Predictive Maintenance and Diagnostics of Machine Tools

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Abstract

The objective of condition-based predictive maintenance applied to machine tools is the "measurement" of the slow degradation taking place in mechanical components in advance of the consequent failures and the evaluation of the residual life in order to better manage the total Life Cycle Cost. An automatic self-tuning of the system should accompany this procedure, in order to always optimize the machine tool performance as an optimal trade-off between surface quality and machining speed. These activities may be performed by intelligent software modules, communicating among them, with the machines, the sensors and the humans. The implementation of some of these modules is taking place in the frame of the project "Intelligent Networked Manufacturing System" (INT-MANUS).

Keywords: Predictive Maintenance, Tuning, Machine Tools

1. Introduction

The development of new approaches for the maintenance of production machines is a very challenging and essential topic. In this paper we present our ideas on possible improvements of current approaches. The implementation of some of the ideas is being carried out in the frame of the INT-MANUS project (NMP2-CT-2005-016550).

The main objective of the INT-MANUS project is to develop a Smart-Connected-Control Platform for manufacturing enterprises. The platform should integrate the information about the production process and manufacturing machines and provide possibilities to access the information for program agents and human personnel. The purpose of the platform is to decrease maintenance costs and increase the efficiency of production process.

With the help of the Smart-Connected-Control Platform, pro-active maintenance will be improved. Machines and personnel will enter machine states, necessary maintenance operations and their schedule into the Smart-Connected-Control platform. The semantics enabled operating system will schedule maintenance operations and inform the production plant supervisor accordingly.

In this article we will speak mostly about the applications relative to predictive maintenance and diagnostics of machine tools.

2. Maintenance approaches

The current approaches for the maintenance of machine tools are:

- **Breakdown Maintenance or Corrective Maintenance** keeps focus on time-efficient and

lower-cost repairing/replacing equipment, only when a failure occurs. This strategy assumes that failure will take place and cannot guarantee zero failure situations. The biggest disadvantages of this method are the high value of failure costs, unpredictable time when failure takes place, undetermined time for maintenance activity (supported product downtime).
- **Preventive Maintenance** is a perspective strategy, based on the knowledge of the mean-time-between failure figures. To minimize breakdowns and to avoid losses due to unexpected stops, Condition-Monitoring Maintenance (CMM) is a basic reference. This strategy focuses on keeping the equipment in good condition to minimize failures, and on repairing components before they fail.
- The objective of **Condition-based Predictive Maintenance** is the "measurement" of the slow degradation taking place in mechanical components in advance of the consequent failures and the evaluation of the residual life in order to better manage the total Life Cycle Cost. An automatical self-tuning of the system should accompany this procedure, in order to always optimize the machine tool performance as an optimal trade-off between surface quality and machining speed.

Several activities are needed to achieve this goal, all of them complex, but even more when put together. These activities may be performed by intelligent software modules, communicating among them, with the machines, the sensors and the humans. The main modules should be:

- Data Mining: it should collect data coming from sensors, perform filtering of the huge amount of data and their interpretation in order to extract a set of significant quality indicators that synthesize the machine status.
- Decision Support: from the comparison between the current values of quality indicators and the values they had when the machine was new, it should evaluate the machine status, the residual life of mechanical components and take a decision about actions to be taken:
    - No action;
    - Self-tune;
    - Schedule maintenance for substitution of mechanical parts.
- Self-tuning: it should tune the main parameters in the NC and servo drives (gains of control loops, speed, acceleration and jerk, etc.) in order to keep a good quality of machining even though by decreasing the working speed.
- Rescheduling: in case maintenance should be scheduled, it should select the optimal time for service intervention and generate an updated process plan for the interested cell, shifting the operations scheduled on that machine to the other machines in the cell.
- Communication: it should notify to human personnel in the plant evaluated data (residual life, machine status, decisions about maintenance, etc.) and exchange information with other machines.

Moreover the collection in a central, remote repository of data relative to failures coming from similar machines working in different environments under different working conditions may help in the diagnosis of failures and in the improvement to the design of the machine tool itself. It would provide a wider information database to be used by learning modules, compare data coming from similar machines, map defects to climate, working conditions, and so on, and thus help in the improvement of machine design.

3. Architecture of the system for Maintenance

Figures 1 and 2 show the logical architecture of the system. Figure 1 describes the Data Mining part in detail: sensors collect data from the Machine Tool; the Data Mining software module is organized in form of a data processing pipeline and can be split in three main phases:

1. Collect data from sensors with the suitable frequency;
2. Since these data are a huge amount, they need to be filtered;
3. Some indicators identifying the state of "health" of the mechanical parts (meaning the status of wearing out of components) can be extracted and stored. Some examples of these indicators can be: vibration critical frequency, damping factor, backlash (error at the inversion of the direction of movement), maximum and average value of current, ripple of current. The selection of parameters, to be used as input for diagnostic and monitoring algorithms (the so called feature extraction), is one of the most critical phases in the whole process.

