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# Model-Based Approach for Assessing Planning Quality in Production Logistics

**TORBEN LUCHT, ALEXANDER MÜTZE, TIM KÄMPFER, AND PETER NYHUIS**
Institute of Production Systems and Logistics, Leibniz University Hannover, 30823 Garbsen, Germany

Corresponding author: Torben Lucht (lucht@ifa.uni-hannover.de)

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**ABSTRACT** For manufacturing companies, reliable production planning and scheduling not only is the basis for efficient order processing but at the same time is an essential prerequisite for the integration and coordination of all participants along the entire supply chain. At the same time, the increasing delegation of planning activities to dynamic software solutions leads to increasing intransparency regarding the planning behavior. It thus becomes increasingly difficult to identify and address inefficiencies or problems caused by the planning processes within industrial supply chains. This paper presents an easy-to-use method for describing, visualizing and analyzing scheduling behavior in manufacturing companies requiring only very few data. In addition, an overview of key planning quality indicators (KPQIs) to be considered in the evaluation of the planning quality is given and structured along the assessment dimensions of plan stability and planning accuracy. The specific application at a maintenance, repair and overhaul (MRO) service provider for complex capital goods demonstrates the benefits and insights to be gained from the model's application, especially in highly dynamic market environments. Using machine learning, characteristic planning patterns can also be statistically determined with the developed description logic and KPQI system.

**INDEX TERMS** Production management, production planning, schedules, stability, data integration.

## I. INTRODUCTION

Production planning and control (PPC) is one of the main beneficiaries of the rapidly increasing availability of data and information resulting from the digital transformation in manufacturing companies. This allows an increasingly more extensive and faster consideration of current system states in planning and control decisions [1]–[3]. Plans that, due to disruptions or other events, can no longer be adhered to can thus be immediately adjusted or "healed" through short-term planning iterations [4]. This generates further planning iterations in addition to the planning cycles that are often carried out periodically (e.g. during the night) [5].

Despite the actuality and accuracy of (production) plans gained through planning iterations, negative effects can also be caused by the dynamics induced in this way (e.g. in demand and production schedules) as well [6]. These include confusion on the shop floor, organizational costs for additional effort in the planning process and fluctuating capacity utilization [7]. Especially at interfaces between areas of the company's internal supply chain such as production and warehousing areas as well as with other companies, serious coordination and synchronization problems or deficiencies in acceptance for the planning system may result [6], [8], [9]. Understanding the company's own planning behavior as well as plan stability and planning accuracy thus forms the essential basis for communicating reliable and robust delivery dates to customers or related business units. It also is a prerequisite to identify inefficiencies caused by the company's planning behavior.

Despite many years of international attention to dynamics in PPC, no suitable, easy-to-use model exists to date that allows a clear description of dynamic planning processes in manufacturing companies and thus provides transparency about their planning behavior. This is why this paper focuses on the research question of how the impact of planning processes on production logistics system behavior can be made transparent and how planning processes can be assessed quantitatively regarding their impact.

First, relevant dynamic-induced challenges in production planning (section II) as well as fundamentals of assessing planning quality including relevant criteria and dimensions

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for the description and evaluation of planning behavior (section III) are structured. On this basis, the plan history diagram (PHD) as an easy-to-use model for the description of plan date histories is developed (section IV) and demonstrated by means of a generic example (section V). Section VI introduces a system of key planning quality indicators (KPQIs) for the quantitative description and analysis of the planning behavior. Finally, their application and potentials for analyzing production systems are demonstrated using the example of a maintenance, repair and overhaul (MRO) service provider for complex capital goods (section VII). Using machine learning, it is shown that planning patterns can be uncovered even in this logistically very demanding competitive environment and thus made accessible for further analyses. Finally, a conclusion is given in section VIII.

## II. THEORETICAL BACKGROUND: DYNAMIC-INDUCED CHALLENGES IN PRODUCTION PLANNING

Dynamics in PPC is not a phenomenon only created by increasing digitalization. Instead, it is inherent in planning as a tool for anticipating future developments of relevant influencing factors [10]. In general, PPC acts as a regulator within a dynamic control loop of production logistics (see Figure 1) [11]. If deviations are detected in production monitoring regulatory measures are initiated. Thus, typical measures to react to deviations are the postponement of individual orders or rescheduling of multiple orders.

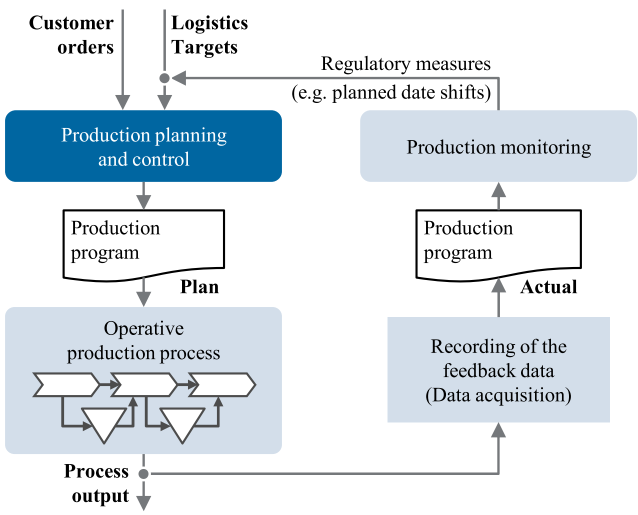



FIGURE 1. Control loop of production logistics (based on [11]).

The level of dynamics also depends on the sensitivity of PPC to deviations from the plan. These mostly result from volatility and variability of environmental conditions as well as from the complexity or the structuring of the planning problem. With elongating or widening planning horizons, this becomes increasingly important, since planning becomes more difficult the longer the events are planned ahead of time [12]. Concurrently, the data required for planning increases, as does the influence of planning-relevant information that is not or only vaguely available [13]. In addition to industrial production, this, in particular, applies to sectors in highly dynamic market environments such as the regeneration of complex capital goods in the MRO industry, where reliable and at the same time ambitious delivery times have to be communicated to customers at an early stage despite sometimes still completely unknown order specifications [14]. Other examples are large-scale projects from the construction industry or research and development [15]. Exemplary approaches of PPC in scientific literature try to meet the challenge of handling dynamics by means of machine-learning [16], [17], but so far often ignore human-in-the-loop aspects [18]. Thus, these approaches do not contribute to the understanding of planning processes.

Besides the organizational handling of dynamics, the availability of data for describing and analyzing a company's planning process in practice also remains a challenge. For example, even modern data warehouses often do not archive plan date histories, as these are neither needed for operational order processing nor used for ex-post evaluations so far. The authors' experience from various projects involving industrial companies shows that, in the long term, usually only the initial and final planning statuses are saved. The extraction of plan date histories often is only possible by restoring daily backups, which requires considerable time and effort in data provision and preparation.

For production logistics, the continuous overwriting of planning data (e.g. planned delivery dates) as a result of planning iterations causes further disadvantages and problems. For example, the planned dates lose their explanatory power almost completely as a reference for the assessment of the scheduling behavior, since all deviations from the plan that have occurred over time are already taken into account in the planning iterations or shifts. As a result, using these planned dates for evaluations, e.g. in the context of production monitoring, is only feasible to a very limited extent and becomes much more like a forecast than a target.

