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Predictive maintenance framework: Implementation of local and cloud processing for multi-stage prediction of CNC machines' health[1]

1.1. Abstract

This paper presents a predictive maintenance framework for CNC machines focusing on a multi-stage prediction of machines' health status. For the implementation of such a multi-stage prediction, the proposed approach includes two prediction layers: the cloud prediction layer and the local prediction layer. Each layer provides a prediction of machine health status in different timescale. The local prediction layer, based on data analysis techniques, is responsible to predict the health status of the machine for a short time period. Thus, this prediction can be used as an alarm aiming to prevent un-expected breakdowns. The cloud prediction layer, based on digital physical-based models, is responsible to provide a more general overview of machine health status using Prognostics and Health Management (PHM) techniques, useful for long timespan strategies definition. This paper presents the proposed approach and its benefits are described and discussed. The proposed approach will be implemented in the PROGRAMS project.

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1.2. Introduction

Maintenance and its related costs continue, over the years, to draw the attention of production management since the unplanned failures decrease the reliability of the system, and also the return on investments [MOU 15]. Taking under consideration that the maintenance accounts for as much as 60 to 70% of the production lifecycle total costs, it is a core activity of most industrial sectors [DHI 06]. More specifically, industrial studies have revealed that the cost of replacing worn-out components may be as high as 70% of the total maintenance cost [VEN 10].

Nowadays, the high complexity is an important characteristic of the CNC machines which are used for industrial applications. Several hundreds of components are required to allow the CNC machine functionality. For example, the implementation of a maintenance strategy requires continuous monitoring of each piece of equipment to be aware of its real deterioration status. Due to the high complexity of the CNC machines, a multi-stage predictive maintenance framework is needed to enable the prediction of machine health status over different timescales, aiming to ensure the prediction over both long and short time periods of operation.

One the one hand, a long-time period prediction of the CNC machines' health status is useful for the precise selection and scheduling of the best moment for maintenance, right before a component breaks down. However, prediction like this requires a long time period simulation and, accordingly, huge computational time. On the other hand, a short time period prediction is required to prevent un-expected breakdowns in the near future. Such predictions are based on the use of historical data and comparison techniques, which require small computational time.

1.3. Method

This paper presents an approach which implements this integration of long and short term prediction in a multi-stage predictive maintenance framework with two different layers: the cloud prediction layer and the local prediction layer. The cloud prediction layer is responsible to provide a more general overview of machine health status using Prognostics and Health Management (PHM) techniques over a long time period. The local prediction layer is responsible to predict the health status of the machine using data driven models over a short time period.

The main pillar of a PHM system is the prediction of the Remaining Useful Life (RUL) that depicts the time after which a system or a machine's component no longer performs its intended function [AIV 2017]. According to previous research, a maintenance action should be executed taking under consideration both health assessment information (such as RUL) as well as additional information from multi criteria mechanisms [PAP 07]. The RUL is the most important parameter to be taken under consideration for the creation and execution of a maintenance plan [OKO 04]. Thus, a number of predictive maintenance platforms are based on RUL prediction to fulfil the needs of the data analysis and knowledge management [MYC 10]. These platforms are based on three main stages: the first stage is responsible for data extraction and processing; the second one focuses on the maintenance knowledge modelling and calculation of RUL; and the third stage provides advisory capabilities for maintenance planning [EFT 12].

In the proposed research, machine component physical-based models will be used for the calculation of the RUL for each machines' components. The proposed method will be used in the PROGRAMS project. More specific, some data will be gathered by the machines' controllers and external sensors, which will be structured and uploaded to a cloud database. Some of this data will be used for the simulation of the digital models, while some other, will be used to update the simulation models, aiming to ensure that the simulated functionalities of the machines will be the same as the real one. Therefore, a digital twin of the real production equipment will be created. Finally, the upcoming process plan of the machine will make up the input for the simulation model. The output of the simulation, in combination with the reliability parameters of the machines and the real time monitored data, will be used for the final RUL calculation. The above procedure is depicted in Figure 1.

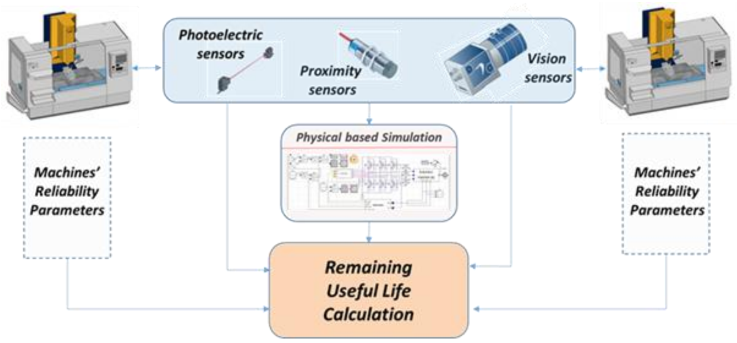

Figure 1. RUL calculation main concept [4]

For the local prediction layer and its prediction techniques, the proposed approach is based on algorithms that use the data-driven approach to prognosis learn models directly from the data, rather than using a hand-built model based on human expertise [SCH 05]. Considering that data batches collected from a repetitive operation are generally similar unless in the presence of an abnormality, a condition change can be inferred by comparing the monitored data against an available nominal batch [BIT 14]. Other researches attempt to address this problem with intelligence-oriented techniques, such as dynamic wavelet neural networks (DWNNs). DWNNs incorporate temporal information and storage capacity into their functionality so that they can predict the future, carrying out fault prognostic tasks [WAN 01].