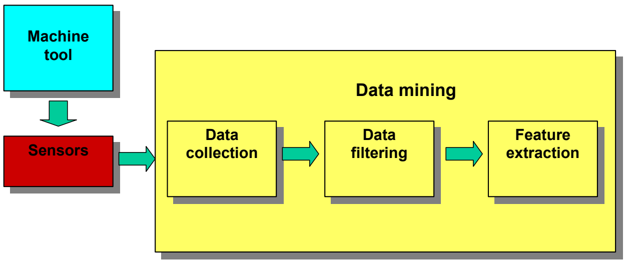

Figure 1: Logical architecture of system for maintenance: data mining

All collected data can be classified using meta-data, e.g. an RDF-based ontology to describe their type, source, dependencies and relations to other data acquired. This can be used for high-level filtering and interpretations applied later on.

Figure 2 shows a complete view of the system architecture: the Data Mining software provides indicators to a Decision Support module that selects the possible action, choosing among the following:

- Do nothing because the system is working very close to an optimal situation;
- Self-tune the system, whenever possible, in order to achieve a different trade-off between accuracy and time; in fact, for instance in the production of moulds and dies, the tuning of a machine tool is usually based on the selection of a suitable compromise: if the working operation is faster, it is normally less accurate, and vice versa. The optimal compromise depends on the kind of operation; for instance during a roughing operation, accuracy is not at all required, therefore the tuning should optimize the execution time (and cost, as a consequence). Usually the wearing out of mechanical components can be balanced through a different tuning that sacrifices the execution time but leaves the quality and accuracy of the result unchanged; typical machine parameters to be tuned for this goal are: speed, acceleration and jerk, gains of control loops.
- After a certain threshold, it is not efficient anymore to slow down the machine, and an intervention for the substitution of a mechanical part is needed. The resulting reorganisation of the plant schedule should be automatically performed.

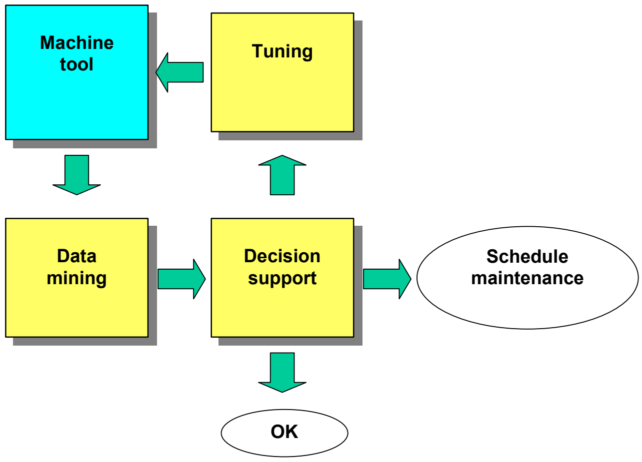

Figure 2: Logical architecture of system for maintenance: complete view

The production plant supervisor should be notified about this decision and the possible reason and mechanical parts to be substituted.

4. Architecture of the system for Diagnosis

A Remote Knowledge Repository should be added. The repository collects information coming from several machine tools (some of them of the same kind, some of them of different kind). An Evaluation Component exploits these information through algorithms able to learn from correlation of data. The result is a much more sophisticated Decision Support module.

The Knowledge Repository has to be able to transform information into knowledge, and learn by the correlation of data. For instance, applying this philosophy to diagnosis, the system will be able to correlate machine failures with factors like the climate or with the use of the machine.

Figure 3 shows the logical architecture of the system for diagnosis.

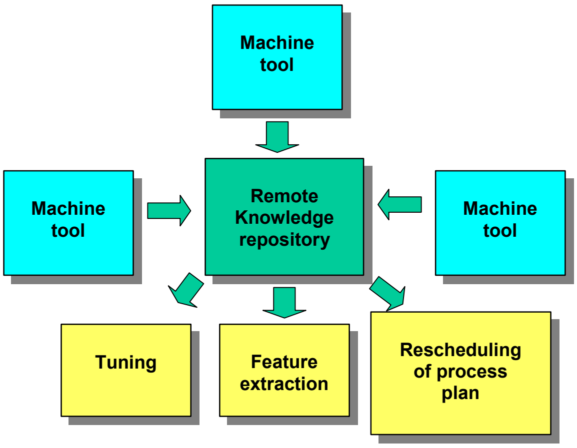

Figure 3: Logical architecture of system for diagnosis

The Knowledge Repository and associated tools for new knowledge discovering will be able to work in four main areas:

4.1 Failure detection and prevention

The goals of this area are:

- To find out the most likely reasons for the fault, and guide the service engineer to easily identify them. For instance, a defect found on a machine can help in the diagnosis of a similar defect on a similar machine.
- To identify the presence of defective stocks.
- To increase the comprehension of malfunctions and breaks.
- To identify the critical parts in the design of products and to improve it by re-designing them, this way increasing reliability and technical quality. For instance, if the comparison of data coming from similar machines shows that the same sub-component often breaks down, the conclusion can be drawn that this component should be substituted by a different one, this way improving the product design.

