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Competence-based personnel scheduling through production data

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Abstract

Personnel scheduling closes the missing link between personnel and production planning in manufacturing companies. Personnel scheduling has a significant impact on the development of employee competencies and the achievement of production goals. Nevertheless, in industrial practice the performance of the employee is not considered in production planning. According to the 5th Global Productivity Study of the Proudfoot Consulting 37% of working time is wasted, which is mainly due to a lack of planning and control. A major reason is the difficult measurability of employee competence and performance.

In this paper, a method that describes the influence of employees on the processing and set-up time and its implementation at a manufacturer of thread parts is shown. For this, production data is statistically evaluated to predict the employee's influence. This information will be used by an algorithm for personnel scheduling. Thus, the highest possible competence development can be achieved in accordance with the utilization of the production.

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Keywords: Personnel scheduling; Manufacturing Execution Systems; Data Collection Systems

1. Introduction

In order to increase transparency and improve productivity, Manufacturing Execution Systems (MES) and Data Collection Systems are used in manufacturing companies. These systems also offer the integration of a competence management in production planning, because they coordinate the production resources for the processing of production orders. However, within such systems, the influence of employee competencies is largely neglected. At the same time, the data acquisition allows access to current production conditions as well as to employee-specific results, like processing and set-up times. This allows to react quickly in the event of a disturbance as well as to analyze the employee's influence on the production goals.

Using methods of data analysis in the production offers considerable potential that is not yet captured [1]. The data contain implicit knowledge about the production, which can be of great benefit. Therefore, the aim of this article is the description of the relationship between employees and production goals for personnel scheduling based on realized production results.

In Article 20, the EU Directive on Data Protection deals with the pre-control of processing operations which may include "specific risks to the rights and freedoms of individuals" and requires the Member States to examine these processes before they begin. In Germany the collection, storage, processing and use of personal data is only allowed in the context of specific purposes [2]. The purpose must be defined before any personal data are collected. According to this, the employer should conclude an employment agreement in order to be able to store and evaluate the personal data of the employees.

2. State of the art

For a description of the employee and its influence on the production goals, the systematic identification of competencies is required. For this, methods of competence management offer a good scientific basis.

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Witzgall takes into account the competencies of an employee by the cognitive abilities, motivation and practical skills. The calculation of the suitability of an employee for the fulfillment of a task is determined by weighting the individual competence factors. Through the representation of the necessary competencies and gaps, competence management can be supported. An integration into production planning to support the personnel scheduling is not considered [3].

Kletti deals with measures to improve employee productivity by MES. He emphasizes the need and the relevance of employee’s competencies for personnel scheduling. He proposes a plausibility check, in which the requirements of an operation are compared with the employee’s competence [4].

Charlin developed a method that enables a medium-term assessment of personnel scheduling, taking into account production orders and the resulting operation requirements. For this purpose, employees are rated on a five-point scale. On the basis of the competence levels, efficiency levels for operation execution are assumed based on expert assessments. Learning effects are also represented by a step function on an expert basis, which predicts competence development based on the number of executed operations [5].

The approaches show that the employee’s influence is not considered in an appropriate way. A prediction based on expert knowledge should be avoided to increase transparency and objectivity. For that reason, important empirical approaches are briefly described.

Wright developed the first description of a learning process in form of a power function [6]. He predicts the execution time (t_n) according to the number of executions (n). t_1 stands for the first execution time. k describes the course of the learning curve and can be interpreted as a learning rate, see formula 1.

$$\mathrm{t}_{\mathrm{n}} = t_1 \cdot n^{-k} \tag{1}$$

Levy created another learning model, which limits progress of the learning process [7]. The limit value c is a constant and limits the possible learning progress as follows:

$$\mathrm{t}_{\mathrm{n}} = c + (t_1 - c) \cdot e^{-k \cdot (n-1)} \tag{2}$$

As commonality of learning processes, the course of competence development can be retained as a power function and an asymptotic course against a fixed limit.