In this research, an already existing data-driven prediction methodology based on Artificial Neural Networks will be used for the local prediction. This proposed data driven method is not a part of the PROGRAMS project. Available historical data will be used for the training of the neural network and the real time gathered data will be compared with the historical one aiming to identify potential upcoming failures.

The strong point of the presented approach is the integration of the physical-based and data-driven methodologies for the prediction of the machines' health status in a multi-dimensional time frame. The benefits of this approach when applied to CNC driven industrial equipment is presented in detail in the following chapter.

1.4. Approach

Two main factors have limited the diffusion of predictive maintenance so far: on the one hand, the huge amount of data that must be preventively collected in order to train and validate the health status prediction algorithms; on the other hand, the somewhat limited choice left to the monitored production equipment owner (replace the worn component or live with it). This scenario however changes drastically when machine tools equipped with CNCs are considered. In fact, latest generation of smart CNCs allow to record internal signals with sample rate near or equal to the CNC cycle time (usually 1-2 ms), to internally analyse real time data to detect if an equipment component is working and under which stress conditions, and to exploit knowledge of equipment's health status to adjust the processing performance.

The data produced can successively be moved to a remote cloud storage (for example a factory wide database) for applications that go beyond the straight process management. The added value of implementing these features directly inside the CNC, as opposed to using external Programmable Logic Controllers (PLCs) and Programmable Automation Controllers (PACs), is that the bulk of machine tool data and the capability for process parameters management are already available and ready to be exploited. In addition, only a limited set of CNCs allow to relinquish the control of process parameters to third party applications, both for quality management and for security/safety reasons. It then becomes clear that a new maintenance paradigm can be originated, by combining these functionalities with an advanced tool capable of using smart (data driven or model based) algorithms, to understand the equipment's current status and to predict the time when it will become irreversibly worn out. With this objective in mind, a smart CNC producer (like FIDIA) can decide to interface its controllers with a new maintenance platform, in order to offer a whole new set of functionalities to its customers.

The health status of production equipment can be computed by data driven algorithms. The main advantage of these tools is that they do not rely on complicated system modelling and can be thus applied directly to the historical CNC records (for training) or even to real time data (for fast evaluation of the current equipment's status). Once the health status of main equipment's components is available, the CNC must then correlate it with the impact it could have on the process. In fact, a worn component is usually not an important enough reason to stop the production and request a maintenance activity. In most cases, when the equipment's status deviates from the nominal one, the operator evaluates the deviation and, based on it, decides whether the machine is still fit for its purpose. In most cases (like for mass produced parts), the operator limits itself to warn the operators that will use the machine in the next shift to monitor it closely. Only in presence of drastic deviations, the operator decides to request a maintenance activity but even in those cases the production is not stopped. Instead the processing parameters are modified (usually by lowering speeds and loop gains) to continue to safely produce (albeit at a slower rate) while waiting for a replacement/repair intervention. By implementing such a functionality directly inside the machine's CNC, it would be possible to directly exploit smart CNC customization features. This functionality (such as FIDIA's *Look ahead*) allows modifying large sets of parameters with a single command. If specific sets of parameters are created for specific machine tool's health status and process conditions, it then becomes a trivial task to correlate the output of the status evaluation platform with an automatic process parameter adaption feature. However, the limits of data driven analysis should be taken into account while using such a method for health status evaluation. The most important one is that these algorithms are able only to detect when the machine performs out of nominal boundaries, but cannot provide any information on which is the cause of such behaviour. On the contrary, a model based approach would allow to actually correlate the deviation from nominal conditions to a specific restricted set of responsible components. This approach has several benefits, since it would allow: (1) to adapt only parameters directly related to the component's behaviour, thus reducing the impact on the whole process; (2) to store information about both the signals and the components that have failed, for components' models improvement; (3) to restrict the set of components that could be malfunctioning, making easier and shorter the duration of the maintenance intervention; (4) a wider time span between the prediction of the incoming failure and insurgence, granting a better maintenance scheduling. It is worth noting that a model based health detection status would greatly benefit from a cloud deployment. On the one side, this would allow using data coming from whole families of identical but widely spread similar machine tools (thus supporting also the machine tool design phase). On the other side, this would limit the computational burden at the factory level, relieving resources that could be better exploited for different objectives. In order to allow a cloud based approach however, the CNC should allow functionalities that go beyond the simple process management. These functionalities include the availability of web based services for sending information to the cloud (relevant sensor data for health status computation), retrieving data from the cloud (the computed components' status) and the writing of information on a database (for successive analysis and model training). In the framework of the PROGRAMS project, FIDIA will integrate its CNCs with the project's platform and test the new functionalities on the pilot line of one of the end users.

1.6 Acknowledgments

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