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Do We Really Know The Benefit Of Machine Learning In Production Planning And Control? A Systematic Review Of Industry Case Studies.

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Abstract

The field of machine learning (ML) is of specific interest for production companies as it displays a perspective to handle the increased complexity within their production planning and control (PPC) processes in an economic and ecologic effective as well as efficient way. Several studies investigate applications of ML to different use cases. However, the research field lacks in research on industry case studies. A broad understanding from a practical perspective and in this context, an evaluation from a data mining and business standpoint is key for gaining trust in ML solutions. Therefore, this paper gives a comprehensive overview of evaluation dimensions and outlines the current state of research in ML-PPC by conducting a systematic research overview. First, the present work provides key dimensions of business and data mining objectives as evaluation metric. Business objectives are clustered into economic, ecological and social objectives and data mining objectives are grouped into prediction accuracy, model's explainability, model's runtime, and model's energy use. Secondly, the systematic literature review identifies 45 industry case studies in ML-PPC from 2010-2020. The work shows that the scientific publications only rarely reflect in detail on a wide range of evaluation metrics. Instead, researchers mainly focus on prediction accuracy and seldom investigate the effect of their results to a business context. Positively, some papers reflect on further aspects and can inspire future research. This resulting transparency supports decision makers of companies in their prioritization process when setting up a future ML-roadmap. In addition, the research gaps identified herein invite researchers to join the research field.

Keywords

Machine learning; Production planning; Production control; Process planning; Economic effect; Ecological effect; Practical reference

1. Introduction

In production planning and control (PPC), the focus is on optimizing production logistical objectives (lead-time, inventory, capacity utilization and adherence to delivery dates), which in turn influence the company-wide targets. Henceforward, the fulfilment of PPC tasks occurs in an environment with several interdependencies, which complicates the corresponding decision process [1,2]. In addition, trends such as shorter product life cycles or higher number of product variants further increase the complexity of PPC [2]. The application of machine learning (ML) can support production companies to overcome the increased complexity within their PPC processes and thus positively influences the fulfilment of objectives [3]. In several studies, the application of ML to different use cases was already investigated, which indicate a positive contribution to fulfilling PPC tasks in comparison to previously used methods [3]. Overall, ML methods are especially used for tasks with high uncertainty or complexity like demand planning, inventory management, lead time prediction or scheduling [4]. In addition, the automation of simple and repetitive tasks (e.g. preparation of shipping documentation) can be supported with ML methods [5]. Supplementary to this, a growing number of publications in this field of research underpins an increased research interest [4]. Even though several studies exist, it seems that authors rarely apply those solutions to a practical context and seldom provide a comprehensive evaluation of the results [6,7]. This means evaluating developed models and also their impact on existing business processes [8–10]. However, this is key to gaining trust in ML solutions and being able to select an adequate solution in a complex decision-making environment, as is the case with PPC [6,2]. The use of new technologies is not an end in itself, but should be understood in order to be able to use it purposefully [8,6,11]. In conclusion, a clear research gap exists in regards to investigating ML-PPC solutions from a practical perspective and providing transparency on the conducted evaluation. Thus, this paper aims in identifying studies which evaluate ML solutions in a practical context and hence due not base on a simulative environment. With answering the research question '*Do we really know the benefit of ML in PPC?*', the basis for real progress in applying ML-PPC solutions is set as the paper aims for more transparency about practical use cases as well as applied dimensions of evaluation.

The research agenda and the structure of the paper consists of five sections: It starts with forming the research question of the paper as presented in this section. Next, the research subject is described by outlining the current state of research in the field of PPC and ML. The section concludes with a research gap, which this paper addresses and underpins the contribution of this work to the overall ML-PPC research field. In order to answer the research question, section 3 expresses the research methodology. On the one hand, by introducing the method of a systematic literature review and the accompanying search strategy to identify a suitable research sample representative of the research object. On the other hand, by setting an analytical framework for the description of the identified research sample and for the analysis of the evaluation dimensions used by the researchers. Both a business management and a data mining perspective are taken into account. Subsequently, section 4 interprets the results of the applied research methodology. The final part of the research agenda and the last section of the paper summarizes key findings and outlines a future research agenda by presenting research gaps. This is a first step towards a comprehensive evaluation of practical applications of ML methods in PPC and thus enabling real progress in adoption.

