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Transfer Learning Framework and Use Cases for Battery Manufacturing Systems

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Abstract

The integration of machine learning (ML) into battery manufacturing systems has led to substantial improvements in various areas such as battery performance, quality control, and predictive maintenance. However, in industrial settings, it is often not feasible to acquire a large amount of data required for conventional ML approaches. Adaptation of new process technology, reconfiguration of cell design and up-scaling of processes are the main reasons for the value decrease of the previous data. Therefore, a swift adaptation to production dynamics gains more attention in the field of battery manufacturing. To tackle this problem, this paper introduces transfer learning in battery manufacturing systems to investigate the relationship between production parameters faster and more accurately with less data requirement. A novel framework termed the "Transfer Learning Cube" is demonstrated to explore the feasibility and efficacy of transfer learning for multiple use cases across three key dimensions: production scale, manufacturing process, and battery cell design. Specifically, two industrial case studies were investigated to test the “Transfer Learning Cube” by analyzing their concepts, obstacles, needs, and solutions. This framework underlines the significant potential of transfer learning in battery manufacturing systems. Despite limited data availability, transfer learning enables the rapid setup of battery production lines equipped with new processing methods and enhances the efficiency of scaling up production lines.

Keywords: Battery Manufacturing Process; Lithium-Ion Battery; Transfer Learning; Artificial Intelligence

1. Introduction

The growing prominence of electric vehicles (EV) in the automotive market, driven by sustainability concerns, has led to an increasing global demand for the battery. The lithium-ion battery (LIB) manufacturing market accounted for 26.7% of the rechargeable battery market in 2019 while it will emerge as a dominant cell manufacturing technology by 2030, with a production capacity share of more than 50% [1,2]. Thus, accelerating battery manufacturing to meet market demand is imperative. Concurrently, advanced battery technologies beyond the LIB are being raised for consideration for better performance, especially in terms of higher energy density and lower manufacturing expenses. For instance, implementing lithium metal for solid-state batteries (SSB) can improve energy content, and using raw materials like sodium or sulfur can lead to lower costs for cell components [3]. When applying these new battery manufacturing technologies, cell factories are facing various changes and challenges. For example, additional mixing and coating processes are needed for sulfidic SSB production. Also, it is necessary to include dry mixing and electrostatic spraying in solvent-free production steps for lithium-air batteries [1]. Therefore, speeding up the ramp-up and the production processes to increase the production yield for battery manufacturing systems (MSs) gains more and more attention.

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The production of LIBs is characterized by high complexity and manifold interdependencies [4]. Any alterations or interventions in one parameter within battery MS can lead to consequential impacts on other parameters [5]. For instance, fluctuations in temperature or humidity during anode production can cause variations in anode mass loading, subsequently influencing the energy density of the cell. To decouple and optimize the complex production processes, data-driven methodologies or machine learning (ML) within battery MS are applied to ensure the desired product performance and production cost efficiency [6]. Despite this, some prerequisites of machine learning, such as the substantial demand for labeled data, often remain unfulfilled in industrial settings. Hence, an efficient approach to applying machine learning methods with scarce data and less effort in battery MS is required. In this paper, a conceptual framework termed the "Transfer Learning Cube" addresses the above issue along three key dimensions to support the promising transfer learning approach to be further implemented.

2. State-of-the-Art

As shown in Fig.1, battery manufacturing process is mainly divided into three phases: electrode manufacturing, cell assembly and cell finishing. In general, current LIB electrodes are manufactured through five standard processes, which are slurry mixing, coating and drying, calendaring, slitting, and vacuum drying [7]. After the electrode preparation, there are three main cell formats for stacking: pouch, cylindrical, and prismatic. Then the electrodes are enclosed within the cell housing. As for LIB, the liquid electrolyte is filled into the cell under specific environmental conditions. At last, the cell is finalized through the formation and aging process. The diversity of manufacturing technologies within each production process contributes to the high complexity of producing battery cells. Various manufacturing technologies are listed under each process in Fig. 1.

