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Procedia CIRP 57 (2016) 259 – 264

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49th CIRP Conference on Manufacturing Systems (CIRP-CMS 2016)

A holistic approach for quality oriented maintenance planning supported by data mining methods

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Abstract

Appropriate maintenance measures, which are carried out at the right time are a key factor to secure plant availability, product quality and process efficiency in modern manufacturing systems. Established maintenance strategies oftentimes lack in combining these strongly related aspects. They are not capable to anticipate in a holistic way and therefore lead to unnecessarily high maintenance efforts, wasted resources and the occurrence of quality and availability impairments.
In order to realize a holistic and anticipatory approach for maintenance planning, a methodology which consistently compiles and correlates various data via "cause and effect" coherences is depicted. By breaking down the production facilities on component level a basis is set to link condition monitoring data, wear data, quality and production data by using data mining methods. This framework enables the identification of maintenance-critical conditions and the prediction of failure moments and quality deviations.

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Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems

Keywords: Maintenance, Predictive Model, Quality,Data Mining, Manufacturing system

1. Introduction

Quality management, maintenance and production control are essential functions in manufacturing systems for achieving desired production targets [1]. The field of maintenance plays an important role to raise the potential of "Industrie 4.0" [2, 3]. In this light the volume of created data and the need of data processing is going to increase considerably within the near future [4]. Therefore, a successful maintenance planning needs to be able to handle this amount of data and at the same time link it with the implicit knowledge of employees.

The main task of maintenance is to preserve the function and performance of a machine or a system. Due to increasing complexity of production, handling and transport facilities as well as increasing automation the role of maintenance is gaining more importance [5].

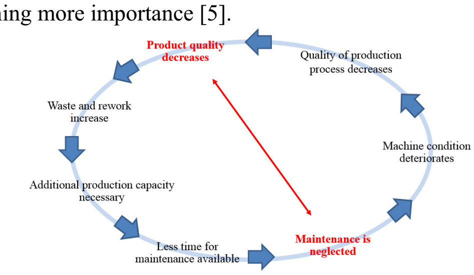

Figure 1. Sphere model of maintenance and product quality [6]

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Peer-review under responsibility of the scientific committee of the 49th CIRP Conference on Manufacturing Systems
doi:10.1016/j.procir.2016.11.045

An equally important role of maintenance is the assurance of product quality by providing an optimal machine status to eliminate system-related loss of quality during production. Thus, there is a causal relationship between maintenance and product quality, as illustrated in the sphere model (fig. 1) [6].

In the area of conflict between economy, safety and availability, decisions have to be made which simultaneously achieve a minimization of costs, a maximization of equipment availability and increased product quality. These measures will lead to an improvement in the system's productivity.

2. Maintenance strategies and approaches

Due to increasing demand for higher quality and more efficient production processes, holistic concepts have to be developed, in addition to the three basic maintenance strategies, failure oriented maintenance, periodic maintenance and condition-based maintenance.

In the context of large-scale production with constant machine loads, conventional maintenance strategies can be applied, whereas in customer order driven production processes, current approaches of preventive maintenance fail as they are not responding to specific load spectrums.

Especially in flexible production systems with a high variation of the production mix and no fixed load spectrum there is a need for anticipative and holistic maintenance strategies (Fig. 2), that jointly consider sensor signals from condition monitoring systems, quality and machine data as well as historical information regarding the failure behavior. [1,7].

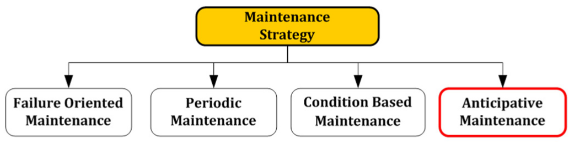

Figure 2 Maintenance Strategies [5]

Predicting the degradation and its effects on the manufacturing process is a central issue within maintenance planning approaches. Most existing models, used to predict machine failures, are based on historical data or data from long term studies about the condition of the machine or its components. Probability models like the Weibull distribution, which describe typical degradation processes of components, are derived from these data sets [7].