2. Current state of research

As the previous section outlines, evaluation is key for understanding the benefits and risks of ML applications. In addition, investigating effects of specific ML solutions in practical contexts can provide important insights about dependencies with other processes. So far, researchers have not systematically reviewed the ways of evaluation across the ML-PPC domain. In this context, research does not consider the linkage between the use of ML methods and business as well as data mining objectives of studied industry case studies in PPC as the following section illustrates.

Usuga Cadavid et al. [7] have analysed 93 ML-PPC papers and assigned those to different use cases of industry 4.0, proposed by Tao et al. [12] and themselves. They give a comprehensive overview and among others outline that the majority of studies uses artificial data and less than half of the papers address an actual implementation of a ML model. A closer investigation of the studies using industry data does not take place. In addition, they do not outline different ways of evaluation [7]. Schmidt et al. [4] focus on ML applications and clustered 94 scientific papers according to PPC tasks of a reference model named Hanoverian Supply Chain Model [1]. However, the authors only show a bibliometric analysis without providing further insights. Other authors have either chosen a more precise aspect in PPC like lead time prediction [13] and scheduling [8,14] or specific methods (e.g. fuzzy methods [15] or deep learning [16]). In addition, reviews exist that have a more holistic view on manufacturing processes [17,16] or are taken within the context of industry 4.0

[18] or cyber-physical production systems [19], without comprehensively displaying ML-PPC applications. Most of those studies do not outline a comprehensive evaluation of practical ML applications. However, Alemão et al., Fahle et al. and Bueno et al. study it partially for their field of study. Alemão et al. highlight within their systematic study about manufacturing scheduling how many and which objectives were reflected in the target function of used reinforcement learning (RL) approaches in the identified studies. They argue that scientific research in developing a solution often focuses on too few aspects to be ultimately practical. The aim of their overview is therefore to lay the foundation for establishing reliable solutions that are suitable for practice [8]. Fahle et al., who cover a wide field of manufacturing processes, centre within their study on industrial use cases using ML or artificial intelligence. Within that scope, they have identified 44 scientific papers. That said, they outline the area of application and the used algorithm, but do not present a structured overview of the respective data mining and business objectives [17]. Bueno et al. focus on PPC in an industry 4.0 context and show as part of their analytical framework that 52 out of 102 analysed studies address performance indicators in relation to industry 4.0. An analysis of the 52 studies displays 13 different performance indicators (e.g. cost, flexibility, productivity, lead time, and customer satisfaction). Most of the identified studies depict the impact of smart PPC on cost, flexibility or reliability. However, ML solutions are only marginally investigated and most of the studied papers do not present the performance in the context of a real manufacturing scenario [18].

In conclusion, an increased research interest in practical solutions can be observed. Nevertheless, none of the reviews so far provides a holistic view on practical ML applications in PPC. Instead, many approaches presented by the scientific community are based on simulation data and do not translate to a business environment [7,11]. A comprehensive presentation of industry use cases using ML applications within PPC accelerates future research and eases the adoption by manufacturing companies. By outlining different evaluation instruments for ML approaches in PPC, decision makers of companies are able to prioritize ML use cases in their company more suitable. Thus, this paper conducts a systematic research overview with attention on scientific papers, which record ML approaches within real business processes. There is a particular emphasis on identifying the progress of the scientific community in reflecting on various objective dimensions, as evaluation is fundamental to making actual progress in data mining [10] as well as to receive effective and efficient PPC processes. Especially in PPC, as several conflicting goals exist, a global consideration of goals is important to avoid suboptimal optimizations [1].

3. Research methodology and analytical framework

To meet the objectives of this study, a systematic literature review is conducted to draw insights from scientific literature about existing ML solutions in PPC. As an immense amount of publications exist in the ML-PPC research domain, systematic literature reviews can give a comprehensive overview of the state of research. Systematic reviews provide insights from existing scientific papers and support the identification of research gaps and common patterns. Aims are to enhance the knowledge base on a concrete research topic and enlighten practitioners as well as policymakers [20]. The second part of the research methodology foresees an analysis of the final publications' sample. This analytical framework consists of three questions that contribute to the overall research question of this work.