Assessing the lateness of completed orders (Figure 2) based on continuously rescheduled plan dates (a) compared to an assessment based on a fixed initial plan date (b) gives a good example of how key performance indicators (KPIs) can have completely different meaningfulness, depending on what they are based on. It can be seen that the same analyzed orders show a significantly increased average lateness with a significantly higher deviation when referring to the initial, fixed plan date. As a result, even with planning iterations to a smaller extent, interpreting logistics analysis methods requires extreme caution.

In order to master the increasingly complex interdependencies in PPC, companies are more and more outsourcing planning tasks to dynamic (advanced) planning systems (APS) [19] and employ (semi-)autonomous mechanisms in PPC [16], [20], [21]. These are capable to continuously and dynamically adapt planning and control operations to changing environmental conditions [22]. Although this supports and allows raising further optimization potential in PPC, it also leads to an increasing lack of transparency of the planning process making it more difficult for users to follow the systems' processes. This not only makes understanding and operating the systems more demanding but also makes it more difficult to make and challenge fundamental configuration decisions. As a result, these systems are increasingly configured and used without in-depth knowledge of production logistics cause-effect relationships [19].

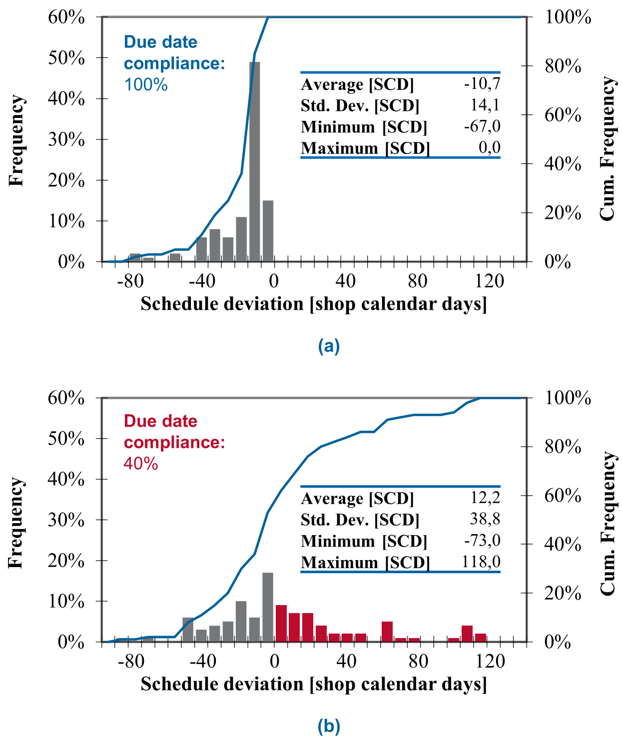



**FIGURE 2. a: Schedule deviation using continuous rescheduling. b: Schedule deviation using a fixed schedule.**

## III. DEFINITION OF PLANNING QUALITY, PLAN STABILITY AND PLANNING ACCURACY

To assess the planning quality, a variety of performance, stability and cost criteria can be used. A basic description of the planning quality as a function of the planning frequency is provided in [5]. Cowling and Johansson [1] also describe the fundamental relationship between planning frequency and plan stability. As a further evaluation criterion, the short-term nature of the planning activities is also taken into account by considering the timespan between a change of a plan and its planned realization. Corresponding examples are provided by Jensen [23] and Dimitrov [24]. These criteria have so far been used primarily in the extension and improvement of planning and optimization algorithms by adding additional constraints or components to the respective objective function. A comprehensive overview of this is, among others, provided by [4], [8], [9], [24].

The variety of assessment parameters listed in the cited work as well as the various terminology used therein shows that an initial definition of the terminology used in this paper is necessary in order to ensure a uniform understanding.

Following, the precision or the degree of congruence of a planned event with its actual realization will be referred to as *planning accuracy*. The term *plan stability*, on the other hand, serves as metric for the consistency as well as the early anticipation of potential changes and corresponding triggers for a planning iteration. In other words, high plan stability means that two successive planning iterations are separated from each other as long as possible and that no or only minor adjustments are made to the plan [9]. In combination, both represent the *planning quality*. In addition, planning quality can be differentiated in several dimensions. A distinction must be made between the *content* dimension and the *date* dimension. The content dimension describes how a plan differs as a result of a planning iteration with regard to the type and quantity of the planned work to be carried out [24]. However, due to the focus of this article, the content dimension will not be discussed in depth in the following. Instead, the focus lies on the date dimension, which focuses primarily on the changes in the remaining throughput time of an event. This represents the time remaining until an event is planned to happen, measured at discrete measurement points over time [6], [24], [25], as well as the number [5], extent and direction of the planned date shifts [8], [26].

Regardless of the dimension, plan stability and planning quality can be considered both over time along the order processing process and at a single point in time. The point in time perspective, e.g. when defined milestones along the process are passed, allows the comparison of several planning objects (e.g. production orders) at a defined point in time. In contrast, the examination of the evolution of a plan date over time addresses the temporal evolution of a plan along the order processing of the respective object of observation (e.g. an order or a project). However, these results can be compared with those of other objects of observation and/or be standardized accordingly. Altogether, four perspectives for the evaluation and comparison of planning quality can be distinguished (see Figure 3).

| | Planning quality | |
|---|---|---|
| | Plan stability | Planning accuracy |
| **Point in time** perspective | Extent of change in the planned dates/contents of an object of observation at a defined point in time along its process chain. | Accuracy or degree of coverage of the planning result at a defined point in time along the process chain with the result that actually is realized. |
| **Timeline** perspective | Quantity, distance and intensity of changes of a planned date / content of the object of consideration along the process chain of the object of consideration. | Chronological development / change of the planning acuteness or deviation along the process chain in relation to the result that actually is realized. |

**FIGURE 3. Perspectives and dimensions for assessing planning quality.**

To visualize the planning behavior described along these assessment dimensions and thus make it transparent, the plan history diagram (PHD) is presented and explained in the following. It serves both as a description model as well as for the definition of important metrics for the definition of a KPQI system for the assessment of planning quality in section VI.

## IV. DERIVATION OF THE PLAN HISTORY DIAGRAM BASED ON THE MILESTONE TREND ANALYSIS

The structure of the plan history diagram is generally based on the milestone trend analysis (MTA), which is widely used in project management. There, it is used to track and visualize the progress of projects and the status of milestones or deadlines over time [15], [27]. A prominent use case is the application of this method as a "Slip-Chart" in the context of NASA's (National Aeronautics and Space Administration) unmanned moon mission "Ranger" [28].

The modeling approach chosen in this paper also leans on the Order Progress Diagram presented by SOEPENBERG *et al.*, which describes the lateness of one or more orders across order fulfillment processes and allows conclusions regarding PPC configurations, e.g. prioritization [29]. Therefore, the measured discrete lateness values at the individual operations are plotted over the respective actual completion date of the process. However, it is important to note that the Order Progress Diagram does not consider planning iterations or planning quality at all; instead, it is more about visualizing throughput time deviations of individual processes compared to average throughput times determined in production planning. Since this paper aims to develop a model for the description and analysis of planning quality, the focus in modeling must be changed and adapted from the observation of individual discrete lateness in the process compared to rigid planning parameters towards iteratively changing production plans in the process and the resulting challenges. Thus, the derivation of the PHD is shown based on the MTA which is thematically closer to the intended model. In general, the MTA can be used to describe changing plan dates or schedules. However, the comparison of plan date history-curves and their interpretation is difficult due to the way of representation. However, with the help of two easy transformation steps (see Figure 4), this can be remedied to derive the plan history diagram.