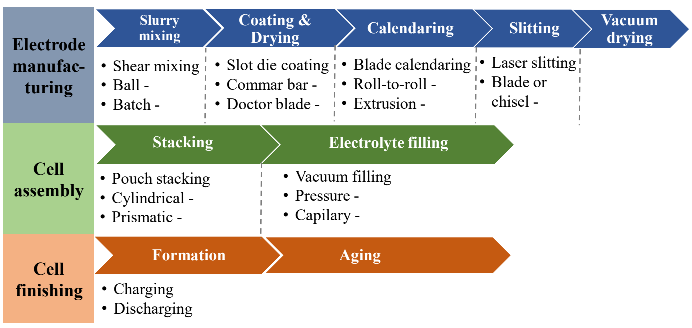

Fig. 1. Battery manufacturing process chain and corresponding technologies[6], [8].

According to [9], the relation between LIB production processes is depicted in Fig. 2, decoupling the complex LIB manufacturing parameters into three main categories, namely process, intermediate product and final product characteristics. Given the high complexity of electrode manufacturing, there has been a growing focus on data-driven methodologies in this field in recent years, along with advancements in digitalization and machine learning (ML). ML-based approaches have significant potential to speed up the optimization of battery manufacturing systems by their capacity to manage multidimensional datasets and offer deeper insights into the interrelationships among manufacturing parameters.

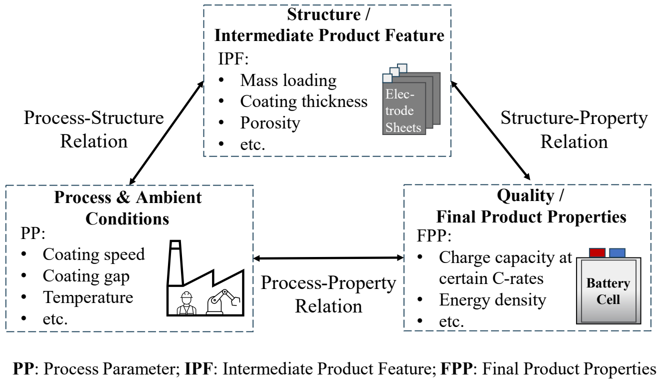

Fig. 2. LIB process-structure-property function adapted from [9].

While the utilization of ML has been extensively examined and reviewed in the battery material domain and characteristic estimation domain, the field of battery cell manufacturing has received relatively less attention. A notable contribution to understanding the current state of ML methods within the field of LIB manufacturing systems is the comprehensive mapping study conducted by [10] in 2023. This study focuses on extracting and highlighting the current focal points from the aspect of processes, product and process parameters of battery cell production. The multi-perspective comparison reveals the ML capabilities in future research to accelerate battery manufacturing. Building upon the insights of the mapping study, further investigations have delved deeper into specific aspects. For instance, Schnell et al. [11] applied CRISP-Data Mining methodology to the data from a real LIB manufacturing scenario. Process dependencies are identified and the main impact factors on predictive quality are investigated. Turetskyy et al. [4] proposed a holistic data-driven pipeline in LIB cell production to acquire and combine relevant data from different sources for further analysis, management and visualization. Moreover, Cunha et al. [12] performed quantitative analysis of parameter interdependencies and the prediction of the slurry manufacturing parameters impact on the final characteristics of NMC cathodes before calendaring, using un-classified raw experimental data. Niri et al. [13] compared different ML models with the experimental data to investigate and achieve the quantitative prediction for LIB cell performance through the key parameters of electrode manufacturing. These studies provide detailed perspectives and contribute to a comprehensive understanding of ML within battery manufacturing systems.

However, the mentioned studies only consider one type of battery electrode or one specific battery production scenario for machine learning. In industrial settings, it is often not feasible to acquire a sufficiently large amount of data required for traditional ML approaches [14]. Adapting transfer learning

(TL) in industry can help represent the relationship between process parameters and product quality faster with less data requirement [15]. Maschler and Weyrich [16] extracted findings from different use cases of deep TL for industrial automation and proposed four base use case categories. This paper offers a foundation for TL in real industrial scenarios. Liang et al. [17] proposed a shared connected DNN for time-series anomaly forecasting to transfer knowledge between two aluminum extrusion electricity consumption datasets.