The literature review bases on the method suggested by Tranfield et al. [20], which was already successfully employed by other authors of the domain [4,7]. As stated in section 2, there is no analysis of the scientific ML-PPC literature in a practical context. The research was performed between 17/12/2020 and 26/01/2021 in the established databases Scopus and Web of Science [21]. Figure 1 summarizes the seven steps of the systematic literature review.

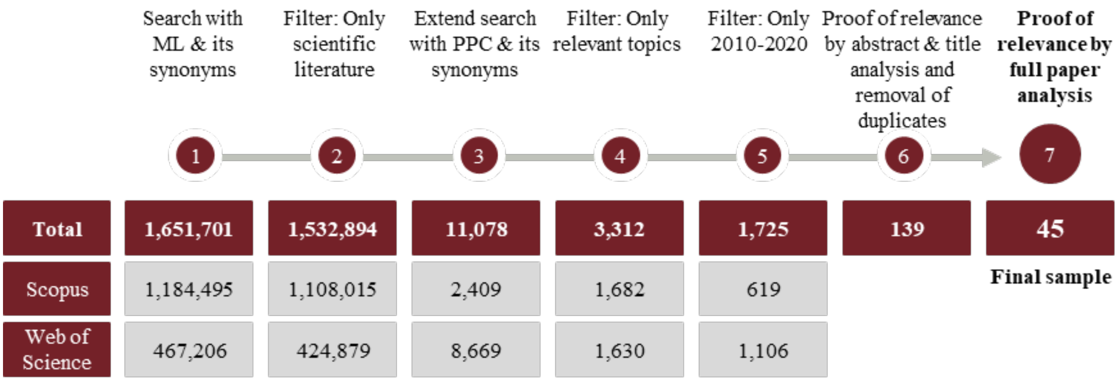

Figure 1: Search procedure of the scientific literature review

The process begins with searching titles, keywords and abstracts of publications within the research field ‘machine learning’ as well as corresponding synonyms. In industrial practice ‘artificial intelligence’, ‘data analytics’, ‘data mining’, ‘deep learning’ and ‘neural networks’ often function as synonyms to ML and are therefore part of the search string [9,10]. The second step foresees a limitation to only scientific literature to ensure high-ranked publications. Henceforward, the search is limited to journal articles and conference papers. In the third step, PPC related terms are added with an AND-function to the search string. As Schmidt et al. point out common PPC terms are ‘production planning’, ‘production control’, ‘production scheduling’, and ‘process planning’ [4]. In the next step, only publications of subject areas, which relate to PPC in production environments, are selected. This is achieved by setting corresponding filters of subject areas (e.g. ‘engineering’) in the databases. In order to facilitate an in-depth analysis – in the fifth step of the search procedure – the sample is limited to scientific papers from 2010-2020. The sixth step foresees to check if abstracts and titles of the remaining publications are mentioning a ML-PPC topic within a production environment. Otherwise, they are excluded. Full papers are necessary for further analysis; consequently, only papers that are available online are part of the final sample. After removing duplicates between the results from Scopus and Web of Science, a sample of 139 scientific publications remains. It should be noted at this point that the assumptions made in conducting the literature search certainly do not lead to a universal identification of all relevant papers. Nevertheless, it can be stated that a representative number of papers were identified and thus a sufficient sample for answering the research question is hereby available. In the final step, the sample is further prepared for performing a detailed analytical framework. Hence, it is necessary to eliminate papers, which do not cover a case study based on real data. Authors who show a simulation-based case study or who do not present a case study cannot contribute to the set research question. It is noticeable that 44.6% of papers show a sole use of simulation data and 23.0% do not examine a case study. In total, the final sample consists of 45 publications. Following, to gain knowledge and insight from the remaining papers, an exploration involves a full paper analysis. This analytical framework consists of three questions that contribute to the overall research question of ‘*Do we really know the benefit of ML in PPC?*’.