3. Method for personnel scheduling

For the prediction of the employee’s influence by the use of production data a high degree of objectivity and transparency can be achieved. At the same time, the collected data is used to update the database as well as the employee’s influence in order to reduce the maintenance effort and increase the validity of the planning results. The resulting information cycle is illustrated in Figure 1.

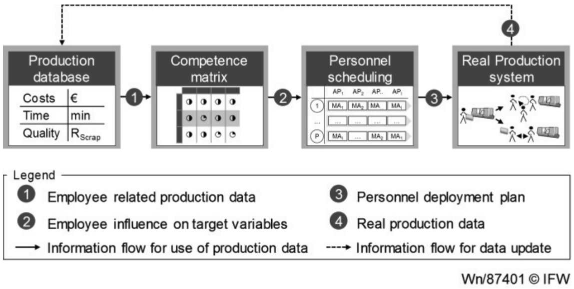

Fig. 1. Information cycle for the use of production data.

The realized production results are stored in a database. Employee-related production data is used to derive the achievement of goals in terms of cost, time and quality. The competence matrix provides the established relationships for the personnel scheduling. The specific personnel deployment plans are implemented in the real production system and realized results are written back into the production database.

For the systematic evaluation of employee reports, a multi-step approach based on the Knowledge Discovery in Databases (KDD) [8] process is selected, see figure 2.

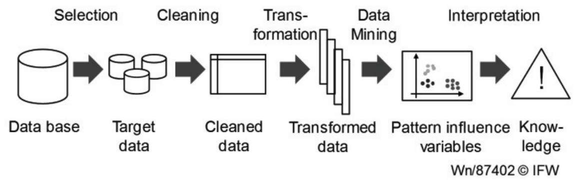

Fig. 2. Modell of the KDD process [8].

The aim of the evaluation procedure is to derive the influence of the employees for personnel scheduling. The objective is to quantify the influence of the individual on the production goals and their development over time.

3.1. Data selection

First, the relevant data to achieve the objective is selected. The employee's influence on time (processing and set-up time) and quality (scrap, rework) is required for decision-making in personnel deployment planning. Within planning systems also standard times for processing a component or setting up a machine are stored. With information about the reported activity, the actual times can be compared with the standard times. To make this comparison, the following information from the production database has to be selected:

- Operation: Description of the operation
- Workplace: Title and description of the workplace
- Employee: Name or number of the reporting employee
- Standard time: The assumed time for processing and setting up the process
- Quantity: Reported number of good and reject parts
- Report: Time stamp for the start and end of the operation
- Activity: Processing, setting up or reworking within the operation

3.2. Data cleaning

In the second step, the acquired data sets are adjusted and preprocessed. If reports contain no information on the number of items, activity or standard times, they will be deleted. In addition, it is to be ensured that the reported results can be clearly assigned to an employee. Therefore, operations with reports from different employees for the same activity are deleted.

3.3. Data transformation

In the third step, the data sets are reduced and transformed. If there are several reports for an operation and one activity from the same employee, the single times and number of items per report are summed. This is the case, when an operation is interrupted and continued later, e.g. when processing a larger number of items per operation. To determine the single time of a report, the time stamps end and start are subtracted from each other, as well as possible pauses during this period.

The resulting total time per operation is divided by the sum of reported items to obtain the actual time per item. The time factor per operation results from the division of the actual time per item and standard time per item. For the resulting time factors limit values can be set to remove outliers before statistical analysis. Equivalent to the time factor, the share of scrap parts is calculated by means of the quotient of the number of scrap parts and the sum of scrap and good parts.

3.4. Data mining

In the fourth step, the data is evaluated using data mining methods. These can be used to summarize objects and to derive connections between them.

For personnel scheduling, it is necessary to determine which past results can be used to forecast future events. Therefore, classification is used to group objects by common attributes. For example, workplaces are grouped by process-specific features, e.g. the manufacturing process, the degree of automation and the used machine control. In addition, the time factors (processing, set-up and rework) of the respective operations are assigned to the reporting employees. The workplace groups (columns) and employees (rows) span the two-dimensional competence matrix. If an operation in the future corresponds to these conditions, the results can be used for the forecast.

