied algorithms are artificial neural networks (ANN), long short-term memory (LSTM), and Autoencoder. Only a few studies propose the use of a RF for TL.[49,50]

The data for training the ML models largely comes from an experimental setup or running production as Figure 8c visualizes. Some studies utilize simulation data. The number of data points is categorized for the source data (Figure 8d) and the target data (Figure 8e). As expected, the source datasets are larger than the target datasets. Since many ML models are pretrained on large image datasets, there is a high number of source datasets with more than 100,000 data points. For the target domain the number of data points decreases below 10,000 or 1000. Figure 8h shows that for the fields of application defect detection, energy efficiency, fault state diagnosis, and tool condition monitoring interpretability are mostly not addressed. Only for predictive quality, a few studies address the topic of interpretable ML.

The utilized TL method is characterized through the categories transfer principle and type of TL for manufacturing, which are displayed in Figure 8 in graph i and j. Evaluating the transfer principles in graph j, it is evident that parameter-based TL is mostly used. Parameter-based often refers to freezing and fine-tuning of layers of a neural network, which relates to the high number of applied neural networks shown in graph g. Feature-based TL, which is often based on domain adaptation methods, is used less frequently. Instance-based TL is only used in fault state diagnosis. There is no approach for relational-based TL in the field of manufacturing. Graph i reveals that cross-domain transfer is most prominent in industrial applications. This is due to the widespread use of image processing and the utilization of open-source models. These models are pretrained on images in large datasets which are not related to manufacturing, but the learned model functions like edge detection are highly transferable.

Figure 8k visualizes the number of studies for different types of manufacturing processes and shows that TL for tool condition monitoring is only applied for cutting processes. In contrast, predictive quality approaches are applied to primary shaping, forming, and cutting and do not have a clear focus. Regarding fault state diagnosis, most studies do not evaluate a manufacturing process (Figure 8k, 1). Instead, many of these studies analyze vibration signals of gearboxes and motor bearings, assuming that these are often used in production processes. There are a few studies about energy efficiency analyzing processes in the field of changing material properties. When detecting product defects, studies mostly do not specify (Figure 8b, 2) the manufacturing process the image data originates from, and if they do, the process is often additive manufacturing categorized as primary shaping (Figure 8c, 3).

To create a better understanding of TL in manufacturing and the different approaches, several examples are given in the following subsections. The examples were chosen for every combination of "type of TL for manufacturing," "transfer principle," and "scope." These three categories enable a good overview of existing approaches.

5.1. Detection of Product Defects

The detection of product defects rarely involves cross-state transfer.[51,52] For example, Pandiyan et al.[51] apply a cross-domain transfer, where the underlying structure of the utilized CNN is based on an open-source model. This CNN is first adapted to surface images from an additive manufacturing process by freezing and fine-tuning specific layers. This parameter-based TL is then used again to better evaluate surface images, which are generated with different materials.

More studies apply a cross-entity transfer.[53–57] For example, Li et al.[57] investigate the detection of defects on various surface images, taken at different manufacturing plants with different measurement devices. The images are analyzed by a CNN, which is pretrained in a cloud on general defects. This pretrained CNN is then deployed to different measurement devices operating in an edge layer, where it is fined-tuned using local data. In this setting the approach of Li et al.[57] also applies two types of industrial TL: cross-entity and cross-domain. Additionally, to utilize a CNN for different additive manufacturing processes in different companies, Mehta and Shao[56] develop an approach based on federated learning. In this approach there are local CNNs at every company, which share their weights with a global CNN to update it. The

CNN is used to detect images, which are taken layer-wise during manufacturing. The study only applies cross-entity transfer, because the CNN is trained on data from the same domain.

As visualized in Figure 8i, most studies about the detection of product defects apply cross-domain transfer.[19,51,57,58,58–69] For example, Ferguson et al.[59] pretrain a CNN on a large open-source dataset. The CNN is used for defect detection and segmentation in X-ray images of casted parts. Other studies, which apply cross-domain transfer, mainly differ through the data source as well as the size of the datasets and the type of the pretrained CNN.

5.2. Energy Efficiency

Panjapornpon et al.[70] identify relevant variables in a petrochemical production line and predict the specific energy demand to find energy-efficient operating conditions. In their work, a CNN is trained on simulated time series data and transferred to different sampling rates of the same time series data. This cross-state transfer is investigated because of the assumption that the CNN learns different relationships when different sampling rates are used.

5.3. Fault State Detection and Diagnosis

A few studies in the field of fault state diagnosis apply a cross-phase transfer from simulation to real production data.[71–74] To generate sufficient fault data for training an autoencoder, Xia et al. [74] simulate different working conditions of a pump. The autoencoder is transferred to analyze pressure signals of a real production process. In contrast, a different scope is examined in the study of Xu et al.[73] by detecting faults in the process chain of a body-in-white production line. The used ML model is tested in a virtual environment to accelerate deployment to the physical environment.

Regarding cross-state transfer studies have explored the scopes of product,[43–45,75–79] process,[80,81] and process chain.[82,83] Wen et al. [77] investigate vibration signals of a motor bearing to classify three fault states with an autoencoder. The authors examine the same motor bearing under changing process settings and are therefore applying a cross-state transfer. In general, the evaluation of signals from a bearing is a common approach.[43–45,75–77,79] Maschler et al.[78] demonstrate an uncommon approach to fault detection, because they concentrated on continual learning based on a regularization algorithm. In their study, they measure pressure signals of a metal forming process manufacturing various products. These signals are classified as normal or anomalous.

Regarding cross-entity transfer, all studies develop a model for evaluating product properties.[40,46,84–91] To investigate TL between different entities, Wang and Gao[40] use a CNN to detect faults in vibration signals of different motor bearings, which work under changing loads. Wang and Gao[40] apply a cross-domain transfer as a result of pre-training the CNN on a large open-source image dataset. To leverage the image recognition capabilities of the CNN, the time-series vibration data reflecting the machine condition and performance was wavelet transformed into time–frequency spectra images. These images were labeled with different fault types. Xu et al.[85] conduct a study regarding cross-entity transfer and the detection of anomalies in the power consumption of a yarn spinning process. The transfer took place between production processes of different plants, in which operating conditions are different. Also, Li et al.[87] realize a cross-entity transfer by transferring a LSTM network from one CNC machine to another. The LSTM is used to detect chatter based on vibration signals. In another example, Yu et al.[88] focus on feature-based TL between different settings of a motor to detect faults of a bearing. The authors develop a CNN and compare various domain adaption methods. Also, for cross-entity transfer, most studies evaluate bearings.