The first question is *‘How are the identified studies characterized in regards to their used learning type of ML, the year of publication and the applied use case?’*. By answering those questions, a frame of the final sample is set. First, to make the vast number of ML algorithms more comprehensible, they can be clustered according to their learning type. Common learning types are supervised learning (SL), unsupervised learning (UL) and RL: SL methods use input factors with assigned output as a learning basis. The model learns to recognize and generalize the relationship between input and output data and uses this to predict outputs for unknown examples. In contrast, methods of unsupervised learning are characterised by unknown output data and serve to categorize or segment data. Methods of reinforcement learning learn to take a decision based on feedback loops [9]. Second, by recording the year of publication, it is possible to explore whether the number of publications by authors engaged in real-data case studies has changed over time. Third, applied use cases in PPC are classified. Accordingly, it shows whether some use cases have been dealt more than others have. The analysis bases on the main sub tasks in PPC as the PPC process normally constitutes of several sub tasks in order to handle the planning complexity as well as the different planning horizons (short-, mid- and long-term) [19,2]. In this paper, similar to Schmidt et al. [4], the sub tasks base on the Hanoverian Supply Chain Model and consist of eleven main tasks for fulfilling an efficient and effective planning, control and monitoring of production orders [1].

Afterwards, a structured overview of the reflected data mining and business objectives in practical ML-PPC case studies is presented for providing insights about the final sample of publications. This leads to the next two questions of the analytical framework: *'How many studies have addressed data mining and business objectives? Which data mining and business dimensions were displayed?*. To answer the set questions, clusters for data mining and business objectives are formed, as shown in Figure 2. To begin with, scientists evaluate developed ML models by using different data mining objectives. Common objectives, which form the basis for the analytical framework of this paper, are prediction accuracy, model's explainability, model's runtime, and use of energy [22,9,10]. Prediction accuracy of a model can be measured using various performance measures (e.g. receiver operating characteristic curve (ROC-curve), mean-squared error or root mean-squared error (RMSE)), depending on the problem at hand [10]. Further explanations can be found in [10], [23] and [24]. Evaluating explainability of a model means to reflect on traceability and understandability of a model's result as well as its solution path [9,10]. Methods generally differ between interpretable white-box models (e.g. decision tree) and ex-post explanations of black-box models (e.g. explanations of attributes) as further explained in [25] and [26]. The model's runtime can be differed between runtime during training and during execution of a model. In this course, runtime highly depends on the used hardware and the model's complexity [27]. As the product of time and power is energy, model's energy consumption also belongs to the presented evaluation dimensions [22,9]. A broad overview on different energy-related evaluation methods is provided in [22].

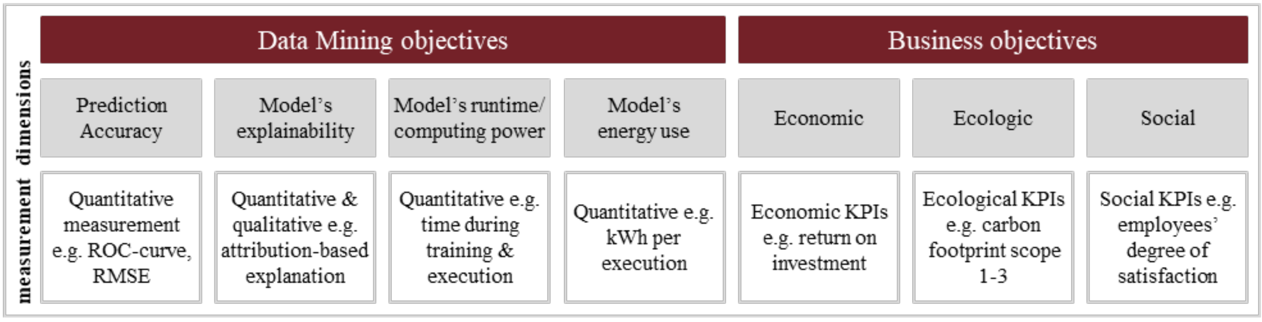

Figure 2: Dimensions of data mining and business objectives, after [28,29,22,9,10]

