“Down with the downtime!”: Towards an Integrated Maintenance and Production Management Process based on Predictive Maintenance Techniques

Hong-Hai Do, Jochen Rode, Reiner Bildmayer

SAP AG
Dietmar-Hopp Allee 16-19
69190 Walldorf
hong-hai.do@sap.com, jochen.rode@sap.com, reiner.bildmayer@sap.com

Abstract: We propose the use of predictive maintenance techniques to facilitate conflict management in manufacturing. A conflict represents a deviation between manufacturing planning and the reality within the manufacturing process. One common cause for conflicts is the unanticipated functional loss of a machine, component, or tool caused by aging and wear. Early detection of such situations can help to limit the impact of conflicts or to avoid conflicts altogether. We propose to use predictive maintenance techniques to automatically detect machine problems at an early stage, and, in assistance with a human expert, to consider the machine’s scheduled down-time/repair-time in production planning. The realization of the idea presupposes a close integration of automation, manufacturing execution, and Enterprise Resource Planning (ERP) functionalities, as well as human expertise. The paper introduces the idea and provides a preliminary discussion on architectural aspects.

Keywords: Predictive maintenance, proactive maintenance, condition monitoring

1 Introduction

Nothing is as constant as change – an old adage that most manufacturers are likely to agree to. Change causes reality to deviate from the plan, which in turn may lead to conflicts (e.g. a production order is allocated to a machine that is currently out-of-order). If not properly dealt with, conflicts may have severe consequences, such as, unfulfilled orders, escalated delivery delay, reduced customer satisfaction, etc. Currently, enterprises often handle conflicts in a *reactive* way. By doing so, negative effects of a conflict, e.g. delivery delay due to machine breakdown, can hardly be undone.

There is a variety of circumstances that may cause conflicts between manufacturing planning and reality. For example, customers unexpectedly change their orders, suppliers are unable to deliver materials in a timely manner, or machine operators are not available. One frequent cause for conflicts is the unanticipated functional loss of a machine, component, or tool caused by aging and wear.

In this paper, we focus on machine failures as a cause for conflicts and discuss a new approach aiming at a *proactive* management of these conflicts. Building on top of existing condition-based predictive maintenance techniques [6, 7] we propose to react to predicted failures by releasing a maintenance work order and by adjusting the production schedule according to the repair time estimated by a maintenance technician.

Various kinds of data related to the manufacturing process, such as machine and material data, can be exploited to estimate the wear degree of machines and to predict potential machine problems. Once he has confirmed the problem, the maintenance technician can determine the required actions, estimate the repair time and schedule the actual repair. The down time of machines is thus determined *in advance* and can be taken into account in the production planning process. Thereby, negative effects of conflicts can be avoided or reduced to a large extent.

The main goal of this paper is to introduce our approach and provide a preliminary discussion on relevant architectural aspects. The remainder of the paper is organized as follows. Section 2 gives an overview of our approach. Section 3 discusses how the approach fits into the common architecture of manufacturing automation systems. Section 4 elaborates on relevant kinds of data and analysis approaches, which can be utilized to predict machine wear and potential problems. Finally, we summarize in Section 5.

2 Process Overview

With the goal of detecting, analyzing, and correcting problems before failures occur, many predictive approaches have been developed for the maintenance of manufacturing equipment. The idea is to compare the trend of measured physical parameters of a machine against known engineering limits in order to identify anomalies or exceptions. Predictive maintenance strategies have been widely applied to manufacturing equipment, where physical parameters like vibration, temperature, pressure, voltage, current, or resistance can be measured and a limit for the physical parameter can easily be determined [6, 7]. For example, a vibration signature can be taken on a machine containing rotating parts and reviewed by a trained analyst for common problems, such as misalignment or imbalance.

As such problems may lead to breakdown of machines and ultimately to conflicts with production plan, our idea is to exploit predictive maintenance techniques for dealing with conflicts in manufacturing. Like in predictive maintenance, we aim at capturing and analyzing different kinds of data related to the manufacturing process to detect problems that are likely to happen and possibly need to be considered in production planning. In contrast to the state-of-the-art, our approach goes beyond merely predicting failures towards a fully integrated and holistic maintenance and production management process.

Figure 1 illustrates our approach, which is based on a closed loop of six steps described in the following:

1. *Data Capture*. In this step, different kinds of real-time data related to the machines and manufacturing process are captured. For example, machine data, such as oil and electricity consumption, is constantly measured by corresponding sensors to determine the current operational state of the machine.

