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Online fault-monitoring in machine tools based on energy consumption analysis and non-invasive data acquisition for improved resource-efficiency

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Abstract

Improving the overall equipment effectiveness of machine tools will improve resource-efficiency and productivity in manufacturing. First step to achieve more effectiveness would require sensors for monitoring of machine availability and quality of machining processes. Abnormal machine conditions are characterized by fault-pattern, which can indicate failure and quality losses. Further, machine failure can shorten the remaining useful life of the components and affect the products. Therefore, it is essential to determine a valuable data source which will enable the extraction of fault-pattern and the allocation of these pattern to machining processes. However, this can be challenging due to lack of open source control architecture, different machine types and automation degree, changing operating loads, and dynamic failure rates in a real environment. Retrofit for online analysis of electrical power intake of machine tools seems to satisfy this challenge. A fault-monitoring framework for manufacturing equipment has been proposed in this paper, based on data stream mining techniques for online pattern matching in electrical power data streams. Complex event processing is applied to ensure scalable data processing for large data volumes and automate the reporting in order to assign the fault-patterns to machining processes and products. This concept is introduced as energy-based maintenance and validated for a powertrain machining line in milling and drilling machines.

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Keywords: Manufacturing systems; Fault-monitoring; Online pattern recognition; Effectiveness

1. Introduction

The last century can be characterized as an important phase in human civilization because of numerous tools and techniques that have emerged for exploiting and utilizing the properties of electrons for a range of human needs. This will be obvious if we examine the contribution of electrical energy in manufacturing systems. Worldwide about 50% of the total electricity consumption is made in industry by conversion using electric motor-driven (EMD)-systems [1]. The highly automated industry of the developed countries in the European Union (EU28) converts almost 60-75% of the entire electricity distributed in four types of EMD-systems to mechanical movement with about 40%, of which, compressors with 25%, pumps with 20% and fans with 15%. This study shows that a fault-monitoring framework based on an analysis of electrical power intake from EMD-systems would have a wide range of applications in industry. For example, the majority of the conversion into mechanical movement is performed by machine tools for machining processes such as turning, milling, drilling, etc. [2][3]. It can be assumed that machine tools, as a part of EMD-systems, perform the core value adding activity in manufacturing.

For example, the average age of machine tools, which are sold as second-hand equipment, is between 25 and 30 years [4]. Particularly, this second-hand equipment enables developing countries to participate in global markets. Furthermore, according to the European Association of the Machine Tool Industries (CECIMO), less than 25% of 3.5 million operating machine tools, which are used by industry in the European Union (EU28), are computer numerical controlled (CNC) [5]. Therefore, it can be assumed that most machine tools do not have LAN/WLAN interfaces for central data processing (cloud computing) and online condition-monitoring system. Cost effective solutions for monitoring and control will improve the overall equipment effectiveness for machining processes.

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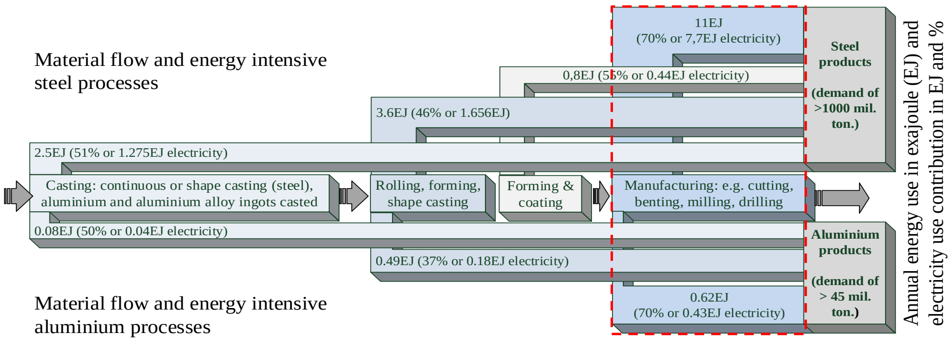

Fig. 1. Accumulated energy in steel and aluminum products worldwide annually [1 EJ ≙ 150 Mio. t CO_2] (according Allwood et. All [10][11]).

Cloud based services like decision support for prioritizing and scheduling of maintenance actions as well as automated allocation of quality losses to products will have a major contribution to increase the resource-efficiency per capita.