Traditional quality management methods use product- and process data for gaining conclusions concerning product quality, which subsequently (after a data analysis) trigger a re-adjustment of the production process, if a deviation from the defined specifications is detected. However, neither machine data, nor production planning and control data are included in this approach.

Different aspects regarding quality control (product, process and production infrastructure) are already covered by existing methods (Fig. 3). Quality oriented maintenance strategies, combining product and machine level by linking the product quality with failure effects of certain components, are provided in the literature. Consequently, a coherence between the degrading machine system and the quality relevant characteristics can be derived [8]. Load oriented maintenance strategies statistically determine the remaining life time by using external measurement parameters. In order to schedule maintenance intervals, machine- and process perspective are combined by linking the production program and failure effects of components [9]. Using a load spectrum dependent service life model allows for aligning operating resources in terms of economical organizational and technological aspects [10].

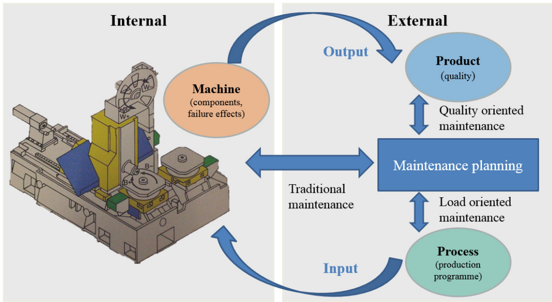

Figure 3. Interactions of maintenance related perspectives

However, even though certain maintenance strategies combine different perspectives, a holistic maintenance strategy, which takes product, process and machine perspective into account, is neither applied in the industrial practice nor published in literature.

3. Current Challenges of Maintenance planning

Increasing cost pressure, individual customer requirements, company internal and external dynamics and therefore increasing market volatility are shaping the field of maintenance [11].

For different reasons it becomes more and more difficult for classical maintenance strategies to derive a minimum between maintenance cost and system-wide downtime costs:

- In case quality of maintenance relevant data is often unsatisfactory, system-wide standards are missing or the same data sets are processed in different systems within the period between failures, it is not possible to derive a significant correlation and analysis of the failure behavior.
- Since information regarding the machine status is incomplete or provided to late, an exact and wear optimized replacement of components is not possible in time.
- Because the applied loads do typically vary from the theoretical load profiles, calculations of lifetime for plant components lose explanatory power.

Therefore, maintenance measures are either carried out at a wrong or unfavorable time. Thus, it is not likely to achieve a replacement of components that is aligned with the present production status and the required product quality. Classical maintenance strategies are buying improved plant availability with increasing maintenance cost due to waste of resources.

For that reason, existing planning tools are facing little acceptance. This fact leads to inconsequent data recording and data maintenance in dedicated systems. As a result the quality of the maintenance planning decreases even further.

However, in the light of "Industrie 4.0" it is foreseeable that more and more data regarding the machine status will be available in real time and may therefore be used for maintenance planning [12]. In this context it will be essential to accomplish and maintain a knowledge management for the maintenance relevant data [2, 3]. In the field of maintenance data mining methods are successfully applied in order to identify failure patterns out of historical data or condition based monitoring [13].

Excisting solutions for maintenance planning do not bring together condition monitoring data, quality management data, recorded machine loads as well as already known downtime patterns. The correlation of these data sets in combination with suitable system models may be used as a basis for decisions regarding optimized maintenance measures, product quality and energy consumption.

4. Holistic approach for anticipative maintenance planning

In order to respond to these challenges an anticipative, proactive quality- and maintenance approach will be introduced in the present paper.

The basis of the presented approach is built by the systematic description product quality-, process- and machine perspective as well as the analysis of already existing fractional solutions for these perspectives. Based on this a reaction model that will be able to forecast and anticipate failure moments and quality deviations is developed. This model offers a set of rules which are proposing maintenance measures anticipatively. Those rules are supported by condition based fault diagnostics such as simulation processes. Moreover, data based methods such as data mining will be used to support the validity of the reaction model.