Figure 4a) shows the basic form of the MTA, which plots the plan date history trend curves of a various number of milestones along the corresponding measurement or reporting dates on the horizontal axis. The bisecting line thus represents all points in time at which the planned date and the measurement date match. The horizontal distance between the respective plan date of a milestone and the bisecting line thus represents the remaining time span until the plan date becomes due. A permanently constant plan date consequently leads to a completely horizontal trend between the starting point and the bisector. If a plan date is shifted into the future (positive date shift), this results in a rising trend. If the plan date is moved forward in time (negative date shift), a falling trend results analogously.

The trend curve, which results from connecting the measuring points, suggests a steady change in the plan-schedule between two consecutive measuring points, which is only recorded and plotted discretely at specific measuring points. However, in practice, plan date shifts are usually done at discrete points in time instead. This is best illustrated by the representation of the planned schedule in the form of steps (dashed lines in Figure 4b).

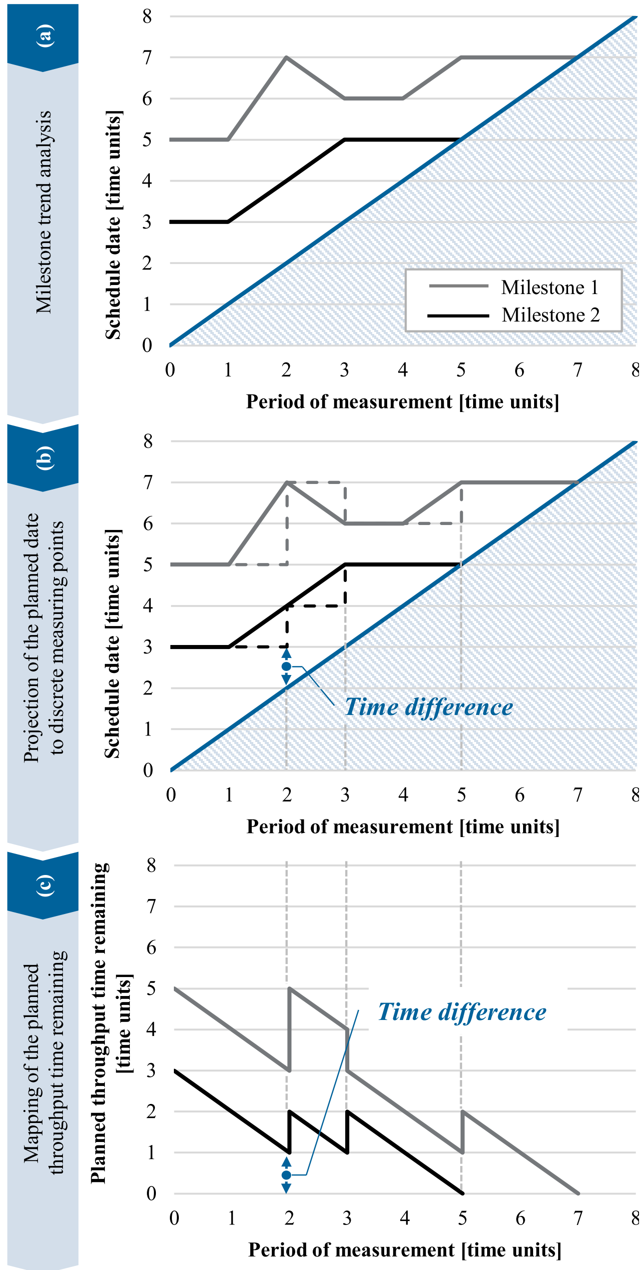



**FIGURE 4.** Transforming the milestone trend analysis into the plan history diagram.

This form of visualization allows easier identification and evaluation of occurring schedule shifts. Even continuous shifts, which in the original MTA's representation would be shown as a line parallel to the bisector, are recognizable as discrete schedule shifts this way. This enables measuring the time difference between any measuring point and the plan date valid at that point in time before and after a plan date shift. Figure 4c) presents the resulting graphs and thus the basic structure of the plan history diagram.

If there is no change in the planned date, the curve trends downwards with a continuous gradient. Positive and negative schedule shifts can be recognized and evaluated in the form of abrupt variations in the curve.

Using this form of visualization, it is also easily possible to standardize different plan data histories to a common point in time (e.g. start or measurement date). This makes it easy to compare plan date histories that are widely separated in time. It also allows the simple recognition of recurring patterns, such as characteristic scheduling routines or gates, from the passing of which systematic changes can be recognized across orders. An exemplary pattern could be a significant reduction of plan date shifts after the successful completion of all procurement activities, which could have led to disruptions in the subsequent processes.

Based on this initial introduction, further indicators that can also be shown in the diagram are presented and discussed in the following section.

## V. APPLICATION OF THE PLAN HISTORY DIAGRAM FOR DESCRIBING PLAN HISTORIES

The goal of this section is to provide a more detailed, practice-oriented description of the plan history diagram based on a fictitious plan history (Figure 5) of a production order. It also serves to introduce fundamental measures for describing plan histories.

Within the plan history, the period of measurement (x-axis) is being measured using the unit shop calendar days (SCD). SCD describe the underlying shift system respectively the working days of industrial companies. If a 7-day week is employed, SCD are equivalent to calendar days (CD). The plan history of the exemplary order starts at SCD 0, at which initial scheduling has been carried out. The determined planned completion date at SCD 0 is SCD 40. After 5 SCD, the order reaches milestone 1, which also represents the first rescheduling point, where a planned date shift ($SPD_1$) of $-10$ SCD is performed.

The planned date shift is shown as a shift of 10 SCD in the negative y-direction. A new planned delivery date (SCD 30) results, which can be determined by prolonging the point "milestone 1" with the planned stability line (dotted line with gradient -1) and is symbolized by a striped triangle.

In the further course of order processing, the planned date is shifted by 5 SCD at SCD 20. This shift occurs at a distance of 10 SCD to the planned date ($DPDS_2$ in Figure 5). After a subsequent greater planned date shift at SCD 25, the order reaches milestone 2, at which no rescheduling takes place. The planned completion date defined at SCD 25 (SCD 55) thus remains valid. After a further shift at SCD 45, the remaining lead time at SCD 50 falls below the limit of the predefined customer communication window for the first time.

