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Interdisciplinary Data Driven Production Process Analysis for the Internet of Production

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Abstract

Recent developments in the industrial field are strongly influenced by requirements of the fourth industrial revolution (I4.0) for modern Cyber-Physical Production Systems (CPPS) and the coherent phenomenon of industrial big data (IBD). I4.0 is characterized by a growing amount of interdisciplinary work and cross-domain exchange of methods and knowledge. Similar to the development of the Internet of Things (IoT) for the consumer market, the emergence of an Internet of Production (IoP) in the industrial field is imminent. The future vision for an IoP is based on aggregated, multi-perspective and persistent data sets that can be seamlessly and semantically integrated to allow diagnosis and prediction in domain-specific real-time. In this paper, we demonstrate an exemplary scenario of collaborative cross-domain work, in which domain-experts from largely different fields of expertise, i.e. heavy plate rolling (HPR), injection molding (IM) and machine learning (ML), generate insights through data driven process analysis in two use cases. Specifically, in the HPR use case, reinforcement-learning was utilized to support the planning phase of the process aiming to reduce manual work load and to ultimately generate process plans that serve as a foundation for a simulation to calculate process results. On the contrary, in the IM use case, supervised-learning was utilized to learn a complex and computationally demanding finite element simulation model in order to predict process results for unknown process configurations, which can be used to optimize the process planning phase. While both use cases had the overall goal to utilize ML to gain new insights about the respective process, the actual ML application was utilized with reversed purpose. Particularly, in the HPR use case, ML was used to learn the process planning in order to calculate process results while in the IM use case, ML was used to predict process results in order to improve the process planning. We facilitate the communication between physically separated domain experts and the exchange of gained insights in the respective use cases by a framework that addresses the specific needs of cross-domain collaboration. We show that the insights gained from two largely different use cases are valuable to the domain experts of the other respective use case, facilitating cross-domain data driven production process analysis for future IoP scenarios.

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Keywords: Production Technology, Industrial Big Data, Internet of Production, Heavy Plate Rolling; Injection Molding; Machine Lerarning;

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1. Introduction

A major challenge of today's modern production systems is to be flexible and adaptable while at the same time being robust and economically efficient [1]. According to the German Federal Ministry of Education and Research, the requirements of Cyber-Physical Production Systems (CPPS) in the era of the fourth industrial revolution, frequently noted as Industry 4.0, are driven by the Internet-of-Things (IoT). The key requirements of such CPPS are characterized by a “demand of strong individualization of products under the conditions of highly flexible large series production, the extensive integration of customers and business partners in business and value-added processes, and the linking of production and high-quality services leading to so-called hybrid products.” [2]. In order to satisfy those requirements, more and more modern production systems feature rich sensor systems to facilitate the acquisition of data during the production processes. In combination with learning algorithms from the machine learning (ML) domain, such data promises to obtain comprehensive information about the state of the product, machine and process. However, the utilization of sensory data acquired for such advanced purposes is generally not an easy and straight forward task. While many machine learning methods are well tested in typical machine learning subdomains such as computer vision (CV) [3–10] or natural language processing (NLP) [11–16], their practical applicability in production technology (PT) domains are a matter of current research, when process chains are approached from a holistic perspective.

While the development of the production technology sector passed through several industrial revolutions starting as early as in the 18th century, the machine learning domain is a comparatively young domain and developed under majorly different circumstances and with different goals. Therefore, every attempt to utilize machine learning methods for the production technology sector poses the key challenge to overcome the gap in background knowledge and methodology between experts of both domains in order to develop a suitable machine learning application for a specific use case. Bridging this gap is an essential step to develop an IoT in the production technology sector, the internet of production (IoP). The concept of the IoP addresses challenges of today’s manufacturing landscape that is characterized by numerous PT-subdomain-silos that comprise sophisticated and specialized models (e.g. simulation or experiment-based) and data. The continuous advancement in each subdomain leads to a high heterogeneity and restrains accessibility of data and knowledge across subdomains. Even the instant and direct access on data from adjacent processes (e.g. milling to heat treatment) is hardly possible and engineers often work with outdated information from other subdomains. Sharing domain knowledge, models and data across all relevant engineering subdomains would provide the ability to increase productivity and agility. A cross-domain data access could provide completely new opportunities for producing companies by combining vertical integration within a domain and cross-domain horizontal collaboration. The vision of the IoP is to enable data-driven cross-domain collaboration by providing semantically adequate and context-aware data from the production technology sector.

