Architecture of a Predictive Maintenance Framework

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Abstract

Predictive Maintenance is a promising maintenance strategy, however existing solutions are isolated from enterprise systems and limited to specific applications. A predictive maintenance framework that integrates the diversity of existing techniques for predicting equipment failure and that incorporates both data from machine level as well as from upper enterprise level is still missing. We propose the predictive maintenance framework that is characterized by a high degree of automation and the possibility to use most state-of-the-art prediction methods. We attempt to create an open architecture that enables third party suppliers to integrate their specialized prediction components into our framework. In this paper we analyze the requirements and introduce the initial architecture associated with such a predictive maintenance framework which is realized in a joint project with SAP Research.

1 Introduction

In industrial facilities, maintenance is an important factor regarding costs and production reliability. Among the available maintenance strategies predictive maintenance seems to be the most promising, because failures are predicted and a timely reaction is possible. Existing solutions for predictive maintenance exist, but these are not integrated with enterprise systems like ERP which can cause costly manual synchronization. In this paper we propose an integrated architecture for a predictive maintenance framework based on web technology which is designed for cooperation with existing system. We are developing this framework in a joint project with SAP Research.

1.1 Maintenance Strategies

When dealing with maintenance of shop floor equipment many strategies have been developed with several accordant definitions. We have extracted relevant definitions for our work which are described in the following. The easiest approach is to maintain equipment as soon as it is broken. This **reactive maintenance** strategy saves the time of creating a maintenance schedule in advance and makes sure nothing is done as long as everything goes “just fine”. However, as soon as maintenance has to be performed, the equipment has significant downtime.

In order to prevent this significant downtime, it has become common amongst manufacturers to do regular maintenance with the aim to prevent the breaking of equipment. Therefore, maintenance tasks are scheduled periodically according to equipment-specific intervals to maintain or replace critical components. This strategy is called **preventive maintenance**. The task can be scheduled in a way that interferes least with the overall production. The drawback of this concept is that, in order to securely avoid breakdowns, the period for maintenance has to be set to the worst case. Hence, maintenance will often be issued when it is not needed yet.

Naturally, the actual condition of a piece of equipment needs to be considered in order to find a more efficient strategy. Thus, **predictive maintenance** was introduced. It is based on the concept of **condition monitoring**, which means that meaningful measurements of the machine state are taken at regular intervals or even constantly. Monitoring and trending these values can help to anticipate problems and failures, thus responding in time to potential breakdowns. The informational basis for the prognosis of future failures can also be obtained from statistical data about the equipment. However, using actual condition information yield more accurate prognoses.

1.2 Aspects of Predictive Maintenance

Predictive maintenance has several aspects, that have to be considered when it is utilized in an enterprise. We will shortly classify them and identify those that are of importance to our framework approach.

Identifying Indicators The basis of predictive maintenance is to identify physical, measurable parameters that indicate wear or aging. We denote them as *reliability indicators*. Monitoring these indicators for irregularities or forecasting the development yields estimations about future failures. The selection of the relevant indicators is crucial, because the predictions are only meaningful if the reliability indicators correlate to the physical state of the machine. Identifying these indicators involves in-depth knowledge of the respective machines [6]. Our framework will provide support for experts that perform this task.

Measuring Indicators Closely related is the field of measuring techniques. The main issue is how to perform measurements directly or indirectly in real world environments. This includes considerations of robustness and costs of the measurement equipment. The development or improvement of such methods is out of scope for our approach. However, we attempt to integrate such technologies for automatic condition data acquisition.

Modeling Indicators Modeling the indicators is necessary to detect deviations and to perform forecasts. It is a necessary step to enable forecasting. Modeling involves among other the determination of the dynamic characteristics of an indicator, the selection of a fitting model and its parameterization. At least parameterization can be performed automatically. This aspect is very important to our framework and we attempt to enable the integration of diverse modeling paradigms, to provide support for model selection and verification and create an architecture that is open for other parties to contribute specialized models for our framework.

Forecasting Indicators Forecasting techniques may be considered the heart of predictive maintenance. Forecasting takes a model of the development of an indicator and yields an estimation of future values of that indicator. Contemporary research focuses on sophisticated techniques like neural networks, filtering or statistical approaches. Again, we envision to enable the integration of these techniques.

