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Improving the Planning Quality in Production Planning and Control with Machine Learning

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Abstract – There are always deviations between production planning and subsequent execution. These deviations are caused by uncertainties, e.g. inaccurate or insufficient planning data (e.g. data quality and availability), inappropriate planning and control systems or unforeseeable events. Production planners therefore use buffers in the form of inventories or extended transitional periods to create possibilities for implementing corrective measures in production control. Buffers, however, lead to increased coordination and control effort and to negative effects, e.g. on inventory, throughput time and capacity utilization. Furthermore, it was found that the reliability of the production plans and thus the planning quality (PQ) can drop down to 25% in the first three days after plan creation [1]. Potentials for more accurate planning remains largely unexploited. **The objective of this paper is to investigate the possibilities to increase planning quality. Two approaches are presented, focusing on reducing gaps between master data and predicted data used during the production planning process.**

Keywords – ***production planning,*** *planning quality, master data, prediction, machine learning.*

I. INTRODUCTION

Industry 4.0, cyber-physical production systems (CPPS) [2,3] and the Industrial Internet of Things have a significant influence on production planning and control (PPC). Deploying CPPS raises several challenges for industries addressed in [4], in particular with regard to extraction of knowledge from heterogeneous data sources, interoperations with production information systems as well as changeability, adaptability and re-configurability in production management. Compared to traditional production planning based on a static knowledge base, smart factories enable a collection of real time information and share from and between products, machines, processes and operations [5]. The application and exchange of data by the elements of a smart factory leads to an automated and decentralized production, which is an essential characteristic of Industry 4.0 [6,7]. However, there is a need to study how the different solutions – enabled by digitalization – can support PPC and contribute to an increased corporate competiveness [8].

PQ is a commonly used term in PPC, but evidently, it is not clearly defined. A new definition for planning quality will be proposed by the authors and it is investigated how this suggested planning quality can be used in production planning systems.

II. RELATED RESULTS IN THE LITERATURE

Literature in PPC approaches the phrase PQ from different angles, considering several influencing factors. The first aspect focuses on classical logistical targets of PPC such as flow times, due dates, setup costs or product features. Since accurate and high-quality planning data is one of the most important parts of a good production plan, master data management is an important aspect in our discussion as well[9]. These first two approaches do not deal with (planned or unforeseeable) changes or uncertainties of the production environment, which are typical elements of the paradigm shift towards Industry 4.0 [10–12]. Therefore, robustness and resilience consider such disturbances. A production plan is robust if its performance is guaranteed – even when facing events not known at the time of planning [13,14]. Resilience is, in contrast, the ability of a system to cope with changes of all kinds [15]. Efficient ways of dealing with uncertainty are either applying stochastic, fuzzy models or using adaptive and cooperative approaches [16]. The overall objective of PPC is the creation of reliable production plans, so as their realization on the shop floor should be close to – or ideally the same as – the production plan as originally planned. The deviation between planning and reality on the shop floor increases up to 75% after just 3 days in medium sized mechanical engineering enterprises [1]. It is desirable to have more reliable production plans. Measuring quality of the prediction, as an alternative, may reveal potentials for bridging the gap between planned and actual figures. Besides, the success of a good production plan depends on the process of decision-making itself. In the era of Industry 4.0, the automation of decision-making processes and the level and way of human engagement are essential topics [17,18] as well. It can be concluded that there is no exact definition of PQ. In the paper a novel industry-oriented concept for measuring, evaluating and improving the PQ is going to be developed.

A general truth is that data does not bring any added value on its own, but in practice, domain-specific knowledge and algorithms are needed to extract useful information from heterogeneous and scalable data sources [19]. Simple statistical analysis is often not sufficient as it is time-consuming and oftentimes do not lead to the desired results. Hence, automated data extraction and analytics methods are needed. Together with the rise of data science as one of the most emerging research and application fields today, machine learning (ML) has gained increasingly high attention in the recent past.

