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Automated production data feedback for adaptive work planning and production control

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Abstract

Higher customer's expectations and new technological developments have resulted in an increased complexity of manufacturing systems. Consequently, work planning and production control have become more crucial than ever to the success of companies. Adaptive work planning and production control approaches offer high potential with respect to flexibility and complexity management. However, the approaches find little use in practice, since the automatic acquisition of all potentially relevant information with additional sensors is cost-intensive and not feasible in many cases. At the same time, the potential of already existing production data, that is stored in Manufacturing Execution Systems (MES), remains untapped. This paper presents a method for automated production data feedback that guarantees a systematic update of production plan data only based on MES data. The functionality of the method is validated exemplarily at a thread manufacturer. The results reveal that an MES can provide a sufficient database for adaptive work planning and production control approaches. Moreover, the developed method can be applied to identify suitable workstations and measurement categories for additional sensor implementation.

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Keywords: Adaptive production planning; Digital manufacturing system; Production data

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1. Introduction

Rising customer's expectations and technological developments have led to an increased complexity of manufacturing systems. Additionally, companies face stochastic disturbances and cyclic demands, which results in an unbalanced utilization of manufacturing capacity. Thus, effective and efficient production planning and control have become a central advantage in competition. While production planning defines the required production technologies and strategies as well as the sequence of the production steps, production control is concerned with reoccurring activities in production, like order release or machine tool allocation, and short-term rescheduling due to unplanned machine breakdowns or deviations from planned times. However, the separation of work planning and production control has proven to be too rigid and inefficient in case of single-part and small-series production due to the following reasons [1]-[4]:

- Generation of unfeasible work plans by neglecting current conditions in production (e.g. machine utilization, tool condition)
- Limited decision-making scope for production control due to limited process alternatives
- Lack of systematic evaluation of routing alternatives due to manual rescheduling by the production planner
- Focus on individual optimization criteria in production planning and control

A consequence of a separated production planning and control are, for example, extended throughput times, nontransparent decision-making and a low ability to react in the event of faults and unplanned events. In order to overcome these challenges, Denkena et al. developed a method for an automatic generation of alternative work plans and an integrated production planning and control [5]. Prototypical implementations have shown that the throughput time can be reduced by approximately 4% compared to the use of linear work plans under laboratory conditions [6].

However, the approach has not been implemented into practice. The main reason for this can be seen in the required effort to maintain a valid database, which is necessary in order to achieve a high level of planning accuracy and acceptance, in a constantly changing production environment. Examples for changes, which occur on a daily basis in manufacturing, are amendments of drawings, new tools, machine malfunctions, stochastic deviations of the throughput time (TPT) or staff shortages. The automatic collection of all potentially relevant information with additional sensors is cost-intensive and not feasible in most cases. On the other hand, the potential of already existing production data, that is stored in Manufacturing Execution Systems (MES), remains often untapped.

2. State of the art

The technical progress in data storage technology and the associated reduction in costs for the collection and storage of data stocks have significantly increased the quantity and availability of production data in production companies [7]. Due to the amount and complexity of the data, manual analysis is usually not effective and efficient. In the literature, methods for an automated analysis of data are discussed under the generic term Knowledge Discovery in Databases (KDD) [8][9]. The term refers to a process for obtaining (statistically) valid, so far unknown, potentially useful and understandable knowledge. According to Fayyad et al., "KDD is the nontrivial process of identifying valid, novel, potentially useful, and ultimately understandable patterns in data" [8]. Different models of KDD process can be found in the literature. Most widely used is the model by Fayyad et al., depicted in Fig. 1 (a). Albeit data mining is just one step of the KDD process, both terms are used partly as synonyms [7][9]. A more detailed description of the KDD process with direct reference to the context of manufacturing is given by Choudhary et al. [11].