In this paper, we demonstrate an exemplary scenario of collaborative cross-domain work between domain experts of three largely different fields of expertise. The scenario contains two use cases from the production technology domain, a heavy plate rolling process and an injection molding process, and aims to gain insights about the two different processes utilizing the respective process data and suitable data driven machine learning analysis methods. Therefore, experts from the production technology domain need to provide the necessary information about the details of the use case and the origin and meaning of the data for the machine learning experts to apply analysis methods purposefully and goal oriented. Subsequently, the machine learning experts need to provide the necessary information regarding the choices of analysis methods and the corresponding results in a consistent way for the domain experts to comprehend the results and the methods with which they were obtained.

We facilitate the communication and the exchange of process data, analysis methods and results between the different collaborators with a custom-made framework. The framework provides a fixed workflow to facilitate the exchange of domain specific knowledge between experts in the production technology sector and the machine learning sector (see Fig. 1). The workflow starts on the production technology side and requires a domain expert to provide information about the process of interest and associated process data that is available. The combination of the provided domain knowledge and the process data is fueled into a schematic visualization

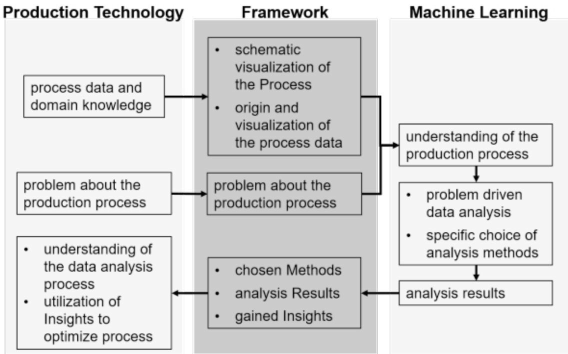

Figure 1: Schematic illustration of the workflow about data and knowledge sharing between the production technology and machine learning domain utilizing the framework.

that utilizes an animation of the process and provides information about the origin and meaning of the process data. Furthermore, various kinds of data visualizations are available to provide an overview of the available data. Thus, experts from the machine learning domain are able to build an understanding of the process of interest and the associated data. The required formulation of a specific problem of the process allows for problem driven and goal oriented data exploration and subsequent analysis. Once a specific analysis on the data is finished, information about the used methods and the results need to be uploaded in relation to the formulated problem of the process providing valuable information about how the data was analyzed and what specific methods were chosen for the specific problem. Thus, process domain experts are able to better understand the data driven process of gaining new insights about the process and are able to utilize this knowledge to optimize their processes.

After this brief introduction, the following section deals with the state of the art regarding the utilization of data analysis and specifically machine learning in the production technology sector. Subsequently, the results of our two example use cases are presented, followed by a discussion of the beneficial combination of the insights gained in both use cases. Finally, we conclude with a summary and an outlook discussing the contribution to the vision of the IoP.

2. State of the Art

In general, model based and data driven methods for process monitoring, analysis and optimization can be distinguished. Data driven methods are characterized by low design effort and a simple form while some of them additionally offer the ability to handle even large amounts of data efficiently. However, they have difficulties with dynamic production processes and varying operating conditions in industrial environments [17]. Model based methods based on prior physical and mathematical knowledge of production processes are well suited to handle dynamic and nonlinear behaviors of industrial processes. Due to the necessary knowledge, they require experts in the domain of each individual production process [17]. Whereas in production technology, model based methods are still important especially for the machine and control level of production processes, data driven models gain importance due to the availability of more and more data and the ongoing digitization of the production industry [18]. For this, the cooperation between data scientists for the application of machine learning and production experts is necessary.

The machine learning domain comprises a huge variety of algorithms and techniques for different kind of tasks and purposes (e.g. for prediction or optimization). In general, the field of machine learning can be categorized in three major paradigms: supervised learning, unsupervised learning and reinforcement learning [19–21]. While the latter deals with creating an intelligent learning agent that develops a certain solution on the basis of interactions with its environment, supervised and unsupervised learning deals with extracting unknown but useful patterns of data.