This triggers the communication of the promised delivery date (SCD 60) to the customer ($PS_{prom}$ in Figure 5), which is marked by the crown symbol. Communication to the customer represents one exemplary action that can be

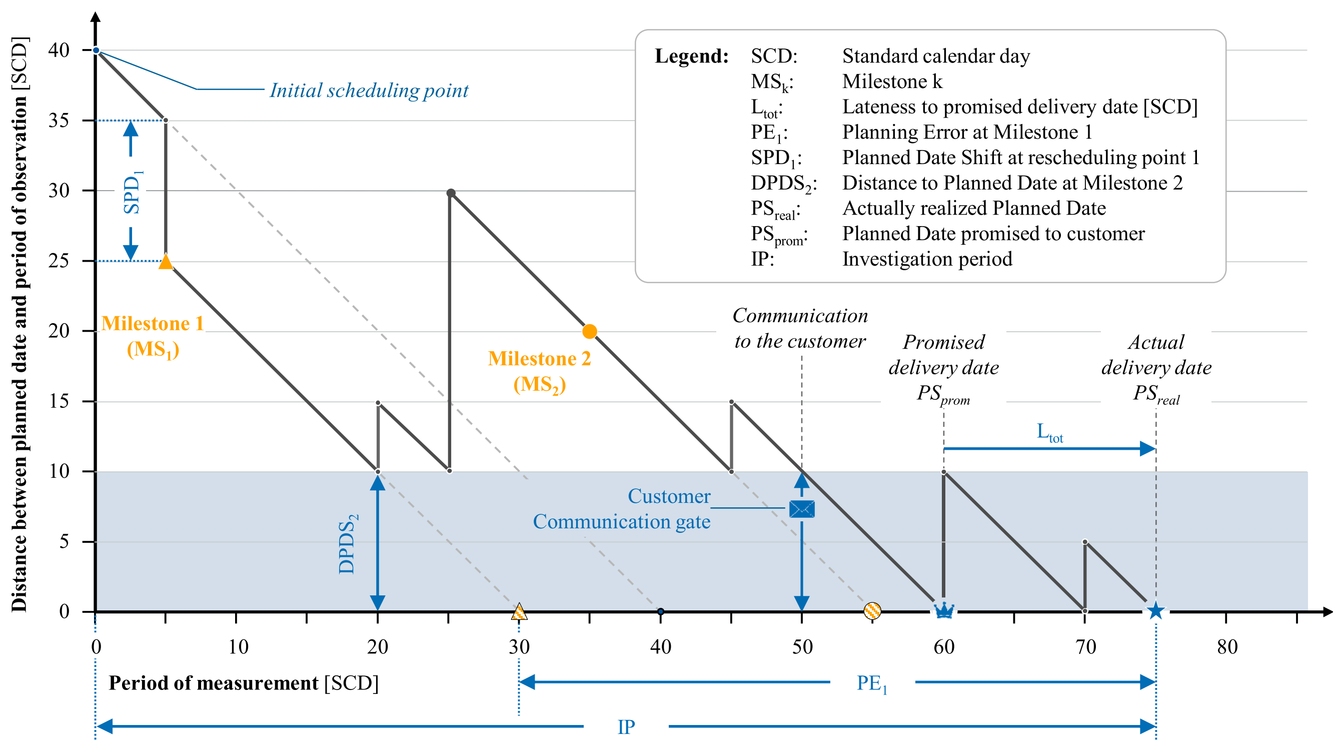



**FIGURE 5.** Exemplary plan history diagram (PHD).

triggered by falling below predefined time windows (crossing the distance of 10 SCD to the planned date). Other examples are the initiation of material order processes or machine setup activities. However, the illustration shows that very late in the product creation process, in this case shortly before completion, it became clear that the previously communicated deadline could not be met after all. This is evident from the fact that the planned date has been postponed once again. The order is finally completed at SCD 75 (Actual delivery date $PS_{real}$) and handed over to the customer with a schedule deviation (lateness to promised delivery date $L_{tot}$) compared to the promised date of 15 SCD. The explanations show that the process understanding can already be significantly increased by considering a single plan history of an exemplary production order.

Extending the focus from a single production order to a product group or production order class also allows the identification of recurring patterns and, if necessary, the derivation of measures to improve logistics performance. Analyzing multiple production orders that correspond to order classes visually is only possible with great effort. This means that in addition to the plan history diagram a key planning quality indicator (KPQI) system is required for an evaluative comparison of plan histories as well as aggregated plan histories of product groups.

## VI. KPI SYSTEM FOR ASSESSING PLANNING QUALITY

To further analyze plan histories, the application of the PHD can be supported by the calculation of key performance indicators, which can be classified according to the evaluation dimensions already presented in Section II, Figure 3. Following this definition, the key figures for evaluating planning quality can be divided into the dimensions of plan stability and planning accuracy. Figure 6 gives an overview of the key figures to be calculated and assigns them to the above-mentioned evaluation dimensions.

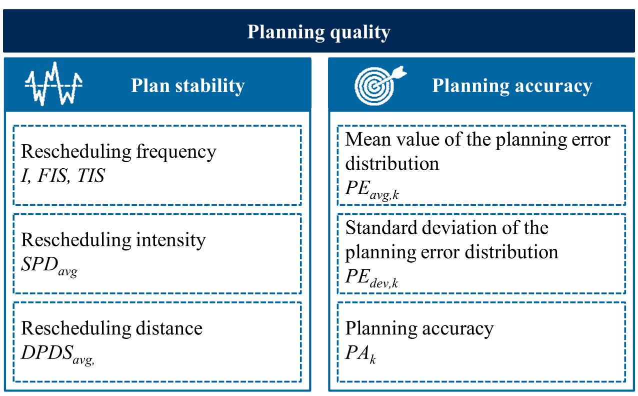



**FIGURE 6.** KPQI system for assessing the planning quality.

The following sections focus on the listed metrics that describe and evaluate *Plan Stability* and *Planning Accuracy*.

### A. PLAN STABILITY

Within this paper, plan stability in plan histories is described by means of three superordinate target categories that are accompanied by three guiding questions:

1) **Rescheduling frequency:** How often are planned dates rescheduled?
2) **Rescheduling intensity:** What is the intensity of planned date shifts?
3) **Rescheduling distance:** What is the distance between rescheduling points and the corresponding plan dates?

Within these three target categories, five metrics ($I$, $FIS$, $TIS$, $SPD_{avg}$ and $DPDS_{avg}$) can be defined for quantitative analysis of plan histories. The focus here is on the plan history of a single production or customer order.

First, metric $I$, the number of planned date shifts within the considered plan history, is explained. Within the descriptive model shown in Figure 5, $I$ is directly recognizable and measurable as the absolute number of peaks in the plan history. In this paper, the individual rescheduling points, at which the planned date shifts take place, are indexed by $i$. A high number of planned date shifts suggests an unstable plan history since a plan tends to have only a short validity period due to the frequent shifts [1]. In particular for the comparison of different production and customer orders, however, a consideration of the absolute number of planned date shifts is not sufficient, but must be set in relation to the investigation period of the plan history, i.e. the time between the first scheduling of the order to the last planned date or the completion date. This parameter is called $IP$ and is defined according to (1).

$$IP = PS_{real} - RP_0 \tag{1}$$

$IP$ Investigation Period [SCD]
$PS_{real}$ Actually realized planned date [SCD]
$RP_0$ Rescheduling Point 0 (initial scheduling point) [SCD]

The $IP$ is intended to take into account that with elongating the investigation period and thus the lead time, the number of planned date shifts, e.g. in the context of weekly planning meetings, can increase. The $FIS$ and $TIS$ indicators can thus be used as normalized metrics for comparing different planning processes. The mean shift frequency ($FIS$), see (2), provides information on how many planned date shifts were performed per SCD in the plan history.

$$FIS = \frac{I}{IP} \tag{2}$$

$FIS$ Mean shift frequency [$SCD^{-1}$]
$I$ Number of planned date shifts [-]
$IP$ Investigation period [SCD]

As a consequence, high values of $FIS$ indicate frequent changes of planned dates and thus unstable plans. By inverting $FIS$, this rather abstract measure can be transformed into the mean time between planned date shifts ($TIS$), which describes a time duration (see (3)).