Next to data mining objectives, a further linkage to an actual business context is as important. In this paper, as shown in Figure 2, numerous business objectives (e.g. return maximization, minimizing carbon emissions) are clustered according to their economic, ecologic and social effect. Business objectives are directed either to one specific cluster or to several ones. In addition, companies usually pursue different business objectives at the same time, which can be neutral, complementary or contradictory to each other [29]. Economic factors usually make up the core of companies' objectives and concentrate on return on investments and its influencing components. Thus, in manufacturing a better process performance is targeted [28]. Nevertheless, as several scientists stress, ecological and social factors are as important as economic factors for attaining a sustainable business [29,7]. Within a ML-PPC context, Usaga Cadavid et al. emphasize that human collaboration and environmental traits should be taken into account when developing a ML model [7]. The ecological dimension contains objectives that seek to reduce the environmental impact. In manufacturing, this is achieved through an improved viable use of resources (e.g. energy, material) [28]. In the light of global ambitions to reduce carbon emissions (e.g. European Green Deal), the ecological dimension might gain additional interest in the near future [30]. Finally yet importantly, the social dimension includes effects on humans (e.g. employees, suppliers) like ethical consequences [31]. Hence, the aim is to reflect on improved work conditions for employees in manufacturing [28]. In a ML-PPC system, for example, the impact on labours' working conditions can be judged [7]. Finally, it should be noted that papers are only counted if they clearly address this linkage in their application section in either a quantitative or a detailed argumentative manner.

Overall, the analytical framework enables a comprehensive investigation of the final sample of the conducted literature review. This paper presents practical use cases in PPC in a transparent way and particularly illustrates the linkage with data mining as well as business management goals. This leads to a comprehensive tool kit for evaluation. In addition, thanks to the research methodology research gaps and areas of focus within the ML-PPC research domain are highlighted.

4. Results

The conducted systematic literature review leads to 45 scientific publications covering real-data-based case studies from ML-PPC research fields from 2010-2020. The fact that many papers were excluded during the review process is in line with the thesis of Usuga Cadavid et al. [7] and Wuest et al. [11], who outline that publications often do not use data from industry use cases. Figure 3 illustrates the results of the first part of the analytical framework, introduced in chapter 3.

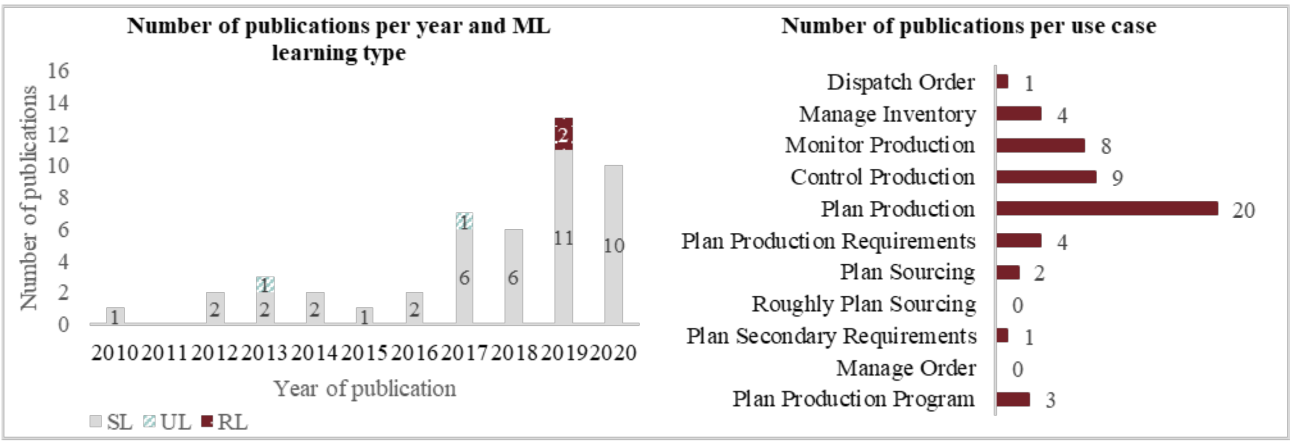

Figure 3: Publications of final sample clustered by ML learning type, publication year and PPC use case