Each of these paradigms can be implemented on the basis of certain machine learning models that mainly differ in their capabilities of handling complex problems, their computational performances and their ability to handle sparse or noisy data [19,20]. One of the most recently researched techniques for this purpose are (deep) artificial neural networks (ANNs) [22,23]. Currently they are successfully applied in different fields of computer science and cyber-physical systems (e.g. image recognition in self-driving cars). ANNs can be used for reinforcement learning as well as for continuous and discrete predictions in supervised learning.

The collaboration of data scientists and production technology domain experts is necessary for a faster and goal-driven analysis of production data, which aims at the enhancement of production processes. The idea of collaborative work is not new though. Interdisciplinarity has gained increasing acceptance since the 1970s and solutions to overcome its challenges are established in various fields, such as environmental and social sciences [24]. Many of them tackle interdisciplinarity from an organizational and ergonomic perspective with the aim to foster personal collaboration (e.g. by building interdisciplinary centers and departments). In addition to that, virtual environments become increasingly important for collaborative work and learning. Thereby technical systems such as wiki systems, mailing lists, and document management systems provide solutions for knowledge sharing and communication between experts of different fields [25,26].

Nowadays, a variety of platforms and workflows for process data analysis are subject of research and everyday production. Various state of the art data analytics platforms that utilize Apache Hadoop and algorithms such as map reduce, provide a convenient service for data scientists for a faster development using reusable modules [27]. Some platforms consider domain specific use case scenarios of manufacturing processes including workflows for life cycle inventory analysis or the integration of computer aided-technologies e. g. for milling and drilling [28,29]. The scope of these systems usually includes only one type of production process. More scarcely, machine learning is applied on a scope of a hole production chain [30] and for several production processes, which are used at a single production site, on product basis [31]. In any case, the systems are customized to very specific needs of a production scenario and aim and an optimization of the product or the complete production system [32].

A cross domain exchange of information and knowledge regarding the application of machine learning in different production processes does not exist according to the knowledge of the authors. However, such an exchange not only between data scientists and engineers but also in-between different production processes could be highly beneficial. Duplicated work could be avoided and effective methods could be shared and developed. An example for a framework for cross domain exchange between production processes is the model-based self-optimization framework. However, the intention of this framework is not the application of machine learning but the integration of advanced control concepts and a shared architecture to achieve self-optimizing properties for different production processes [18].

3. Use Case #1: Heavy Plate Rolling

The first use case comes from the production technology domain of heavy plate rolling and deals with a metal forming process aiming to produce thin metal sheets. This section provides a summary of the most important points regarding the description of the use case, the used methods and its results, however, the details about the application of reinforcement learning for the design of pass schedules can be found in our previous work [33].

3.1. Use Case Description

Heavy plate rolling is quantity-wise the most important metal forming operation worldwide [34]. During heavy plate rolling, the thickness of a work piece is reduced by passing between two work-rolls whose gap is smaller than the work piece height (see Fig. 2). The rolling process consists of multiple of those passes, summarized in the pass schedule, in which the casted ingot is rolled into semi-finished or finished products. The final product properties like strength, creep and fatigue resistance are determined by the continuous evolution of, inter alia, mechanical properties, temperature and grain size during the passes.

Due to its relevance, a plethora of mathematical models, e.g. RoCaT [35] and Slimmer [36], exist that can accurately predict this evolution and hence the resulting product properties for industrial pass schedules. However, designing an optimal pass schedule is mostly based on expert knowledge due to the dependency of each passes result on all previous passes.

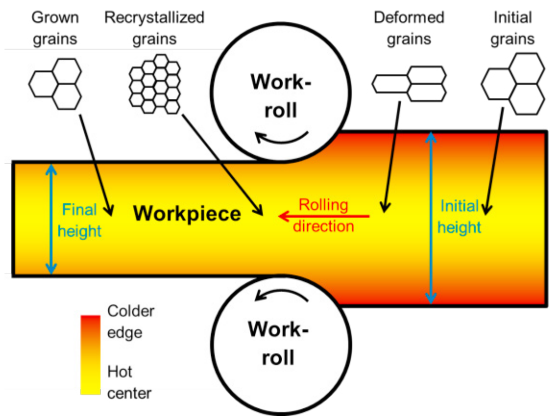

Figure 2: Schematic illustration of the rolling process including the temperature distribution and grain size evolution during a pass.