The observation that fault state diagnosis mostly investigates bearings is also true for cross-domain transfer.[40,41,48,92] But there are studies for milling,[93] turning,[94] welding,[95] semiconductor manufacturing,[42] or robotics,[47] too. For example, Wen et al.[41] perform a cross-domain transfer by pre-training a CNN on a large open-source dataset and testing it on images from vibration signals of a motor bearing. To create the images, the signals are transformed into RGB values by using a self-developed method. The CNN classifies the vibration signals indicating a healthy or damaged bearing. Zhang et al.[92] used a pretrained Transformer from the field of natural language processing to detect faulty signals from various sensors. The authors transferred the parameters of the Transformer to evaluate time series data of bearings, gearboxes, and a hydraulic system. Zabin et al.[48] aim to capture spatial and temporal features from vibration and acoustic signals of a bearing. To achieve this, the authors transform the signals into images and evaluate them using a combination of CNN and LSTM.

5.4. Predictive Quality

To reduce the number of required experiments for an injection molding process, Tercan et al.[18] predict the product weight based on process parameters with an ANN. The data of the source domain is created by a simulation, and the data of the target domain is derived from real experiments. This setting describes a cross-phase transfer. In a similar work, Ramezankhani et al.[96] study the prediction of the final part thickness based on images and numerical values for a thermoforming process. They apply TL only to the images by training an encoder-decoder model on simulation data and transferring it to the production data. This study stands out, because it utilized Shapley values to enable an interpretable ML model.

Li et al.[97] employ TL to predict process quality under various working conditions in a forging process. The production data, consisting of time series, is used to extract features via a CNN. These features are used to train a SVM, which creates a regression model for predicting forging size and forging force.

Another approach for injection molding is presented by Tercan et al.[98] The authors predict the deformation of geometrically different products based on process parameters. This study investigates a cross-state transfer because each product requires a different tool. They generate the data with a simulation and use the data as input of an ANN, whose last layers are replaced for each product. The objective of the study of Wang et al.[99] is to predict the surface quality using regression analysis based on vibration signals and process settings for a turning machine. In their study, they employ domain adaption to facilitate the transfer of an ML model across different machines realizing a cross-entity transfer. However, it is important to note that the study lacked a comparison with a model trained exclusively on the target data, which diminishes the validity of the proposed approach.

For cross-domain transfer, the approach of Li et al.[100] includes pretraining a CNN on ImageNet and applying it with retraining and fine-tuning on images taken during a process of selective laser melting. The CNN classifies the amount of porosity in the images. Bisheh et al.[101] investigate a similar approach for laser scribing. In this approach, a CNN classifies three areas in images: scribe, debris, and part background. Deng et al.[102] apply federated learning on cutting processes assuming that different enterprises manufacture similar products. In their approach the ML models predict the process parameters of cutting processes. The presented method consists of domain adaption and the exchange of weights between models.

5.5. Tool Condition Monitoring

Regarding tool condition monitoring, there are studies investigating cross-state,[103,104] cross-entity,[105,106] and cross-domain transfer.[103,107–109] Sun et al.[104] predict the remaining useful life (RUL) based on vibration signals of a milling tool. To calculate the RUL an autoencoder extracted features, which were input of a regression model. A cross-state transfer took place by changing the tool and the process parameters. Also, Park and Park[105] investigate the remaining useful life based on vibration signals, but for a grinding tool. The authors achieve a cross-entity transfer by acquiring data from different machines with different process parameters. The data consists of two open-source datasets and are used to train a LSTM. Regarding cross-domain transfer Molitor et al.[107] use a pretrained CNN as most TL studies. The CNN is utilized to classify images showing different wear patterns. Additionally, a GAN generates synthetic data to increase the diversity of the dataset.

6. Application of Machine Learning in Battery Cell Manufacturing

ML in battery cell manufacturing is mainly used in five fields of application: 1) analysis of CERs, 2) defect detection, 3) energy efficiency, 4) process optimization, and 5) predictive quality. These fields of application are compared in **Figure 9** in relation to the different categories explained in Section 3.3. In graphs b through i of Figure 9, the number of studies for every field of application is shown in the same order. In the following paragraph, general results derived from Figure 9 are presented, before a detailed description of approaches regarding the fields of application is provided in the subsections.

ML in battery cell manufacturing is primarily used for analysis of CERs (40%)[6,7,110–124] and the improvement of the product quality through predictive quality (33%)[8,125–134] or process optimization (16%).[10,135–139] Only a few studies developed an approach regarding defect detection (9%)[140–142] or energy efficiency (2%).[9] Figure 9a shows that through these studies, most of the process steps of battery cell manufacturing are considered. The majority of approaches about the analysis of CERs investigates the relationships between electrode production and formation and aging.[7,113,116,119–121,123,124] Also, electrode production[6,110,111,114,115,117,118,122] and cell assembly[112] are a field of application. In contrast, predictive quality is equally spread across all process steps, since many of these approaches apply process chain models,[8,126,129–132] as can be seen in Figure 9c. Process optimization focuses on electrode production.[10,135,137–139] There is one study about energy efficiency regarding the drying process.[9] Defect detection is applied to stacking[140] as well as formation[142] and testing.[141] Figure 9b presents that the analysis of CERs is concentrating on coin cells, whereas predictive quality mainly analyzes pouch cells. This may be because producing coin cells requires less material and therefore a larger parameter space can be analyzed at less costs. From Figure 9c, it can be derived that studies evaluating a process or a process chain are in the majority. The data for this comes in nearly all studies from an experimental setting as Figure 9d clarifies. A few studies use data from simulations,[10,110,112,135–137,139] but there are only two approaches validated on data from a running production.[128,142] This underlines the need to scale up and validate existing approaches. Regarding the size of the modeled datasets, Figure 9e illustrates that there is no study above 10,000 data points; instead, most studies analyze datasets below 100 and 1000 data points. Figure 9f makes clear that numerical data is mostly utilized. Only a few studies evaluate categorical data in addition,[6,114,118,120,129–131,134] time series,[128,135] or images.[136,138,140,141] Figure 9g shows that the focus is on supervised ML, especially on regression tasks. Unsupervised ML (dimensionality reduction,[115] clustering,[115] anomaly detection[126,142]) is applied only in three studies. Figure 9h depicts that neural networks[6,8,9,110–112,114,124–126,128,134,139] are used most frequently and that tree-based methods[7,110,112,117,119,121,122,129,140,142] are also popular. Then follow gaussian process regressions (GPRs),[110,114,116,118,133,137,138] boosting methods,[114,120,123,124,127,128] SVMs[6,112,114,124] and linear models.[122,130–133] Figure 9i highlights that interpretability is considered in many studies. Especially for the analysis of CERs it is essential to interpret the results of the ML model.