The left side of Figure 3 shows the number of publications per year and ML learning type. From 2010 to 2016, less than three publications apply ML to a PPC use case in an industry context. From 2017 onwards, the number of publications steadily increased with a peak in 2019. Looking at the used ML learning type, mostly supervised learning approaches were identified. Most cases did not combine a learning type with another learning type. The right side of Figure 3 illustrates the number of publications per use case. It clearly displays that the scientific research community mainly applies ML models to 'Plan Production', 'Control Production' and 'Monitor Production'. Within this, to state the three most common sub tasks, 16 publications deal with lead time prediction and its influencing components (for example [32–34]), 8 publications cover production control (for example [35–37]) and 4 publications address sequencing (for example [38]).

Next, Figure 4 and Figure 5 visualise the results of the second part of the analytical framework, that form the key contribution of this paper. The left side of Figure 4 shows the covered evaluation aspects in relation to a ML model itself. It clearly states that most studies (51.1%) purely focus on prediction accuracy. In total, 95.6% of the sample evaluated on prediction accuracy, 33.3% on model's explainability, 22.2% on model's runtime, and none on energy use. The right side of Figure 4 presents the counted publications in regards to reflected dimensions of business objectives. 80.0% of the sample do not evaluate on business objectives.

The remainder reflects on economic (20.0%) and ecologic (2.2%) aspects. Social aspects were not addressed in detail.

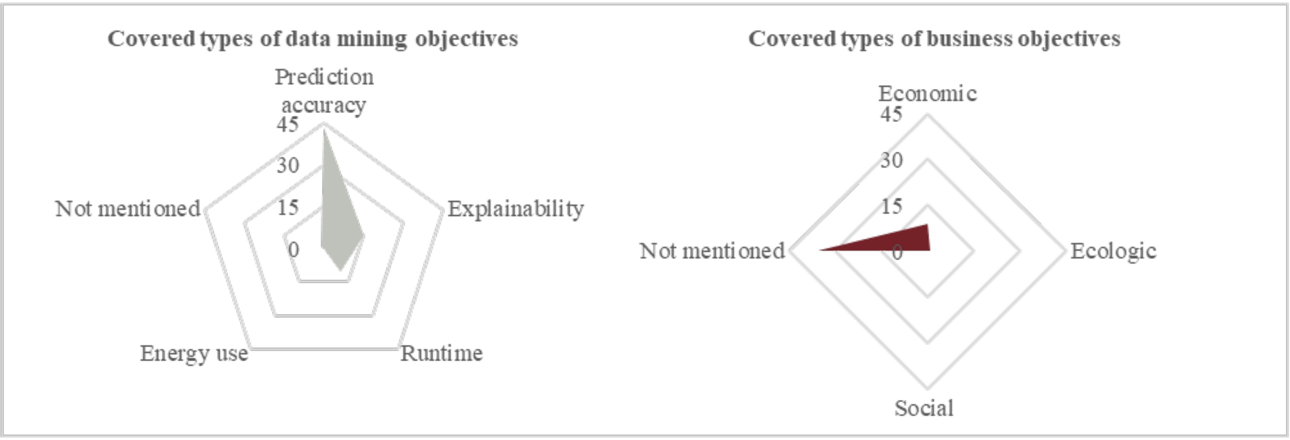

Figure 4: Publications of final sample grouped by types of data mining and business objectives

Figure 5 illustrates how comprehensive the authors evaluate their industry studies. It expresses that most often one or two data mining objectives and zero to one business dimension were reflected. None of the identified papers comprehensively investigates on economic, social and ecologic objectives and simultaneously broadly studies different data mining objectives. In regards to data mining goals, almost all papers (97.8%) evaluated on one data mining objective and 44.4% of the sample reflected on more than one data mining objective. The three dimensions of business objectives are underrepresented as only 9 out of 45 papers address business objectives. A paper of Moerzinger et al. is the only paper that covers two dimensions of business objectives and two data mining goals [39].