For example, Horenbeek at al [6] analyze the impact of tool-wear on energy consumption by correlating the energy consumption of cutting tools over time, for cutting processes. They demonstrate that the environmental optimum maintenance interval is significantly shorter than the economic interval, if the more energy-consuming resulting from tool-wear is considered. Existing monitoring infrastructure in manufacturing systems usually cannot consider the environmental aspects, because of missing or not accessible condition data of machines tools.

It is well-acknowledged that tool-wear and breakage can cause a loss of quality in a product and shorten the remaining useful life of machine components [7]. If the loss of quality is in an acceptable range of tolerance, the product needs to be post-processed. If it is out of range, the entire product is scrapped. The impact on the resource-efficiency of such faulty processes depends on the material and the depth of production.

An example of material and energy flow in steel and aluminum manufacturing is illustrated in Fig. 1 [10] [11]. It shows the worldwide annual accumulation of electrical energy use in steel and aluminum products according to the production steps. The production step before casting is not considered, because most steel and aluminum scraps are added to the casting process for a new material life-cycle. If it is considered that less than 20% of the electricity is generated by renewables in Europe, 1 kg steel would accumulate more than 500 kg carbon-dioxide after the last manufacturing process step [8]. For example, the weight of an average truck engine cylinder head of raw material is more than 200 kg and the finished part around 160 kg, removed chip during manufacturing process is ca. 40 kg. In that case the accumulated carbon-dioxide, just for the electrical energy, it would make more than 80 tons per part.

The economic aspect in the context of the equipment life-cycle, for just maintenance and support for machine tools, accounts for 60 to 75% of the total life-cycle costs [9]. It is obvious that such faulty machining processes have a high impact on environment, resource efficiency and decreases the resource productivity.

The focus of this work is to monitor, log, and report abnormal machine behaviors automatically by a online analysis of the electrical energy intake of machine tools. The aim is to support a better prioritizing of the maintenance schedule in order to avoid unscheduled downtime and quality losses. Further aspects considered are to improve localization of quality losses in machining lines, as well as aggregating and providing Manufacturing Execution Systems (MES) relevant information. An advanced online fault-monitoring framework is developed to enable customized maintenance scheduling and improve quality control in metalworking and machining-based manufacturing. The following four steps are presented in this paper to describe the development procedure:

(i) *Monitoring survey:* A preliminary maintenance strategy survey was conducted by a European automotive manufacturer to identify the industrial requirements for online fault-monitoring systems and to establish the potentials for improvement. This is summarized in Section 2. (ii) *State-of-the-art review and analysis:* A literature review was conducted on online fault-monitoring systems according to existing standards used in manufacturing. Monitoring scopes were analyzed based on electrical power signals from machine tools, and is presented in Section 3. (iii) *Developed concept for online fault-monitoring:* Based on the survey and state-of-the-art analysis, the requirements for an advanced fault-monitoring framework were identified. The elements of the developed concept are discussed for online data-processing, and data-analysis in Section 4. (iv) *Evaluation:* The proposed concept is currently being deployed remotely, via a prototype for three machine tools, as a part of a machining line at the case study facility. The case study is used in order to evaluate the deployed system and the maintenance concept within the European FP7 project "Knowledge, Awareness and Prediction of Man, Machine, Material and Method in Manufacturing" (KAP) with industry stakeholders. The evaluation results are presented in Section 5.

2. Survey in automotive industry for online monitoring

A survey is carried out with the partners of the KAP-project (FoF.ICT.2010.10.1) to identify the barriers for online fault-monitoring to enable condition based maintenance. Most preventive maintenance actions consider the recommendations of machine vendors or the experience of maintenance technicians on the production line. Recommendations from vendors are based on a statistical analysis of failure rates for single machines in an artificial environment. However, the serial production conditions in industrial facilities are hardly to forecast. Even when the recommendations would be optimal,