The evaluation of *TIS* and *FIS* contributes to the assessment of the rescheduling frequency. Low *TIS* values indicate rather low plan stability due to the short time intervals between rescheduling cycles.

$$TIS = \frac{1}{FIS} = \frac{IP}{I} \tag{3}$$

| | |
|---|---|
| $TIS$ | Mean time between planned date shifts [SCD] |
| $FIS$ | Mean shift frequency [SCD$^{-1}$] |
| $I$ | Number of planned date shifts [-] |
| $IP$ | Investigation period [SCD] |

The evaluation of the plan stability of plan histories is further supported by the evaluation of the rescheduling intensity. For this purpose, the shift of the planned date carried out at a rescheduling point must be known or calculated.

By calculating the mean absolute planned date shift ($SPD_{avg}$), it is possible to evaluate how extensive the average shift per rescheduling cycle was over time. In the context of an intensity analysis, the direction of the planned date shift is not taken into account and absolute values are considered (4). Thus, an expediting and a postponement of planned dates do not balance out each other.

$$SPD_{avg} = \frac{1}{I} \cdot \sum_{i=1}^{I} |SPD_i| \tag{4}$$

| | |
|---|---|
| $SPD_{avg}$ | Mean absolute planned date shift [SCD] |
| $SPD_i$ | Planned date shift at rescheduling point $i$ [SCD] |
| $I$ | Number of planned date shifts [-] |

High values of $SPD_{avg}$ indicate that planned dates are shifted far into the future and/or the past when they are rescheduled. Thus, the temporal extent of schedule shifts can be analyzed by calculating $SPD_{avg}$ in the sense of the second guiding question.

Answering the third guiding question, on the other hand, requires evaluating the rescheduling distance of the planned date shifts that have been carried out. This parameter is a supplementary indicator for evaluating the plan stability, as changes at very short notice (a few days before the valid planned date) can have a negative impact on downstream processes and delivery performance towards the customer [24]. By calculating the "Mean distance to the planned date" ($DPDS_{avg}$), the short-term nature of planned date shifts can be quantified. The calculation rule for $DPDS_{avg}$ can be seen in (5). Lower $DPDS_{avg}$ values indicate that planned dates are adjusted at shorter notice. Thus, low values of $DPDS_{avg}$ indicate low plan stability. *I, FIS, TIS,* $SPD_{avg}$ and $DPDS_{avg}$ are used to describe the target categories rescheduling frequency, rescheduling intensity and rescheduling distance based on key figures as dimensions for evaluating the plan stability of a single plan history.

$$DPDS_{avg} = \frac{\sum_{i=1}^{I} DPDS_i}{I} = \frac{\sum_{i=1}^{I} PS_i - RP_i}{I} \tag{5}$$

| | |
|---|---|
| $DPDS_{avg}$ | Mean distance to the planned date [SCD] |
| $DPDS_i$ | Distance to the planned date at rescheduling point $i$ [SCD] |
| $I$ | Number of planned date shifts [-] |
| $PS_i$ | Planned date at rescheduling point $i$ [SCD] |
| $RP_i$ | Rescheduling point $i$ [SCD] |

In industrial practice, especially when carrying out a key figure-based comparison of different plan histories, however, it must be taken into account that considerable differences between lead times may occur among different production or customer order classes. If, for example, two plan histories are to be compared which are based on orders with strongly diverging order lead times, the absolute values of $I$, $SPD_{avg}$ and $DPDS_{avg}$ must be normalized, if necessary, with the specific order lead time or the investigation period (in analogy to *FIS* and *TIS*). For example, a modification of *FIS* and *TIS* is conceivable, within which the absolute number of planned date shifts $I$ is not related to the length of the investigation period (*IP*), but to the order lead time. However, these and other possibilities of normalization will not be focused on in detail in this paper.

### B. PLANNING ACCURACY

The planning accuracy represents the second evaluation dimension of the planning quality. Company-specific milestones $k$ within plan histories $j$ are to be defined for the evaluation of the planning quality of planned dates. These are used to calculate the planning error $PE_{k,j}$ for the planned date $PS_{k,j}$ valid for the respective milestone $k$ (6).

$$PE_{k,j} = PS_{real,j} - PS_{k,j} \tag{6}$$

| | |
|---|---|
| $PE_{k,j}$ | Planning error at milestone $k$ in plan history $j$ [SCD] |
| $PS_{real,j}$ | Actually realized planned date of plan history $j$ [SCD] |
| $PS_{k,j}$ | Planned date of plan history $j$, valid at milestone $k$ [SCD] |

Figure 7 illustrates the relationship between a defined milestone $MS_k$, the associated planned date $PS_{k,j}$, the actually realized planned date $PS_{real,j}$, and the planning error $PE_{k,j}$, which can be calculated as the difference between $PS_{k,j}$ and $PS_{real,\mathrm{j}}$. For illustrative purposes, a milestone is shown here to mark the targeted completion of semi-finished procurements 20 SCD after the start of the order.

According to the definition, a positive planning error ($PE_{k,j} > 0$) describes a late placement of planned dates $PS_{k,j}$ compared to the actually realized planned dates $PS_{real,j}$, while negative planning errors ($PE_{k,j} < 0$) indicate an early placement. To analyze the milestone-specific planning accuracy, the described planning errors are calculated in the planned schedule of a class of orders.

A class of orders can be formed, for example, based on the product group the orders belong to. The calculation of all planning errors $PE_{k,j}$ at the milestones $MS_k$ of all planned

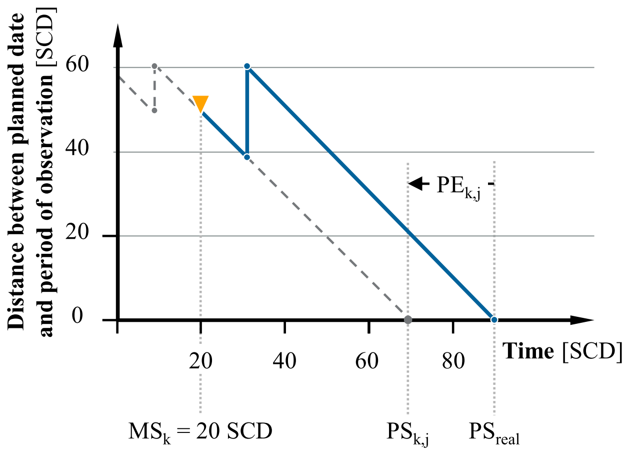



**FIGURE 7.** Example for the assessment of the planning error.

dates $J$ of an order class to be analyzed forms the basis for the calculation of two aggregated key figures for the evaluation of the planning quality. First, the average planning error at milestone $k$, $PE_{avg,k}$ is defined in (7).

$$PE_{avg,k} = \frac{1}{J} \cdot \sum_{j=1}^{J} PE_{k,j} \tag{7}$$

| | |
|---|---|
| $PE_{avg,k}$ | Mean planning error at milestone $k$ [SCD] |
| $PE_{k,j}$ | Planning error of milestone $k$ in plan history $j$ [SCD] |
| $J$ | Number of analyzed plan histories [-] |