6.1. Analysis of Cause-and-Effect Relationships

To analyze CERs, ML models were created that consider different manufacturing processes as shown in Figure 9a. These models are developed for individual manufacturing processes[6,110–112,114,115,117,118,122] as well as process chains[7,113,116,119–121,123,124] (Figure 9c). An example for a process model of the coating process provides Liu et al.[118] In their work, they apply a Gaussian process regression and calculate

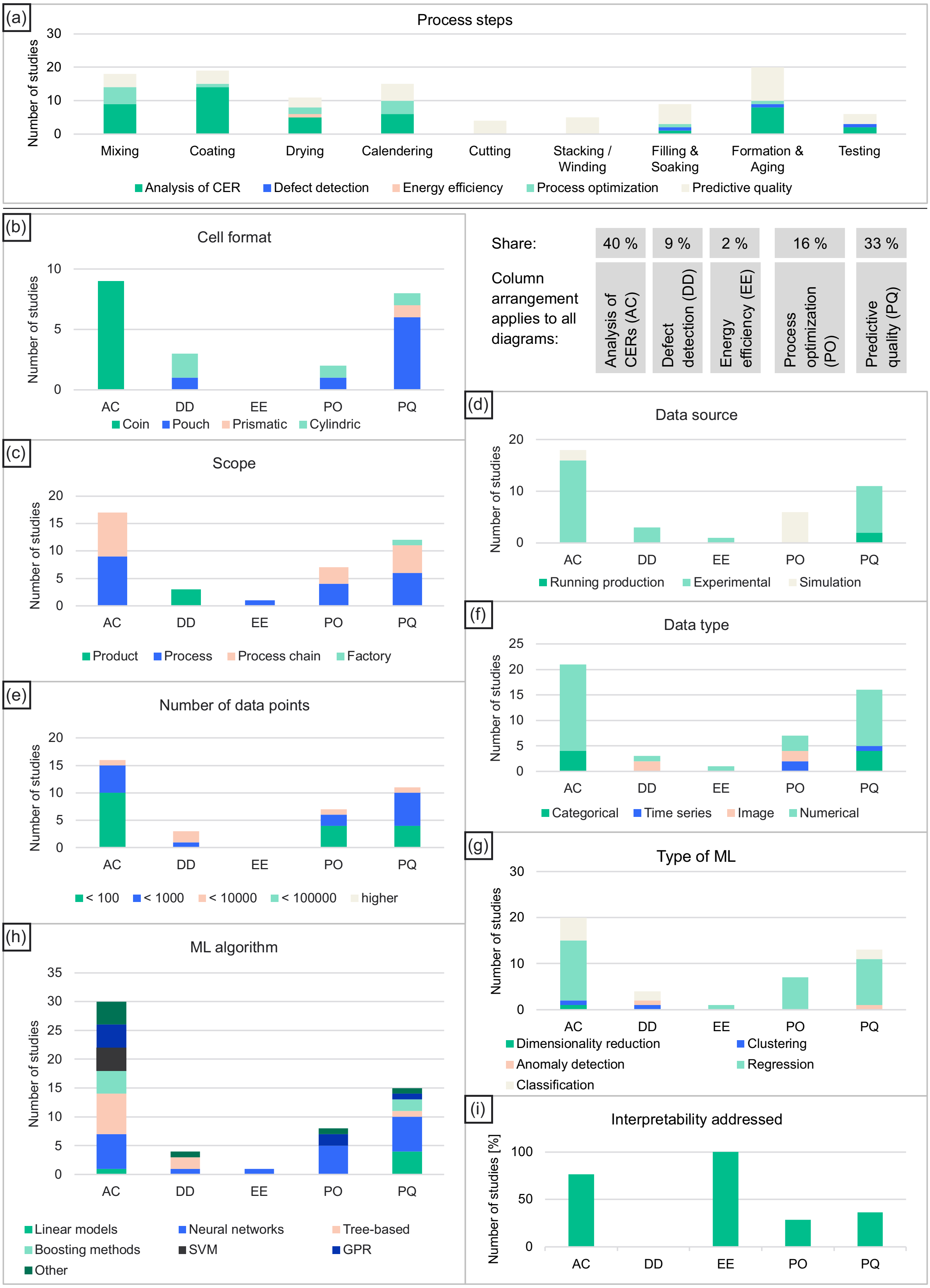

Figure 9. Fields of application in ML (AC: analysis of CERs, DD: defect detection, EE: energy efficiency, PO: process optimization, PQ: predictive quality) and the number of studies regarding a) production process, b) cell format, c) scope, d) data source, e) dataset size, f) data type, g) ML function, h) ML algorithm, and i) interpretability addressed.

the feature importance to find the most influential variables. The regression is used to predict the mass loading based on slurry properties and the coating gap. El Malki et al.[112] also utilize a process model, but they described the filling process in cell assembly. To reduce computational costs, the authors train a surrogate model based on simulations. The model should identify relevant parameters and support in solving design problems. A surrogate model for coating with a slot die is developed in Seo et al.[110] In another study, Niri et al.[122] improve the interpretability of an ML model by calculating the feature importance and the accumulated local effects (ALE). The enhanced interpretability facilitates the analysis of how slurry properties and process parameters of the coating process affect electrode properties.

To develop a process chain model, Liu et al.[120] use the composition of materials to predict the conductivity, thickness, and the half-cell capacity via a classification algorithm. In their study, they apply a sensitivity analysis consisting of Gini importance and predictive measure of association to analyze correlations. Drakopoulos et al.[116] utilize production data of the complete electrode process chain to predict the cell performance and determine the influence of certain variables, but the developed model shows a high uncertainty. Niri et al.[123] aim for bringing coating and drying parameters in relation with the final cell performance. They develop an ML model based on a design of experiments (DoE) and interpret it based on indices of mean decrease in impurity and Shapely values. In a similar study, Niri et al.[124] focus on correlation analysis and developing a support vector machine (SVM.) Liu et al.[7] developed an interpretable random forest (RF) by applying ALE. The goal was to predict the cell capacity based on electrode properties.

6.2. Defect Detection

The approaches of Din et al.,[140] Liu et al.,[141] and Pan et al.[142] can be categorized in the area of defect detection of final or intermediate products. Din et al.[140] investigate the detection of defects on welded terminals after the housing of the battery cell. To create more images showing a defect and balancing the data an oversampling method is used. The images are processed by a pretrained and fine-tuned CNN which means parameter-based TL is applied. Instead of using a CNN for detecting defects on the surface of the final battery cell, Pan et al. [142] aim for detecting particles in the electrode stack by utilizing the HiPot measurement and formation parameters. In their study, they use a RF for feature selection, before an algorithm called local outlier factor (LOF) is utilized for anomaly detection.