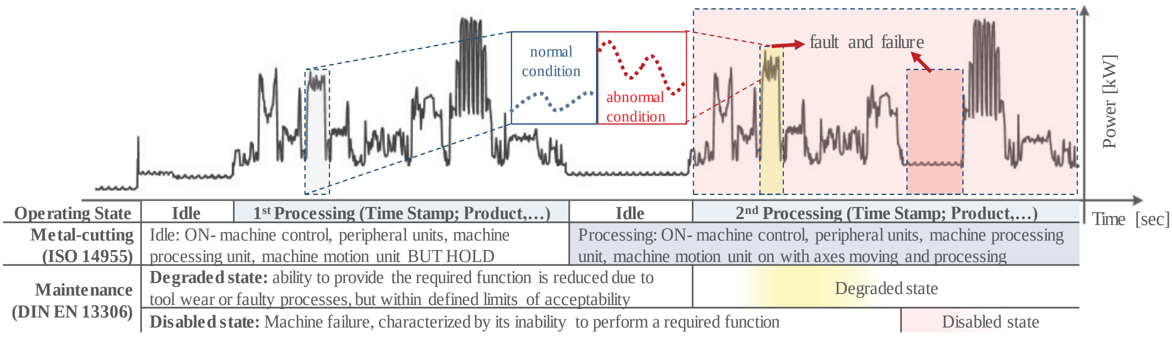

Fig. 2. Monitoring approach: Comparison of electrical power intake, operating states and definition of degraded state for metal-cutting machine tool.

the maintenance actions lead to scheduling problems in production because of the fact that each machine on the machining line has several maintainable components with different failure rates caused by tool-wear. These problems cannot be solved optimally without accurate data of the machine's condition.

Additionally, machining lines usually consist of machines from different vendors and external and in-house customized machines with varying degrees of automation and number of embedded sensors. These factors hamper the extraction of data and increase the number of possible failure modes. The complexity for the maintenance engineer increases with each machine vendor using their own nomenclature to identify embedded machine sensors for monitoring. Even the control system is partly under the responsibility of machine vendors and the recommended data is not easily available for the user.

Existing methods for online fault-monitoring in scientific literature are mainly based on data acquisition from embedded sensors at the component level of machines, which is defined as the functional hierarchy levels 0-2 (Sensor-/actor, programmable logic controller (PLC), fieldbus) according to IEC 62264 [12]. Retrofits with sensors or data access at these levels are mostly machine-specific and, therefore, both time- and cost-intensive.

Also, the troubleshooting capabilities, needed for identifying faulty machining processes that can cause a quality loss, are limited due to the lack of available and unified machine condition data. Even the experience from quality engineer is not usually harmonized with the experience of the maintenance engineer or technician stuff. Therefore, cost-intensive preventive or corrective maintenance actions are applied in manufacturing, with the consequence of more scrub or post-processing of products. These actions decrease the resource productivity by over-maintenance or unplanned downtime, a shorter operational lifetime of equipment, and quality losses.

In order to achieve an improvement, online data-acquisition and -processing for several types of machines with different machining processes, non-embedded sensors on machine level are required. Since the in-process monitoring of electrical power usage in manufacturing has become technologically and economically viable, this data-acquisition method is promising for online fault-monitoring [13]. The major advantage is that this measurement does not interrupt or delay the machining processes, and could be applied for online monitoring of the five types of EMD-systems.

The leading research question out of these survey is: "How can electrical power data be presented on the production line to increase the overall equipment effectiveness by supporting decisions?" This research question is based on three assumptions: 1) the presentation of suitable decision support indicators will allow maintenance engineers to better prioritize and schedule their actions; and 2) machine operator will be given relevant training, authority, and motivation to make machine shut-down decisions based on fault-monitoring to avoid repair costs, downtime, and quality losses; and 3) the machine condition data labeled to products and machine tools, will indicate quality of machining process and enable quality engineers to improve their troubleshooting capabilities.

3. Online fault-monitoring in machine tools

Monitoring, according to the maintenance terminology DIN EN 13306, is an activity performed manually or automatically, with the intention of observing the actual operating state of a machine [14]. Fig. 2 shows the monitoring approach presented in this paper according to relevant standards for operating states for machine tools and maintenance terminology.