As with the definition of the individual planning errors $PE_{k,j}$, positive values of $PE_{avg,k}$ allow the conclusion that planning dates are placed too late on average, while negative values indicate that they are placed too early. The consideration of the parameter $PE_{avg,k}$ with respect to the occurring planning errors can be extended by the calculation of the standard deviation to describe the dispersion of a planning error distribution. The calculation rule is defined in (8).

$$PE_{dev,k} = \sqrt{\frac{1}{J} \cdot \sum_{j=1}^{J} (PE_{k,j} - PE_{avg,k})^2} \tag{8}$$

| | |
|---|---|
| $PE_{dev,k}$ | Standard deviation of the planning error distribution of milestone $k$ [SCD] |
| $PE_{avg,k}$ | Mean planning error at milestone $k$ [SCD] |
| $PE_{k,j}$ | Planning error of milestone $k$ in plan history $j$ [SCD] |
| $J$ | Number of analyzed plan histories [-] |

The combined evaluation of $PE_{avg,k}$ and $PE_{dev,k}$ allows the assessment of the position as well as the repetitiveness of the deviations between realized dates and the dates valid for the milestones. A condensed evaluation of the planning accuracy at the milestones, on the other hand, is possible by calculating $PA_k$ (see (9)). This relative key figure reflects the proportion of planning errors within a company-specific permissible planning error tolerance in the total number of planned dates considered.

$$PA_k = \frac{n_{tol,k}}{n_{tot}} \cdot 100 \tag{9}$$

| | |
|---|---|
| $PA_k$ | Planning accuracy at milestone $k$ [%] |
| $n_{tol,k}$ | Number of planning errors in planning error tolerance ($PE_{k,j} \in [T_{L,k}, T_{U,k}]$) [-] |
| $n_{tot}$ | Number of measured planning errors [-] |

Figure 8 shows a planning error distribution for a fictitious plan history as well as the corresponding key figure values for $PE_{avg,k}$, $PE_{dev,k}$ and $PA_k$. The parameter $PE_{avg,k}$ shows a value of 10.07 SCD. Planned dates that were valid at milestone k under consideration are consequently positioned too late by an average of 10.07 SCD. The standard deviation $PE_{dev,k}$ of 14.33 SCD indicates a broad dispersion of the planning error distribution.

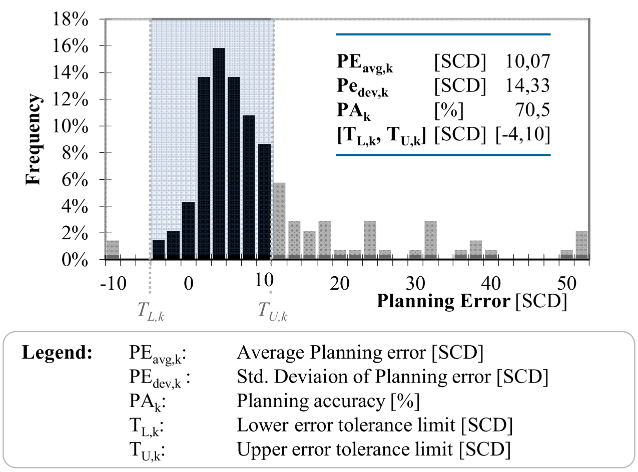



**FIGURE 8.** Exemplary planning error distribution.

The repetitiveness of generated planning errors is therefore to be rated as low. In the example, the planning quality is calculated by setting a tolerance field with respect to permissible planning errors to $[-4, 10]$ that corresponds to a value of approx. 70.5%. The proportion of planning errors that lie within the defined tolerance field are colored blue in Figure 8.

## VII. CASE STUDY AT AN MRO SERVICE PROVIDER

The methodology developed in the previous sections for visualizing plan histories and evaluating planning quality by means of key planning quality indicators (KPQIs) for plan stability and planning accuracy has been deployed at an MRO service provider. In the following, excerpts of the study are presented in an alienated form.

Figure 9 shows a generic representation of the internal supply chain of MRO service providers that is passed by complex capital goods for the overhaul or regeneration process (following [30], [31]). The macro processes *Disassembly & Inspection*, *Repair*, *Reassembly* and *Quality* *assurance* thereby represent the elementary process steps in regeneration. Start and completion of each of these are marked by a milestone. In the following, this reference supply chain is used to discuss the use case.

Milestone (MS) I represents the induction of the capital good into the MRO shop. After disassembly and inspection, the required work scopes are determined and the components can be forwarded to the repair shop (MS II). Once this is done (MS III), reassembly can begin, resulting in a rebuilt capital good (MS IV). Finally, the capital good has to undergo a quality assurance test. If the test is positive or if the necessary rework is completed, the capital good can be used again for operation and leaves the supply chain of regeneration (MS V).

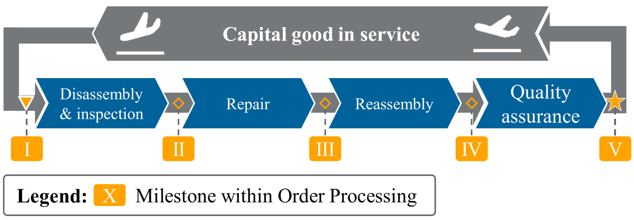



**FIGURE 9. Milestones along the generic MRO supply chain (exemplary).**

In addition to the special supply chain structure, the MRO branch is also characterized by highly variable work scopes and an often large number of different product groups that are overhauled in one production plant [14].

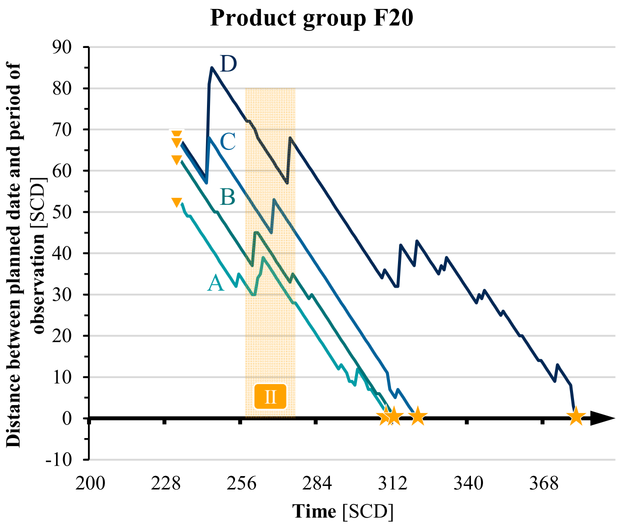
Within an initial process and data analysis, the exemplary applicability of the models presented in this paper was ensured. It was possible to extract the history of the planned completion dates for each order precisely in the complete period of time between milestones I and V from daily standard customer service reports by using a big data and business intelligence (BI-)platform. Furthermore, it was possible to extract the necessary actual dates of the individual milestones from the company's Enterprise Resource Planning (ERP) system.

At the same time, during data preparation it was identified that the planned completion dates are frequently postponed, so that a classic analysis (cf. Figure 2) without into account taking the plan history would only provide very limited information on lateness, ongoing planning processes, rescheduling intensity and possible causes. Hence, the applicability of the presented methodology could be ensured.

## A. ANALYSIS OF PLAN STABILITY

In an initial investigation, the plan history Diagram (PHD) was used to identify potential characteristic rescheduling points and peculiarities in the plan history. In order to perform an aggregated analysis, the plan histories of all orders of a product group were shifted to a virtual receiving date as the start of observation (SCD 231) and overlaid on top of each other, resulting in a set of curves and enabling an analysis of the plan stability over time.