This leads to complex interactions between process parameters, material properties, machine boundaries and product properties as well as the multitude of optimization objectives being simultaneously relevant [37] (see Figure 3). The intended height reduction (a process parameter for each single pass) determines the strain based on the material properties which influences the product properties such as the grain size. However, the maximum possible force exerted by the work-rolls (a machine boundary) limits the maximum height reduction. In addition the strain is accumulated over all passes. A different evolution of the accumulated strain therefore entails a different grain size evolution. Thus, finding a pass schedule that reaches the final product properties is a difficult task as it is. However, if further optimization objectives, like minimal energy consumption, reproducibility or minimizing machine wear, are introduced the task cannot be formulated as a closed optimization problem.

Thus the problem is typically solved by backwards iteration, i.e. starting from the finished product, designing the previous pass and then using the mentioned models for a forward calculation to make sure the specifications are still met. This procedure is repeated until the initial product specifications are the origin of the pass. However, after the initial design much experimental iteration is still required to obtain a working solution entailing significant additional financial expenses. Hence, the goal of this use case is to introduce experts from the machine learning domain for the design of pass schedules. The goal is providing a proof of concept for the applicability of machine learning to pass schedule design in heavy plate rolling. Ultimately this concept aims to enable a decision

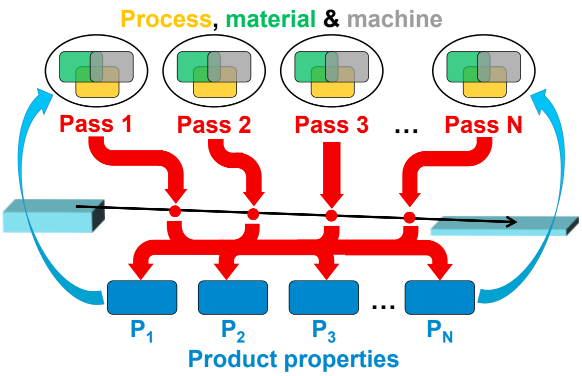

Figure 3: Schematic interactions of the different parameters (process, material and machine parameters) over the course of a pass schedule.

support system helping engineers to design more efficient processes.

In order to educate machine learning experts on the intricacies of the use case and the origin and meaning of the data, we utilized our framework to visualize the heavy plate rolling process in a schematic animation that depicts how the process is executed and what kind of data comes from what source (see Figure 4). The visualization allows to track the change in time of the data, e.g. the temperature of the workpiece, during the process, providing the machine learning experts with the necessary information to perform goal oriented data analysis.

3.2. Methodology

In order to employ machine learning methods for designing pass schedules, a database is required to enable the learning process. About 300.000 pass schedules, totaling over 1.000.000 single passes, are provided with varying process parameters, e.g. inter-pass time, height reduction, temperature and rolling velocity. All pass schedules are calculated using RoCaT and the results as well as the distribution of process parameters are made available in the data base.

For the machine learning application, reinforcement learning is chosen since it allows the users to target specific goals, e.g. a specific height and grain size, by tailoring the reward-function accordingly. As a first step towards predicting full pass schedules with various optimization goals, the reward-function is set to focus on the two most important work piece properties, geometry and grain size. That means, finding a combination of passes that lead to the target geometry and grain size with as few passes as possible. In addition a correction term for the reward-function concerning the grain size is introduced for the linear

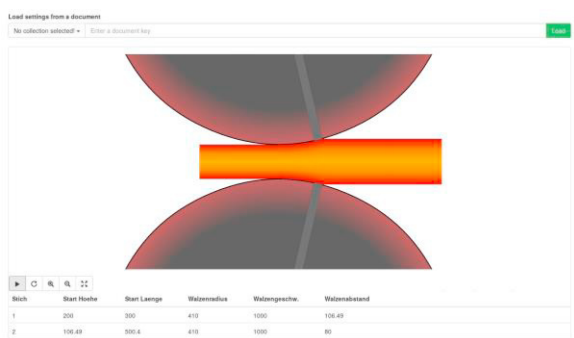

Figure 4: A screenshot of the framework's GUI showing the animation of the heavy plate rolling process.