The aim of a fault-monitoring system applied in industry, according standard IEC 61508-Part4, is to detect, report, and log abnormal conditions during the processing state, which can indicate a machine degradation or failure [15]. A failure is typically an event, which is characterized by temporary termination of the ability of a machine to perform a required function. This operating state corresponds also to the disabled state. Machine failure is unlike the degraded state, which is mainly characterized by abnormal condition/fault-pattern. But this fault-pattern can be indicative for quality losses in products, or even of future machine failures. According to ISO 9001, fault-monitoring can improve quality management by displaying quality related indicators such as the failure- and fault-rates [16]. The labeling of fault-pattern is essential for quality control purposes. On the other hand, the failure rates and the deviation of normal energy consumption pattern can be used to determine machine individual maintenance schedules. Therefore, for these purposes, it is important to distinguish between two classes of fault-pattern: (1) within the defined limits of acceptable quality tolerances, and (2) out of acceptable quality tolerances. These quality tolerance, before tool-brake can be identified by the quality engineer based on the machine condition data and product quality inspection.

Monitoring scope based on electrical power data: Research around signal processing related to online and condition-based monitoring (CBM) focuses on (1) appropriate models that will be able to determine a single machine condition or even predict future failures, and (2) selecting the appropriate data sources and signal features for the extraction of useful indicators regarding machine condition [17].

Table 1. Monitoring scope based on electrical power data for machine tools on component level and used data- processing in literature.

Monitoring scope	Data processing	Machining
Machine tool state: feed drives wear [18], fault diagnosis and maintenance planning [19]	Time and frequency domain analysis for motor current, [18] and power data [19]	Diverse machining processes [18] [19]
Process conditions: process –state [20] and process -fault [21]	Motor power, cross-correlation [20], statistical analysis [21]	Turning and milling, [20], drilling [21]
Tool conditions: tool-wear [22] and -breakage **[**23]	Motor power, model based estimation [22], comparison between theoretical power and measured spindle power signal [23]	Milling, drilling and turning [23], drilling [22]
Chip conditions: chip-disposal and –breakage [24]	Motor power, neuronal network [24]	Drilling [24]

Balazinski et al. [25] showed the cutting forces to be a more effective indicator of tool condition than either acoustic emission or vibration signals for the turning process. It is considered that the spindle motor power is proportional to the resultant cutting force in machine tools, which is therefore indicative of tool-wear and breakage. Existing literature discussing electrical energy consumption for metal-cutting machine tools shows that the specific cutting energy is significant higher to the fixed energy consumption [26][27][28]. If it is considered that the operating load of machine tools in industry, especially in batch production, is mostly close to stress limits, because of efficiency reasons, which increases additionally the acquirable cutting energy signal. It can be assumed that much of the electrical power intake will be used for the cutting process. Table 1 summarizes selected monitoring scopes based on current and power data analysis mostly at the component level, which is not easy accessible for online data acquisition for several machine types. This literature review shows that existing methods for diagnosis and prognostics use most modern CNC machines and, it is confirmed that the online data acquisition is usually done at the component level with embedded sensor systems [29]. Further, most applied methods prove the possibility to monitor the machine tool states, process conditions, tool conditions, or chip conditions based on current and power data.

However, using embedded sensors do not permit the so-called "plug and play" monitoring, required from the industry survey, because of existing several types of machines tools with and without embedded sensors. The automatic identification of event data like operating state of machine and the labelling of faulty-pattern to products are usually not considered. Also, the impact of such degraded and disabled states of energy efficiency and resource productivity are not quantifiable within most existing CBM approaches.

The monitoring scopes described in this paper based on non-embedded sensors which can easily retrofit on different type of automated machine tools for online monitoring of operating states and fault pattern. The proposed concept allows scalable integration and analysis of large data volumes for the purpose of detecting and visualizing ongoing processing states, including fault, and failure from several hundreds or thousands machine data streams. Main aim here is, to support maintenance schedules and quality control by considering minimal requirements for data acquisition and system calibration.

4. Concept for online fault-monitoring

These concept describes mainly online processing, analysis and visualization of indicators for decision support, which are extracted out of the electrical power use of a machine tools. These indicators are extracted out of the electrical energy consumption, which are typical for the ongoing operating state of the machine tools and contain a number of sub-pattern, which are characteristically for sub-processing states. The evolution of those indicators during processing state and over time are indicative of degraded and disabled processing states. These concept is therefore introduced as "Energybased Maintenance".

