A RUL Calculation Approach Based on Physical-based Simulation Models for Predictive Maintenance

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***Abstract*— The main objective of this paper is to present a Remaining Useful Life (RUL) calculation approach, based on physical based simulation models, for the predictive maintenance of a production plant using Prognostics and health management (PHM) techniques. The resources of the production plant are modelled in order to enable the simulation of their functionalities. A smart control system is developed, aiming to gather machine data, both from the machine controller and the external sensors, before providing them as input to the simulation tool. The outcome of the simulation is the prediction of the machine's health status, which then is used for the identification of the machine's maintenance activities. Efficient algorithms and technologies for data analysis and prediction are utilized. In this way, the condition and the status of the machines can be predicted as a result from the simulation of physically-based models, without the machines' operation being stopped, as it happens in the common predictive maintenance solutions.**

Keywords—predictive maintenance; RUL prediction; physical-based model; FMECA; PHM;

I. Introduction

Nowadays, industries rely on high complexity machine tools, made up of several hundreds of components, each of which should be monitored and maintained. The best solution to this problem would be for one to be aware, every time, of the real deterioration status of each piece of equipment. This knowledge would enable the selection and scheduling of the best moment for maintenance, right before a component breaks down. Traditional predictive maintenance techniques were designed to help with determining the condition of the in-service equipment, but their approach could not be realistically applied to a real industrial environment without the development of supervisory control tools, capable of automatically collecting data from a vast number of devices, which understand when a component needs maintenance in order for the appropriate corrective intervention to be scheduled. Information about the real component remaining lifetime can only be achieved by combining different techniques (trend analysis, components modelling, simulation), while the determination of the best maintenance schedule has to rely on the correct assessment of each component's impact on the whole system apart from its compatibility with company production deadlines.

The Failure Mode, Effects and Criticality Analysis (FMECA) is the most common methodology in order for a successful predictive maintenance of a production plant to be achieved. The FMECA is, in turn, composed of two separate analyses: the Failure Mode and Effects Analysis (FMEA) and the Criticality Analysis (CA). The first analysis mainly focuses on the definition, identification and elimination of known or potential failures, problems and errors of a machine. When it is used for criticality analysis, it is also referred to as a failure mode, effects and criticality analysis. The utilization of this methodology enables the identification of known and potential failure modes, their causes and effects, the prioritization of the identified failure modes as well as the planning of the corrective actions for the corresponding failure modes. Although, the main disadvantage of FMECA is that it neither provides nor suggests any method of computing the failure rate of a component, even though this information is fundamental for the completion of the criticality analysis process. This gap can be filled with the PHM techniques. Prognostics is an engineering discipline, focused on predicting the time at which a system or a component will no longer perform its intended function. An estimation of this value is the Remaining Useful Life (RUL), which is an important concept in decision making for contingency mitigation. The discipline that links studies of failure mechanisms to system lifecycle management and optimization is often referred to as PHM.

TABLE I. FMEA and PHM characteristics

FMEA	PHM
✓ Identification of failure modes. ✓ Identification of causes and effects for each failure. ✓ Based on experience with similar products and processes.	✓ Prediction of future performance of a system. ✓ Prediction of the time at which a system will no longer perform its intended function.

II. Method

PHM has gained more and more attention in both academia and industry. Extensive research has been carried out by universities and research institutes for the development of

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algorithms and solutions for system diagnosis and prognosis. A number of these methodologies are based on ontology. Ontology implementation allows the definition of the entities, and their relationships, which are involved in the design for reliability, maintenance diagnostics, prognostics and maintenance planning [1]. Ontology can be considered as the core of a knowledge management system, since it provides a formal and explicit description of concepts in a discourse domain [2]. The Paris' Law and Kalman Smoother have been combined in a generalized fault and usage model, which aims to provide an improved component health trend and a better estimation of the remaining useful life. This state observer technique is a backward/forward filtering technique that has no phase delay [3]. Furthermore, a stochastic model of the equipment degradation evolution has been developed through the Gaussian Process Regression (GPR) for prognostics. The distribution of the RUL, before failure, is estimated by being compared with a failure criterion of the future degradation states, predicted by GPR [4].

PHM solutions for typical components such as bearings, gearboxes and spindles as stand-alone packages, have grown and proved to be reliable enough for industrial application. However, utilization of PHM solutions at plant level, is still very much restricted by the lack of solutions to collect, connect and control data/information from multiple sensors for the provision of valuable health assessment and prediction results for optimal maintenance allocation. In this research, there is a presentation of the extensive use of physically-based models, aiming at a successful PHM implementation. As aforementioned, the main pillar of a PHM system is the prediction of the Remaining Useful Life as it depicts the time at which a system or a component will no longer perform its intended function.