approach. Since the grain size is usually allowed to be in a range around the desired value a correction term $\lambda(d_t)$ is added. Here the reward is maximal if the desired value is reached exactly but still positive if it is in the allowed range. The reward-function r_t is chosen to be a linear combination of the target grain size and height:

$$r_t = \frac{\Delta h}{h_t - h_{target}} + \frac{\Delta d}{d_t - d_{target}} + \lambda(d_t)$$

where Δh is the height reduction per pass, Δd is the grain size reduction per pass, h_t and h_{target} are the current and target height, d_t and d_{target} are the current and target grain size respectively and $\lambda(d_t)$ is the correction term for the grain size. The details of the reward shaping process, especially regarding the correction term $\lambda(d_t)$ can be found in one of our previous works regarding the use of reinforcement learning for heavy plate rolling [33].

3.3. Results

During the optimization, a pass schedule is compounded via the learning algorithm by choosing each pass from the provided database and applying the reward-function to the resulting pass schedule. Compounding a single pass schedule is one iteration, while finding an optimal pass schedule takes several thousand iterations. During this iterative process the learning algorithm learns to find an optimal pass schedule based on maximizing the value given by the reward-function. This evolution of the learning process is visualized in Figure 5.

After only 1.000 iterations neither the desired geometry nor the grain size, represented by the work piece height and grain size respectively, are met. After 5.000 iterations, they are still not achieved although progress has been made and the desired height is missed only by a few millimeters. It takes 10.000 iterations to consistently find a working pass schedule that meets the desired geometry and grain size. However, the pass schedule is not optimal yet. After around 20.000 iterations the previous solution was improved upon by finding another solution which requires only five passes instead of six passes that achieves the desired geometry and grain size.

Thus, the first application of reinforcement learning to designing a pass schedule for heavy plate rolling displays promising results and serves as a proof of concept since multi-object optimization is successfully achieved. The details of the methods, especially with

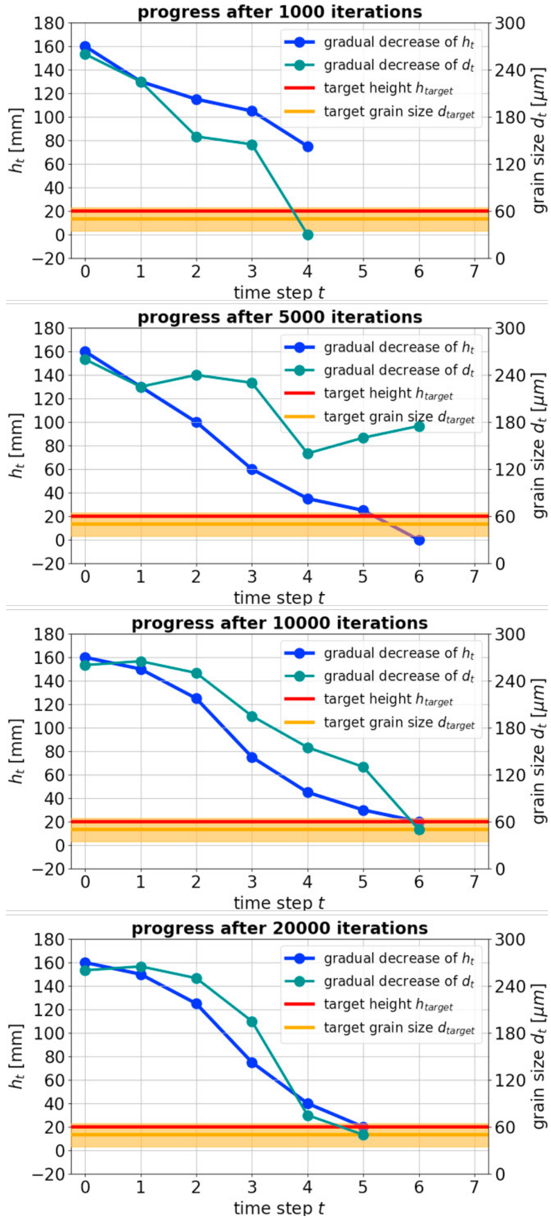

Figure 5: Evolution of the number of passes, height reduction per pass and grain size for various iteration steps.

respect to the reward shaping process and the interpretation of the results can be found in our previous work [33].

4. Use Case #2: Injection Molding

The second use case lies in the field of injection molding process design. This section describes the use case and provides a summary of the gained results from applying supervised machine learning. Further details about the approaches, the used methods and the results can be found in our previous work [38].