6.3. Energy Efficiency

Regarding energy efficiency there is one approach by Thiede et al.,[9] which has the goal to identify parameters across the process chain related to the energy demand. These process parameters are used to predict the energy demand in different operating states and calculate the resulting costs.

6.4. Process Optimization

Most studies about process optimization investigate electrode manufacturing (Figure 9a) and cover a specific manufacturing process[135,136,138,143] as well as a chain of processes[10,137] (Figure 9c). Regarding the former, the study of Galvez–Aranda et al.[135] aims for optimizing the electrode microstructure by predicting microstructural properties after calendaring. The predictions are generated with a CNN trained on time series data of a physics-based simulation. In another example, Marcato et al.[136] calculate discharge curves by using a CNN to predict lithium concentration and potential at different time steps. The CNN is a surrogate model developed with images from electrochemical simulations. Vijay et al.[143] develop a CNN as a surrogate model for the mixing process to accelerate the simulation of the electrode structure based on time series data.

Duquesnoy et al.[10] and Duquesnoy et al.[137] created synthetic data with simulations to train an ML model and to predict electrode properties and optimize the production. Duquesnoy et al.[10] set up a DoE to create the parameter space for the simulations. Duquesnoy et al.[137] use the same dataset, but different parameters as wells as a different algorithm.

6.5. Predictive Quality

Predictive quality approaches regarding one manufacturing process concentrate on the final step of formation and aging.[125,127,128,132–134] Hoque et al.[133] measure the internal resistance of batteries during cycling and use this information to create a model to predict the capacity degradation. With this model the cycling duration, and therefore production times, can be reduced. Besides, the authors show that their model can be applied to other batteries when the resistance dynamics and operating conditions are similar. A similar aim has the work of Weng et al.[132] in which the cell resistance is measured after formation and used to predict the cycle life. Additionally, Stock et al.[134] develop an ANN bringing electrochemical impedance spectroscopy into relation with cycling performance of pouch cells. Their aim is to increase throughput and product quality by predicting the cycle life. The study of Zhang et al.[128] aims to improve the accuracy of capacity predictions while increasing interpretability with Shapely values. The authors apply an ensemble learning method consisting of a Gradient Boosting Machine (lightGBM) and an ANN. The lightGBM evaluates numerical data and the ANN time series of the formation process.

Studies evaluating a process chain mostly focus on integrating parameters from all manufacturing processes.[8,126,129–131] Thiede et al.[130] develop a concept for data mining and including data from the complete process chain of battery cell manufacturing to predict quality relevant properties of the battery cell and its intermediate products. In a case study, they use intermediate product properties to predict the final product properties. The underlying model enables the analysis of influencing factors. Turetskyy et al.[129] investigate this approach more in detail with a deep dive into data acquisition and data management.

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7. Comparison of TL for Manufacturing and ML in Battery Cell Manufacturing

The comparison of TL for manufacturing and ML in battery cell production is based on the comparison categories presented in Section 3.3. This section highlights the differences and similarities between the two fields to assess the applicability of TL in battery cell production. The methodological procedure for comparing and identifying use cases for TL was explained in Section 3.4. In this section, the comparison categories are first discussed, which are summarized in **Figure 10**. In each case, the percentage number of studies for a particular subcategory is shown. In Section 7.1 similar TL and ML approaches are identified and compared with each other. This comparison leads to use cases, which are described in **Table 3**. Additionally, Section 7.2 describes challenges for the application of TL in battery cell production derived from the comparison. Based on these challenges the feasibility of the use cases is evaluated.

Figure 10a shows the fields of application for both literature research and the number of corresponding studies. The fields of application defect detection, energy efficiency, and predictive quality are present in TL as well as in ML for battery cell