In addition to this general approach of handling large amounts of data, there are also concrete methods for adapting planning data in the literature. Monostori et al. [12] give an extensive overview about the use of cyber-physical systems in production planning. Geiger and Reinhart [13] pointed out that actual production data is crucial to the success of adaptive planning methods. Thus, they developed a Radio Frequency Identification (RFID) based approach to obtain accurate data from the shop floor. For this purpose, components and production resources (e.g.

machines) are equipped with RFID transponders and enriched the main database with relevant product and resource-specific data (e.g. target work plan, times and costs, planned job sequences and machine utilization). After the data acquisition and transformation, the data sets are segmented into clusters of variances between target and actual values of TPT components (e.g. process-time, setting-up time, wait time, transport time). Aiming to identify correlations between TPT deviations and product specific attribute, binary decisions trees are set up. Information about the current condition of the production are also taken into account [13][14].

However, the method by Geiger and Reinhart has some drawbacks with respect to its practical implementation. First, RFID transponders are used to collect component-related data. The integration of such transponders is not feasible for some components and, as mentioned above, for many SME. Second, it can be assumed that the deviations of the target values from the actual values are subject to continuous fluctuations, which is why clustering must be repeated continuously. Since the decision tree for assigning the correction values from the clusters to the TPT-components depends on the result of clustering, the subsequent method steps must also be executed for each recalculation. The calculation effort can quickly become too high to guarantee a process-parallel update [14].

In contrast to the aforementioned approach, the following section presents a method that guarantees a systematic update of production plan data based on typical MES data only and with little computing effort. Thus, the method allows a process parallel execution.

3. Method for automated production data feedback

3.1. Data preparation

The method for automated production data feedback for adaptive work planning and production control is shown in Fig. 1 (b) and based on the model by Fayyad et al. [10]. In the first step, the production planner identifies potentially relevant influencing factors for time delays in the production process (e.g. machine tool in use, processing step to be executed, component characteristics, and responsible employees) and exports the corresponding historical data records from the MES database. This manual and company-specific selection ensures that the scope of the analysis meets the conditions in the company (e.g. the selection of suitable attributes describing the product, such as diameter or length) and company-specific agreements (e.g. regarding the handling of employee-related data).

Next, available data is adjusted to avoid the identification of incorrect correlations and overlooking of additional correlations. For this purpose, incomplete data records are removed, outliers are identified by statistical analyses, e.g. box-plots, and excluded for further analysis. A study with an industry data set confirmed the common rule in literature, according to which the whiskers of the box plot should correspond to 1.5 times the interquartile range.

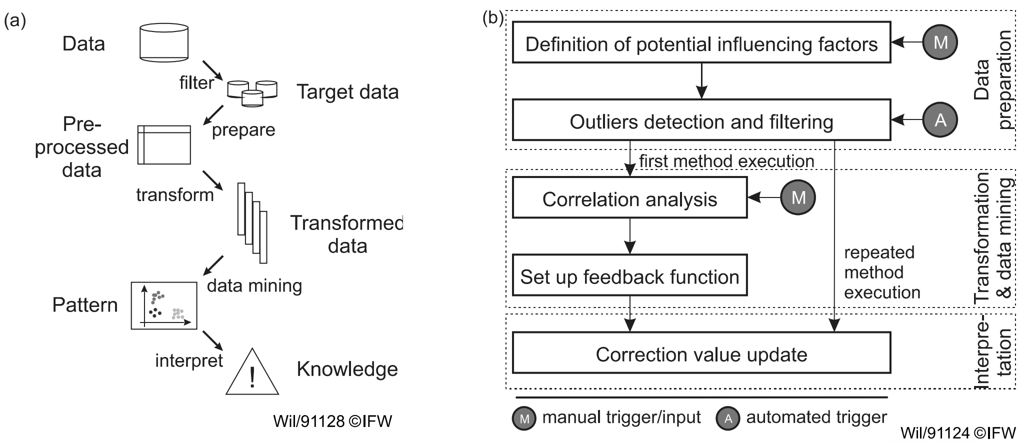

Fig. 1. (a) KDD-process by Fayyad et al. [10]; (b) Method for automated production data feedback.