Thus, a lack of a comprehensive study investigating the feasibility of TL in battery manufacturing is obvious, since most ML applications in battery manufacturing focus on specific cases, which don`t take transferability into account. TL is an established approach that is proven in other manufacturing fields, such as anomaly detection [18], time series prediction [19], fault diagnosis [20] and quality management [21]. However, there is no TL for battery manufacturing so far. The proposed conceptual framework addresses this issue by presenting a visualized model of TL across three key dimensions for battery manufacturing system.

3. Methodology

3.1. Concepts of Transfer Learning within battery manufacturing systems

Traditional ML methods involve individual datasets tailored for specific learning tasks. Learning occurs in isolation without leveraging past knowledge acquired from other tasks. However, in TL, similarities between datasets can be identified. This allows prior knowledge or the pre-trained model to be transferred from previous tasks to new ones instead of training from scratch. Thus, the learning process can be more efficient, accurate, and requires less training data. (See Fig.3) Within battery MS, TL is promising due to the production dynamics from the changes of the recipe, materials or machines.

The main definitions about TL in battery MSs are listed as follows.

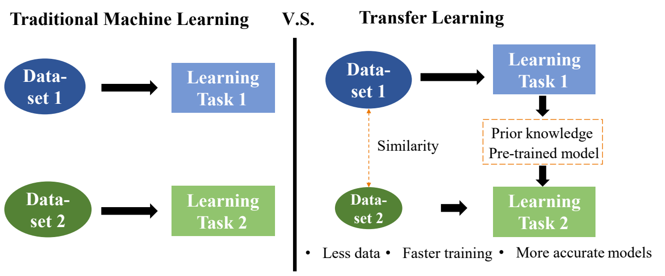

Fig. 3. Illustration of TL concept [22].

- Domain $\mathcal{D}$: The domain for a specific use case in battery MS represents production features and is used as input for further ML methods.
- Task $\mathcal{T}$: The task of the battery MS can be varied such as quality control, process optimization and so on. Depending on different aims, the output variable can be process parameters or intermediate product properties like mass loading of electrode, or final product characteristics like energy density of the battery cell.
- Source/Target: Generally the dataset with sufficient samples and labels is chosen as the source domain and task for a good transfer foundation, such as the existing battery production line. In contrast, the dataset with scarce samples or some unlabeled data is selected as the target domain and task to receive the prior knowledge, such as a new similar production to be ramped up or a new manufacturing technology.
- Transfer learning (TL): Given a source domain and learning task, a target domain and learning task, transfer learning aims to enhance the learning performance of the target task by using the knowledge extracted from the source domain and task.
- Deep TL: A pre-trained deep learning model, such as a deep neural network (DNN), can serve as a feature extractor or initializer at a higher level of abstraction for TL. The knowledge encoded in the weights and biases of the pre-trained model is transferred to a new domain with limited labeled data. Three basic models for deep TL are illustrated in Fig. 4. The pre-trained network is applied directly to the source domain and task without any retraining. Fixed feature extraction method is to freeze gained features from the first few layers of the pre-trained model and retrain the last layer for a new regression task. By fine-tuning method, the pre-trained model on the new task or domain-specific dataset, deep TL enables the model to adapt and learn task-specific features while retaining the common knowledge learned from the source task.

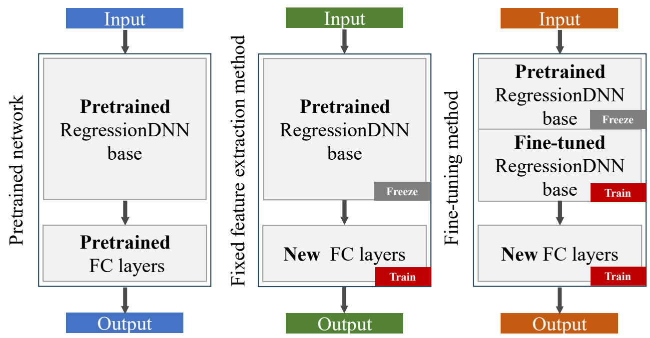

Fig. 4. Basic models for deep TL. (FC layer: Fully Connected layers)

3.2. Transfer Learning Cube

To structure and systematically identify TL use cases, the proposed “Transfer Learning Cube (TL Cube)” is a conceptual framework along the three key dimensions of battery MSs (see Fig. 5). It can be used to assess the viability and scope of TL for multiple use cases in the field of battery MSs in terms of production scale, manufacturing technology and battery cell design. The quantity of sub-cubes within a given volume is not constrained, with the representation typically using three subcubes along each dimension to elucidate the model. The variables corresponding to each axis are subject to determination and modification based on the particular application. Some examples and explanations of variables corresponding to each axis are demonstrated as follows.