At the very beginning of the development of ML, the vast majority of papers were published in journals related to the topic area of Computer Science. However, with increasing demands to computational capabilities and big data analytics, the area is growing, with far-reaching applications in diverse disciplines. Nowadays, many different disciplines use ML algorithms, as was shown in 2012 [20]. The first ML applications in management science can be found e.g. in finance or marketing [21]. In 2009, Choudhary et al. identified that emerging application of ML in PPC has not been systematically explored [22]. However, in the following years, several research papers were published in production management focusing on applying ML for advanced planning and scheduling [23], quality improvement, process monitoring and defect analysis [24]. Yet, researchers did not intensively focus on (sub-)topics relevant for PPC – such as flow time prediction, lot cycle time prediction or lead time prediction, and thus the improvement potentials are not completely identified and used up.

The results of our literature survey determine that the current trend in PPC is to employ ML-based simulation and optimization algorithms. Furthermore, it can be recognized that the focus of purpose in most analysed publications is either on production scheduling (47%) or other applications (33%), while prediction of planning relevant times is rarely (20%) focused as shown in [19].

III. PLANNING QUALITY – DEFINITION AND APPLICATION POSSIBILITIES

Until now, there has been no uniform mathematical definition and no uniform understanding of the term PQ in the scientific literature within the framework of PPC. Therefore, we will briefly explain and define what is meant by the term PQ.

PQ is foreseen as a key indicator for the planner to assess the reliability of the production plan in the planning phase (*time t*) and to continuously improve operational reliability of production plans in forthcoming phases (*time t+n*). In principle, planning quality is high when:

Ideally no deviation, but a deviation in an at least an acceptable range (which can vary depending on different industrial context), between predicted times and actual times (e.g. lead time, set up time, operation time) exists. Reliable dynamic-based prediction models are required to continuously reduce the deviation. Ideally no deviation between planning times and the predicted times exists. A novel data-driven approach is required to generate production plans when times are functions of features, and to evaluate and minimize the gap between planning time and predicted time. The PQI (Planning Quality Index) shall be formulated mathematically in the course of further research to be able to use it as a KPI and for objective decision making.

The application of ML to increase PQ is the main innovation of this paper. The method in which high quality production plans are created lead to the development and evaluation of two possible, but quite different approaches.

Evolutionary Approach:

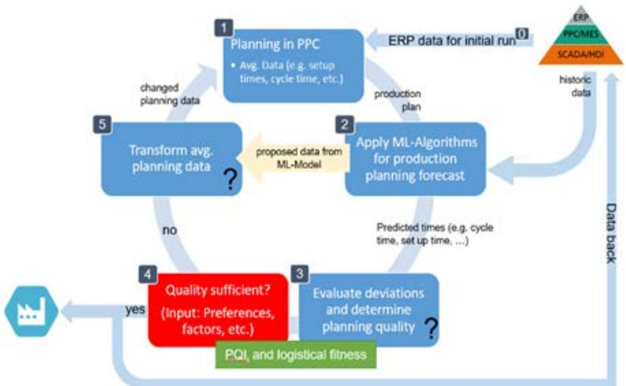

Figure 1. Evolutionary approach

The overall approach consists of six steps, numbered from 0 to 5 while step 1 to 5 run in ongoing loops. It is assumed that in every iteration, the planning quality is increased. This iterative process aims at continuous improvement is the reason why the consortium named the approach

“evolutionary”. The planning starts with the generation of an initial production plan, whereby the planning itself is carried out by the conventional planning system, e.g., ERP or MES of the company, and the planning data is coming from the master data of the underlying system (steps 0 and 1). The production plan is the input for the second step. In step 2, ML models, which have been trained by utilizing historical data from the company prior, are employed to predict different time slices such as cycle time, setup time, operation time, etc. In the next step, the deviations between the planned times and the forecasted times, as well as their impact will be evaluated. The results are summarized in a dashboard, showing the logistical fitness as proposed by Lödding et al. [25], and the newly developed PQ index. Depending on the impact of the deviation, the quality will give feedback about the reliability of the production plan. In the fourth step, the planner will decide whether the production plan meets the preferences and the objectives of the company or not. If not, it will be possible to change the planning related master data by using the support system that is capable of recommending the planner some alternative proposals to change the data. The overall decision, and therefore, the responsibility stays with the human (i.e. human-in-the-loop model) [18]). After the refinement and adjustment of the planning data, the planning can be restarted and the cycle starts again.
If the planner is convinced of the key performance indicators (KPIs) in step 4, he/she can activate the plan and the planning related master data that was used to create the production plan, will be transferred to planning systems. The innovative characters of the proposed evolutionary approach can be specified as follows:

- Providing an evaluation method for the assessment of the production plans in Step 3.
- Creating a dashboard to comprehensibly provide feedback to the planner through visualizing the main KPIs. Establishing a recommendation method for proposing planning data that are more suitable.