4.1. Use Case Description

Injection molding is the most important method for the production of complex shaped products in plastics processing. In the process sequence of injection molding, the plastics material is plasticized by a rotational movement of the screw in the plasticizing unit (see Figure 6). Afterwards, a translational screw movement injects the melt into the cavity of the mold and compensates thermal shrinkage by applying a packing pressure. In the mold, the plastics material cools down until the completed molding can be ejected. During the startup of an injection molding process, the operator has to determine suitable process parameters for a production, which provides the desired quality features. In the industrial environment, mainly trial and error methods relying on the knowledge of the operator prevail [39]. Therefore, the operator choses settings for parameters such as the injection speed, the mold and barrel temperatures, the packing pressure and the cooling time based on experience and recommendations of the material supplier. The settings are varied until the desired part quality is realized. In the scientific environment, many approaches to optimize and systematize the process set-up have been analyzed. Therefore, knowledge-based approaches as well as methods relying on machine learning have been applied [40,41]. Due to the high dependency of the process on the geometry of the molded parts, knowledge-based systems are only useful if a lot of data of very similar parts are available [42]. Machine learning methods rely on data obtained in a design of experiments or during the ongoing production. This data is only valid for a specific part and material. For new parts, the design of experiments has to be performed all over again in form of expensive

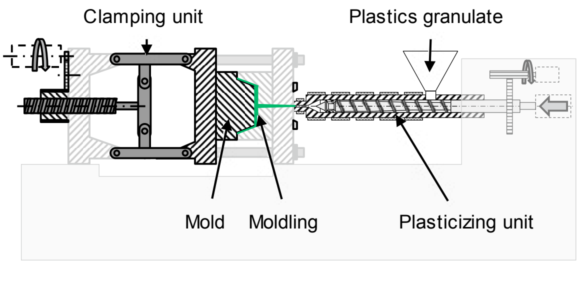

Figure 6: Schematic illustration of the injection molding process.

injection molding trials [40]. Therefore, the application of machine learning for the process setup could not yet be established in an industrial environment. In the future, however, approaches to transfer insights gained from process data to similar yet unequal processes could provide solutions for this in an IoP environment. Until now, the data basis in single production sites are too small to generate enough data under similar conditions.

In the field of injection molding, a variety of numerical simulation tools such as Moldflow (Autodesk, Inc., Mill Valley, USA) or Cadmould (Simcon kunststofftechnische Software GmbH, Würselen, Germany) enable a prediction of effects of certain process parameters and design choice to process and product quality. Most simulation software tools discretize the cavity and possibly the mold into finite elements and use the Hele-Shaw model to predict the flow behaviour of the melt and determine velocity, pressure and temperature fields [40]. Design of experiments and optimization of parameter setting can be performed based on simulation software without the need for practical experiments. However, the necessary simplifications and assumptions cause inevitable differences between the real process and the prediction of the simulation [43,44]. Consequently, optimized parameter settings obtained from simulation software can only be a starting point for the process set-up at the injection molding machine.

4.2. Methodology and data basis

In this use case, machine learning is applied in order to predict the effects on different setting parameters to the part quality enabling an optimization of the process set-up. To correct the inevitable gap between simulation and real data, a hybrid approach using simulation and experimental data is used. This approach aims at reducing the number of required injection molding trials at the machine and consequently facilitate the cost-efficient use of machine learning for the process setup in injection molding.

In order to provide the data basis, injection molding simulations and experiments are conducted to analyze the effects of melt temperature, mold temperature (water inlet temperature), cooling time, injection time, packing pressure and packing pressure time on part weight and dimensions of a simple plate specimen and a more complex box specimen (see Figure 7). As

