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Quality in production planning: Definition, quantification and a machine learning based improvement method

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Abstract

The reliability of production plans drops drastically within several days after plan creation. The reasons for the deviation between planning and execution are manifold. Causes can be e.g., uncertainties, inaccurate or insufficient planning data (e.g., data quality and availability), inappropriate planning and control models and systems or unforeseeable events, leading to high control effort in order to reach the desired logistical KPI's, such as due date reliability or lead time. The paper addresses this problem with machine learning and states a methodological approach to measure and improve the quality in production planning. Although the term "planning quality" (PQ) has been used several times by the scientific community, a standard definition of PQ in the field of production planning and a clear distinction to other similar concepts like "robust planning" is still missing. Furthermore, PQ and its application within the production planning process are evaluated with a real industrial use case from the steel manufacturing industry.

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Keywords: production planning and scheduling; resilience; machine learning; planning quality; prediction

1. Introduction

The importance of logistics performance, quantified by delivery time, inventory levels, capacity utilization or lead time, is becoming increasingly important for sustainable business success [1]. Production planning and control (PPC) coordinates all relevant logistics activities along the entire order processing chain and therefore contributes significantly to ensuring the economic realization of the production program reaching the desired logistics performance [2] [1]. Moreover, complexity in planning is driven on the one hand externally due to fluctuations in demand and supply

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within the past two years caused by the Covid-19 pandemic and the resulting crisis [3]. However, this trend cannot be considered as new, but it evolved in the past decades and is likely to continue in the future. Furthermore, complexity within PPC is driven by the interaction between the production system, the increasing number of digital artefacts and the social aspects named as “cyber-physical sozio-system” (CPSS) [4]. This results in increasing complexity and a non-linear behaviour of the CPSS, making predictability even more complex. [6][7][8][9][10]

The production plan as result of the operative planning process is the basis for order and resource allocation. Reliability of the plan is of highest interest for companies, to ensure efficiency as well as on-time delivery. According to Schuh et al. the reliability of production plans drops drastically within several days after plan creation [23]. Generally a wide number of scientific publications deals with the challenge to create more reliable production plans [11].

The reasons for the deviations can be e.g., uncertainties, inaccurate or insufficient planning data (e.g., data quality and availability), inappropriate planning and control models and systems or unforeseeable events [12]. CPSS and the paradigm of Industry 4.0 offer new possibilities for the industry to become more resilient and productive. Cloud computing, big data, artificial intelligence and embedded systems, just to name a few, are enabling technologies and enlarge the capabilities in PPC as more and real time data is available. Research by Dombrowski and Dix and by Bueno et al. shows that the logistics goals of due-date reliability, capacity utilization, and lead time can benefit most from the use of I4.0 technologies, such as ERP enhancements, big data applications, and IIoT in scheduling, capacity planning, and production control. [6] [13]

However, specifically in the area of planning, a large need for research is identified. Explicit reference is made to the need to develop ”intelligent decision support systems, frameworks, architectures, and models to advance and consolidate smart manufacturing planning and control”. [13] The feedback of the knowledge stored in the data represents a central approach for the future planning flow. [14]

Therefore, the objective of this paper is to address this problem and state a methodological approach to measure and improve the quality in production planning using I4.0 technologies. The solution approach builds on historical data analysis and uses machine learning prediction, moreover, contains systematical comparisons of planning, predicted and real data. To start with, the term “planning quality” (PQ), used several times by the scientific community in the past years but not defined and distinguished from terms like, due-date reliability or robust production planning, needs to be defined. Section 2 therefore gives an overview about how quality in production planning is used in the scientific literature. Furthermore, a definition of robustness will also be given, before we enter the PQ and its application within the production planning process and evaluate it with a real industrial use case from the steel manufacturing industry.

2. Literature Review

Production planning is not a static system. This makes the evaluation of (planning) quality difficult. Quality according to DIN EN ISO 9000 is defined as *the capability of a totality of inherent characteristics of a product, a system or a process to fulfill requirements of customers and other interested parties.* In the following the state-of-the art is reviewed in two particular areas, namely planning quality and robust planning, that deals with uncertainties in production systems and tries to create stable plans.