Function-based Approach:

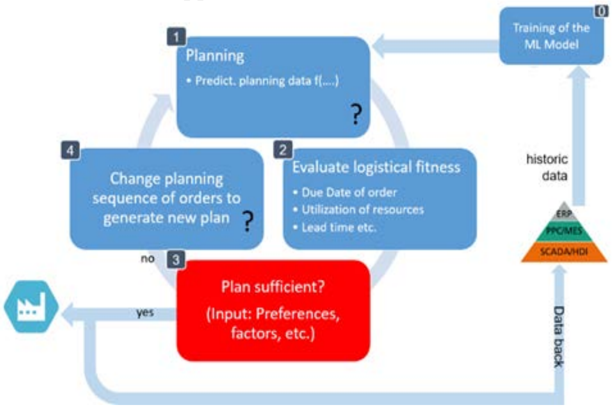

Figure 2. Function-based approach

The second approach differs, as the planning cannot be carried out by the standard/conventional planning system. Whereas in the evolutionary approach the quality of the production plan continuously increases, in the function based-approach, the PQ is always set to high, while the other logistical fitness of the plan will be optimized iteratively as shown in Figure 2.
Step 0 is necessary to generate the prediction models and therefore be done regularly. Based upon these ML-models of the planning related data, a novel planning method generates production plans. The novelty of the planning models lays within the usage of the dynamic set of functions (i.e. an extendable vector of possible functions) for the planning related data and not a single value or a set of values. The general approach looks as follow: orders will be subsequently scheduled, always taking the current information of the production plan as information for the prediction models of the planning related data. Some features for the prediction will not be available at the time of planning, and will therefore these dynamic elements will be predicted with different models. As there is no comparable approach in the field of research, this will be the highest overall innovation within this approach.
After planning the evaluation of the logistical fitness follows. The logistical goal weighting of the company (e.g., avg. lead-time of 6 weeks, timeliness of 87% of all orders, etc.) models the benchmark, a production plan must reach. Since the PQ is already high, only these KPIs must be checked. In Step 3, the planner again decides, whether the plan is acceptable or not. If not, he/she will try another planning sequence. As a support function, the system offers several strategies (based on the order size, due date, costumer priorities etc.) Additionally, the planner can do manual changes. If the sequence is defined he/she starts the planning again. These steps will be repeated until the plan is satisfactory. If so, the plan can be transferred/released to the enterprise resource system (ERP) / manufacturing execution system (MES). In sum, the innovative characters of the proposed function-based approach can be specified as follows:

- Providing a novel planning method for dynamic times.
- Creating a recommendation method to propose changes in the planning sequence.

IV. RESULTS AND DISCUSSIONS

The objective of both approaches is to increase the planning quality in the sense of smaller deviations between planning and subsequent execution. The key is seen in incorporation of uncertainty in the planning phase by carrying out production planning on the basis of dynamic instead of static time values. Only with the use of dynamic time values (e.g. standard times for machining and set-up) the interdependencies of different influencing factors, that occur naturally can be depicted close to reality. These influencing factors can be well known, but most planning system do not offer the possibility to consider them in planning or scheduling activities. In the worst case these influencing factors remain unknown or at least undetected. An example for the former case could be fluctuations in the machining and set-up times per week and/or shift. This is commonly caused by different skill levels of employees or the actual machine or tools that executes the job. Even though these effects are well known, most companies do not have the resources to levy and document all the effects so that a system would be able to process the information. Still this information is available in the past that and ML is able to quantify the impact to some extent.