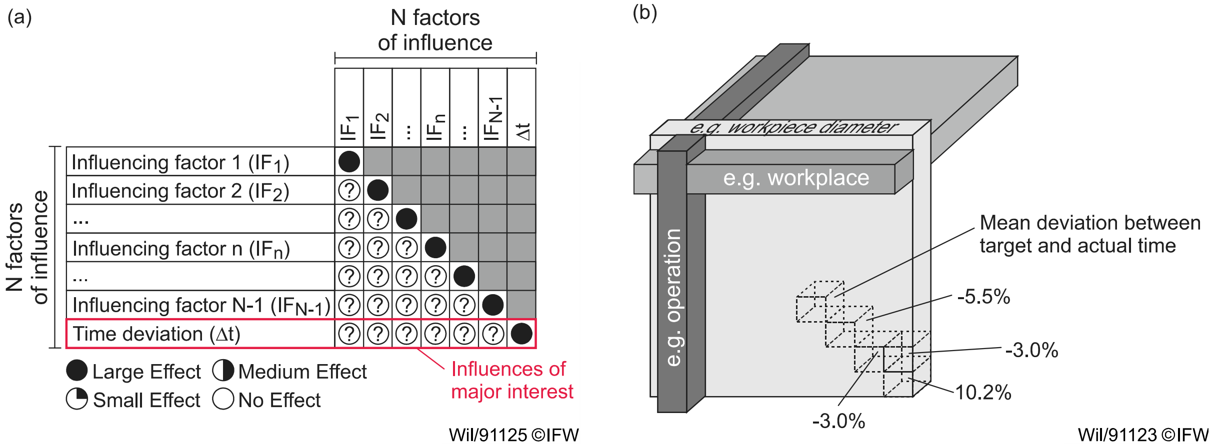

Fig. 2. (a) Correlation matrix with *N* potential factors of influence; (b) Principle of production data feedback (example for three significant influencing variables).

3.2. Data transformation and data mining

The dependencies between the identified potential influencing factors are examined through a correlation analysis. The focus is on the influence on the time difference between planned and actual time values. A separate analysis is carried out for each TPT component. This means that the correction values represented by the mean deviation between target and actual value can be calculated for each TPT component. In this study, a Pearson-Correlation is used to identify potential dependencies. The total number of selected influencing factors N determines the dimension of the correlation matrix (see Fig. 2 (a) with an $N \times N$ correlation matrix). To interpret the effect size r of each factor combination Cohen provides the limits shown in table 1[15].

For factors that cannot be examined within the Pearson-Correlation, since nominal and metric scale levels have to be compared (e.g. the dependency of the time deviations from workstation or work step), the error reduction measure η^2 is used. This represents a measure of the achievable percentagewise improvement in prediction by including the variable examined. As a result, η^2 can provide indirectly information about the strength of the correlation to the time deviation. In literature, there are different approaches for assessing the intensity of dependency to calculated values of η^2. While Richardson discusses various limit values, Cohen suggests the levels shown in table 1, which will also be used within this paper [15][16].

Table 1. Overview of correlation classes.

Correlation strength	Effect size	Error reduction measure
No correlation	$r < 0.1$	$\eta < 0.1$
Small correlation	$0.1 \leq r < 0.3$	$0.1 \leq \eta < 0.25$
Medium correlation	$0.3 \leq r < 0.5$	$0.25 \leq \eta < 0.4$
Strong correlation	$r \geq 0.5$	$\eta \geq 0.4$

3.3. Interpretation

In the last step, the identified patterns are interpreted. All influencing factors with a medium or strong correlation are regarded as significant and used for production data updates. Fig. 2 (b) shows exemplarily the result for identifying three significant influencing factors. For each possible combination of influence factors, the mean percentage of all available time deviations is calculated and these values are uniquely assigned to the corresponding factor combination. The method is not subject to any dimensional restrictions.