Figures 10 and Figure 11 present the resulting PHDs with the overlaid plan histories for four selected orders of the product groups F20 and P10 over the period under consideration provided in SCDs. Furthermore, the key figures of plan stability for the entire product group are given. According to the underlying shift model, 7 SCD in this example correspond to one calendar week.




| Key performance indicators [average for entire group] | |
|---|---|
| Avg. number of planned date shifts: | $I_{avg}$ = 10,5 |
| Avg. investigation period: | $UZ_{avg}$ = 84 SCD |
| Avg. mean time betw. planned date shifts: | $TIS_{avg}$ = 8 SCD |
| Avg. mean absolute planned date shift: | $SPD_{avg}$ = 13 SCD |
| Avg. mean dist. to planned date: | $DPDS_{avg}$ = 37 SCD |

**FIGURE 10. Plan history diagrams and key planning quality indicators for product group F20.**

For product group F20, the plan histories of orders A, B and C are very similar. Especially in the second half of these plan histories (starting approximately at SCD 270), they are very stable except of a few planned date shifts. However, this cannot be stated for the plan history of order D, which is characterized by many small to medium planned date shifts, especially from SCD 312 onward. A comparison of the four analyzed plan history diagrams in the first half of the plan histories shows similarly shaped shifting respectively rescheduling patterns. This applies in particular to the time period around milestone II (cf. orange zone in Figure 10).

In case of the visualized plan histories of product group P10 (Figure 11), it is more difficult to identify comparably clear patterns. Compared to the PHD's of orders of product group F20, it is noticeable that the assumed respectively planned lead time at the initial planning was approximately the same for all four orders, whereas there were significant differences in product group P10, recognizable in the PHD's.

It is also noticeable that the distance between planned date and period of observation of article C of product group P10 declines into negative values shortly before completion. This allows the assumption that, despite the otherwise comparatively high frequency of rescheduling, planned dates that

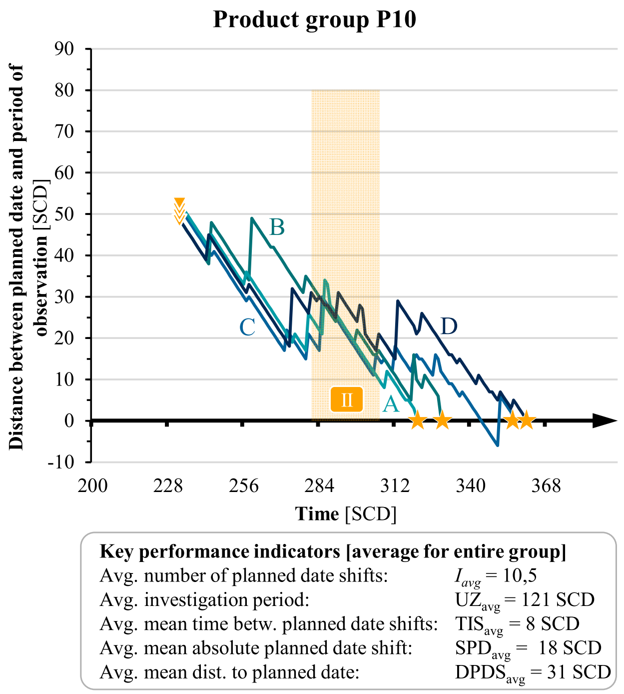



**FIGURE 11. Plan history diagrams and key planning quality indicators for product group P10.**

have already passed are in some cases no longer adjusted systemically. Taking a look at the orange area for product group P10, analogous to product group F20, and reflecting the range of the actual dates for milestone II, there are no significant shifts of the planned dates at this point. The PHD's of the four orders overall appear more diffuse. Finally, regarding the key figures for both product groups, it can be derived that the plan stability for both is to be assessed almost equally. For both product groups, a planned date shift takes place every 8 SCD on average. The average mean absolute planned date shift $SPD_{avg}$ (F20: 13 SCD/P10: 18 SCD) and the average mean distance to the planned date $DPDS_{avg}$ (F20: 37 SCD/P10: 31 SCD) are not fundamentally different as well. However, despite similar key figures for plan stability, the characteristic curves of the plan dates are clearly differentiable from each other.

### B. MACHINE-LEARNING BASED CHARACTERIZATION OF PLAN HISTORIES AT PRODUCT GROUP LEVEL

Since a comparison of the plan history diagrams in Figure 10 and Figure 11 allows the assumption that plan histories are somehow characteristic for a product group and thus a positive correlation between plan history and product group could exist, this hypothesis was verified in a further investigation by means of machine learning. Due to the present classification problem (Which product group does the PHD / the plan history belong to?), a Gradient Boosted Decision Tree Algorithm (GBDTA) was selected in the following implementation [32]. The implementation was done by visual programming using the open-source KNIME Analytics Platform (Version 4.3.0). For the GBDTA the default configuration of both nodes provided by KNIME "*GBDT Learner*" and "*GBDT Predictor*" was applied.

A dataset consisting of 302 rows and the following columns/features was used to conduct the assessment:

- Randomized and anonymized order number
- Product group (e.g. F20 or P10)
- Planned date shift at milestones I, II, III, IV per order
- Planning errors (ex-post) at milestones I, II, III, IV per order

Regarding the interpretation of the results, it should be noted that the data set used was comparatively small.

For the exemplary investigation and for reasons of alienation, the data of three product groups was used. The relative shares of the product groups in the dataset are shown in Table 1. The columns/features to be considered were intentionally restricted based on the dedicated milestones, so that eight features were available for determining the product group of an order. The GBDTA was trained with a data partition of 80% (242 orders), afterwards, the product group was predicted for a test set of 20%, respectively 60 orders. The results are shown in Figure 12 using the form of a confusion matrix and statistical key figures. It can be seen that by means of the GBDTA, even on the basis of a few milestone-related features, such as the planned date shift and the planning error in this case, the product group can be predicted with 80% accuracy. In particular, the product groups F20 and I30 seem to be confidently identifiable by the selected set of

**TABLE 1. Planning accuracy indicators for three selected product groups and milestones A-D.**

| | | Milestone I | | Milestone II | | Milestone III | | Milestone IV | |
|---|---|---|---|---|---|---|---|---|---|
| Product group | Quantity | $PE_{avg,A}$ [SCD] | $PA_A$ [%] | $PE_{avg,B}$ [SCD] | $PA_B$ [%] | $PE_{avg,C}$ [SCD] | $PA_C$ [%] | $PE_{avg,D}$ [SCD] | $PA_D$ [%] |
| F20 | 131 | 32.59 | 51.30 | 25.36 | 63.48 | 15.02 | 83.48 | 8.45 | 93.04 |
| I30 | 93 | 138.46 | 3.28 | 125.70 | 6.56 | 62.11 | 31.15 | 31.03 | 59.02 |
| P10 | 78 | 66.39 | 18.52 | 51.61 | 20.37 | 15.35 | 79.63 | 7.20 | 88.89 |

The table shows the average mean plan error $PE_{avg,k}$ of the valid plan on the following day of the reached milestone for all orders of a product group. Furthermore, the planning accuracy is given, which was calculated on the basis of a tolerance interval of ± 20 SCDs.