Fig. 3 show the information flow chart between the maintenance and quality engineer, as well as maintenance technicians. Once adequate reference operating states are selected, such as the power profile for processing- and sub-processing states presented in Fig. 2, the current degradation state of the process can be automatically determined and their evolution can be estimated. Common methods for machine diagnoses are restricted of specific type of machining processes and studied mostly for finite and stored data sets (offline/database-driven applications) [29]. Therefore, most methods have limited applicability for online monitoring of several machine types with different operation loads, and thousands of features and events in parallel.

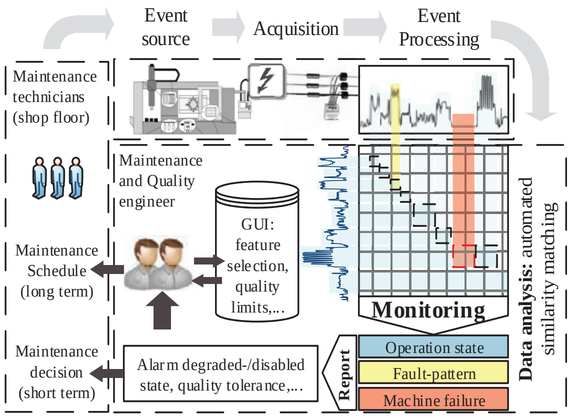

Fig. 3. Control cycle of information flow for online fault-monitoring.

To manage the data handling in real-time it is necessary to combine so-called declarative relational and temporal analytics in order to be able to process the income sensor data points per time tick or rather "on the fly". In this context, declarative is a style of building the structure and elements of computer programs that expresses the logic of a computation without describing its control flow. In other words, a program that describes what computation should perform and not how to compute it. Common declarative languages include those of database query languages (e.g., SQL, XQuery), regular expressions, logic and functional programming, and configuration management systems. Common declarative relational programming is constraint- and logic- programming or model-based, which is the mathematical representations of physical systems. Most described diagnose methods in the literature use model-based programming approaches, which are machine-specific and hardly adaptable to different types of machines, production loads and possible combinations of cutting materials. As combination of declarative relational with temporal analytics, Complex Event Processing (CEP) as a processing platform has been introduced for business intelligence [30]. This platform allows the continuous querying on data streams (sensor data points per time tike "on the fly") with the required logic.

In EBM context, the selected reference pattern describing the processing state, can be interpreted like a query or an agent looking for the specific subsequence, and the essential logic, are algorithms for similarity matching. For this reason, the applied algorithms for similarity matching require constant space and time per time-tick. In 2007, Sakurai et al. [31] first introduced the requirement for the commonly used algorithm, Dynamic Time Warping (DTW) distance, in order to determine distances between two feature vectors, as SPRING framework. The combination of CEP and the SPRING framework is sufficient for the purpose of energy monitoring, which was first proposed in the European Project KAP as the energy monitoring framework [32]. The described approach in this project has the scope to promote awareness of total energy consumption for the factory including all energy carriers [33]. The scope for the described framework in this paper is to enable online fault-monitoring, and to support maintenance actions based on an analysis of electrical power use of machine tools. As shown in Fig. 3, for individual fault-monitoring of several machines, fast initialization procedure of characteristic reference pattern for operating stages and sub-processing are required. Considering the need of accuracy in evaluating the condition of ongoing processing states with a reference state, similarity matching as well as selection of accurate reference profile to determine the normal and abnormal machine condition are required.

The framework presented in this paper considers these requirements by improving the initialization procedure and unsupervised training of the similarity matching algorithms. The improvement is primarily obtained for the threshold identification in order to distinguish similarity matches and distances between reference processing pattern as well as sub-processing pattern for ongoing operating states. These allow online extraction and analysis of fault-pattern.

Initialization procedure for monitoring: The initial starts with the selection of the reference pattern done by an operator, as presented in Fig. 4, out of the arbitrarily recorded electrical power data from the machine tools. The operator uses a graphical representation to select the desired operating state, the selected data sequence is described by a time stamp and value. At least three repeats of selected pattern in the data stream is required in order to extract the initial feature with its unique threshold, which determines the matching distance between two similar pattern. These requirements are based on the assumption that at least two of the three processing states are within the defined limits of acceptable quality tolerances to avoid more than 50% of processed products.