4.2 Evaluation of the Residual Life of Mechanical Components

The main objective of this component is the evaluation of the residual life of mechanical components, calculated as a percentage. This is a very complex task for several reasons:

- It is affected by different kinds of factors (climate, typology, rate of use etc.).
- Historical data are usually missing or cannot easily be interpreted.
- A mechanical axis is composed of a certain number of sub-components. Sometimes the influence of the degradation of one of them will be preponderant, in other times it will be negligible, and the influence of another component will be more significant.

The easiest way to perform the evaluation of the residual life is through a set of thresholds on the health indicators calculated through the Data Mining procedure. But obviously the setting of values for the thresholds is an extremely complex task even for very experienced engineers. Thus it is necessary to implement an “intelligent” way of performing the evaluation. The idea is to use fuzzy logic to dynamically modify these thresholds as a consequence of the previous evaluations made on similar machines (or on machines where the same mechanical components are used). As a consequence, this system will be provided of a learning ability.

The result will be an evaluation of the residual life and as a consequence a decision recommended to the operator.

4.3 Tuning of machine parameters

Tuning of machine parameters requires to hold a deep “understanding” in the form of models and specification values that describe abilities, borders and specialties of machine types and even of machines themselves. Some of them can be derived from specifications available – even in written form – from the manufacturer of machine tools. Others can only be acquired while the machine is running or be derived from statistical data acquired during the runtime of the machine. Other parameters may not be specific to machine but to the application field of the product, like the automotive or aerospace industry, defining different requirements towards exactness etc. All these classifications have to be integrated in one descriptive model to build relations and draw implications from these about the influence of the tuning parameters and to automatically keep the system learning and models growing while the machines are used.

4.4 Rescheduling of the process plan

Processes can be modelled using different representations like EPC (Event-driven Process Chains) for high-level processes down to NC data on machine level. For integration, all the different models, representations and different states need a common process-driven, i.e. flow-centred, meta-model. This common meta-model is needed to specify and recognize connections and interdependencies between process-steps, machines, tools, etc. Rescheduling of process plans is based on time definitions and restrictions that allow for calculating the processing time for a task on a specific machine. A very complex and not fully describable and accomplishable problem is the fulfilment of a special type of task with a different machine type not planned or even over-qualified for this task (maybe even not initially built for this task) under economic restrictions. Like using a full-featured production centre for the task of a milling machine, which will do the job but increase cost tremendously.

Additionally, these modules should evolve by learning from the results of previous operations, which will require a wider information database for better and faster learning capabilities of the software. Even more important is the definition and implementation of a common model that requires the definition of a common interface, exchange mechanisms and an interpreting software.

Static and dynamic learning and decisions making mechanisms like rule-based reasoning, case-based reasoning, fuzzy logic, neuronal networks etc. have to be evaluated in order to find a feasible solution to the operative problems in the described production environment.

5. Conclusion

Figure 4 shows the resulting architecture for the whole system. After data collection from the sensors the data will be partially processed locally and after filtering sent to the SCC platform for storing and high-level analysis. The system then will apply its decision-support techniques and if necessary send notifications to control systems. Using the control systems it will always be possible to visualize the whole industrial plant as a colour-coded map, see the production machines connected to the SCC platform, check their status and if necessary modify it. Visualization of

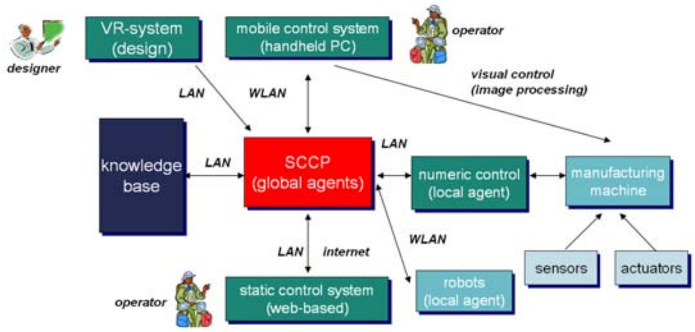

Figure 4: Complete architecture of system

robots and their routes with possibility to change them is also planned. The main modules are:

5.1 Mobile control system

This system works on a small tracked wearable PC or PDA with an additional camera, which can be used by operating personnel directly at the industrial plant. It has global view over the whole industrial plant and local view for machines or parts analysis. The system works in real- or near real-time and provides additional information support for the personnel, like escape routes in case of emergency etc.

5.2 Static control system.

There is a web-server integrated with the SCC platform, which allows connections from both local computers and other computers connected to Internet. Different security policies can be applied.

5.3 Knowledge base repository

This is basically a remote DataBase where several data are stored and that is able to transform information into knowledge, and learn by the correlation of data.

5.4 Smart-Connected-Control Platform

This communication platform allows the exchange of information among all system components: control systems, local agents, global agents, knowledge repository and visualization tools.

In this article we presented our ideas about new approaches for predictive maintenance and diagnosis of production tools, which play an important role in the

INT-MANUS project.

A success of this philosophy will represent a significant breakthrough in the maintenance and diagnosis of machine tools, but will also pave the way for different kinds of applications, all of them sharing the target of increasing the efficiency of production process.

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