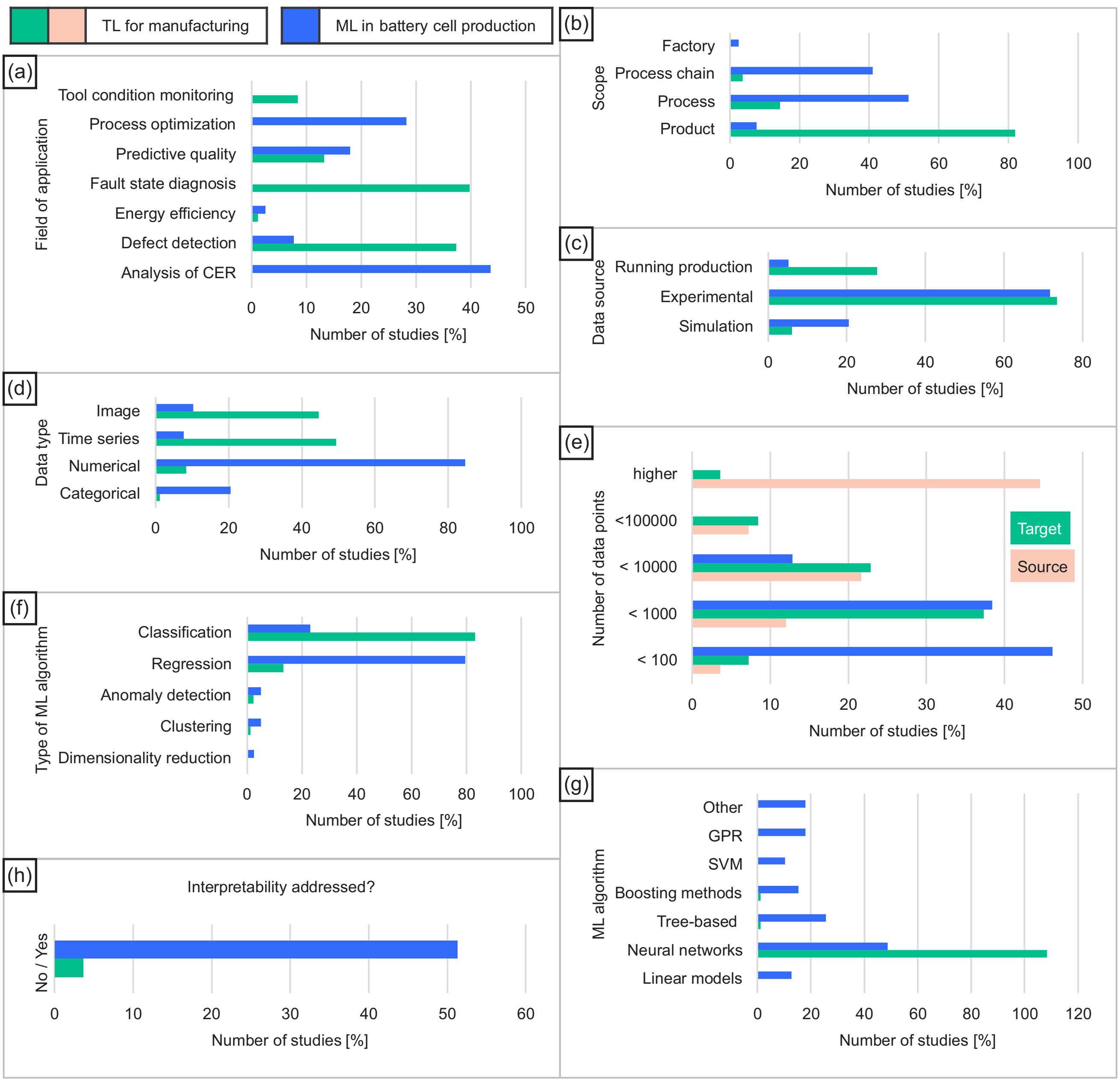

Figure 10. Number of studies for the different comparison categories separated into TL for manufacturing and ML in battery cell production: a) field of application, b) scope, c) data source, d) data type, e) number of data points, f) type of ML algorithm, and g) ML algorithm, h) interpretability addressed compared to tree-based algorithms used for battery cell production.

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Table 3. Overview of potential use cases of TL in battery cell manufacturing.

	Manufacturing process (source/rarget)		Production scale (source/target)		Product design (source/ target)		Type of TL	Field of application	TL example	ML example	Feasibility
a	None	Cell assembly	Pilot	Pilot	Different domain	X-ray images	Cross-domain	Defect detection	Ferguson et al.[59]	Din et al. [140]	●
b	Simulation	Production	Lab	Lab	Simulation	Production	Cross-phase	Analysis of CERs	Tercan et al.[18]	El Malki et al.[112]	◑
c	Formation process A	Formation process B	Pilot	Pilot	Battery cell design A	Battery cell design B	Cross-state	Analysis of CER	Li et al.[97]	Zhang et al.[128]	◕
d	Coating machine A	Coating machine B	Lab	Pilot	Coating A	Coating B	Cross-entity	Analysis of CER	Wang et al.[99]	Seo et al.[110]	◑
e	Process chain A	Process chain A	Pilot	Pilot	Design A	Design B	Cross-state	Predictive quality	None	Turetskyy et al.[129]	◑
f	Process chain A	Process chain B	Series/ Near-Series	Series/ Near-Series	Design A	Design A	Cross-entity	Predictive quality	None	Turetskyy et al.[129]	◑
g	Drying machine A	Drying machine B	Pilot	Pilot	Design A	Design A	Cross-entity	Energy efficiency	Panjapornpon et al.[70]	Thiede et al.[9]	◕

production. In contrast, fault state diagnosis and tool condition monitoring are not available in battery cell production, whereas analysis of CERs and process optimization are. This does not mean that tool condition monitoring could not be a use case for TL in battery cell production, since there are tools affected by wear. For example, the blades used for cutting or the calender rolls used to compress the coating require maintenance. Also fault state diagnosis could be relevant for battery cell production to develop predictive maintenance solutions.

Figure 10b makes clear that most TL approaches describe a model which evaluates a product. A common use case is defect detection based on images[51,56,57,59] or analyzing time series data to detect faulty operating states of the system or machine.[40,74,77,78,85,87,88] In conclusion, a relation of process and product parameters through a process model is not in the scope of most TL studies. On the contrary, ML in battery cell production is pursuing modeling of interrelations. For example, the input and output parameters of the coating process are modeled.[6,114,115,118,122] Often, the modeling of the interrelationships is extended to a process chain in order to predict final product properties.[7,116,123,124,129,130] A possible reason for this difference between TL and battery cell production could be that transferring process models is more difficult, since the learned relations are more complex and less generalizable.

When comparing the data sources in Figure 10c, the mentioned lack of data from the running production of battery cells becomes clear. However, there are TL approaches for running production making the application of TL in future ML studies in the mass production of battery cells possible. One reason for the lack of data from mass production could be that ML in battery cell production is more of a new topic, because their development is in correlation with the ongoing ramp up battery cell production.

By comparing the used data types in Figure 10d, it becomes clear that TL focuses more on images and time series, whereas ML concentrates on numerical or categorical data. This reflects the investigated fields of application (Figure 10a) as well as the size of the datasets (Figure 10e) and the type of ML algorithm (Figure 10f). The underlying relationships regarding this have already been explained in Section 5 and 6. One possible reason why TL focuses on images and time series is the large number of pretrained open-source models for these data types. These open-source models offer a high level of generalizability, as they have been trained on very large data sets. For example, residual networks, which have been trained on large image datasets, are utilized often.[41,51,59,144,145] The mentioned generalizability is probably not applicable to the complex relationships present in the numerical data of process parameters and product properties. Although, the investigation of complex relationships is a key application for ML in battery cell production.

The size of the datasets shown in Figure 10e indicates that TL is mainly used on datasets with more than 1000 data points to train the source model. In contrast, the data sets from battery cell production mainly have a size below 1000 and 100 data points. However, this does not automatically imply a reduced applicability of TL, as the number of TL studies using other data types and types of ML is significantly larger. One conclusion that can be drawn is that there are only a few TL studies that use datasets that are in the range of the size of the datasets of the ML approaches.

The results shown in Figure 10f further reduce the number of comparable approaches between TL and ML in battery cell production, as the types of ML algorithms used differ significantly. Classification is the predominant type of ML for TL, whereas regression is primarily applied in ML for battery cell production.

Figure 10g illustrates that neural networks are a key algorithm for both TL and ML. Consequently, the technical applicability of most TL methods to various ML approaches is likely. However, many ML approaches utilize other algorithms that rely on less common TL methods, such as domain adaptation.