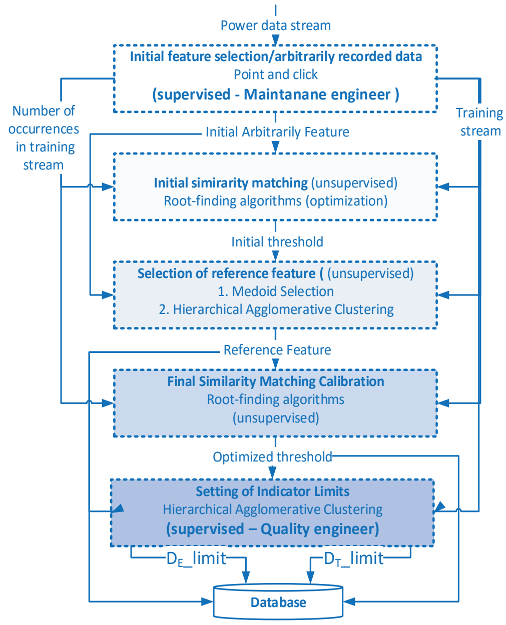

Fig. 4. Flow chart for the initialization and calibration procedure.

The optimized SPRING's algorithm is based on a continuous calculation (income sensor data points per time tick) of the DTW distance metric for possible matching of candidates from the observed electrical power data stream. Possible candidates, whose DTW distance, when compared to the initialized feature, does not surpass a certain so called SPRING threshold (ST), will not be reported as a match. The ST is unique for each feature, and needs to be optimally determined for fault-monitoring. Existing algorithms to determine ST are based on manual trial and error.

The proposed solution combines the SPRING algorithm with a numerical optimization, called Brent´s root-bracketing method, is used to determine the optimal STs. The problem of finding the optimal value for an ST that will allow SPRING to match the correct number of occurrences in the initial streamed data can be transformed into a root-finding algorithm. The goal in this case is,

$$f\,(ST) = n \qquad (1)$$

where $f\ (ST)$ is the function that describes the number of identified occurrences, ST is the threshold and n is the occurrences in the arbitrarily recorded stream. If the following substitution is made in Equation (1):

$$g\,(ST) = f\,(ST) - n \qquad (2)$$

then,

$$g\,(ST) = 0, \qquad (3)$$

Equation (3) expresses the need for estimating the value of *ST* so that *g (ST)* equals zero or, in other words, the classic root-finding problem. Brent's method was preferred to other similar root-finding algorithm as it combines the inverse quadratic interpolation with the well-known Newton´s method (also known as the Newton-Raphson method), and therefore, tends to converge more quickly, and robustly.

The first *ST* routine starts with an arbitrarily selected energy profiles representing the futures of processing state of the machine. It is not known how well this selected initial futures is defined within the limits of acceptable quality tolerances for the processing state. The initial feature can be fully described by the list of timestamps (duration) to value (power). Therefore, the electrical energy intake over time and the duration of this energy use are characteristics for a feature. In order to determine a representative feature, a symbolic representation of the DTW distance by energy (DE) and time deviation (DT), between initial feature and occurrences, is chosen for visualization. Based on the DE and DT indicators of each occurrence, hierarchical clustering is applied so that occurrences with common characteristics are grouped together. Hierarchical agglomerative clustering was chosen as it only necessitates minimal operator input; only the number of desired clusters has to be inserted by the operator, whereas other clustering methods need tolerance values in order to function.

Having extracted the most representative cluster of features, the next step in the proposed solution tackles the problem of identifying the best characteristic feature also called medoid in the selected cluster. In order to do so, while preserving the characteristic shape of the new reference feature, the medoid is selected [35]. In this case, because minor elastic deformations in the time axis should not influence the selection of the medoid, the DTW distance is used in order to compare each occurrence with the other occurrences. The occurrence which satisfies the following criterion is then selected as the new reference feature:

$$\min \sum\nolimits_{\mathrm{i,j=1,i\neq j}}^{k} dist_{DTWi,j} \qquad (4)$$

where *i*,*j* the lines and rows of the distance matrix corresponding to each occurrence, *k* the total number of occurrences in the cluster and distDTWi,j the DTW distance between occurrence *i* and *j*. In the last step, the optimization for the threshold with the reference feature is repeated, and the procedure is ready for monitoring. The next section describes the prototypical implementation and the automotive use case.