This model is realized within the following 4 steps (Table1):

Table 1 Model-realization within a 4 steps-process

Step 1: Development of a framework
• Illustration of production facilities on component level incl. their load profiles • Identification of the current condition states of real process objects and information-transfer to the developed framework
Step 2: Data analysis and simulation study
• Selection and preparation of historical data (product quality, process and machine data), condition monitoring data and load data • Exploration of maintenance relevant parameters to derive conclusions concerning load-induced wear and quality deviations
Step 3: Parameter study
• Correlation and compression of the derived parameters • Validation and classification of the determined interrelations of parameters
Step 4: Development of the anticipatory maintenance model
• Derivation of generally applicable rules • Implementation and test run of the model

Step 1: In order to capture the behaviour of the system, the machine is split up in its maintenance relevant components. Due to machine-data, such as positioning of the tool slide, current consumption of drive units, data of accelerator and temperature sensors etc., load profiles can be determined analytically. If additional machine or tool-data is necessary, appropriate sensors and measurement devices have to be installed.

Step 2: Parallel to the development of a generally applicable system-framework, maintenance relevant historical data from various data collecting systems is analyzed to enable the identification of failure effects and the detection of quality-relevant cause-and-effect coherences. By a logical linkage of these datasets maintenance relevant machine parameters are derived.

In order to reveal necessary load profiles (such as rotation speed, speed, acceleration profiles) as well as cutting volumes of each NC-program a simulation study is conducted. Together with the structure of maintenance relevant components, the simulator is able to estimate the prevalent process forces. As a result, load/time-functions for each NC-program can be determined.

Step 3: Load spectra of identical machining centers, but with different production program, are compared and correlated with previous identified failure effects, to gain further information about maintenance relevant influencing factors. A validation and classification of the explored parameters is therefore possible.

Step 4: As a last step, generally applicable planning rules for the proposed model are derived. Data-mining methods within this process-step enable a half automatic and rule-based data correlation and creation of prognoses concerning the condition of machine and tool components and variations in product quality.

The generated knowledge about maintenance and quality relevant trends throughout the manufacturing process is linked with current production planning data. As a result, the developed model is able to suggest anticipatory quality- and maintenance measures by the integrated set of rules. These rules can be used in a maintenance planning tool where they form the basis for decision making. With a suitable set of rules, it is possible to forecast failure, to visualize wear and to predict quality trends for single machine components as well as a whole system. As a consequence, the utilization of necessary resources can be optimized to reduce maintenance cost and the plant availability can be increased since maintenance measures are initiated in time and in coordination with the whole production line and the production program.

An approach model for the realization of quality oriented maintenance planning rules is described later in this paper (Chapter 6)

5. Use of data mining methods for a quality oriented maintenance planning

On several levels of production, processes and involved entities (both resources and products) are subject to increasing transparency:

- Low-level prerequisites of immediate transparency are becoming affordable and are experiencing increasing penetration (e.g., sensors accessible to both low-level control loops and databases, or easier and more reliable assignment of unique identities by using automatic identification techniques and unique identifiers);
- Technologies supporting communication, storage and retrieval of data experience rapid development;
- Sharing of information across organizational borders or between hierarchical levels is currently gaining importance, both by communication between interfacing

entities in production, and by bridging the borders of formerly disjoint data sources and repositories.

Access to data from different hierarchical levels and entities involved in production does have the potential of operational improvement based on accurate information. With adequate methods, (i) dependencies and constraints regarding the processes and entities can be extracted, and (ii) they can be combined with up-to-date, accurate information about the status of resources and processes. Specifically, for the case of failure mitigation and maintenance, this means that maintenance activities can be better planned to fit into complex production processes and their execution can be optimized for various criteria, in the presence of operational constraints. Moreover, based on dependencies and trends extracted from data, it is possible to make predictions and issue early warnings based on phenomena that are not directly apparent either to experts or to diagnostic systems restricted to surveying a limited subset of production resources and processes.