The model-based (also called physically-based) RUL prediction method has to answer two main needs: the collection of sufficient monitoring data for the purpose of capturing the degradation process in a limited time and the establishment of a reasonable life prediction model. Based on health assessment information, namely the RUL, as well as on additional information about multi criteria mechanisms, it can be determined whether a maintenance action should be executed [5]. RUL is the most necessary parameter, which should be predicted/estimated for the creation and execution of a maintenance plan [6]. Predictive maintenance platforms have been developed with the aim to cover the needs of the data acquisition and analysis and knowledge management, focused on RUL prediction [7]. These platforms are based on three main pillars; the first pillar is responsible for data extraction and processing, the second one focuses on the maintenance knowledge modeling and calculation of RUL and the third pillar provides advisory capabilities of maintenance planning [8]. A knowledge management case should be implemented for the collection of sufficient monitoring data as a technique to identify, represent and distribute information for utilization, reuse and transfer of knowledge [9]. As for the life prediction model, the ARIMA model has been implemented for the estimation of the remaining useful life, based on historical data, analyzed by symbolic dynamics techniques [10]. In addition, strategies based on real-time prediction of the remaining useful life, under the simultaneous consideration of economic and stochastic dependence, have been developed aiming at determining the optimal trade-off between reducing the remaining useful life of some components and decreasing the set-up cost of their maintenance [11].

III. Approach

In this research, the RUL calculation will be based on the simulation of machine component physically-based models. The required data for the RUL calculation will be gathered both by the controller of the machines as well as the simulation physical-based model of the machines through Virtual Sensors. Some of the gathered data will be used in order to update the simulation models, aiming to ensure that the simulated functionalities of the machines be the same with the real one. As in reality, the same tasks will be assigned to the simulation models aiming to use the simulation output for the RUL calculation. It is important to highlight that RUL is not calculated only by the outcome of the simulation. A combination of the simulation results, the reliability parameters of the machines and the monitored data are used for the final RUL calculation.

As it was previously mentioned, PHM exploits the estimation of the equipment's remaining useful life for the identification of the optimal time in order for the next maintenance action to be carried out. The main objective of this research is the calculation of the remaining useful life of each machine, in a production plant, based on the combined

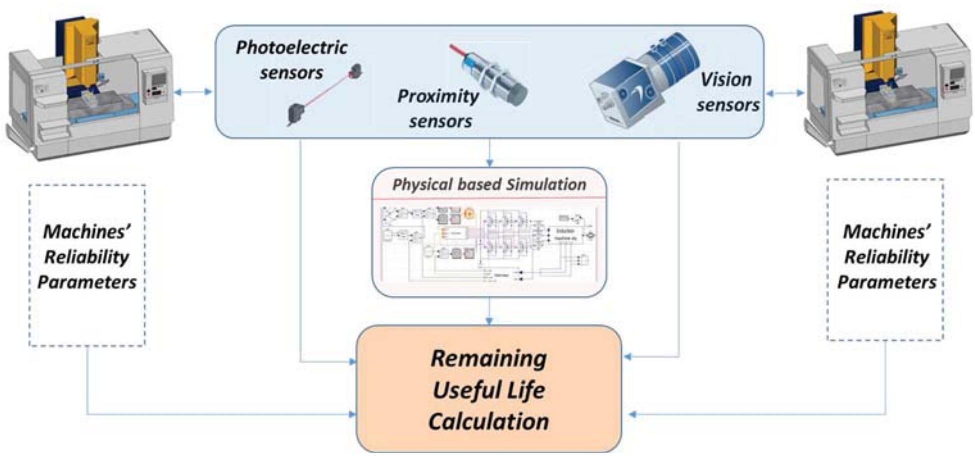

Fig. 1: RUL calculation main concept

examinations of the machines' controller data as well as the machines' physical-based simulation.

The procedure for addressing this challenge includes four steps. The first step consists of the advanced physical modelling of the machines. Except for the kinematic and dynamic characteristics of the machines, a set of virtual sensors will be integrated into the machines' simulation models. The functionalities of the virtual sensors are described in detail hereunder. The second one focuses on the synchronous simulation tuning of the physical-based machine models. As the simulation of the machines' models is used for their RUL calculation, the machines' models should be tuned continuously in order to avoid possible deviations between their real and simulated functionality. The third step consists of the simulation of the physical-based models using as input gathered sensors and machines' controller data, while the fourth step includes the combining of the simulation outcome and monitored machine data, aiming to predict the machines' remaining useful life. The reliability parameters of the machines have been integrated inside their simulation models. Each step is described in detail below.