2.1. Planning Quality

The term planning quality has been used several times in the literature in the past. Kempf et al. [15], for example, asked the question about the quality of a production schedule, i.e. how ”good” a schedule can be. For this, it would first be determined that a schedule must first be feasible and acceptable. Feasibility means that no constraints are violated, consequently schedules are physically implementable. Acceptability of schedules, on the other hand, means that the schedule cannot be improved by trivial changes. For answering the question ”what is a good schedule”, it is found that several perspectives are needed to define quality. First, the number of planning schedules to be considered plays a significant role. Here a distinction is made between evaluating only one schedule or several. If only one schedule is analyzed, the result is decisive. It leads to bad quality and execution fail. When evaluating groups, the different schedules are compared with each other.

A further perspective, which has a significance for evaluating of planning schedules, is the distinction between absolute and relative evaluations. For absolute measurement, the average or best historical performance of the factory can be used, possibly as a lower bound in conjunction with the upper bounds mentioned above. For relative measurement, the average historical performance can be used as a benchmark. In a planning problem with multiple competing objectives, the total set of efficient plans is generated, which leads to an additional view of the quality of planning. The decision of how to weigh the different metrics is left to the human decision maker in reality. According to Kempf et al. [15], balancing multiple objectives and competing goals leads to complexity in assessing quality. In addition, quality can also be divided into static and dynamic measurements. Static measurements quantify the outcome of the plan independent of the environment. Dynamic measurements take into account disturbances and determine how robust the schedule is with respect to these disturbances (cf. below)

Gerland and Lesh [16], on the other hand, evaluate the quality of a plan selection algorithm according to the frequency with which a goal is achieved. Conversely, the quality of a plan selection algorithm can also be measured by the number of times a plan is not executed. From this it can be concluded that the quality of a plan is higher if the previously defined goals are achieved. For the evaluation, four risks are defined, which have an impact on goal-oriented planning.

The idea of goal achievement is also pursued by Cavalieri et al. [17]. When assessing quality, a large number of dynamic events must be taken into account. These dynamic events include machine breakdowns, late deliveries, and absences. These factors continuously affect scheduling techniques. These techniques are said to be good when the specified system properties, i.e., goals, are maintained despite the above dynamic events, the internal and external environment.

2.2. Robust Planning

In connection with PQ, the term robustness is repeatedly used. This term is also increasingly discussed in the literature and leads to an inconsistent understanding. Differences are often used as a measure of robustness. For example, the robustness of a schedule can be understood as the maximum absolute deviation of the worst case to the optimal solution (Daniels et al.) [18].

In Bongaerts et al. 1999 [19], robustness is defined under the concept of predictability. This is a measure that defines what is known in advance. It refers to the stochastic distribution of a value and thus indicates with which certainty a variable can assume a certain value or lies in a certain range.

One approach to define robustness is a measure which can be understood as a function of the variability of the objective function value. Consequently, a schedule is considered robust if the variability is lower [20].

In addition to the above definitions on robustness, there are also differentiations and delineations. Herroelen and Leus [21] divide robustness into two groups, solution robustness and quality robustness. Solution robustness is understood as the resistance of the activity start times to the input data. Whereas quality robustness is the resistance of schedule performance to interruptions.

Similar differentiations are cited in the literature between the terms robustness and stability by Goren and Sabuncuoglu [22]. Robust is the term used to describe schedules that still exhibit acceptable performance under unpredictable impacts. Stable schedules, on the other hand, do not show any essential deviation from the original schedule even under disruptions and revisions.

We use the term PQ because we work with *planned* operation or lead times and we systematically compare these planned values with the real and predicted ones. Moreover, the quality and therefore the reliability of production plans might be a good indicator describing the goodness of the production process. However, the definition of robust planning used by Bongaerts and Goren and Sbunsuoglu is very close to our understanding.

3. Evaluating the planning quality in an industrial use case

It was found that the reliability of the production plans and thus the planning quality (PQ) can drop to 25% in the first three days after plan creation [23]. Potential for more effective planning remains largely unexploited. According to our understanding the PQ is high when:

- deviation between predicted and real times is in an acceptable range (depending on the industrial context),
- ideally, no deviation between the planning and the predicted times exists.

In this section the PQ will be defined and illustrated in an industrial use case. For prediction purposes machine learning (ML) learning algorithms will be applied - what is a wide spread approach in PPC in the era of inudstry 4.0 [24] [25]. First an overview on the data structure and dataset is given. Then, the applied main features are presented, followed by the prediction results. Finally, the PQ is defined and discussed.