Nevertheless, it has, by now, become clear that this will not come about by merely making “any” data accessible [14]. Challenges will, namely, arise from a number of circumstances that gain importance in large and complex systems:

- The heterogeneity, error rate, low abstraction level, and large amount of data may render “conventional” aggregation and data processing approaches inadequate in the face of high scalability and performance requirements.
- For similar reasons, human intuition in selection and evaluation of candidate models or rules can rarely be consulted as the amount of data and complexity of possible dependencies transcend the limitations of human comprehension (which is often biased by existing experience anyway, and may thus preclude the recognition of unknown but all the more important dependencies).
- Preliminary knowledge of large-scale dependencies may be far from reality, as existing knowledge has never before covered production systems to the required complexity. Traditionally, engineering models pursue a bottom-up perspective which is rarely feasible for large-scale, complex systems with many possible interactions.
- Many dependencies are present in an implicit form distributed over large datasets which may rule out a number of — often model-based — methods right away.

Possible solutions to the above challenges by automated or machine-aided means have been subject to intense research in the past decades. While some systems are limited in complexity and allow the targeted application of a single approach selected beforehand (e.g., feature selection by evaluating neural network learning performance [15]), the size and complexity of problems related to entire production systems require both the application of high-performance handling of “big data” [16] and advanced approaches, combining several methods for extracting relevant dependencies from large datasets [17].

Finding dependencies — co-occurrences, at least — in large datasets is an important domain of data mining, and a variety of suitable methods exist that can locate relations of interest in low-level data typically produced on the operational level of production processes. *Association analysis* (or association mining) has been evolving for several decades now [18], and is a generic approach that can accommodate a variety of algorithms for performing the data processing steps. In this approach, (i) data are filtered for frequent (co-)occurrence (denoted as *support*), and (ii) frequently occurring cases are filtered for the presence of a given form of dependency, typically implication, with the ratio of cases matching the assumed relation referred to as *confidence*. In its very basic form, simple thresholds are applied to calculated measures of support and confidence, and matching data are extracted. However, further extension of the original concept can also care for:

- Preliminary cleansing or rectification of data to match stringent physical or causal constraints, or assumed parameter ranges of processes [19];
- Addition of further refinement to prevent unwanted phenomena as misclassification by false positive/negative samples, or omission of relations that may have severe consequences in physical systems but occur so rarely that they do not pass a primary support threshold (e.g., alarms for production processes running in nominal ranges most of the time still need knowledge about exceptions which are rare by nature) [17];
- Introduction of components for “exploration” beyond known dependencies as an adaptation to gradual changes [20]; or
- Application of modular structures supporting the competitive testing of several algorithms on the same corpus of data [17].

Initial acquisition, maintenance and ongoing exploration of relations form a vital part of steps 2 and 3 in the four-step model-building process. Association mining in its most complete form can comprise the backbone of step 2, while several methods for maintenance and adaptive evolution of associations used in complex mining frameworks can also be run independently of a coherent mining activity, and make an important contribution to step 3.

While maintenance planning itself is carried out independently of mining activities, the latter can continually provide a key contribution to creating, refining, maintaining and adapting the models used by the planning algorithms and early warning mechanisms. It is important to stress that today’s dynamically changing production systems require more than static models derived in a one-shot procedure, and provisions must be made for revising, adapting or extending the models on a regular basis by (semi-)automatic means exploiting the constant influx of massive low-level data.

6. Approach model for quality oriented maintenance planning rules

6.1. Product quality

Product quality in manufacturing processes can be described as deviations of geometric features in the processed products [21]. These deviations can be determined and controlled by multiple predefined measuring points, whereby each measuring point has to fulfil specific quality characteristics (such as roundness, flatness, parallelism etc.) within defined tolerance limits.

The variability of product quality is caused by the joint interaction of production specific variables. Two kinds of production specific variables can be distinguished [7, 14]:

- *Adjustable process parameters* (e.g. forward feed, cutting speed, feed motion etc.) can be adjusted offline and depend on the production program of a certain machine. Each production program requires its specific process parameters to achieve a certain process output.
- *Conditions of process objects* (like machine components, tool components and auxiliary substances) can change over time or due to overstraining failures and significantly affect the desired product quality and productivity. The securing of optimal condition states is subject of maintenance measures.