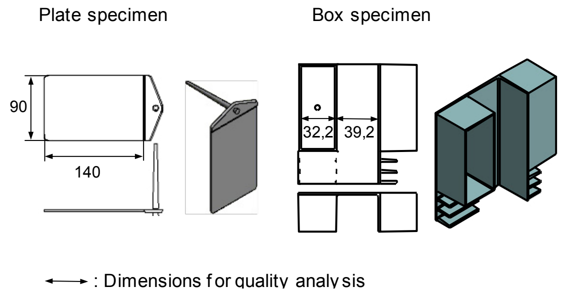

Figure 7: Analyzed specimens in injection molding simulations

material a polypropylene (PP) of type PP 579S (Sabic Petrochemicals B.V., Saudi Arabia) is used. The simulations are performed with the software Cadmould 3D-F. The experiments with the plate specimen are carried out on an injection molding machine of type Allrounder 370A (Arburg GmbH & Co KG, Loßburg, Germany). For the box specimens an injections molding machine of type 160 1000 CX (Kraussmaffei Technologies GmbH, Munich, Germany) is used. For both parts, six parameters are varied in a central composite experimental design with 12-star points, a full factorial design with 64 test points and a central point. The generated data is transformed and stored into the implemented framework that facilitates the collaboration between the injection molding and machine learning expert. For example, data statistics and visualizations help the analyst to retrieve relevant data sources and to gain knowledge about the molding process.

4.3. Results

Both the experimental data from simulations and real experiments are used to create a combined machine learning based approach for retrieving more accurate numerical predictions of quality criteria of molded parts. The main concept is to pre-train a deep neural network on simulation data (so called warm start) and to adjust the model for real experiments. For the evaluation, the coefficient of determination (R^2) is calculated with the cross-validation method [45]. This ensures that the networks are tested on data held back from training.

First results of the conducted analyzes show that a neural network trained only on real experimental data can accurately predict the part weight and the dimensions on the basis of setting parameters. Here, when training on the whole training set of experimental data, the best performing neural network achieves an R^2 test score of about 0.89. However, using prior observations from the simulation for pre-training not only increases the accuracy when using only few experimental data but also increases the stability of the predictions. Figure 8 illustrates the test scores of a neural network - consisting of three hidden layers and using hyperbolic tangent activation functions – when training it on different portions of available training data. Since the convergence of neural networks depends on some random factors (e.g. initializations of network weights, shuffling of data), 10-fold cross validation is used for each portion. The results clearly show that a pre-trained network quickly adjusts itself to the real data and performs better for small data sizes than the network learned from scratch. In addition to the improved predictive performance, the learning results are reached much faster with the combined approach: the number of training epochs (i.e. iterations) is reduced by a factor of 5 to 10.

In sum, it can be seen that transferring knowledge gained from simulation data to real experiments is realizable and beneficial by the use of neural networks. Thereby a network is able to learn the core relationships in the simulated process and subsequently adjusts itself to the real process. The proposed approach offers a great potential to overcome the gap between simulation and real data in manufacturing process planning.

Figure 8: Comparison of a neural network-based combined approach (with warm start on simulation data, blue curve) and traditional approach (only training on experimental data, red curve) on different portions of experimental data regarding the predictive accuracy (R^2-score). For all portions, 10-fold cross validation is conducted (mean curves plus/minus standard deviation)

5. Cross-Use-Case Knowledge Transfer

The vision of the IoP includes cross-domain collaboration and the beneficial exchange of insights between different domains. In this context, beneficial means that a concept for the application of machine learning for a specific use case is transferred to another majorly different use case while utilizing the insights that were gained from the application of the concept in the original use case.

In our cross-domain collaboration scenario, we aim to transfer the insights gained from utilizing machine learning for the process planning of heavy plate rolling to the process planning of injection molding. Additionally, we aim to utilize the insights from the injection molding use case with respect to the combination of simulation data and real-world experimental data for the transfer of the reinforcement-learning agent to the real-world rolling mill. Similar to the exchange of process specific information, data and analysis results between domain experts from the respective use cases and the machine learning domain, we make use of our framework to exchange the relevant information between the domain experts of both use cases to facilitate the exchange of beneficial knowledge and insights from the other respective use case.

5.1. Transfer from Heavy Plate Rolling to Injection Molding

The key result of the application of reinforcement-learning in the heavy plate rolling use case showed that an RL-agent is able to find sequences of single passes that form a pass schedule, which achieves a specified geometry of the resulting workpiece while driving the grain size towards a specified corridor. Figure 5 shows that a solution for a pass schedule with six passes was improved upon, reducing the number of necessary passes to five while maintaining the overall result, i.e. reaching the target height and target grain size. Aiming to transfer the concept to the injection molding use case, the result suggests that current parameterizations of the injection molding process that lead to a workpiece with specified characteristics can possibly be improved upon by training a reinforcement-learning agent with the available simulation data. The agent's goal could be to find a parameterization of the process that leads to a specified result while minimizing for example the total process duration.