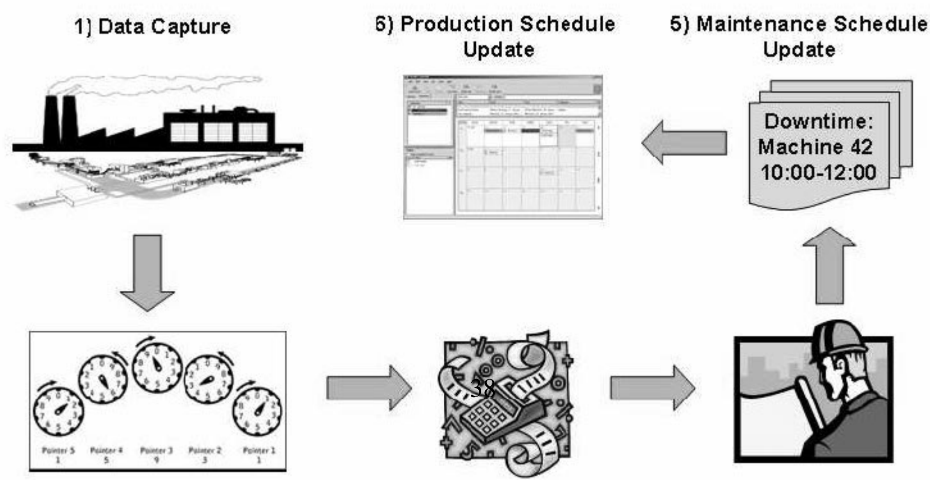
2. *KPI Generation*. Relevant data is captured in form of streams, leading to large amounts of data accumulated over time. The data needs to be aggregated and filtered in order to generate Key Performance Indicators (KPIs), which can help predict machine problems. This form of data abstraction is required in order to systematically reduce details and provide the decision-making process with only critical information (statistics, correlations, etc.).

3. *Problem Prediction*. The KPIs are constantly surveyed by corresponding analysis algorithms in order to detect anomalies, exceptions, or trends. This can be done using simple threshold-based rules or complex data mining approaches. Once a particular trend is detected, a report is generated, predicting the machine problem that is likely to happen in the near future. The report also explains based on which data and rules the problem was predicted.

4. *Review & Estimation*. Automatic prediction may not always be of high accuracy. In order to ensure the relevance of the problem report, a maintenance technician reviews the report and decides whether or not maintenance measures are needed. If maintenance is required, the technician estimates the required repair time..

5. *Maintenance Schedule Update*. The maintenance technician adjusts the work order proposed by the system while considering the severity of the problem, the availability of maintenance personnel and material, the current production plan, and perhaps the input of the production manager. The maintenance work order is being scheduled. In particular, a time slot is determined with necessary work force and material allocated for executing the maintenance task.

6. *Production Schedule Update*. Based on the maintenance work order and the estimated repair time, the capacity calendar of the affected resource is updated to reflect its unavailability during repair. Furthermore, the production schedule is modified accordingly.



3 Architecture Overview

According to the ISA-95 standard [8], automation and control systems in manufacturing can be organized in a layered structure as shown in Figure 2a. Note, that the strict separation of functionality into these layers is not necessarily the best approach for designing manufacturing control systems (e.g., interfaces between the layers are problematic) but it serves well to illustrate the location of the individual components of our approach. Layer 1 consists of field devices, i.e. machines and equipments, whose task is to execute the basic manufacturing operations on materials. Layer 2 comprises machine controllers, such as Programmable Logic Controllers (PLCs), which control the operation of single machines. Layer 3 contains a Manufacturing Execution System (MES), which executes and coordinates the manufacturing process over a range of machines, manufacturing lines, or cells. Layer 4 comprises the Enterprise Resource Planning (ERP) system providing enterprise-wide functions for planning of resources.

Figure 2b illustrates how the steps (indicated by corresponding numbers) of our approach described in the last section fit into the common manufacturing architecture. Equipped with sensors (layer 1), the controllers from layer 2 can sense and capture data describing the current state of the manufacturing process, such as current machine parameters, the quality of the obtained product (a.k.a. SPC: Statistical Process Control), etc. (Step 1, Data Capture). As the controllers only have limited storage capacity, the data needs to be forwarded to the MES located at layer 3 although some pre-filtering may already be take place at layer 2. In the MES, the data is aggregated and accumulated over time, so that comparative analysis can be applied to generate relevant KPIs (Step 2, KPI Generation).