The coherence between a certain product quality characteristic and the multivariate interaction of production specific variables can be described with the following equation [21]:

$$Y = f\ (\mathbf{X}, \mathbf{z})$$

Wherein

$$\mathbf{X} = \begin{pmatrix} X_1 i_1 \\ X_2 i_2 \\ X_3 i_3 \\ \vdots \\ X_n i_n \end{pmatrix} \text{ and } \mathbf{z} = \begin{pmatrix} z_1 h_1 \\ z_2 h_2 \\ z_3 h_3 \\ \vdots \\ z_n h_n \end{pmatrix}$$

Where Y stands for a product quality characteristic, **X** for the adjustable process parameters and **z** represents the conditions of process objects [21]. $i_{1,2,\ldots,n}$ and $h_{1,2,\ldots,n}$ are impact factors, which represent the degree of influence of a production specific variable on the certain product quality characteristic.

The equation clearly shows that an optimal quality- and maintenance decision for a single product quality characteristic or process object is depending on the decisions regarding the other factors [21]. As a result, a holistic perspective has to be taken up, considering the strong relations of product quality-, machine- and process view [1].

6.2. Quality oriented maintenance planning

For interlinking quality related data and manufacturing process data, data mining methods are often used to display meaningful and striking patterns between two or more data sets [22]. Quality deviations are identified in real time and by using data mining methods, quality related cause-and-effect correlations are displayed [8]. However, since an interaction between the process variables exists, a separate view on single components does not lead to an optimized maintenance schedule [21].

Therefore, before combining failure effects and product quality characteristics a systematic preparation of the required data fields is necessary. A three level structure has been chosen to describe failure effects as well as product quality characteristics in an adequate and complexity-reducing way (Fig. 4).

The knowledge about which machine component within the collected data influences a certain product quality characteristic and to which extent is partially implicit available. Experienced production-, maintenance- and quality employees know about certain interactions, however a systematic use of this knowledge does not exist. To disclose this implicit knowledge, especially empirical analyses can be successfully adopted [8].

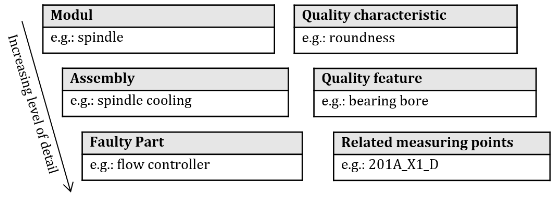

Figure 4. Systematic structure of failure effects and quality characteristics

A two-dimensional "Quality-matrix", similar to the proven "house of quality", is designed to discover such cause-and-effect coherences. The matrix represents all possible failure effects on the vertical axis and all product quality characteristics on the horizontal axis (Fig. 5). By discussing each cell of the matrix in an interdisciplinary team of production-, maintenance- and quality employees and deciding about the extent of the coherence (0 = no coherence; 0,25 = low coherence; 0,5 = medium coherence; 1 = strong coherence), hypotheses can be formulated.

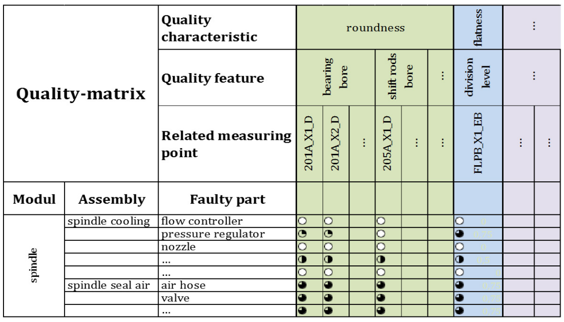

Figure 5. Quality-matrix

The identified hypotheses are verified or falsified with historical data and the application of data mining methods. Due to the iterative character of the proposed concept, also new, previously unknown correlations can be discovered.

As a result, generally valid rules, describing the combined behaviour of failure effects and product quality characteristics, can be derived.

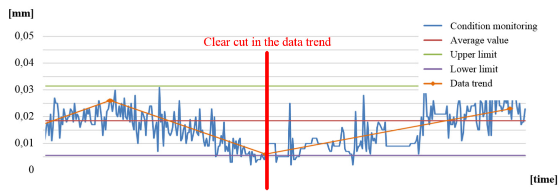

Figure 6. Clear cut in the Data-Trend

Once the identified rules are applied in a maintenance planning tool they will be harmonized with the condition monitoring data on a regular basis.