Moreover, in the case of personnel scheduling, it is necessary to determine how the past values are to be evaluated in order to enable them to make the forecast. The arithmetic mean value of a workplace group-employee combination is calculated for each activity. Using the arithmetic mean values in the cells of the competence matrix, the influence on the processing, set-up and reworking time can be described. The arithmetic mean of the scrap shares in the cells of the competence matrix allows the forecast of future scrap parts.

To describe the long-term impact of personnel scheduling the time evolution of the indicators is analyzed. For this purpose, the arithmetic mean values of the time factors and scrap shares as well as the number of reported operations are determined for each month within the evaluation period. The monthly calculation of the arithmetic mean value results in a discrete time series for each workplace group-employee-activity combination. The time series makes it possible to determine the moving average for each month during the period in order to derive the development of employee influence. The weighted moving average of the discrete time series x(t) after n consecutive months is given by equation 3.

$$\mathrm{m_x}(t) = \frac{1}{n}\sum_{i=0}^{n-1} w_i \cdot x_{t-i} \quad (3)$$

Where w_i is the weighting of the respective monthly mean value. Because the numbers of reports per month differs, the mean values are to be evaluated by a weighting. For this purpose, the number of reported operations N in month i is divided by the number of reported operations to month n.

$$\mathrm{w_i} = \frac{N_i}{\sum_{i=0}^{n-1} N_i} \quad (4)$$

3.5. Data interpretation

Finally, an evaluation of the employee-related production data and the determined time factors is performed. In order to make a statement about the forecast quality, the variance of the time factors of a workplace group-employee-activity combination is examined by the standard deviation. Further evaluation of the results is carried out by display histograms and moving average of the time factors.

4. Evaluation of personnel scheduling

4.1. Collection and evaluation of production data

In the following section the method for the derivation of the employee's influence and its development is applied in cooperation with a manufacturer of thread parts organized as workshop production. In the production, 33 people are employed performing operations like milling, turning, drilling and grinding on manual and CNC machines.

Within the **data selection** the database of the productions data acquisition systems, which has been running for 16 months, is accessed. In this, approximately 40,000 feedbacks from the production department are collected. Approximately 80% were registered for the activity processing as well as about 20% for the activity set-up. On the activity rework only 0.69% of the replies are made. Only 0.76% of messages contains scrap parts. The scrap rate is 0.36%. A distinction is made between material- and production related scrap reporting. The bulk of scrap parts are material related and for purchased semi-finished products, which is therefore independent of the employee. Due to the small number of feedback to production related scrap, the influence of the employee on that target variable is not investigated further.

Through the **data cleaning**, the number of operations is aggregated to 10,877. For most operations there are multiple reports per activity. This is due to the relatively long processing and set-up times by an average of 3.2 hours and 1.5 hours, so that operations are interrupted and continued. At the same time operations are continued by other employees. These operations are removed, because of an ambiguous assignment to an employee, before the data is evaluated.

As part of the **data transformation**, the reworking reports for an operation are added to the processing reports, because of the small number. This simplification is allowed because rework occurs after completion of the operation, which has the same effect as a longer processing time during the operation. Thus, delays can be determined independently of the actual reported rework. Subsequently, the reported quantity and single times are summed and divided by the standard times. The resulting time factors for the processing and set-up are finally checked by a limit value for outliers.

All time factors that exceed three times of the standard time will be removed as defective reports. In this way, it can be avoided that unrealistic time factors, for example, due to a delayed logout of an already completed operation, distort the results. The limit of the time factor of three is assessed as realistically according to the responsible production manager of the thread manufacturer. By this limit 10.02% of time factors are excluded, so that 9,787 operations remain.

In the next step, **data mining** is carried out, in which the individual time factors are grouped and the employee's influence and its development are derived. The workplaces are grouped into 23 workplace groups based on the manufacturing process and the degree of automation. These include, for example, the manual and CNC turning, manual outside and inside whirling or CNC external whirling. In addition, the time factors are distinguished by processing and set-up.