The KPIs are constantly surveyed in the MES by means of corresponding algorithms, which can detect trends or exceptions as early symptoms of some machine problems (Step 3, Problem Prediction). As soon as the problem is verified and confirmed by a technician, the MES triggers the ERP system to generate a maintenance work order (Step 4, Review & Estimation). The ERP system updates the maintenance plan to incorporate

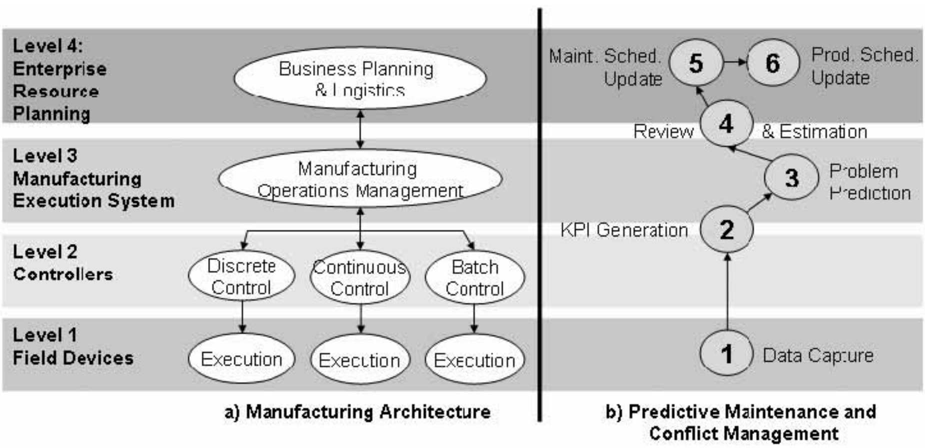


Figure 2. Mapping of our approach to manufacturing architecture according to ISA S95

the new maintenance task (Step 5, Maintenance Schedule Update). Once the maintenance task is scheduled, the ERP updates the production plan, thereby considering the unavailability/reduced availability of the corresponding machine during the time slot reserved for the maintenance task (Step 6, Production Schedule Update).

Our approach presupposes a close integration of the automation layer, MES, ERP functionalities, and human expertise, which also represents a major challenge with the currently available solutions. In particular, we observe a strong segmentation of the market according to the different layers. Key players, such as SAP and Siemens, mostly only focus on the functionality of a particular layer and offer products for the specific layer, e.g., SAP's mySAP suite for the ERP layer [4], and Siemens' SIMATIC IT for the MES layer [5]. While there are already some efforts towards standardized models and interfaces, such as ISA-95 [8], OPC [3], etc., substantial research work is still needed to address a number of issues, such as plant-to-business integration (contrary to common belief ISA-95 does not fully address the problem), flexible aggregation of real-time manufacturing data, plant/enterprise-wide integration, management, and analysis of manufacturing data, integration of maintenance planning and production planning.

4 Data Management and Analysis

The foundation of our approach is a comprehensive and flexible infrastructure to capture and manage relevant data of the manufacturing process and to enable the prediction of machine wear and problems. In a first step, we identify all kinds of data that may give hints to or make behavior and wear of machines predictable. We differentiate between *Machine data*, *Material data*, *Procedural data*, *Product quality data, and Observation data*. Figure 3 illustrates the different kinds of data and their context in the manufacturing process. We discuss the different kinds of data in the following:

- *Machine data*. This data includes all information captured during the operation of a machine. Examples include e.g. operation hours, current oil or electricity consumption. This information is already widely utilized for condition monitoring/condition-based maintenance. Typically, machines have embedded sensors to capture such data. With a high capture frequency, vast amounts of data may be accumulated, requiring powerful solutions like data historians or high-performance databases to archive and manage machine data.
- *Material data*. This data covers the properties of the product material, such as structure and composition. A product may be manufactured with different materials, which in turn may cause different wear effects to the machine or tool. Material properties may be added to the data already contained in the production order.
- *Procedural data*. This data stems from the procedure to process the material and to produce the desirable product. For CNC (Computer Numeric Control)-enabled machines, the information is typically provided with the CNC program for controlling the movement of the machines. Like material data, procedural data, such as required machine speed and pressure, directly determines the behavior of machines and should be considered to predict machine wear.