5. Prototypical software implementation

The developed concepts have been implemented as software application and validated in an example of CNC machining centers for milling and drilling processes, which is used in a machining line of a major European automotive manufacturer. The machine center is monitored over 6 months. To ensure the easy retrofitting for data acquisition, market-available three-phase current-voltage transformers "Carlo Gavazzi WM3096," are used to meter, the electrical power intake on the main connection of the machine tool. The data are transit via Ethernet/LAN to the central server. An Open Platform Communications (OPC)-Server is used to receive the data from the access point with a refreshing time of 250 msec. for each sensor with a TCP/IP addresses. As shown in the KAP project, the choice of sample rate depends on the variability of the observed signal between 1 msec. and 1 sec. [32].

CEP implementation: The presented concept has been implemented prototypically as a stand-alone software application. Market-available CEP-Esper platforms have been used. Esper is a product for event stream processing, which analyze the input data stream as series of events. The major advantage of these data type is low latency in continuous processing milliseconds for high data rates. Microsoft's Visual Studio was used for developing the software and SQL designing the database of reference data respectively. The incoming electrical power data streams are considered as time series. Each power value is modelled as a single event. These events are characterized by timestamp and observed value. The timestamp can be either the time where the meter logged the power or the time where the value arrived in the CEP input adapter. Logging the data on the meter can increase the accuracy of the streamed data, but reduce the processing speed and increase the latency. The input adapter translates the time series data from the meter to input event stream data. The optimized DTW-SPRING algorithm is the logic, which detects the ongoing operating state, such as processing and sub-processes, and calculates the deviation indicator and distance from the initialized reference feature continuously. These means the optimized DTW-Spring algorithm calculates the distance for each income sensor data points per time tick respectively to the reference time sequences and assign a similarity as distance. The analysis is done on the OPC-Server based on the raw data transmit from the power meters.

6. Validation for improved resource-efficiency

The software prototype can distinguish and report between two types of alarm events: First is degradation state related, which is characterized by abnormal condition/fault-pattern in the energy consumption during processing state of a machine tool. Monitoring of these fault-pattern is indicative for quality losses in products, or even of machine failures. Therefore, the fault-pattern related indicator, supports the quality engineer, firstly to determine machine specific and production load specific quality tolerances, and monitor these during the processing state of each machine. Second is disabled state related, which is characterized by a failure-event and the permanent or temporary termination of the ability of a machine tool to perform a required function. Such failure-event supports mainly maintenance engineers to set the next maintenance schedule based on individual machine condition. Bothe alarm events, supports also the better allocation of product with quality loses or of machines for inspection.

For example, if a failure event appears the first time, the maintenance technician will be informed with an alarm report, as shown in Fig. 3. After fixing the machine, the maintenance action relevant information, e.g., what was repaired, will be logged from the technician in the EBM system. This procedure labels the pattern, which is representative of the detected sub-processes as faulty-pattern to the processed product and maintenance information. The quality engineer can check this product afterwards for any quality losses and mark the quality tolerance for the fault-monitoring system. This quality tolerance defines the area for the indicators to allocate the machine condition right before the occurrence of the next failure. If the reported event of a future process indicates similar behavior, i.e., it surpasses the quality tolerance, the alarm report can be issued. Now, the online fault-monitoring system will be monitored if the detected event indicates any deviation regarding the marked quality limits, or if the detected pattern, characteristically suppresses more similar to the previously labelled fault-pattern.

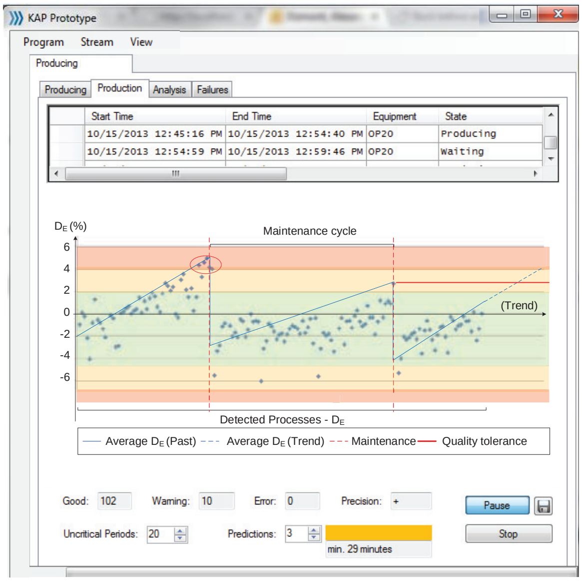

Fig. 5. Graphical representation of fault monitoring for CNC machine.