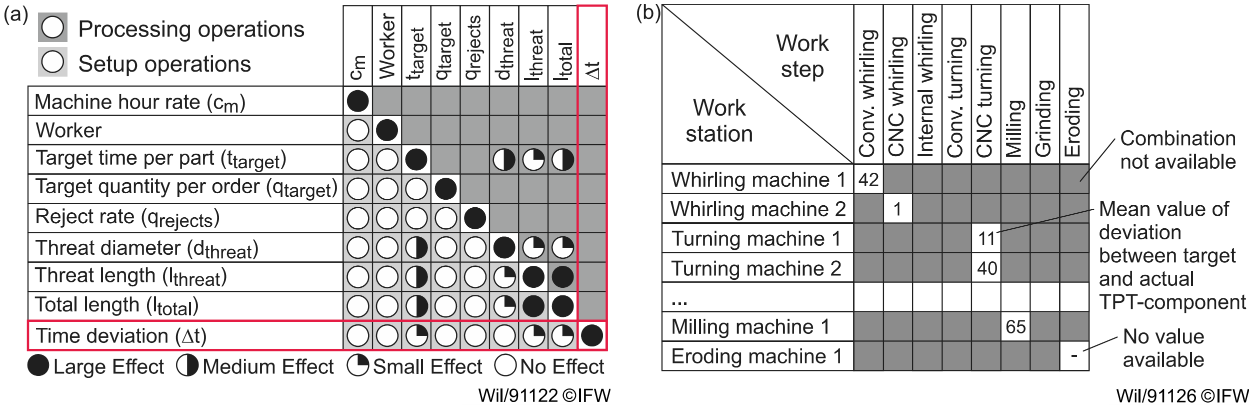

Fig. 3. (a) Results of Pearson-Correlation; (b) Excerpt of resulting workstation-workstep-matrix for setup operations.

The steps presented do not have to be executed completely with each method call. The correlation analysis must be performed during the first method execution. Afterwards it can be repeated manually if fundamental changes are made to the production environment or the product structure. The same applies to the selection of potential influencing factors. The other steps can be fully automated and require very little computing effort, which guarantees process-parallel data preparation and update.

4. Results of exemplary method application

In the following chapter, results of an exemplary application of the method based on actual data sets from a threat component manufacturer are presented. The analysis was carried out for setup and processing times. First, the MES data for completed orders from a two year period were exported via an SQL query and outliers were determined and removed according to equation (1) and (2). After incomplete data records were filtered out, a total of 19,854 useful data records were available for the subsequent correlation analysis, of which 9,357 related to setup operations and 10,497 to processing operations.

In Fig. 3 (a) the results of the Pearson-Correlation are shown. Taking into account the significance limit, as defined in chapter 3.3, the Pearson-Correlation provided no relevant correlations for setup and production processes.

The additional investigation on the influence of the work steps and workstations using η showed for setup operations the work step under consideration has an average influence (η = 0.30) and the workstation used has a strong influence (η = 0.48) on the deviation from target to actual setup time. With respect to the processing operation only a minor effect of the work step (η = 0.20) and a medium influence of the workstation (η = 0.30) was calculated. As a result, both factors are relevant for setup operations in relation to the significance limit mentioned. For production operations, however, the time deviation depends mostly on the selected workstation.

Based on the results of the correlation analysis, the feedback function was defined. In the case of processing operations, this corresponds to a simple list, which assigns the average percentage of processing time deviations to the available workstations. The results can be summarized in a matrix. Fig. 3 (b) depicts exemplarily an excerpt of the workstation-workstep-matrix for setup operations.

5. Summary and Outlook

The successful application of adaptive work planning and production control requires extensive data acquisition. However, the implementation of additional sensors or tracking devices is not affordable for most companies, especially for SME, and sometimes technically not feasible. The data basis of an MES can fill this gap. Therefore, a method for automated production data feedback based on the KDD process was presented in this paper. A major advantage of the method over the state of the art is that only the mean values of the previously determined relevant influencing factor combinations have to be recalculated for new production data. The more complex correlation analysis can also be repeated if necessary, but without significant changes in the production environment or the introduction of new products there is no need for action.