The interpretability of ML models is crucial in many studies on battery cell production. In contrast, TL rarely addresses this aspect. This difference arises from the algorithms used and the underlying use cases, which often do not focus on understanding

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7.1. Deriving Use Cases for Transfer Learning in Battery Cell Manufacturing

The next step is to determine which TL and ML studies are most similar to each other in order to identify promising use cases. The procedure for this has been explained in Section 3.4. In summary, each TL study is compared with each ML study, and the number of same categories is calculated. A total of six comparison categories are used, which means that a maximum of six matches can be achieved, which is illustrated by the heatmap shown in **Figure 11**a. The heatmap shows the TL studies on the *y* axis and the ML studies on the *x* axis. The comparison is limited to the representative studies used to explain the fields of application in the subsections of Section 5 and 6. To further narrow the comparison, only links with 5 or 6 matching categories are examined. The resulting comparisons with the highest similarity are shown in Figure 11b and are discussed below with regard to possible use cases. Additionally, use cases which have not been detected by the comparison method are presented. All use cases are classified with the TL cube method adopted from Wang et al.[30] and summarized in Table 3.

The comparison shown in Figure 11 reveals five TL approaches that have the most similarities to ML approaches in battery cell production: Tercan et al.,[98] Wang et al.,[99] Tercan et al.,[18] Li et al.,[97] and Ramezankhani et al.[96] These studies have in common that they develop a regression model for predictive quality in the scope of a specific manufacturing process. Furthermore, they can be grouped into the type of TL they apply. As described in Section 5.4, Tercan et al.[18] and Ramezankhani et al.[96] investigate a cross-phase transfer. The

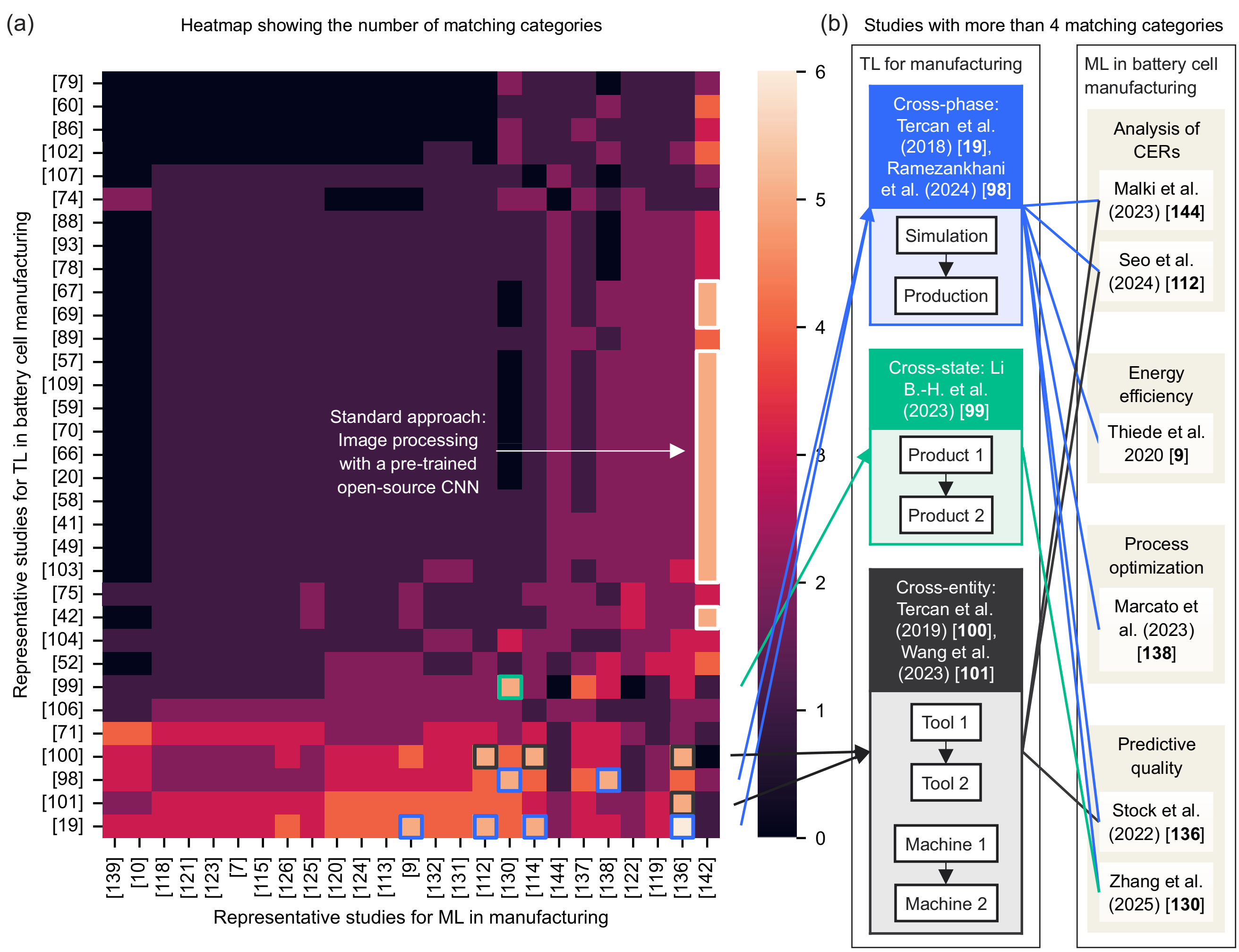

Figure 11. Number of matching categories between representative studies visualized in a heatmap a) and most similar studies b).

former for an injection molding and the latter for a thermoforming process. A cross-state approach is developed by Li et al.[97] The third group consists of the cross-entity approaches of Tercan et al.[98] and Wang et al.[99] In Tercan et al.,[98] TL is used because of changing geometrical properties of the product which made the use of different tools necessary. The TL in the work of Wang et al.[99] is based on domain adaptation and not on the used ML model. The authors aim for a cross-entity transfer between different milling machines.

Similarly, the studies about ML in battery cell production can be grouped according to the field of application. In both studies, Seo et al. [110] and Malki et al.[112] create surrogate models based on data from simulations for the analysis of CERs: Seo et al.[110] for coating with a slot die and Malki et al.[112] for the wetting process during filling. Regarding energy efficiency, Thiede et al.[9] develop an ANN for the drying process to identify influential variables and to predict potential savings. To optimize the formation process, an electrochemical simulation is used by Marcato et al.[136] to derive a surrogate model. In their study, a CNN predicts the concentration of lithium. The studies of Stock et al.[134] and Zhang et al.[128] in the field of predictive quality focus on the formation process, too. Stock et al.[134] classify the quality of battery cells with an ANN based on information acquired during cycling. Zhang et al.[128] predict the cell capacity with an ensemble learning method which analyzes time series as well as numerical data. Din et al.[140] apply defect detection to a welding process in cell assembly and already utilize TL by using the most common approach of classifying images with a pretrained CNN (see Figure 8b,g). As a result, the study shows high similarities with most TL studies. This kind of TL approach is already a use case in battery cell production and investigated in the studies of Yang et al.[20] and Chen et al.[21] Nevertheless, the cross-domain transfer regarding image processing could be relevant for other manufacturing processes. For example, Ferguson et al.[59] present a TL approach for defect detection by evaluating X-ray images. The evaluation of X-ray images exists as quality control in cell assembly which makes it a possible use case for cross-domain TL. The corresponding use case is described in Table 3a.