Therefore, the rules are constantly compared and adjusted to the operative environment, for example, if a clear cut in the data-trend of the condition monitoring data is identified (Fig. 6).

7. Conclusion and Outlook

The presented approach is based on an anticipatory maintenance strategy, supporting best possible product quality, optimized plant availability and reduced maintenance costs. The key of the methodology is to build conclusions based on the interaction between condition- and load data as well as historical quality- and machine data, using data mining methods for deriving patterns and finally to plan rule-based anticipative maintenance measures.

The model will be implemented in a maintenance control center for production lines which aims for forecasting and anticipating failure and reveal deviations in quality on real-time basis. Such a maintenance control center is an example for the use of planning and simulation tools as well as the interaction between human and machine, which becomes more and more important in times of "Industrie 4.0". In this context it is important to point out that the development aims at a system that allows the human to make the final decision. By using data mining algorithms, different sources of knowledge can be linked in real time. Since the operator is able to apply his implicit knowledge not only the quality of decision making will increase, but also the acceptance of the planning support will grow [23].

It is obvious that a simultaneous optimization of production and maintenance is reasonable due to the dependence of the machine status and the feasibility of production activities. Therefore, future research efforts are necessary in order to align a holistic maintenance planning approach with machine allocation planning. This combination has the potential to ensure availability as well as a resource and energy efficient utilization of production facilities [24].

The linkage of machine, product and process perspective allows a step in the direction of a "zero defect production". For this reason, a change in thinking needs to take place. We need to step away from the out-dated motto "What are the costs of maintenance?" towards a new perspective: "What are the costs maintenance is able to prevent?" [5].

Acknowledgement

The methodology regarding the holistic maintenance approach mentioned above has been developed within the research project "Maintenance 4.0", funded by the Austrian Research Promotion Agency (FFG), Grant number 843668. The existing approach will be further developed as part of the project "EPIC" funded by the European Union, Grant number 664403