Fig. 5 shows the development of the DE indicator over several machining processes for one type of product and between two consecutive maintenance activities. Each point represents processing step and can be allocated to a specific product. Within the observed data stream, all processing states and machine failure can be recognized with these approaches. Further, continuous monitoring of the DE indicator allows the observation of trends. Such trends, in combination with the range of acceptable quality limits, which mark the yellow and red area, can trigger alarm reports for the maintenance stuff. The four processing states right before the first monitored machine failure, circled in red, were faulty processes which led to quality loses in the product. The schedule of the next maintenance cycle base already on the fault-monitoring system.

The described fault-monitoring system allows the extraction of information for maintenance purposes out of the observed electrical power intake of a machine tool. Further, electrical power consumption during the processing state is characteristically for a product type and machining process. Therefore, products can be tracked over several machines and operating states and relevant information can be extracted. This information includes electrical energy consumption per operating state and product, start and end time of operating state, as well as disabled or degraded states of a machine.

Areas for industrial applications: Industrial stakeholders such as production planners, and quality and maintenance engineers, within the KAP project, tested the presented software prototype. The main identified areas of application for improved resource-efficiency and productivity are: Availability related areas are (1) monitoring and forecasting of equipment failure related to tool degradation, such as interruption in production due to breakdown, including tool breakage, (2) support for a better synchronization of tooling change time, interruption in production due to worn out tools, e.g., cutting blades. Performance related areas are (1) monitoring and faster allocation of speed loss, discrepancy between targeted and actual processing speed due to high work load or imperfect work method, (2) log of duration for minor stoppages like idling/waiting, interruption in production due to idle workstation, e.g., waiting for maintenance actions. Quality related areas are: (1) improve quality loss allocation and adjustment, interruption in production due to correction of quality problems, e.g., reworking a drilled hole, (2) decrease interruption of production for additional invasive measurements for extra inspection of product or machine tool. Environment related fields are: (1) monitoring of energy consumption for non-value adding activities, (2) monitoring of energy consumption per product to determine the individual carbon-dioxide footprint.

7. Conclusions and Outlook

The proposed fault-monitoring framework for manufacturing systems provides a number of features that go beyond state-of-the art, such as existing condition monitoring and maintenance standards for machine tools. This fault-monitoring framework contains data stream mining techniques, and a CEP engine that provides indicators for decision support in order to schedule energy-based maintenance actions and to allocate product-specific quality losses out of electrical power intake from the machine tools.

Unlike the indirect observation of degraded operating processes and abnormal machine behavior, such as vibration, and force at the component level, the fault-monitoring framework presented can be observed at the machine/cell-level. The major advantage here is that, other than experience from maintenance and quality engineer, no further information is required in order to initialize and monitor the operating process from other data sources automatically. Additionally, data acquisition based on the hall-effect sensors (power meter) allows high flexibility, low-cost and simple retrofit for a range of machine tools with different automation degrees, without access to a specific machine controller.

A further advantage to analysis at the machine level is due to the fact that, in an industrial environment, the specific cutting- to fixed-energy consumption is significantly higher for the machining processes studied. This fact allows better monitoring and labeling of operating processes out of electrical power data, because of the lower noise of the signals, which is less influenced by external perturbations.

Further, development including the expansion of these approach of all electric driven equipment. Such ubiquities monitoring framework would allow real-time knowledge extraction to support decision making along organizational hierarchy. The integration in Manufacturing Execution Systems (MES) and Enterprise Resource Planning (ERP) would allow the automated assessment of such event reports considering the decision of human operators and the impact on resource consumption. Such digital knowledge extraction could use to train an artificial intelligence across the supply chain to translate and asses the “best” decisions according other field of applications with the goal of stimulating the sustainable growth.

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