Figure 11b shows that the studies applying cross-phase TL are similar to studies regarding analysis of CERs,[110,112] energy efficiency,[9] process optimization,[136] and predictive quality.[128,134] To create a use case, cross-phase transfer requires a situation in which experimental data is not sufficient, and simulation data can support the development of an ML model. As explained, there are studies using simulation data to develop an ML model for coating,[110] filling,[112] and formation.[136] If this model uses measurable features, a transfer to real production data can be a use case for cross-phase TL, which is visualized in the TL cube in **Figure 12**b and summarized in Table 3b. As example serves the study of Malki et al.[112] When comparing cross-phase transfer with the approach of Thiede et al.[9] in the field of energy efficiency a use case is unlikely because the development of a simulation would mean that the influential variables are already known. The studies about predictive quality[128,134] focus on the formation process and to apply a cross-phase transfer a simulation similar to their approach is needed. This simulation could be

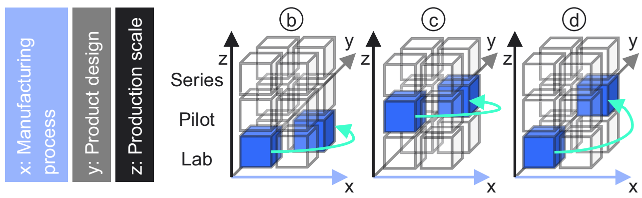

Figure 12. Exemplary visualization of use cases by using the TL cube.

difficult to realize. For example, Stock et al.[134] measures various parameters with electrochemical impedance spectroscopy and the cycling behavior. Still, cross-phase TL is a viable use case for battery cell production, since there are various approaches using simulation data.[10,135,137]

Regarding cross-state transfer Figure 11 shows that the approach of by Li et al.[97] is similar to the study of Zhang et al.[128] This comparison could lead to a use case for the formation process, which could be caused by different cell designs, each requiring distinct procedures. This use case can occur in pilot line production and is described in Table 3c and Figure 12c. The change of the final product design will most likely lead to changes in the intermediate product design-making cross-state transfer also in other process steps applicable. For example, Fernandez et al.[23] applied parameter-based TL to the coating process transferring knowledge between different chemistries.

Finally, Figure 11 visualizes that the cross-entity approaches[98,99] share the most similarities with studies about analysis of CERs[110,112] and predictive quality.[134] Applying cross-entity transfer to the approach of Seo et al. [110] would mean a transfer from one coating machine to another. This could be a use case during upscaling, for example, from laboratory to pilot line production or from pilot line production to sample production. This transfer from one machine to another could also cause a change in the used coating tool. The cross-entity use case for coating is listed in Table 3d and shown in the TL cube in Figure 12d. The next similar study of Malki et al.[112] deals with the filling process of prismatic cells. Here, the used electrolyte or the size of the cell could change, but coating is a more relevant example because it has the highest scrap rates in the process chain[146] and has great impact on the final product.[7,124] Regarding the study of Stock et al.,[134] a cross-entity transfer would be applied to the cycling process. The cycling process consists of multiple systems which each charge and discharge several cells according to a defined protocol. The cycling systems are designed to apply the same protocol to every cell making a cause for a cross-entity transfer unlikely. The most likely reasons for the application of TL in the cycling process are different protocols or cells and therefore a cross-state transfer as described in use case b.

In addition to the use cases identified in Figure 11, further use cases might be relevant for battery cell manufacturing. For example, there is no comparison to a predictive quality approach, which develops an ML model for a chain of process steps. Regarding this, the work of Turetskyy et al.[129] shows the greatest similarity to TL approaches. In their study, an RF is trained using categorical and numerical data to predict final product properties. When using this model in a pilot line, a reduced performance of the model is likely to occur due to changes in an individual process step. Therefore, a cross-state transfer is described as use case e in Table 3. Furthermore, a cross-entity transfer could also be a use case if there are production lines at different locations. This could be the case during upscaling of series production. (Use case f in Table 3) When applying a cross-phase transfer as demonstrated by Tercan et al.,[18] to the approach of Turetskyy et al.,[129] a simulation of the investigated process chain is required. For example, the simulation of the entire process chain of battery cell production was pursued in Thomitzek et al.[147] The simulation of every process step represents an enormous effort and is therefore not included as a use case.

Only TL approaches about predictive quality or defect detection have been compared. Therefore, additional comparisons could be helpful to investigate the applicability of fault state diagnosis and tool condition monitoring. For fault state diagnosis, a suitable use case was not found. This is due to the reason that these TL approaches are mainly based on time series and classification, which are not often evaluated in battery cell production (see Figure 10d,f). In addition, the advantage of using ML for fault detection, on which fault diagnosis is often limited, is relatively low, because most of the times fault detection can be achieved with fixed thresholds. An application of tool condition monitoring to battery cell production requires a manufacturing process, which is heavily affected by tool wear. This could be the case, when cutting electrodes with roller cutters or compressing the coating during calendering. Since the literature research did not produce a fitting ML approach, no use case is created. Also interesting for manufacturers of image-based measurement systems could be a federated learning approach as described by Mehta and Shao[56] (see Section 5.1). Another missing comparison concerns energy efficiency, for which Panjapornpon et al.[70] and Thiede et al.[9] investigate a similar use cases. Both aiming to find energy intensive variables, Panjapornpon et al.[70] in a chain of chemical processes and Thiede et al.[9] for battery cell manufacturing. Panjapornpon et al. [70] applies a cross-state transfer, which could be investigated for the approach of Thiede et al.[9], since various changes in the process chain could lead to a different energy consumption. The corresponding use case g is listed in Table 3.

7.2. Challenges for the Application of Transfer Learning in Battery Cell Manufacturing

Before TL can be applied, a suitable ML use case has to be implemented. This requires coordination with relevant stakeholders and the selection of a use case with high potential impact. In battery cell production, a process developer might prefer analyzing CERs of a specific process step, while a quality engineer may be more interested in predicting critical product properties based on data from multiple process steps. Applying TL to an ML use case introduces additional challenges that can significantly affect the feasibility of TL.