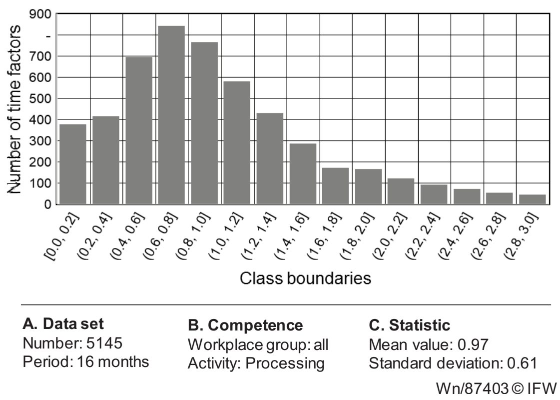

Fig. 3. Histogram of the time factors of the processing time.

For **data interpretation**, Figure 3 shows the histogram of the time factors for the processing time of all workplace groups. The class boundaries indicate the range in which the number of time factors are counted. Thus, the distribution shows that most of the time factors are in the four classes between 0.4 and 1.0 of the target time. The number of time factors greater than 1.0 decreases degressively with higher class boundaries. However, a class in which most of the time factors are clearly present is not available. The most pronounced classes are between 0.2 and 0.6.

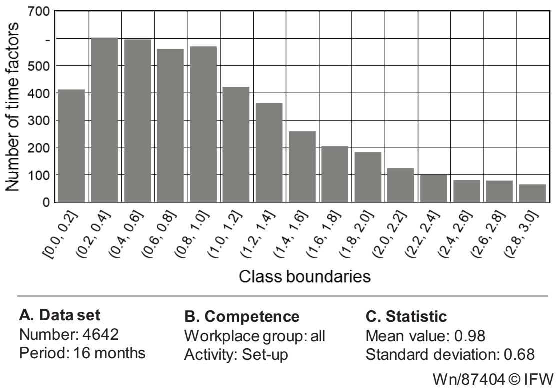

Fig. 4. Histogram of the time factors of the set-up time.

Figure 4 represents the distribution of the time factors of set-up. Compared to the processing times, there is a class with the strongest characteristic. This is between 0.6 and 0.8. With smaller and larger classes, the number of time factors decreases in both directions. The mean values with 0.97 or 0.98 as well as the standard deviation 0.61 or 0.68 are comparable for both distributions. The mean values demonstrate that the average standard time for the processing and set-up time is met very precisely. However, the distribution of time factors across all workplace groups and employees is very wide. For example, operations such as maintenance measures are recorded in the production data acquisition. These are assigned to a workplace group and not to an activity. Therefore, the time factors of individual workplace group-employee combinations are examined next.

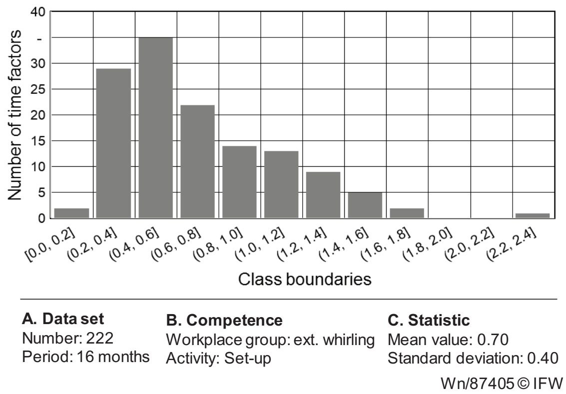

Fig. 5. Histogram of the time factors of the set-up time of employee 1.

The core competencies of the manufacturer of thread parts are the whirling processes for internal and external threads. These are used to produce multi-start threads with a length of 10 mm to 20 m, diameters of 10 to 300 mm, made of different materials as well as profiles. Therefore, the influence of different employees within the workplace group external whirling is examined. The distribution of the time factors of employee 1 for setting up this workplace group is shown in Figure 5.

The distribution of the 222 time factors is narrower and has the strongest expression in the class 0.4 to 0.6. Employee 1 seems to be very experienced. This can be stated because of an average of only 0.7 of the standard time and because of the low variance of the results. In order to make further statements, the histogram is compared with that of another employee for the same workplace group-activity combination, see Figure 6.