Decision Making Reacting on predicted failures is as important as inferring the prediction itself. A decision on how to react on a prediction has to consider both maintenance and production issues. Decision making, therefore, includes an answer to the question how to possibly correct the anticipated fault as well as when the correction has to be scheduled so that it interferes least with current production plans. We attempt to tackle this task in close cooperation with existing enterprise systems.

1.3 Challenges

The challenges we face are closely related to the improvement of information integration as well as information exchange.

We intend to work on a flexible architecture for a predictive maintenance framework, which is feasible in different contexts inside the manufacturing domain. Therefore, isolated solutions with limited application fields should be avoided through our framework.

Another challenge is to describe shop floor equipment and corresponding indicators for machines reliability in a uniform manner and in sufficient detail. Therefore, we need to develop suitable techniques for describing and managing such data.

Furthermore, IT-infrastructures in shop floor level and enterprise level are very heterogeneous and may not be used interchangeably. The challenge here is to bring together technologies of different application domains.

Moreover, we consider the integration of all relevant data into the proposed framework. This integration means consolidation and condensation of data to information for upper layer systems, i.e. systems at ERP level. In other words, information exchange in a vertical manner is essential for optimizing maintenance operations regarding efficiency.

Last but not least, we focus to support third party vendors for participating at our framework. In that case, we aim at developing an open platform for external experts (e.g. machine vendors or process experts) that are able to easily use generic framework functionalities. This includes the flexible integration of various computing algorithms, forecasting techniques and modeling processes.

The rest of the paper is organized as follows: After the initial analysis for the predictive maintenance framework is discussed in section 2, we present the architecture of the proposed framework in section 3. Section 4 describes related work from research and industry. Finally, section 5 draws the conclusion and describes our future work.

2 Analysis

As already described, preventive maintenance can cause a significant overhead in maintenance operations in a shop floor environment. Unnecessary maintenance can be avoided by an adequate information exchange between shop floor environments and ERP systems. Different industry and research projects work (as outlined in 4) on the optimization of maintenance. However, solutions developed until now are isolated and depend on specific use cases. Additionally, there is no vertical information integration in current solutions.

Our aim is, therefore, the development of a framework for predictive maintenance whose main characteristic is flexibility due to the integration of:

- relevant data available on the shop floor and in upper-level enterprise systems
- existing indicator sensing techniques

- state-of-the-art indicator model approaches and machine life cycle models
- existing forecasting techniques

Focusing the manufacturing environment the framework provides the basis for a sophisticated failure prediction upon which subsequent decision systems may issue maintenance actions. In the following the requirements and benefits of the framework we envision are analyzed.

2.1 Connection to ERP

Responsible for enterprise-wide resource planing, an ERP system possesses information concerning production plans, orders and personnels as well as branch-specific data. Furthermore, to support a well-organized production process, ERP systems in the manufacturing context rely on a factory model. The factory model designed by an ERP system integrator represents factory equipment namely machines and its components in an adequate level of detail. Information provided by the ERP system are essential for the prediction process since more advanced techniques may consider production plans, machine setup and machine interdependencies in the predict equipment failure.

On the other hand, the prediction and suggestion for maintenance operations has to be integrated in ERP systems to be appropriately reacted on. Therefore, the bidirectional link to an ERP system is one of the main concepts for establishing predictive maintenance in manufacturing environments.

2.2 Data Acquisition and Processing

The second essential data source besides upper-level enterprise systems is the shop floor which provides measurable equipment data and production-specific i.e. quality data. Equipment data e.g. machine operating hours or meantime between failure is assigned to a physical machine or machine component. Quality data, on the other hand, refers to measurable data concerning a defined workpiece that is currently processed e.g. gages of a workpiece or the accuracy of the production process. Thus, another important core task in order to realize a framework for predictive maintenance is the acquisition of equipment data and production-specific data.

After data has been captured it must be saved in a database which creates a historic view of how the equipment has been used over time. This history serves as basis for the examination of indicators which represent the reliability of a machine or machine component.

An essential issue to be covered by the framework is the processing of reliability indicators. This means that all relevant equipment data assigned to a reliability indicator must be modeled through a modeling concept such as stochastic models or neural networks. The result of the modeling phase is a model which reflects the indicator's behavior up to the present. A subsequent phase deals with the forecast of reliability indicator's future behavior and the notification as soon as a critical state is predicted. Hence, failures of machines or machine components can be foreseen and maintenance tasks scheduled before machine malfunction occurs.