3.1. Data Preparation

The main data base of the industrial use-case is built by production confirmation data retrieved from the company's ERP system covering 6 years from 01.01.2015 to 31.12.2020. Each record in the confirmation data table corresponds to a production operation and provides key features of the confirmed process, such as order identification, machine number, time stamp as well as product and steel related characteristics. The first step of data preparation comprises the filtering of irrelevant confirmations arising through rework operations, quality checks as well as performance feedback's. In order to avoid biased results caused by partial confirmations and split lots, the authors additionally apply a rule-set for identifying start- and end events of an operation. Based on the included timestamps the filtered and prepared data set can then be utilized for calculating the lead-time for each operation of an order serving as foundation for prediction and planning quality assessment.

3.2. Initial Dataset

After data preparation 83,212 production orders, 876,377 data entries stayed in the dataset. Because of internal processes just one part of this data should be considered in the analysis. First, some start and end conditions must be formulated and applied to filter the dataset (left side of Figure 1 with start and end conditions). Then, the outliers must be removed (arrow on Figure 1). The eliminated data does not represent typical production processes (they have e.g., internal research purposes) and therefore they will not be part of the analysis. After applying the rules – showed in Figure 1 – 62,010 production orders, 764,684 data entries can be found in the dataset. Figure 2 depicts the order lead time distribution with mean and median.

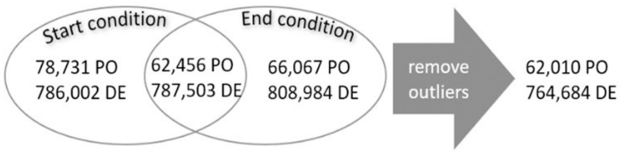

Fig. 1: Number of production orders (PO) and date entries (DE) after filtering and outlier detection

3.3. Main features

Based on previous experiences some initial steps have been carried out in the field of feature engineering. A systematical and thorough feature generation and selection is not part of the current work, this will be done later in the research project. In the current version the following features are used for prediction purposes:

- Wide and thickness of the metal sheets,
- Median of order lead times calculated by quality levels (228 unique values) and batch numbers (7101 unique values),
- Logical variable marking the special production lots,
- Predefined group labels according to frequency.

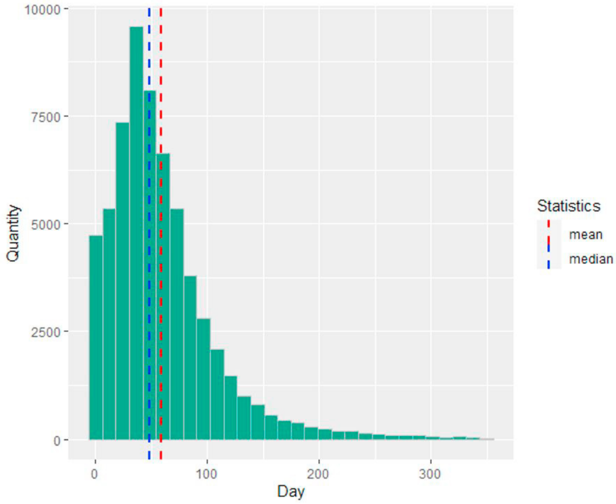

Fig. 2: Histogram of order lead times in day

3.4. Prediction and Accuracy

After chronological ordering the first 70% of the data was used for training and the rest 30% for prediction. The normalized root mean squared error (name, using the minimal and maximal lead time values for the normalization) and R-squared (R2) were used to evaluate the prediction accuracy of a linear regression and a random forest models. As benchmark the mean of order lead times (65 days, depicted on Figure 2) were applied. The results are summarized in Table 1. As the random forest model has the highest accuracy, it will be used for prediction purposes.

Table 1: Summary of the prediction results

Error measure	Benchmark	Linear regression	Random forest
$nRMSE$	14%	11 %	9%
R^2	Inf	0.56	0.57

3.5. Planning Quality

In the given use case the company has planning data on operation level. Production operations are planned for particular weeks. The planned week of the first operation is the planned start of a production order. The planned end of the last operation is identical with the planned end of the production order. The planned start and end weeks of the production orders are available in the ERP system.