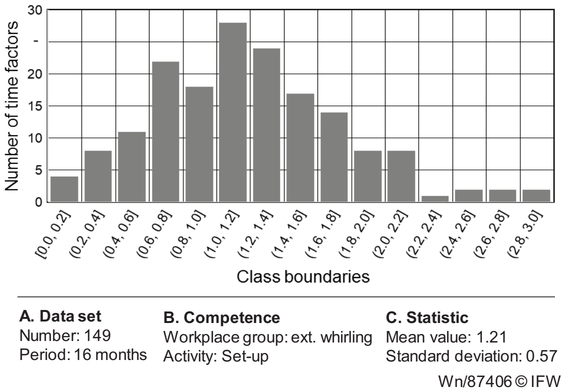

Fig. 6. Histogram of the time factors of the set-up time of employee 2.

In this illustration, the distribution of the time factors is shifted to the right. In addition, the amount of time factors decreases degressively with increasing and declining class boundaries. The average value of 1.21 and the standard deviation of 0.57 are higher than those of employee 1. The higher mean value indicates that employee 2 has a lower competence compared to employee 1. The greater spread of the set-up times compared to the standard time also assumes that a stronger development of employee 2 occurred compared to employee 1 within the period of 16 months. The number of reports of employees 2 (149) compared to employees 1 (222) supports the assumption that employee 1 has a higher experience and hence lower learning effects.

In order to prove the hypothesis of different learning effects, the time evolution of the employees' influence is examined. For this purpose, the mean values of the time factors and the number of reported operations for each month of the evaluation period are determined according to chapter 3. This results in the time series of mean values for the workplace group external whirling combined with the activity set-up. The weighted moving average of this time series is shown in Figure 7. In addition to the development of employee 1 and 2, two more employees are shown, who have also submitted reports for this combination.

The moving average of the time factors of employee 2 shows a declining course. With increasing time, the deviation from the target time of about 2.5 decreases to 1.21. In comparison, the course of employee 1 is relatively constant and fluctuates around a value of 0.7. Furthermore, it can be shown that employee 2 has not assigned any report for setting up this workplace group in the first month of the period.

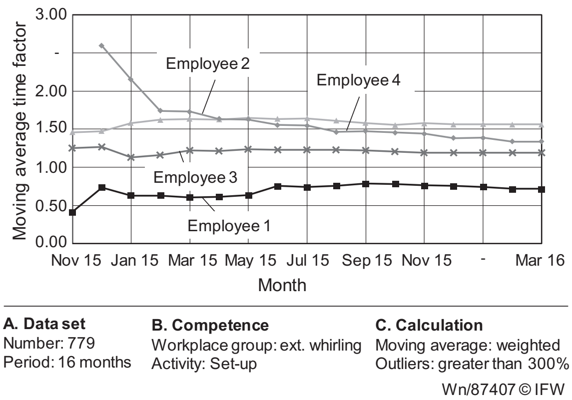

Fig. 7. Development of time factors for set-up.

Therefore, one can confirm that a strong competence development of employee 2 took place during the considered period. However, the comparison with employees 3 and 4 also shows that a high time factor is no sufficient evidence of a continuing competence development. Finally, from May 2015, the time factors of the employee 4 are higher than those of the employee 2, without changing particularly during the time. Thus, independent of the employee's experience, there are also employee-specific influences on the achievement of production goals. Moreover, the employee generates the data manually, so that an inaccuracy remains and the planner must validate the results before use for personnel scheduling.

4.2. Personnel scheduling

The task of the following personnel scheduling is the allocation of personnel to maximize the competence development. For this purpose, a decision algorithm is developed. In order to increase the efficiency of the learning process, inexperienced and experienced employees can be assigned together for an operation. In order to increase competence development in situations of low utilization, employees with high time factors are allocated. The control variable learning capacity is accordingly defined as the permissible time factor of an employee for an operation. If the time factor is less than one, the employee is suitable as a trainer.