The proposed procedure is flexible in a way that reliability indicators are user-defined and may apply to different business levels in an enterprise.

2.3 Information Integration

The vertical integration of all significant information is essential for improving the flow of information between shop floor level and enterprise level. The long-term objective is to combine all indicator models of a regarded system and to derive an overall health state estimation for the complete system. For instance, if a machine is examined at component level, reliability indicators are modeled for selected machine components. The great challenge, however, is to bring these models together and to create a health statement for the reliability of the entire machine. Such a statement is important for the machine operator in the shop floor to identify abnormal behavior prematurely. Moreover, the health state estimates for single machines may be further combined to an estimation for a machine system which is essential for production planning at branch level.

2.4 Benefit for Factory Carriers

The benefit of the proposed framework is to decrease maintenance cost by supporting a variety of predictive maintenance methods and the possibility to enrich them with data acquired from both the shop floor and upper-level enterprise systems. Knowing future equipment failure in advance enables the factory carrier to better plan production and maintenance operations, to minimize factory downtimes and to abide by business agreements.

To summarize this section, factory carriers are able to achieve highly optimized shop floor environments, which is integrated with ERP systems by using this framework. The main impact of our framework is the ability to include the current and future equipment health state in the planing of maintenance and production.

3 Framework Architecture

The architecture of the proposed predictive maintenance framework is depicted in figure 1. The framework consists of different layers and obtains flexibility by taking a service-

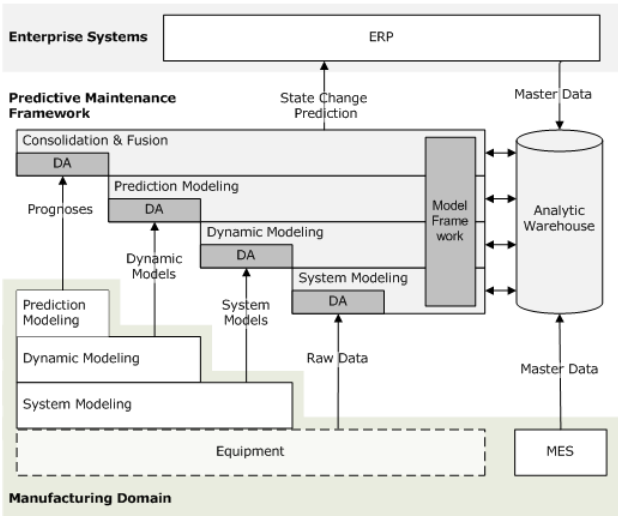

Figure 1. Architecture of the predictive maintenance framework.

oriented approach. Each layer is composed of services that realize at least one of the following tasks:

- data acquisition (DA) from the shop floor
- execution of layer-specific tasks
- access to the analytic warehouse
- access to the model framework

The framework environment and its components will be described in the following.

3.1 Framework environment

The environment in which the framework resides may be described by the *manufacturing domain* on the one hand, and by *enterprise systems* such as an ERP on the other hand.

The manufacturing domain is characterized by a multitude of equipment, communication mechanisms and vendor-specific solutions. Besides the physical equipment the manufacturing domain also includes IT-infrastructure such as PLC, MES and SPC to control the equipment and the production process. We consider the MES as part of the manufacturing domain because by supervising the production it manages data "close" to the shop floor.

ERP as a representative for upper-level enterprise systems mainly provides master data to enrich failure prediction methods with additional data. Furthermore, the ERP is considered the destination for a consolidated notification about a predicted health state change of a certain equipment or system.

3.2 Data Acquisition Service

The data acquisition service found on each framework layer realizes the distinctive staircase interface to the shop floor. The interface is developed in different complexity depending on the degree of consolidation, reduction and aggregation of maintenance relevant data (e.g. equipment data, quality data). The main reason for developing such a staircase interface is the fact that functionality assigned to the different layers is either implemented in the framework components or provided by components situated in the shop floor (e.g. machines, PLC, field devices, sensors and actors). For example, a rather complex shop floor component may provide a complete prediction itself, while another supplies a model, and a more simple component provides raw data only. Therefore, reacting on the given situation in real-world production plants the staircase interface easily extends and adapts to existing systems. To cope with the above mentioned heterogeneity of the manufacturing domain, different standards for shop floor data access will be applicable.