**Example for interpretation:** The valid plan at milestone II was on average 51.61 SCD off the finally realized date for product group P10. Of the 78 orders considered, the currently planned completion date at the time of the milestone matched the finally realized actual completion date with a tolerance of ± 20SCD in 20% of the cases.

input values. Moreover, *Cohen's kappa* ($\kappa$) as an indicator of determination, reaches a value of 0.693 and thus indicates a *"substantial strength of agreement"* according to [33].

For the present example, it was possible to show that plan histories are highly specific for specific product groups. The results indicate that basic process steps differ between the product groups and that the general uncertainty concerning the actual workload resulting in planning errors differs between the product groups. This allows for the hypothesis that planning errors can be systematic for a product group; e.g. due to a high constant backlog at work stations required for the overhaul process.

| Confusion Matrix | F 20 (P) | I 30 (P) | P 10 (P) | |
|---|---|---|---|---|
| F 20 (A) | 21 | 2 | 2 | 84,00 % |
| I 30 (A) | 1 | 16 | 2 | 84,21 % |
| P 10 (A) | 4 | 1 | 11 | 68,75 % |

(A) – Actual (P) – Predicted

| Overall Statistics | Accurancy | Cohen's kappa (κ) | Correct / Incorrect |
|---|---|---|---|
| | 80,00 % | 0,693 | 48 / 12 |

**FIGURE 12. Confusion matrix and statistics of ML-based examination.**

### C. ANALYSIS OF PLANNING ACCURACY

As part of the analyses conducted in this exemplary study, the planning accuracy was examined in more detail, as well. Here, the focus lay on the following question: How does the planning accuracy quantitatively develop while the order processing progresses?

In order to provide an explanation, the available data was transformed for an analysis of the planning accuracy over time and aggregated by product group. The result is shown in Table 1. It can be seen that the mean planning error deviates significantly from 0 at all milestones, but decreases with increasing order processing progress. This phenomenon is to be expected from a production logistics point of view, since the remaining work contents and thus also the remaining lead times decrease with increasing production progress, the amount of available information increases and the unplannable uncertainty decreases accordingly.

Analogous to the mean planning error, the increase in planning accuracy can be seen with increasing progress in production. Comparing the three product groups examined in the table, it is noticeable that the improvement of the mean planning error as well as of the planning accuracy varies in intensity between the milestones. Thus, it can be stated that only for product group F20 a planning accuracy of more than 50% is already given at milestone I, and the increase of planning accuracy is comparatively linear. For product group P10, on the other hand, there does not appear to be any significant increase in the information available for planning between milestone I and milestone II, which could lead to a correspondingly higher planning accuracy. The increase in the planning accuracy between milestone II and milestone III, on the other hand, is enormous (60%). It can be assumed that between milestone II and milestone III a large part of the existing information uncertainty might be eliminated. For product group I30, the planning accuracy up to milestone IV is very low at approx. 59%. Here, it is necessary to review the detailed reasons for this in order to be able to initiate appropriate countermeasures.

### D. IMPLICATIONS FOR PRACTICAL APPLICATION

The use case points out that planning patterns can be identified as specific characteristics for product groups, for example applying a GBDTA to the analyses presented in this paper. It also demonstrates that an integrated implementation of data preparation and forecasting is easy to establish using open source software such as KNIME Analytics Platform. Hence, an application (e.g. in production monitoring) does not require additional expensive software or hardware. However, the required (planning) data is recorded to a very limited extent in many companies. Even though most modern IT systems already are able to track planning data histories, they are mostly not saved for reasons of data efficiency. The potential for deeper analysis and insights into the operational and planning processes of companies should lead to a rethinking of this data efficiency policy. It is highly recommended to save planning histories at least for important milestones within order processing to allow for respective analyses.

## VIII. CONCLUSION

The PHD and the framework for assessing planning quality in production logistics in form of the KPQIs presented in this paper allow for a systematic description and investigation of planning processes in industrial practice by facing the so far hardly addressed problem of logistics performance evaluation in production environments with frequent planning iterations. This closes a research gap in the description of lateness and planned date shifts during order processing with frequent planning iterations and extends the theory of logistic models for describing and analyzing the behavior of production logistics systems by a new perspective. While existing approaches are largely based on rigid planning dates only allow very limited insights performing date-oriented analyses (see section II), the presented approach allows a deeper analysis and understanding of the behavior of the planning system. This is of particular importance when analyzing online planning systems like APS that are based on continuous rescheduling.

The supplementary system of KPQI opens up the possibility of a quantitative comparison of several plan histories and at the same time creates the basis for the aggregated examination of a large number of data records. Thus, a long-term integration of the analytical methodology into production monitoring is possible and, in addition, a lasting contribution is made to the elimination of the still strongly evident "blind spot" of inefficiencies caused by planning (iterations). Machine learning-based analyses as those carried out in the exemplary case study can support the developed models in order to enable further insights into measures that need to be introduced to improve the underlying planning processes.

For example, it is conceivable to cluster plan histories by categories and characteristics which, in addition to product classification, have an influence on planning quality. Identified planning process-related disturbance factors or inefficiencies then can be countered appropriately. For example, the cluster-specific consideration or adjustment of safety times or communication windows is conceivable. The selection of appropriate measures on the one hand depends on the results of the investigation. On the other hand, the potential measures must be checked for conformity with the logistics objectives as well as for procedural and contractual applicability, if necessary. Consequently, future work needs to focus on assessing potential measures to reduce planning errors and improving planning robustness. In particular, the application of artificial intelligence for the identification of critical features that account for major planning shifts needs to be elaborated as a basis for sustainable process improvement in PPC in depth. With regard to the MRO branch, the use of flexibility measures, such as spare parts pooling, to compensate for planning and process uncertainties must be examined in greater detail. It must be determined how much flexibility needs to be provided according to the achievable planning quality. Although the PHD is developed without focusing on a specific industry and so far there is nothing indicating that it cannot be applied to traditional manufacturing companies. However, it is necessary to investigate the practicability and the benefits of the PHD in this environment, too. In this context, it is of particular interest which use cases can be identified beyond make-to-order production with project characteristics and whether, for example, an application of the PHD in highly automated flow production is promising.

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**TORBEN LUCHT** was born in 1991. He received the M.Sc. degree in industrial engineering with a focus on production technology from RWTH Aachen University. Since 2018, he has been a Research Associate in the field of production management with the Institute of Production Systems and Logistics (IFA), Leibniz University Hannover.

**ALEXANDER MÜTZE** was born in 1994. He received the M.Sc. degree in industrial engineering with a focus on production engineering and operations management from Leibniz University Hannover. Since 2018, he has been working as a Research Associate in the field of production management with the Institute of Production Systems and Logistics (IFA), Leibniz University Hannover.

**TIM KÄMPFER** was born in 1992. He received the M.Sc. degree in production engineering and logistics from Leibniz University Hannover. Since 2019, he has been working as a Research Associate in the field of production management with the Institute of Production Systems and Logistics (IFA), Leibniz University Hannover.

**PETER NYHUIS** was born in 1957. He received the Dr.-Ing. degree in mechanical engineering and the Habilitation degree from Leibniz University Hannover. After working as a manager in the field of supply chain management in the electronics and mechanical engineering industry, he has been heading the Institute of Production Systems and Logistics, Leibniz University Hannover, since 2003.