In order to be able to represent these dynamics as realistically as possible using an ML algorithm, it is essential to ensure high data quality. In both approaches, the prediction provided by the ML algorithm can be as reliable and valid for the actual production system as the underlying historical data source that is used. For further discussion we want to focus on different data sources for MES data. We distinguish between Plant Data Acquisition (PDA) and Machine Data Acquisition (MDA) data. MDA data can generally probably considered to be more reliable compared to PDA data as the actual machine status is automatically captured. E.g. status like "no spindle rotation" and "no malfunction" indicate that the process has obviously been completed and a time feedback via MDA is done correctly. In the same case with a feedback via PDA there can be either a time delay in the feedback of the machine operator or feedback is missing at all.

Therefore, in the case of PDA feedback, higher fluctuations and less quality training data are to be expected in comparison to MDA data. However, this does not mean that the approach is only applicable for MDA generated data or data that is generated with a simulation model of the production system. Longer observation periods and therefore a larger data source help to increase the reliability. In conclusion, it can stated that the use of reality reflecting data is essential.

To insure that the machine statuses are mapped in production planning, it is furthermore important to consider them as input features of the ML algorithm. Depending on the input data of the machine statuses, the underlying causes should be questioned instead of a direct link between the change of the data and a change of the production plan. Example: Under the assumption that the machining times of the machine increase over time, a variety of causes can be assumed, such as a change in the condition of the machine tool or the production machine (e.g. blunt tool, slow feed). In this case, it seems reasonable to invest resources to adjust the machine condition instead of generally increasing the machining times. It is important to provide the production planner with a decision support system in order to present decision options and their effects on the planning system. It seems conceivable to constantly increase the processing times due to a lack of investment in old machines or to restore the original machine condition. In the second case, the actual machining times should be significantly reduced. A major advantage of the function-oriented approach is the not required time-consuming master data maintenance, but instead the approach generates benefits through the dynamic adjustments of the relevant values. However, it should be noted that the logic of the ML algorithm can only create a production plan on the basis of the current data situation. Missing or defective data usually leads to a reduced PQ. Even if the condition of the machine worsens, immediate repair of the machines and the associated shortening of the processing times is generally not to be expected nor is it appropriate. Permanent monitoring and visualization of the machine status, can alternatively be used to initiate measures to reduce production time. As an example, a maintenance or change of the production parameters shall be mentioned. As an ideal solution, the integration of a logic into the ML-algorithm can be considered, which makes it possible to examine data from different data sources, machines, etc.. The algorithm can assist in interpretation and decision making, or if required to perform appropriate weighting of individual data and states. By weighting, the effects of individual influences on production planning can be adapted and implicit knowledge of planning can be represented to further increase PQ.

Evolutionary Approach:

Since this approach uses the existing production planning system, there are fewer interventions in the current, existing system. This means that the existing systems do not become obsolete and can still be used to generate production plans. The evolutionary approach is meant to be an additional decision support system (DSS) to the actual planning system. Within this additional DSS a comparison is made between the planned times and the predicted times (cycle time, set-up time, operating time, etc.), the probability that the planned and the predicted time is calculated in feedback to the planner is given in form of various KPIs and the PQ index. Furthermore the planner gets feedback why a certain time prediction is different from the planned time. Based on the chosen ML method "driver" for predicted times can be identified and give a note to planner. Since the system is an additional system, the implementation is expected to be easier and quicker. Furthermore, the acceptance by the planners is expected to be higher as the actual planning is still done by the existing system. Transparency and sovereignity of the planner about decision-making is an important factor for the acceptance of employees and proves to be a significant advantage of this approach.

Function-based Approach:

As the production plan is created directly using the time prediction models and these models get updated frequently, the quality is independent from the stored master data. Furthermore, the "dynamic" models are always updated automatically. The authors expect this approach to need a smaller number iteration cycles. The reason for this lays in the fact, that the system always uses the planning data, that most likely depicts the later execution. The iterations are needed to meet the objectives for the logistical KPIs. Therefore the number of iterations are expected to be similar to the current number of iterations that are needed today for creating a proper plan. However there are several open research questions that need to be answered. Within the function-based approach the planning algorithm pics one order after the other. This means, that the prediction only considers orders that have already been planned. However, subsequent orders have an impact on the features that are used for the prediction e.g. the WIP when, an order arrives at the same workstation and the prior planned order is not finished. It is therefore crucial to derive correlations from planned orders and unplanned orders in the planning process. According to the authors, further research is needed to define a way in which the necessary features for the time prediction can be determined.