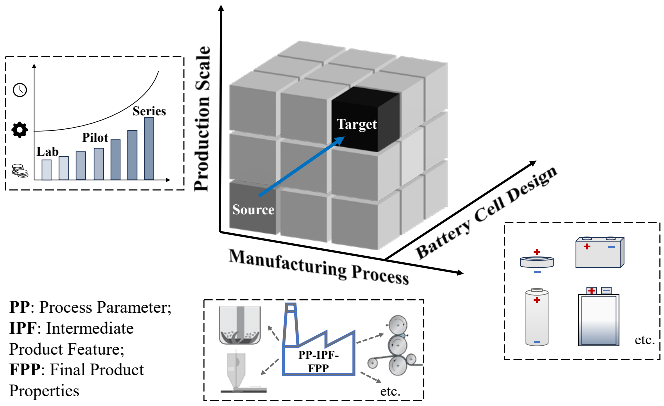

Fig. 5. Overview of TL Cube for battery manufacturing system.

Production scale: In general, production scale in the current manufacturing system is separated into three main levels: prototype scale, pilot scale and series scale [23]. In this paper, “laboratory scale” is used instead of “prototype scale”, since laboratory scale is part of the prototype phase and some of our use cases consider the laboratory production of battery cells. While there may be higher-dimensional or more finely-grained levels in the future, the main emphasis of this paper remains on these three levels as typically utilized.

Manufacturing process: It encompasses a set of parameters crucial to manufacturing processes. In battery MS, “Manufacturing process” can range from broad concepts like "process chain parameters" to specific elements such as "coating process parameters”. The process parameters of different battery manufacturing technologies can likewise be grouped here, such as “lamination process parameters” of solid-state batteries, and “extruding and calendaring process parameters” of lithium–sulfur batteries. Alterations of battery materials and structures are analyzed in the scope of manufacturing process as well.

Battery cell design: Battery cell design refers to the configuration and architecture of individual cell e.g. in terms of general cell concept (e.g. pouch, prismatic, cylindrical), involved material system (e.g. NMC, LFP), or dimensions. Variables corresponding to this axis can be the traditional components of the battery cell, such as “anode”, “cathode”, “electrolyte”, “cell format” or specific use-case-oriented terms like “single-layer cell format”, “multi-layer cell format” etc.

Therefore, this “TL Cube” addresses the gap in TL within battery manufacturing and provides a conceptual guideline to support the researchers and the industry in categorizing their specific use cases. Source domain and target domain can be illustrated on the TL cube to visualize their discrepancy in terms of battery manufacturing. Whereas the development of specific TL methods is not the main point in this paper, the framework supports to identify promising TL strategies along the three dimensions which facilitates further implementations.

4. Exemplary industrial transfer learning use cases

4.1. Electrode Production Technologies (Leydenjar)

Leydenjar is a Dutch battery company, that produces pure silicon anode for higher energy density and thinner cell format. One-step Plasma Enhanced Chemical Vapor Deposition (PECVD) technology [24] is used for anode production instead of the traditional five steps (See Fig. 6). To enhance the quality of anode, various adjustments and tests were conducted on the production recipe, such as altering process parameters like speed, airflow, power, etc., to observe the potential variations in the mass loading, which is one of the main intermediate product features (IPFs) of anode.

The industrial cost of conducting a single recipe test is substantial. For instance: 1) Time cost: Adjusting machine parameters and setup of the production line for a new recipe entail significant time consumption. 2) Material cost: Anode materials are costly, and multiple physical experiments based on trial-and-error methods can accumulate considerable material costs. 3) Cost of quality testing: Despite the assistance of advanced detection machinery, the quality testing process is not continuous and requires human resources and time.

Fig. 6. One-step PECVD anode production machine in Leydenjar.