DM objective / Business objective	No dimension covered	One dimension covered	Two dimensions covered	Three dimensions covered
No type covered	0	1	0	0
One type covered	19	5	0	0
Two types covered	13	2	1	0
More then three types covered	4	0	0	0

Figure 5: Relationship between data mining types and dimensions of business objectives of the final sample

In conclusion, this section framed the identified studies and outlined a structured overview of reflected data mining and business objectives in industry ML-PPC use cases. The next section considers the results for presenting research gaps and similarities.

5. Conclusion and future research agenda

This work has identified different dimensions of evaluation and has outlined the current state of research in ML-PPC industry case studies. However, two-thirds of ML-PPC studies, published between 2010 and 2020, do not cover real industry cases. A reason could be that it might be difficult for researchers to get access to production data as companies often classify them as confidential. Nevertheless, researchers should aim for applying their developed models to real use cases, as a reality gap might exist between simulation models and real environments. Henceforward, industry use cases form the basis for concluding on potential benefits of ML solutions and for answering the set research question. In total, 45 studies of industry case studies in ML-PPC were found. Within this scope, the motivation of the paper was twofold.

First, the conducted systematic review presents that mainly the PPC tasks 'Plan Production', 'Control Production', and 'Monitor Production' were reflected in real data case studies. This is in line with the findings of Schmidt et al. who investigate this for simulation-based as well as real data-based case studies from 2009-2019 [4]. Still, future research should also aim to address other PPC tasks (e.g. 'Plan Production Program' or 'Manage Inventory). In addition, publications about sequencing are rare herein. It shows that this often addressed research field still lacks in industry application, probably due to a wide spread of RL solutions. In order to apply RL models to real industry cases, a sufficient digital twin is necessary, as the cost for training in a real environment would not be sufficient [10,11]. This might explain the rare findings of RL cases within the final sample. SL models are mostly presented, as several regression and classification tasks exist within PPC [7,11]. In regards to development over time, it can be anticipated, that in line with the generally increasing research interest in ML-PPC [3,4], real industry applications also gain in importance.

Secondly, a structured overview of reflected data mining and business objectives in practical ML-PPC case studies was prepared. The work shows that most researchers do not comprehensively evaluate their ML models in order to conclude on benefits of ML sufficiently. The systematic review displays that ML models were mostly evaluated purely in regards to their prediction accuracy. However, the cost in the sense of time and computation power was regularly not assessed. With an increasing number of deployed ML models within different industries, the energy use should not be disregarded. In addition, time of training gains in a more frequently changing production environment of importance and time of execution is of significance especially for real-time tasks (e.g. in production control) [11]. Thus, clear research gaps exist in these matters. Next to the evaluation of models itself, the models' effect on business objectives is even more underrepresented in the final sample. In total, 80% of the papers do not reflect on business objectives. In PPC, this is of risk, as several contradictory objectives exist: On the one hand, between the economic, social and ecological dimensions and on the other hand also within dimensions. As from the current nature of PPC, research is economic driven [1]. This might explain why those business objectives are more often presented in the identified studies then social and ecological objectives. Nevertheless, future research should consider social, ecological and economic implications for accomplishing a viable business model [29]. Further, as ML-PPC case studies generally focus on specific sub tasks in PPC, it is of importance to reflect on consequences towards other tasks [1,11]. Otherwise, a risk occurs that only sub optimal solutions and not a global optimum is found. In conclusion of this paper, an answer to the set research question – *if we really know the benefit of ML in PPC?* – is given as follows: Currently, due to a lack of a broad evaluation, researchers and practitioners cannot yet clearly state the benefit of ML in PPC. Thus, more industry case studies across different ML learning types and use cases are needed in future research and researchers should evaluate their results broadly. Consequently, the findings can be further developed towards a conceptual framework that enables a broad evaluation metric. This can be supplemented by the state of research from different research fields. Further, a summary of different key performance indicators as well as methods of measurement can enrich this overview.

The work delivered transparency on the current state of research in real ML-PPC use cases. For the future, it can be concluded which dimensions should be considered additionally, when developing ML-PPC solutions. An awareness of different dimensions of evaluation was created, that supports decision makers of companies in their prioritization process when setting up a future ML-roadmap. As previously stated, evaluation is important to making real progress [10], thus researches should join the research field and focus on the research gaps identified herein.

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