3.3 Indicator Modeling Layers

Although a multitude of equipment and data-specific prediction techniques exist, we define the general prediction process as a sequence of modeling steps. First, the static relation between one or more system input values and the reliability indicator is described in the system modeling layer. Next, the indicator's dynamic behavior over the time is modeled in the dynamic modeling layer. Finally, the modeling phase culminates in inferring the future behavior of the reliability indicator which is done in the prediction modeling layer. Thus, a prediction process is an ordered set of model instances where each provides their respective results to the next model in the chain. The concrete prediction process depends on the equipment and the properties of the data that is available and therefore, on the selection of appropriate model instances.

3.4 Consolidation & Fusion Layer

The consolidation & fusion layer is responsible to represent a consistent and integrated view of the shop floor for the ERP. This includes the fusion of several predictions for the same ERP equipment entity, e.g. because an equipment consists of several components, that are not represented individually in the ERP. Another fusion task occurs when several prediction processes work in parallel for the same ERP equipment entity, e.g. to increase the overall accuracy. Finally, the consolidation & fusion layer triggers the notifications to the ERP according to user specifications.

3.5 Analytic Warehouse

The analytic warehouse serves as a layer of abstraction to present an integrated view on all relevant data to the models of the prediction process. The integration task that is encapsulated in the analytic warehouse involves schema and data integration of master data from the enterprise systems with the process and model data from the manufacturing domain. We do not try to solve this problem in a generic way, but instead assume that this is done when the framework is actually deployed. The analytic warehouse is considered the informational basis for the prediction process. Besides the obviously necessary master and process data, statistical information shall be held here. This includes information about the occurrences of failures and their respective causes, the results of maintenance inspections and actions. Hereby, we hope to build per equipment statistics that can help to rate predictions from the prediction process.

3.6 Model Framework and Repository

The model framework and repository represents one of the central ideas of the predictive maintenance framework. Its purpose is to provide an unified and abstracted view on the variety of the modeling techniques (with regard to system, dynamic and prognosis modeling) integrated in the framework. This is achieved by determining the commonalities and variabilities of modeling approaches. Common to all approaches is the determination of the model structure and model parameters as well as the validation of them. However, the algorithms how these tasks are carried out vary and depend on the model purpose (e.g. static, dynamic or prediction model). To support system integrators and machine vendors in model deployment as well as model development the framework offers flexible extension points for integrating new models on the one hand, and semantic model annotations on the other hand. The semantic annotations include additional information that suggest the correct use of the model e.g. in the intended domain.

3.7 Proof of Concept

For further validation of our concepts we will implement the proposed framework in a demonstrator (fig. 2). Therefore, as a demonstrator we use a miniature of a machine system that consists of machines for drilling, milling and turning. All machines are connected with conveyor robots and additionally with a high rack storage area. The complete model factory is controlled by a Siemens SIMATIC S7 SPS with an additional Siemens SIMATIC NET OPC Server and a simple MES (Manufacturing Execution System). First we defined a production scenario in which we consider the production of shafts (e.g. for the car industry)

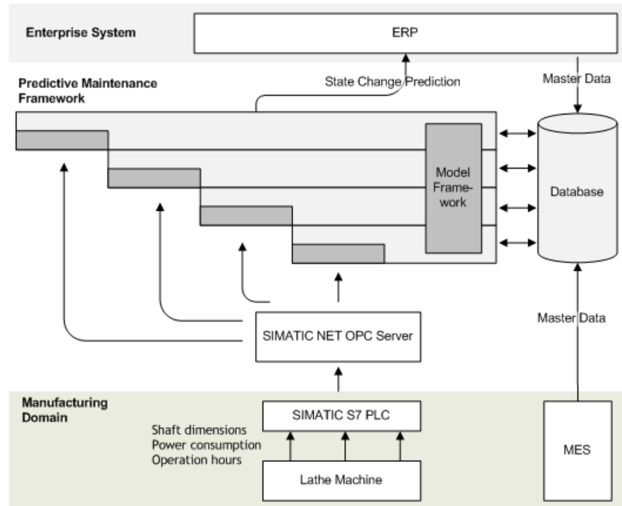

Figure 2. Schematic view of the demonstrator

with strictly defined lengths and diameters. The production plan is divided into several work steps which include the operations drilling, milling and turning.