The result of the algorithm is the personnel deployment plan with the assigned employee and trainer for each operation. To evaluate the deployment plan, the employee utilization is calculated. The expected time effort for each operation is determined and summed up. To take into account the employee individual time, the standard time is multiplied by the time factor. In addition, the time for the trainer is considered. Another goal of the personnel scheduling is to assign a competent employee for as many operations as possible. The success rate represents the share of allocated operations. Unallocated operations must be carried out by overtime or additional resources.

To evaluate the method, the personnel scheduling for a period of 14 days is applied. For greater clarity, the employees are classified in five groups of four employees. The groups are defined as interns, apprentices, assistants, specialists and masters, with the average time factor increasing from group to group. First, the employees are assigned with a learning capacity of one. The low permissible time factor leads to a time-oriented personnel scheduling. The resulting utilization per employee is shown in Figure 8.

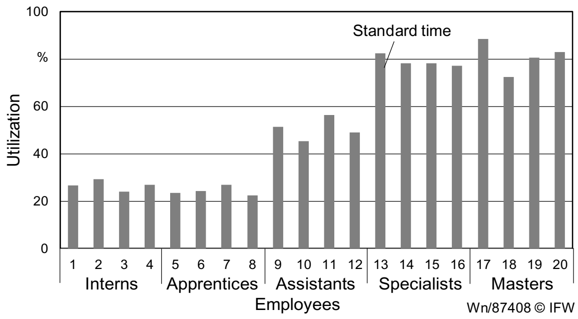

Fig. 8. Employee utilization for time-oriented personnel scheduling.

Due to the low learning capacity, the utilization results only from the standard time of the assigned operations. The utilization increases with the average competence. In total, 88% of the operations are successfully allocated to an employee, which leads in an average to an employee utilization of 52.32%. The low level of utilization indicates an uncritical situation, why the learning capacity is increased to two. The result of the more learning-oriented personnel scheduling is visualized in Figure 9.

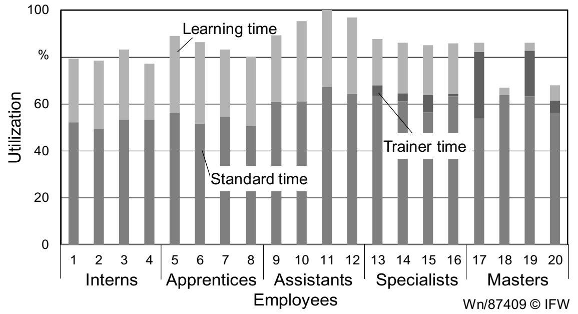

Fig. 9. Employee utilization for learning-oriented personnel scheduling.

Because employees with high time factors as well as trainers are assigned, the utilization rises to 84.62%. In particular, the share of learning time is increasing due to the high learning capacity. As a result, employees with low average competences are busier. The employees with high average competence are also used as trainers. In addition, the success rate also increases, with the result that 97.63% of operations are allocated. The workload is distributed evenly over the employees. The assistants are most heavily utilized. Furthermore, the interns and apprentices are about 80% busy. Finally, the highest possible competence development is achieved in accordance with the utilization of the production.

5. Conclusion

The investigations have shown that production data can be used to describe the employee for personnel scheduling. The data allows the prediction of employee influence on the processing and set-up time. The impact on the quality could only be described through the rework time, which was added to the processing time. The statistical examination of the time factors has shown that employees have a different influence on the achievement of production goals. Furthermore, it could be demonstrated that a development of this influence occurs, which is individually different. For example, experience is a major influence factor that can be measured by the number of operations reported.

The learning capacity within personnel scheduling shows the influence on the achievement of the production goals. Using the time- and learning-oriented personnel scheduling, limit values of this control variable were analyzed. The increase in learning capacity leads to an improvement of the production goals. The comparison demonstrates that the learning capacity significantly affect both the amount and the distribution of employee utilization. Due to the permissible time factor, the learning times and the development of competencies are increasing. In particular, the learning capacity leads to a more balanced utilization. The method can be used to find the maximum of competence-developing assignments taking into account the production utilization. In future work, the willingness of workers to teach is to ensure, for example by social competences. In addition, incentive systems such as competence-related wages must be examined.

Acknowledgements

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