One key challenge in applying TL could be the inclusion of multiple process steps. This increases the number features influencing the model output,[8,129–131,148,149] compared with models developed for a single manufacturing process.[6,112,115,118,122,134,150] A higher feature count typically demands more training data and leads to a more complex model, which can hinder the transfer to a similar task. This assumption is supported by Figure 9b, which shows that process chain models are rarely investigated for TL in manufacturing.

In addition, modeling a process chain makes it more challenging to assess the similarity of source and target task due to a more complex traceability of the production data. Especially in prototype and pilot production where many activities are manually done and constantly changing because of different experiments, traceability is hard to achieve. Therefore, traceability is a critical factor in evaluating and implementing use cases for TL. Another factor which should be considered is the rise in costs due to additional experiments needed to create a robust ML model.

Another challenge for TL use cases presents the production scale, because lower production scales provide less data and less homogenous data. In battery cell manufacturing, upscaling is a critical phase in the ramp-up of the production. This phase introduces significant challenges across scales due to differences in equipment, process parameters, and environmental conditions.

However, the implementation of TL in the upscaling process holds substantial promise for accelerating the production ramp-up by improving the knowledge transfer.

Based on the outlined challenges, the feasibility of the identified use cases can be estimated. Use case a, described in Table 3, demonstrates the highest feasibility because it focuses on a single process step and does not involve upscaling. Additionally, this use case utilizes image processing, which is the most prominent application of TL, as explained in Section 5. Use case b is less feasible because it requires a simulation and is situated in the lowest production scale. Use case c shows higher feasibility, as it also concentrates on a single process step, but avoids upscaling a manufacturing process. Moreover, this use case has been validated in the context of the coating process.[23] In contrast, use case d involves upscaling a process step, which introduces significant variability and reduces the feasibility of TL. Use case e does not involve upscaling but focuses on modeling a process chain, which may reduce the applicability of TL. Use case f is situated in near-series production, where larger datasets can be expected. However, the transfer occurs between different production lines, which introduces variability. The last use case g is similar to use case c, making it more feasible.

A general challenge is to provide proof that TL in battery cell manufacturing is beneficial compared to traditional ML and other methods to cope with data scarcity. Well-known examples of these methods are data augmentation, multitask learning or physics-informed ML. More specifically, data augmentation generates new data samples or transforms existing data. It can improve generalization by altering characteristics of the training dataset.[151] Multitask learning represents a learning paradigm in ML that transfer knowledge between tasks by simultaneously training the model on them.[152] As for physics-informed machine learning, it aims to embed fundamental physical principles into the development of data-driven models.[153] This diminishes the dependence on large-scale datasets, as the model is guided by pre-established physical laws rather than having to infer them solely from empirical data.

8. Summary and Outlook

This review investigates the applicability of TL in battery cell production by comparing TL approaches from other industries with ML approaches in battery cell production. Based on that suitable use cases were derived. The application of TL is motivated by the digitalization and the utilization of ML during scale-up of battery cell production. TL could enable a knowledge transfer when upscaling manufacturing processes and the training of ML models when data is scarce. Especially in the prototyping phase of battery cell production the data is scarce, because of high product variety and different manufacturing processes as well as various workflows.

The screening of TL approaches for manufacturing led to five main applications regarding their benefit for production: defect detection, energy efficiency, fault state detection and diagnosis, predictive quality, and tool condition monitoring. About 46% of the categorized studies focus on defect detection and about 33% fault state detection and diagnosis, which indicates the fields the research concentrates on. Especially defect detection serves as a large field of application, because of the widespread use of image processing. Image processing provides the possibility to apply an ML model, which is pretrained on a large open-source image dataset to handle data scarcity in the manufacturing data. The other most used data type is time series data for fault state detection and diagnosis. A reason for this is the possibility to transform time series data to images, which can be evaluated by pretrained models.

The screening of ML approaches in battery cell production led to five main applications regarding their benefit for production: analysis of CERs, defect detection, energy efficiency, process optimization, and predictive quality. About 45% of the categorized studies focus on the analysis of CERs and about 27% on predictive quality, which indicates on which fields the research concentrates on. The conducted categorization of ML approaches confirmed results of previous reviews but was necessary to enable a detailed comparison with TL approaches.

The comparison reveals that a difference between TL for manufacturing and ML in battery cell production is that the latter focuses on modeling relationships between input and output parameters of a manufacturing process, whereas TL concentrates on evaluating output parameters. This may complicate the utilization of TL approaches since they are validated on less complex relationships. The applicability of TL approaches is further reduced, when comparing the evaluated data type as well as the type of ML algorithm. ML in battery cell production mainly uses numerical data and regression algorithms, but TL images and time series for classification tasks. Also, interpretability of the ML model is included in the concepts of about 52% of studies in battery cell manufacturing, but only in 4% of the screened TL studies.

Based on the comparison, similar studies were identified, which serve as examples for use cases to apply TL in battery cell manufacturing. One of these use cases describes the transfer of an ML model trained on simulation data to production data. For this use case, an evaluation of possible simulations is required. The next use case utilizes a pretrained model to evaluate X-ray images from cell assembly. Also, electrode manufacturing can provide a use case for transferring a model between different entities or states of a manufacturing process. For example, in laboratory production, the coating process uses a different coating tool than in pilot production. A probably simpler use case is found when a different product design occurs in the development process leading to different parameter settings for the manufacturing process and to data or concept drifts. Another use case is the prediction of the energy consumption, which is a huge cost factor in battery cell manufacturing. An ML model learned on data from one production line could be utilized in another production line. Also highly relevant is the prediction of product properties based on intermediate product properties and process parameters for quality assurance.

Thinking about challenges for the application of TL in battery cell manufacturing, a holistic traceability solution is required to evaluate the similarity of data and consequentially the transferability of an ML model. Besides, it is needed to compare and validate the performance of ML models. Another challenge for the transfer of an ML model poses the complexity of the relationships in the process chain of battery cell production, since ML is preferably used to describe complex relations to generate a benefit. To provide a greater benefit for a transfer, larger differences may be considered which could be a challenge.

Future studies should verify the applicability of TL in battery cell manufacturing. This review provided possible use cases for this. The verification should include traditional ML and similar methods. One of these methods is data augmentation, which could reduce data scarcity. Additionally, the use of multitask learning or physics informed ML could be beneficial. Further research could usefully explore how transformer models can be utilized, since they are currently not applied in battery cell manufacturing but gain increasing importance in other fields. For example, for the forecasting of time series data.

Conflict of Interest

The authors declare no conflict of interest.

Keywords: battery cell · electrode · machine learning · production · transfer learning

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