Furthermore, the reward-function was modelled in such a way that process parameterizations that are potentially harmful for the rolling mill are punished severely aiming to protect the real-world experimental setup when the RL-agent is transferred to it. The same concept can be applied to the injection molding use case where restrictions of the real-world setup need to be formulated and incorporated into the reward-function when learning with the simulation data.

Furthermore, the functional dependence of the reward-function on the input parameters Δh_t, h_{target}, Δd_t and d_{target}, i.e. whether the dependence is linear, quadratic or trigonometric, results in different nuances of the learned behavior. Depending on the functional dependence, the agent preferably minimizes the number of single passes within a pass schedule or the number of suggested pass schedules with wrong results over the course of the learning procedure. The details of the influences of the reward-function shaping can be found in [33]. Transferring these insights to the injection molding use case, the results suggest that it is possible to ascribe different degrees of importance to the optimization of specific process parameters by shaping the reward-function accordingly. For instance, the reward-function can be shaped in such a way that the reduction of the overall duration of the injection molding process is considered to be more important than the fraction of waste products or vice versa.

5.2. Transfer from Injection Molding to Heavy Plate Rolling

The injection molding use case showed that knowledge from the virtual domain (i.e. simulation) can be used for more efficient planning of the real-world process by the use of artificial neural networks. Thereby, after being trained on virtual data, the model needs to adjust itself to reality by further training on real-world experimental data. Thus, the transfer of knowledge and the additional learning is not done by domain experts but by the trained machine learning model itself. Transferring these findings to the heavy plate rolling use case possibly helps for the next step, i.e. to transfer the reinforcement-learning based planning process to a real-world rolling mill. Here, too, the trained RL-agent could learn to optimize pass schedules that are based on the RoCaT simulation tool and subsequently transferred to the real rolling process. Similar to the result in the injection molding use case, the result would be a more efficient workflow for optimized pass schedules.

The success of such an approach not only depends on the predictive capability and the complexity of a machine learning model, but also on the size of the gap between simulation and reality. Regarding the injection molding use case, the evaluation results indicate a sufficiently small gap: the model achieves high performances even with few real data. In fact, when looking at the simulation and real data, obvious similarities in form, progression, and functional relationships can be observed. The data only differs by an offset regarding the quality output. An artificial neural network can handle this offset, e.g. by adapting some of its parameters (i.e. bias weights), effectively utilizing its learned internal structure when adapting to the real-world process with minimal change of the learned weights. There arise the questions of how the gap between calculated pass schedules from RoCaT and schedules from a real-world rolling mill occurs and how to apply a neural network to bridge this gap.

6. Summary and Outlook

This paper presents two use cases for applying machine learning algorithms to production technology, heavy plate rolling and injection molding. In the case of heavy plate rolling, reinforcement learning was successfully applied to the design of pass schedules. Here a pass schedule that meets the target height and grain size at the same time was designed within 20,000 iterations. For injection molding it was shown that pre-training a neural network on simulation data increases the accuracy and stability when applied to experimental data. This enables more efficient predictions of an optimal process setup by requiring less experimental data.

Within the scope of the IoP, we therefore demonstrated first initial steps to reach the vision of aggregated, multi-perspective datasets that allow prediction and planning by the application of machine learning. To extend these steps, the continuous application of the analytics part in combination with an automatically generated data base will be next steps towards a usage in real production systems. On one hand, the data can be derived from simulations and experiments, on the other hand from real production data.

It was also demonstrated how cross-domain knowledge transfer can be achieved via a common framework. By creating a shared environment for both use-cases and all domain experts it was even possible to achieve Cross-Use-Case knowledge transfer. In this context the insight that pre-trained neural networks improve accuracy for injection molding will probably be transferable to heavy plate rolling. Similarly accounting for machine restrictions during reinforcement learning for heavy plate rolling will be transferable to injection molding if the process setup will be optimized.

Future work will be focused on improving Use-Case specific results. Goals will be including more optimization goals in heavy plate rolling and finding an optimal process setup for injection molding, for example. The transferability between Use Cases also needs to be demonstrated by applying the techniques from one Use-Case to the other and achieving improved results.

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