All the obstacles need to be taken into account when Leydenjar aims to speed up its attempt at the new recipe. Additionally, it was found that each adjustment to the recipe is based on accumulated prior knowledge from previous manual operations. Therefore, adapting transfer learning in Leydenjar`s anode production is feasible. By extracting suitable feature knowledge from current recipes and applying it to new recipes, the new prediction of anode mass loading can be achieved.

The “TL Cube” can serve as a guide to assist Leydenjar in exploring the implementation perspective of TL in their specific production case. Given their primary objective of uncovering similarities between different recipes and transferring useful information to new recipes, while maintaining the production scale unchanged at the pilot scale level and the object of quality control being the single-sided and double-sided anode, the focus can be placed on the "manufacturing process" dimension of the “TL Cube”.

For the "manufacturing process" axis, the approach can be refined as follows: firstly, an existing recipe (including different process parameters like power, temperature, etc.) for single-sided anode with a sufficient amount of labeled data is selected as the source domain for training a pre-trained base. Secondly, the new recipe for double-sided anode is identified for testing as the target domain. Then, the similarity between the two domains can be defined and the discrepancy between them can be measured as well. Therefore, the TL cube tailored to Leydenjar's specific scenario is depicted in Fig. 7 below. Thus, the source domain is the single-sided anode production process at the pilot line, and the target domain is the double-sided anode production at the pilot line. Both source and target tasks remain consistent, focusing on predicting IPF, specifically anode mass loading.

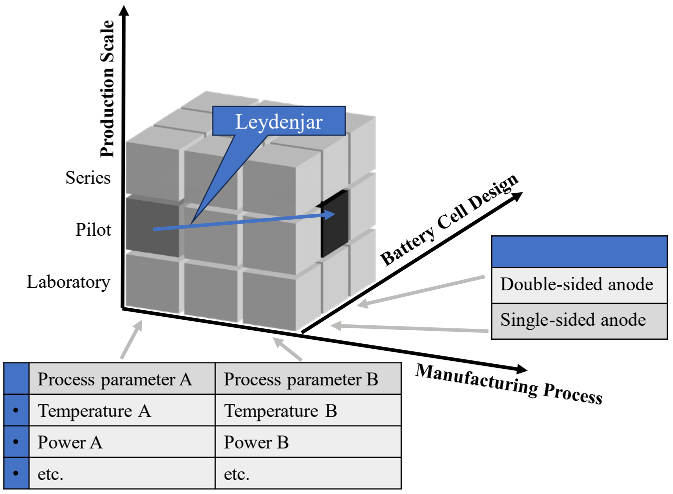

Fig. 7. “Transfer Learning Cube” for Leydenjar`s scenario.

4.2. Production scale up from lab to pilot line (PowerCo SE)

The next use cases have been developed in cooperation with the cell manufacturer PowerCo SE. PowerCo focuses on ramping up battery cell production to cover the constantly rising demand for automotive applications. Additionally, of high importance for the company is to optimize the design and performance of battery cells through research and development to create competitive advantages.

To accelerate the upscaling process of battery cells, early deployment of ML models in the production ramp-up, such as those described in [10], could be beneficial. However, early use of ML models is hampered by data and concept drifts due to the large number of experiments in the laboratory phase. Furthermore, the upscaling process is characterized by different cell formats. At the beginning, smaller cell formats like coin cells or single-layer pouch cells are used to reduce experiment costs. After a cell design is found, which should be further developed, the manufacturability needs to be checked with industrial sized production processes. This ultimately leads to changing manufacturing processes and an increased dissimilarity in the data of the first upscaling phases.

To overcome these challenges, TL is a promising method to improve the utilization of ML models in the upscaling process of battery cell production and accelerate the product development process. Fig. 8 shows the classification of the use cases of PowerCo into the “TL Cube”. The example contains three use cases with different complexity levels regarding their feasibility. As complexity increases, so does the difference between manufacturing processes and cell design. The highest feasibility is expected in use case 1.