The exemplary method execution at a thread manufacturer has shown that the method can be implemented in practice with little effort. As initially assumed, the MES can provide a sufficient database to make complex and expensive sensor retrofits for the introduction of adaptive work planning and production control obsolete. In addition, it was shown that often there are only a few influencing factors on target/actual time deviations, whereby the complexity of the method is further reduced. For example, the time deviation of processing operations depends only on the selected workstation. In addition, the work step was identified as an influencing factor for setup processes. As a result, the data feedback for setup times could be limited to a simple workstation-workstep-matrix. Moreover, the presented method can be used to support a digitization strategy. For this purpose, additional measurement categories are included into the analysis and sensors based on the results selected.

The next step is to examine to what extent the use of the method in the planning and control phase has a positive effect on the achievement of the company's objectives. This investigation is part of an ongoing research project and will focus on the effect on usual performance parameters, such as throughput time, reject rates and costs.

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References

[1] Denkena, B.; Lorenzen, L.-E.; Schmidt, J: Adaptive process planning. Production Engineering 6:1, pp. 55-67, 2012
[2] Phanden, R. K.; Jain, A.; Verma, R.: Integration of process planning and scheduling: a state-of-the-art review. International Journal of Computer Integrated Manufacturing 24:6, pp. 517-534, 2011
[3] Schuh, G.; Potente, T.; Hauptvogel, A.: Methodology for the evaluation of forecast reliability of production planning systems. Proceedings of the 47th CIRP Conference on Manufacturing Systems, 28.-30. April, Windsor, pp. 469-474, 2014
[4] Kreutzfeldt, J.: Planen mit Bearbeitungs-alternativen in der Teilefertigung. Dr.-Ing. Dissertation, Leibniz Universität Hannover, 1994
[5] Denkena, B.; Dittrich, M.-A.; Winter, F.: Adaptive process planing and control, In: Denkena, B.; Mörke, T.: Cyber-Physical and Gentelligent Systems in Manufacturing and Life Cycle. Academic Press, London, 2017
[6] Schmidt, J.: Integrierte Arbeitsplanung und Fertigungssteuerung auf Basis von Zustandsinformationen, Dr.-Ing. Dissertation, Leibniz Universität Hannover, 2015
[7] Beierle, C.; Kern-Isberner, G.: Methoden wissensbasierter Systeme. Grundlagen, Algorithmen, Anwendungen. 4. Aufl., Vieweg + Teubner, Wiesbaden 2008
[8] Fayyad, U.; Piatetsky-Shapiro, G.; Smyth, P.: From Data Mining to Knowledge Discovery in Databases. AI Magazine 17:3, pp. 37-54, 1996
[9] Ester, M.; Sander, J.: Knowledge Dis-covery in Databases. Techniken und Anwendungen. Springer Verlag, Berlin, Heidelberg, New York 2000
[10] Fayyad, U.; Piatetsky-Shapiro, G.; Smyth, P.: The KDD process for extracting usefull knowledge from volume of data. Communications of the ACM 39:11, pp. 27-34, 1996
[11] Coudhary, A. K.; Harding, J. A.; Tiwari, M. K.: Data mining in manufacturing: a review based on the kind of knowledge. Journal of Intelligent Manufacturing 20, pp. 501-521, 2009
[12] Monostori, L.; Kádár, B.; Bauern-hansl, T.; Kondoh, S.; Kumara, S.; Rein-hart, G.; Sauer, O.; Schuh, G.; Sihn, W. ; Ueda, K.: Cyber-physical systems in manufacturing. CIRP Annals - Manufac-turing Technology 65, pp. 621-641, 2016
[13] Reinhart, G; Geiger, F.: Adaptive scheduling by means of product-specific emergence data. Proceedings of the 2011 IEEE International Conference on Industrial Engineering and Engineering Management, pp. 347-351, 2011
[14] Geiger, F.; Reinhart, G.: Knowledge-based machine scheduling under consideration of uncertainties in master data. Production Engineering 10:2, pp. 197-207, 2016
[15] Cohen, J.: Statistical power Analysis for the behavioral sciences. Lawrence Erlbaum Associates, Hillsdale NJ, 1988
[16] Richardson, J. T. E.: Eta squared and partial eta squared as measures of effect size in educational research. Educational Research Review 6:2, pp. 135-147, 2011