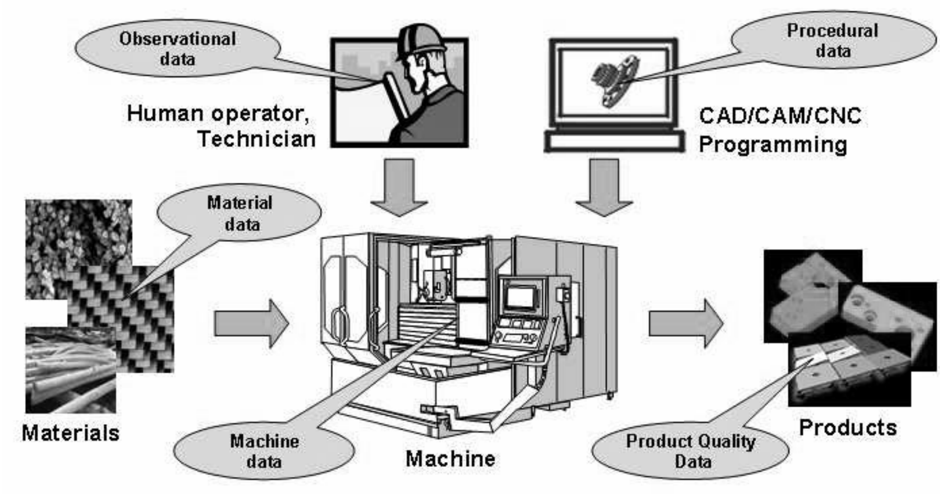


Figure 3. Manufacturing data with impact on machine wear

- *Product quality data*. Products are the output of machines in manufacturing and embody the fingerprint of the machines. The quality of the manufactured products can give hints to the current state of the involved machines or tools. Quality data, especially deviations from an "ideal" product, may be obtained from quality control and exploited to predict machine problems.
- *Observation data*. Machine operators and technicians may provide additional data about the equipment status. This information can supplement the sensor data or even provide the only input for measures that are not or cannot be monitored automatically. Since not every problematic situation can be foreseen and planned for, human experience adds flexibility to the system.

While existing predictive maintenance approaches mostly only utilize machine data, we aim at advancing the state of the art by also exploiting material data, procedural data, product quality data, and observational data. However, the kinds of data differ from each other in many different aspects and require different approaches for handling. This leads to several challenges concerning both the management and analysis of the captured data.

Machine data will likely represent the largest portion of data to be managed as it is measured and transmitted at real-time by corresponding machine sensors. Typically, it comprises numeric values, which are of similar format and structure even for different machines. On the other side, material, procedural, product quality data, and especially observational data may strongly vary even in format and structure for one machine according to the different materials and manufacturing processes employed. Hence, the major challenges concerning data management are a) the construction of a powerful data model capable of representing the different kinds of data, and b) the provision of a high-performance infrastructure able to handle large amounts of real-time data.

The ultimate goal of the data analysis is to turn raw data into knowledge about machine wear and potential problems, i.e. to generate relevant KPIs for predictive maintenance and conflict handling. In turn, the different kinds of data with different characteristics presuppose different analysis approaches. For real-time machine data, existing data mining approaches, such as for statistical, trend and cluster analysis [1, 2] can be employed to detect anomalies or exceptions in data. On the other side, the quantification of machine wear from other data is still an research topic. For material data, a possible approach is to compare against data of standard materials, for which the influence on machines is already known or pre-defined. From procedural data, the influence on machine aging can be estimated by accumulating those impact factors known or pre-defined for single machine operations. Considering quality data, it is necessary to consider the entire record of historical data on machine wear and product quality in order to estimate corresponding models of dependencies between them.

5 Summary

We have described a new vision and integrated process for managing conflicts resulting from equipment failures. First, we focus on machines as an important cause for conflicts and employ automated predictive maintenance techniques to predict machine wear and potential machine problems. Second, once a human expert determines that maintenance measures are necessary, we integrate the scheduled down-time of the affected equipment into the production planning and scheduling process, so that that future conflicts and their negative effects can be avoided or mitigated as much and as early on as possible . The approach exhibits various opportunities for further research, such as, to address the issue of interoperability between the automation layer, MES and ERP functionalities, to develop new techniques for the integration and management manufacturing data, and to predict and quantify machine behavior from different kinds of data.

References

1. Berkhin, P.: Survey of Clustering Data Mining Techniques, Accrue Software, 2006. http://www.accrue.com/forms/download_literature.html
2. Jain, A.K., M.N. Murty, P.J. Flynn: Data Clustering - A Review. ACM Computing Survey, 31(3): 264-323, 1999
3. OPC Foundation: OLE for Process Control (OPC) Standard Specifications, 2006. http://www.opcfoundation.org/
4. SAP: mySAP Business Suite, 2006. http://www.sap.com/solutions/business-suite/
5. Siemens: SIMATIC IT, 2006. http://www.automation.siemens.com/mes/simatic-it/
6. Bengtsson, M.: Condition Based Maintenance System Technology – Where is Development Heading? Proceedings of the 17th European Maintenance Congress (Euromaintenance 2004), Barcelona, Spain, 2004
7. McKone, K.E., E.N. Weiss: Guidelines for Implementing Predictive Maintenance. Production Operations Management, 11(2), 109-124, 2002.
8. ISA: Enterprise-Control System Integration (ANSI/ISA-95.00.01), 2006. http://www.isa.org/