For applying predictive maintenance in this scenario we focus on the lathe machine, which possesses different sensors in order to measure quality data as well as machine specific data. The commonality of all measured data is the relation to an indicator expressing the reliability of the regarded lathe machine. As examples for such indicators we have chosen the work piece dimensions as quality data and the power consumption of the motor component as machine specific data. Both indicators are measured in discrete intervals regarded as a stochastic process and therefore modeled as a dynamic model. After the dynamic modeling has been carried out a stochastic prognosis model will be adopted. This model enables the factory carrier to predict the behavior of the regarded indicator in future. The reliability of the lathe machine falls significantly if an indicator achieves a previous defined threshold. In this case, it can be determined that the regarded machine needs maintenance in order to avoid failures. Therefore this message can be propagated and processed at ERP level (e.g. through instructing the maintenance engineer with the best experience for this maintenance case).

4 Related Work

Related projects that do at least partially attempt to create a framework for (predictive) maintenance are outlined in the following.

The IMS Watchdog Agent™ tool kit [2, 7] of the Center for Intelligent Maintenance Systems is a toolbox of algorithms for assessment and prediction of a machine's performance . This corresponds to the aspects modeling and forecasting indicators and leaves out decision making. No integration with enterprise systems or MES is included. Hence, the reaction on predicted failures involves much human interaction and manual synchronization between the Watchdog Agent™ instances and the enterprise systems. The Watchdog Agent™ also does not offer a versatile interface to the shop floor but is a rather monolithic solution.

SIMAP[3] is a predictive maintenance application that was designed for industrial processes. It is based primarily on neural networks for modeling and forecasting indicators. It continuously gathers data from different sensors and tries to detect anomalies with respect to the normal behavior of the monitored components. SIMAP also contains functionality to schedule maintenance actions. However, so far it was deployed only in a rather small setup for a wind turbine. Scalability of the decision making module to larger setups is questionable. And yet again, no integration with enterprise systems or MES is included.

Such an integration was realized in the PROTEUS project[1]. PROTEUS is a generic platform for e-maintenance, i.e. it integrates existing maintenance management applications to enable a comprehensive work flow. Hence, the goal of PROTEUS is different to our framework, since PROTEUS was designed to support maintenance operations itself, e.g. spare part inventory management. We focus on the prediction when maintenance will be necessary. This functionality is not found in PROTEUS.

Another, large integration project is PROMISE [4]. It aims at developing a comprehensive product life cycle management platform to capture, manage, and analyze product data from all life cycle phases of the product. One possible usage scenario is predictive maintenance. The overall scope of PROMISE is large and involves also research into hardware components, so called *product embedded information devices*, that can be used for measuring indicators. However, PROMISE does not intend to structure the tasks of predictive maintenance as we attempt to.

TATEM [5] is an ongoing project that aims at improving aircraft operability and safety and at the reduction of maintenance costs by detecting present and incipient faults. TATEM covers all aspects of predictive maintenance, but focuses exclusively at the application in aircrafts. We however, aim at the application in industrial settings, which impose additional challenges by it's heterogeneity.

5 Conclusion and Future Work

The evolution of maintenance strategies has reached the stage of predictive maintenance taking the actual equipment state into account and predicting future equipment failure. Predictive maintenance may be considered a multi-step process including the identification, acquisition and modeling of relevant wear indicators as well as the development of machine-specific life cycle models and the determination of future failures by using forecasting techniques. Current research already addresses these issues individually. However, an integrated approach in the sense of a predictive maintenance framework is still missing.

The predictive maintenance framework we envision is characterized by the following core concept: Rather than developing new mechanisms, the framework integrates already existing and well-established data acquisition and indicator modeling techniques. This includes a possibility for third party suppliers to blend in their specific methods. Furthermore, the framework will reside between the shop floor and ERP systems enabling the use of data both from field and enterprise level to be incorporated in advanced prediction techniques.

To realize our vision of such a framework we will develop an open and flexible architecture that will provide a unified view on a variety of data acquisition and modeling techniques so that they can be conveniently selected and adjusted to the constraints of a particular manufacturing environment. Furthermore, since forecast dimensions are configurable and model-dependent, different model categories together with their possibilities and restrictions should be explored in detail. As a proof of concept the architecture will be implemented in a demonstrator, bearing standard tasks like deployment issues and model selection. Through the implementation we seek to discover unveiling fields of obstacles which will guide us toward more future work.

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