Step 1: Advanced physical modelling of the machines

This step focuses on the advanced physical modelling of the machines. The definition of the kinematic and structural model of the machines takes place in the first stage. The complete model of each machine consists of a number of elements, which represent its dynamic behaviour based on the modelling of the mechanical, electrical, hydraulic and other functions. In order to have a successful and functional model that can be simulated in an acceptable computational time, it has to be defined which component of each machine should be modelled. Some of the machine's components are defined as black boxes (without any knowledge of its internal workings) or as grey boxes (using theoretical data to complete its model) or as white boxes, meaning that the exact functionality and the working mechanism of this component is known. In the second stage of this step, the virtual sensors of the model are defined for the completion of the machine's simulation model. The virtual sensors are modelled as a layout of elements and their functionality is to monitor and gather data from the physical-based models during their simulation. Therefore, it is important to have defined and specified the data to be gathered from the model's the simulation in order to be used in the algorithm of RUL prediction. The use of virtual sensors, at each element and function of the model, increases the computational time of the model's simulation. Lastly, the third stage of this step focuses on the definition of the modelling parameters, which will be used to update the physical model, based on the controller and sensor data. These parameters will be editable and will be associated with the synchronous simulation tuning with aim to adjust the behaviour of the machine's model with that of the real machine. More details about the synchronous simulation tuning will be described below.

Step 2: Synchronous simulation tuning of the physical-based model

This step focuses on the synchronous simulation tuning of the physical-based models. The aim of this step is to achieve the digital twins of the real behaviour of the machines and the simulated one. The most important phase of this methodology is the definition of the data that should be monitored both by the physical sensors the machines are equipped with and by the controller of the resources. According to Step 1, the modelling parameters form the base for the definition of these data. The monitored data should be translated into information in order to be used as input to the synchronous simulation tuning tool. A data synthesis technique will also be utilized having taken under consideration both the physical and the computational reductions. The synthesized data target at tuning the models via the updating of the modelling parameters. A part of this step is to define the priority of the online real time machine's components tuning. On the one hand, the synchronous tuning of the simulation models will be responsible for keeping the precision of the digital twins achievement over 95% but on the other hand, it is not necessary for all modelling parameters to be continuously updated. Some of the modelling parameters will be tuned with lower frequencies than others because of their lower effect on the simulation process. A weight factor table defines the frequency of tuning for each machine's component. In this way, the computational time is reduced.

Step 3: Simulation of the machines' functionality

The main objective of this step is the simulation of the machines' physical-based models. After the modelling of the machines (Step 1) and their tuning during their operation (Step 2), their simulation is the next step. The same tasks that the real machines have to perform are used as input to the simulation. These tasks are performed virtually by using the simulation software and their outcome, in combination with the monitored machine data, are used for the RUL calculation of each machine (Step 4).

Step 4: RUL calculation

This step focuses on combining the gathered sensors and the machines' controller data as well as the simulation of machine physically-based models for the calculation of RUL, under real operational conditions. The models integrated simulation allows for the prediction of the system's behaviour under different working conditions. The monitored parameters are related -indicatively- to temperature, voltage, current and power. They are gathered by the machine's controller directly, whilst the physically-based simulation models use the Virtual Sensors as described in Step 2. All these measurements are filtered and grouped for a specific time phase. This filtering and grouping are performed in order to avoid capturing random abrupt changes of the parameters which are not important to the equipment's condition. The outcome of this step allows for the online calculation of the machines' RUL during their operations.

Last but not least, it is important to mention that data acquisitions mechanisms such as FIWARE IoT and OpenIoT can be implemented in order to gather data from different sources and organize them. The data of each sensor as well as the data of the machine's controller are uploaded in a Cloud database. Efficient algorithms are used to process and combine the gathered data aiming to provide the generated information to the simulation software. This information is used as input for the simulation and for the tuning of the simulation models.

IV. Conclusion

The aim of the approach presented is to provide a satisfactory solution for the calculation of each machine's RUL of a production plan, aiming at its predictive maintenance, through PHM techniques. More specifically, the utilization of a physically-based simulation model offers a variety of advantages. At first, the condition and the status of the machine can be predicted as a result from the simulation of physically-based models, without the machines' operation being stopped, as it happens in the common predictive maintenance solutions. In addition, using this method, there is no requirement for collection previous/history data of the machine's condition. This RUL calculation method enables the continuous update of information, related to the machines' condition since it can be executed in the loop, in a very short time. In this way, it is feasible to know the status of each machine for each one of its tasks. In case that a statistical analysis is required to be implemented, this method can be used for data generation since the user can provide as input virtual tasks. Last but not least, the user is able to know of the way that the machine's condition will be affected by the execution of a task even before its execution. Consequently, the specific method can be used in order to support the user on assigning the tasks on the machines. Last but not least, the presented approach is an opportunistic maintenance strategy within the context of flexibility and process management [12].

The authors plan to proceed with a future study that will focus on the implementation of the proposed approach in a real production plant. In addition, the validation of this RUL calculation approach will take place according to predictive maintenance validation metrics. It is expected that this method will be more accurate and fast with the use of data synthesis algorithms. The final aim of future work is the achievement of digital twins in the production plan. In addition, a more detailed modelling of machine components is aimed, as it will eliminate any possible errors and uncertainties, thus leading to a more accurate RUL calculation.

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