The order lead time can be estimated with the help of machine learning models. Using the planned start time from the ERP system and summing it up with the predicted lead time results in the predicted end date of the production order. This predicted end date determines a predicted end week of a production order. In the historical log data the real start and end weeks are available. Comparing the real, actual production order end data with planned and predicted values gives the possibility to evaluate the planning quality. The deviation between real end date and planned (ERP) or predicted end date can be calculated as follows:

$$dev_{plan} = end_{real} - end_{plan} \tag{1}$$

$$dev_{pred} = end_{real} - end_{pred} \tag{2}$$

These deviations defined in with the above equations can have three different values:

- Zero: There is no deviation between the real and planned or predicted dates. In the use case it means, that the production order is finished on the planned or predicted week.
- Negative: It means that the planned or predicted end date is later, than the actual one. E.g., -2 means, that the production order is finished two weeks earlier as it was planned or predicted.
- Positive: A positive deviation is a delay. E.g., 2 means, that the production order is finished two weeks later as it was planned or predicted.

Figure 3 visualizes the planning quality of planning and prediction data on the given dataset related to the log data with the help of a probability density function. The narrower and closer to zero the probability density function is, the higher the planning quality is. The mean of the prediction dataset (-0.28 weeks) is closer to zero as the mean of the planning dataset (1.97 weeks). But the standard deviation of prediction (5.9 weeks) is higher than the one of planning (4.9 weeks).

If both the lower absolute mean and lower deviation belong to the same method, than this method obviously outperforms the other one and results in a higher planning quality. If it is not the case the following considerations might help to find the most appropriate method:

(i) Comparison of the relative standard deviations;

(ii) Comparison of the reciprocal value of the relative standard deviations;

(iii) Comparison the number of orders in a predefined time period.

The relative standard deviation (i) formula can be calculated as follows:

$$RSD = \frac{sd}{\overline{x}} \tag{3}$$

where, sd is the sample standard deviation and $\overline{x}$ is the sample mean. This measure focuses of the deviation of the samples (RSD_{plan}=2.5; RSD_{pred}=40.1). In case of (ii) the sample mean is rather in the focus ($RRSD_{plan}$=0.39; $RRSD_{pred}$=0.02). As an alternative it might be convenient to check the number of production orders with a predefined accuracy (iii). In the given use case it might be stated, that the prediction is in an acceptable range if the deviation is the range [-1;1]. The method with higher proportional rate in the predefined deviation range might be accepted as a more suitable method with higher planning quality. The number of production orders in this predefined range is 38% and 32% for planning and prediction, respectively. The most suitable method for evaluating the planning quality might depend on several issues and might be influenced by several considerations

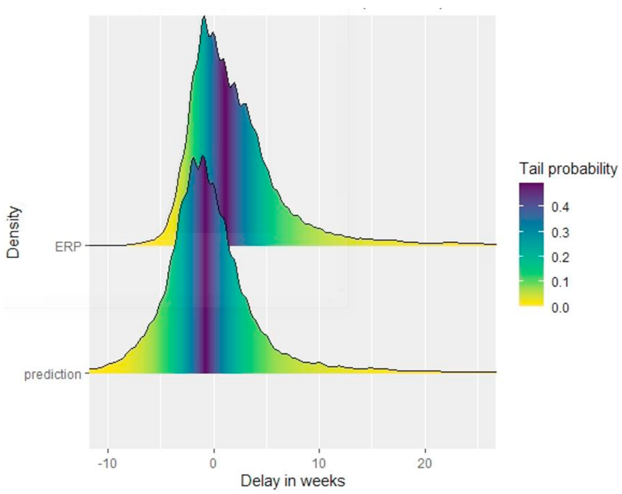

Fig. 3: Planning quality for the analyzed orders

4. Conclusion

The definition and quantification of the PQ was the main focus of the present paper. First, an overview was given on similar production planning related terms quality, planning quality and robust planning. The paper defines planning quality as the deviation between real, actual date and planned or predicted end date of a production order. In the presented industrial use case, concerning the mean of the dataset the the prediction outperforms the currently applied planning approach. However, regarding the standard deviation the current used planning has better performance than the prediction coming from the machine learning algorithms. Considerations have been made how the most appropriate method might be identified.

The next step in the near future will be the application of systematical feature engineering for improving prediction accuracy. A better model performance might result in a narrower probability density function and therefore in a better PQ. As a next step, different time frames will be analyzed. On longer term, different approaches will be developed and applied that might facilitate the practical application of a continuous PQ improvement.

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