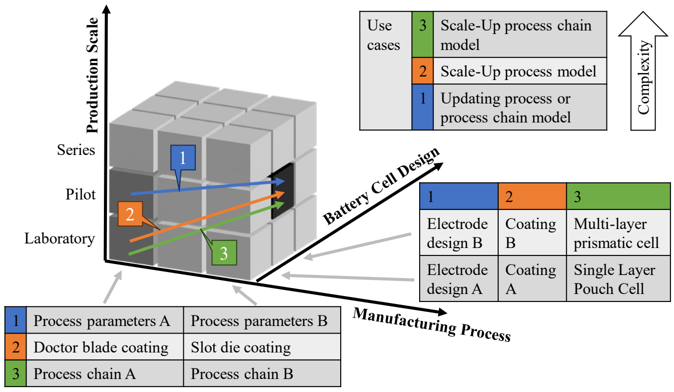

Fig. 8: “Transfer Learning Cube” for PowerCO SE`s scenario.

Use case 1 (Fig. 8, blue) is similar to the one presented by Leydenjar, but has a different motivation. In this use case, a new electrode design has successfully been tested on laboratory scale and is now to be produced on pilot scale. In pilot production, a ML model is in use based on the data of a previous electrode design A. This ML model is for example utilized for predictive quality, to reduce the scrap rate. Applying this ML model on the new electrode design B presumably leads to a reduced accuracy of the model. This is caused by necessary changes in the manufacturing process, which are categorized as process parameters A and B on the corresponding axis of the TL cube. Fig. 9 illustrates that the ML model, which is updated to the new electrode design, can be a process or process chain model.

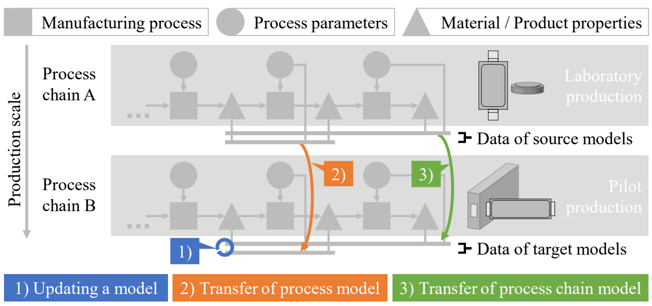

Fig. 9. Differences between the use cases related to the production data used.

A more complex application of TL in the upscaling process is transferring a ML model from laboratory scale to pilot scale. This is described by use cases 2 (Fig. 9, orange) and 3 (Fig. 9, green), which differ in the number of process steps included in the ML model. It is assumed, that the transfer of a process model is easier than the transfer of a process chain model. This assumption is based on the fact the amount of dissimilarities increases with more process steps. The utilization of the ML models is similar to use case 1, as the aim is predictive quality and a faster ramp up of the manufacturing process.

In use case 2, the transfer takes place from a coating process using the doctor blade technology to a coating process using slot die coating. Regarding the cell design axis of the "TL Cube", the coating properties are expected to vary. Use case 3 considers a transfer from process chain A to B, which includes different manufacturing processes and at different production scales. The cell format in laboratory production is a single-layer pouch cell and in pilot production a multi-layer prismatic cell.

5. Conclusion and outlook

In this paper, we proposed a conceptual framework named "TL Cube" for discovering the adaptation of TL in battery manufacturing system across three key dimensions: production scale, manufacturing process, and battery cell design. The three dimensions represent parameters from a general perspective in battery manufacturing that vary frequently and require optimization considerations. Two exemplary use cases are illustrated and demonstrated based on the proposed framework. Leydenjar has leveraged the "TL Cube" to uncover the potential for recipe transfer within their production line, mainly focusing on process technology aspects. In addition, the potential of TL in the upscaling process of battery cell production was identified using examples of PowerCo SE. These examples are visualized utilizing the "TL Cube". Therefore, the framework could serve as a guide for the practical application of TL in battery manufacturing systems.

In future works, the framework will be a starting point for TL adaptation in battery manufacturing systems. With a comprehensive understanding of the transfer background provided by the "TL Cube," experiments of specific TL approaches in battery manufacturing system can be conducted, such as fine-tuning and domain adaptation. The potential of TL in battery cell production to speed up the existing ML approaches under the constraint of sparse data for new manufacturing scenarios will be investigated as well with the support of the "TL Cube". Additionally, the "TL Cube", initially tailored for battery manufacturing, can be adapted to other manufacturing domains due to its versatile concept.

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