References

[1] Colledani, M., Tolio, T., 2012, Integrated quality, production logistics and maintenance analysis of multi-stage asynchronous manufacturing systems with degrading machines, Annals of the CIRP, 61, p.455–458.
[2] Güntner G., Eckhoff R., Markus M., 2014, Bedürfnisse, Anforderungen und Trends in der Instandhaltung 4.0, Projektkonsortium Instandhaltung 4.0, Salzburg Research Forschungsgesellschaft m.b.H.
[3] Acatech, 2015, Smart Maintenance für Smart Factories – Mit intelligenter Instandhaltung die Insustrie 4.0 vorantreiben, acatech – Deutsche Akademie der Technikwissenschaften
[4] Bauernhansl T., 2014, "Die Vierte Industrielle Revolution – Der Weg in ein wertschaffendes Produktionsparadigma", in: Industrie 4.0 in Produktion, Automatisierung und Logistik, Springer, p.5-35.
[5] Matyas, K., 2013, Instandhaltungslogistik, 5. Vollständig überarbeitete und erweiterte Auflage, Carl Hanser Verlag, München.
[6] Rasch, A., 2000, Erfolgspotential Instandhaltung, Erich Schmidt Verlag, Berlin.
[7] Siener, M., Aurich, J.C., 2011, Quality oriented maintenance scheduling, Annals of the CIRP, 4, p.15–23.
[8] Aurich, J.C., Siener, M., Wagenknecht, C., 2006, Quality Oriented Productive Maintenance within the life cycle of a manufacturing system, 13th CIRP International Conference on Life Cycle Engineering, p.669–673.
[9] Boog, M., 2011, Steigerung der Verfügbarkeit mobiler Arbeitsmaschinen durch Betriebsdatenerfassung und Fehleridentifikation an hydrostatischen Verdrängereinheiten, (Vol. 4). KIT Scientific Publishing
[10] Renger, U., 2010, Strategischer Betriebsmitteleinsatz auf der Basis von Total Cost of Ownership, Dissertation, TU Wien.
[11] Schuh G., Potente T., Thomas C., Hauptvogel A., 2014, "Steigerung der Kollaborationsproduktivität durch cyber-physische Systeme", Industrie 4.0 in Produktion, automatisierung und Logistik. Wiesbaden: Springer Fachmedien 2014; p.277-295.
[12] Biedermann, H. (2014): Anlagenmanagement im Zeitalter von Industrie 4.0. In: Biedermann, H. (Hrsg.): Instandhaltung im Wandel. Industrie 4.0 – Herausforderungen und Lösungen. Köln, p. 23-32.
[13] Nemeth T., Bernerstätter R., Glawar R., Matyas K., Sihn W., 2015, Sicherstellung von Produktqualität und Anlagenverfügbarkeit durch einen echtzeitbasierten Instandhaltungsleitstand – Instandhaltung 4.0, in ZWF 09/2015, p.569-573
[14] Shu-Hsien L., Chu P.-H., Hsiao P.-J-, 2012. Data mining techniques and applications–A decade review from 2000 to 2011, Expert Systems with Applications 39.12 (2012), p.11303-11311.
[15] Viharos Z., Monostori L., Kemény Z., 2007, Automatic Partitioning Of Problems Through Submodel Decomposition A Promising Technique of Digital Enterprise Technology, Digital Enterprise Technology, Springer US, 2007, p.165-173.
[16] Viharos Z., Sidló, C., Benczúr A., Csempesz J., Kis K., Petrás I., and Garzó A., 2013, "Big Data" Initiative as an IT Solution for Improved Operation and Maintenance of Wind Turbines. European Wind Energy Association (EWEA) Conference, "Make your vision reality", 4-7. February, 2013, Vienna, Austria pp. 184-188.
[17] Zheng L., Zeng Ch., Li L., Jiang Y., Xue W., Li J., Shen C., Zhou W., Li H., Tang L., Li T., Duan B., Lei M., Wang P., 2014, Applying data mining techniques to address critical process optimization needs in advanced manufacturing, in Proceedings of the 20th ACM SIGKDD international conference on Knowledge discovery and data mining (KDD '14). ACM, New York, NY, USA, 2014, p.1739-1748.
[18] Rakesh A.; Tomasz I., Arun S., 1993, Mining association rules between sets of items in large databases. Proceedings of the 1993 ACM SIGMOD international conference on Management of data - SIGMOD '93. 1993, pp. 207–216.
[19] Karnok D., Monostori L., 2011, Extracting process time information from large-scale noisy manufacturing event logs, in: The 44th CIRP International Conference on Manufacturing Systems - New Worlds of Manufacturing. CIRP, Paper 37. Wisconsin, USA,
[20] Dasu T., Johnson T., 2003, Exploratory data mining and data cleaning. Wiley Series in Probability and Statistics Vol. 479. John Wiley & Sons
[21] Chen, Y., Jin, J., 2006, Quality-Oriented-Maintenance for Multiple Interactive Tooling Components in Discrete Manufacturing Processes, IEEE Transactions on Reliability, 55/1, p.123-134.
[22] Liebera, D., Stolpe, M., Konrad, B., Deuse, J., Morik, K., 2013, Quality Prediction in Interlinked Manufacturing Processes based on Supervised & Unsupervised Machine Learning, 46 Conference on Manufacturing Systems, 7, p.193 – 198.
[23] Lingitz L., Hold P., Glawar R., Sihn W.,2014, "Integration von Lösungskompetenz operativer Mitarbeiter des Shop-Floors in die Produktionsplanung und -Steuerung", in: Kersten, W., Koller, H., & Lödding, H. (2014). Industrie 4.0. - Wie intelligente Vernetzung und kognitive Systeme unsere Arbeit verändern. Schriftenreihe der Hochschulgruppe für Arbeits-und Betriebsorganisation eV Berlin, p.177 - 197
[24] Neugebauer, R., Fischer, J., Praedicow, M., 2011, Condition-based preventive maintenance of main spindles, Production Engineering, 5/1, Springer, p.95-102