The proposed approach is designed to replace the current planning system with a new planning algorithm. The planner has the option of weighting the KPIs (on time delivery, lead-time, stock, etc.) and thus manually adapting the priorities for production planning. Since the PQ index is always high, it is important to check the corresponding KPIs and only implement the production plan when the KPIs deliver sufficient results. A further advantage of this approach is that, in contrast to the Evolutionary Approach, no adjustments of master data have to be carried out, but a collection of the feedback data is necessary to train the ML algorithm.

Evaluation of the approaches:

For the functionality and correct use of both approaches to increase planning quality, it is also important when which approach is applied. Therefore, in addition to further developing the approaches, attention should be paid to creating an evaluation method for the two approaches. This should clearly demonstrate the advantages of each approach as well as the complexity of implementation and ensure that the right approach is always used depending on the application, the industry and other influencing factors in order to achieve optimal results.

Implementation in ERP/MES:

In order to ensure that both approaches are fully functional and can be used separately from the implemented ERP or MES solution, they must made accessible platform-independently. Different variants of ERP and MES systems in the industry do not represent restrictions for the application of the new approaches. Therefore the transfer of historical data for the training of the ML model is a general solution and must guarantee a data transfer at any time, although the training data can consist of individual characteristics depending on the application case. Even if the accuracy of the production plan prediction increases with the amount of used training data, it is important not to select a disproportionately large amount of data. The horizon of the data also has an important influence. The use of long-term data ensures that the results are based on a long history, while the use of short-term data is suitable for representing outliers and random events. The storage of data duplicates in MES and ERP has to be prevented as well.

In each planning run, only the delta from old and new data is to be transferred, which guarantees speed advantages in the data transfer and keeps the transfer duration low. In fact, data transfers are not only possible for order confirmations, but also for partial confirmations via MES or ERP. According to the current status, however, only historical data of a completed order (order confirmation) is used to forecast production plans. Since the time horizon of the data used can influence the result of the prediction, it is also possible to differentiate between two variants of time-based use. In variant 1, the time horizon extends over the entirety of all training data, with all previous training data having an unknown influence on the result. In variant 2, the time horizon can be individually selected according to the principle of ongoing planning, which has advantages, for example, for the more accurate reproduction of short-term events. It is assumed that old data is less valid and can lead to distortions. In the further course of a research project, the advantages and disadvantages of different time horizons on the quality of production planning will be investigated.

An essential basis for a successful introduction and use of these approaches in ERP or MES is an analysis and optimization of the existing process flows. A large part of the benefits that can be realized by the integration can hardly be evaluated in advance using quantitative criteria. The improvement of the internal production planning is an essential benefit of the presented solution, but its valuable support in the entire order processing is difficult to present. The benefit assessment in particular is considered problematic, since only parts of the achievable benefits can be quantitatively assessed in advance, for instance adherence to delivery dates or error avoidance. Another element that needs to be considered are the basic hardware requirements at the factory level that the constant use of ML algorithms in planning entails. A quantification of the required computing power is evaluated in the course of a research project.

V. CONCLUSIONS AND OUTLOOK

During the work, a mixture of the two approaches was discussed. In the first place an evaluation method for the two approaches should be developed. The function-based approach appears to be smarter due to the usage of a new planning method based on historical data creating a production plan immediately, instead of creating a production plan with master data and then comparing it with forecast data. However, both approaches have to be examined more closely in the further proceeding of the research before an exact assessment can take place.

In fact, production plans are currently created from ERP or MES data. The acceptance level of employees in the planning department depends strongly on the recognisability of deviations between the predicted and the classic (ERP/MES) production plan. This is a clear advantage of the Evolutionary Approach. The confidence of the planner in a production plan, which was created by an unknown planning logic, could initially be low and thus lead to a restraint on the implementation. Therefore, it becomes clear that no matter which approach is chosen, the transparency of the approach must be consistent and comprehensible for the employee. Only if the two approaches are accepted and trusted a correct implementation can be achieved and the planning quality in production planning increased what leads to an optimization of the logistic target values.

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