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PROGNOSTIC HYBRID MODEL FROM DATA FUSION ON MACHINE TOOLS

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Abstract – This paper proposes an enhancement of RUL prediction method based on degradation trajectory tracking under the scope of machine tools. The operational condition data of the machine over time provides the potential degradation state at the next estimation iteration step, based on data-driven techniques. The model-based approach is considered as long-term prognostics method assuming that a physical model describing the degradation behaviour is available. Fusing the aforementioned techniques outputs a hybrid model for RUL estimation.

Keywords: RUL, trajectory tracking, hybrid model

1 INTRODUCTION

Preventive maintenance reveals to be a big concern within the maintenance arena. Increasingly it is being invested to identify the best technique that enables to choose different maintenance management actions and their consequential scheduling based on diagnosis and prognosis methods. It seems to be more convenient to research on how to detect a failure before it occurs than on the corrective maintenance actions to deploy after it. This is what could be understood as prognostics, and it is strongly related to the remaining useful life (RUL) estimation of the observed asset [1]. However, the homogeneity of the concept is not stated yet. A number of several definitions for prognostics have been proposed:

- An estimation of time to failure and risk for one or more existing and future failures modes [2]
- Prediction of future health states and failure modes based on current health assessment, historical trends and projected usage loads on the equipment and/or process [3]
- Address the use of automated methods to detect and diagnose degradation of physical system performance, anticipate future failures, and project the remaining life of physical systems in acceptable operating state before faults or unacceptable degradations of performance occur [4]
- The capability to provide early detection and isolation of precursors and/or incipient fault condition to a component or sub-element failure condition, and to have the technology and means to manage and predict the progression of this fault condition to component failure [5].

2 METHODOLOGIES FOR PROGNOSIS

Many approaches for RUL prediction exist, whose applicability is highly dependent of the available knowledge on the monitored system. There are several ways to classify the different techniques according to the field of application. For the purposes of this research, RUL prediction under the scope of machine tools; the following group division has been considered [6, 7 and 8]:

- Knowledge-based methods: symbolic models that use empirical relationships described in words belong to this group. These models are based on work orders and maintenance reports; they are good for general descriptions of causal relationships, but verbal descriptions are not effective for detailed descriptions of complicated dependencies and time varying behaviours. The knowledge-based approach relates to the collection of stored information from subject matter experts and interpretation of rules set. One of the most common techniques that cope with the consistency problem that may pop up when trying to combine explicit and implicit knowledge, a regular issue when using these types of methods, is the fuzzy logic.
- Data-driven methods: this kind of methods relies on relationships derived from training data gathered from the system. The data source usually comes from monitoring condition system, applying thresholds for features in time series data, temperatures and other observable condition indicators. In most cases, some of the following steps are mandatory to correctly deploy data-driven methods: time and frequency domain analysis, extract most sensitive features and noise removal. The techniques belonging to this group can be further subdivided in stochastic or statistical models. Stochastic models provide reliability-related information and they are based on the assumption that the times of failure of identical components can be considered statistically identical and independent random variables and thus be described by a probability density function. Bayesian networks (static or dynamic) are which most often appear in research, including Markov models (Markov and semi-Markov processes; hidden and semi-hidden Markov models; etc.) or estimation with adaptive

filters (Kalman, Particle Filter). Statistical models estimate the damage initiation and progression based on previous inspection results on similar units. Time series prediction, trend evaluation, autoregressive models or proportional hazards modelling are the most meaningful techniques in this subgroup.

- Model-based methods: in this category, the behaviour of a failure mode is characterized using physical laws, covering the formulation of a system with equations and damage modelling. These methods assume that this behaviour may be described analytically and accurately, providing RUL estimation by solving a deterministic equation or set of equations derived from empirical data. Crack propagation failure modes are the most commonly developed behavioural models for prognosis. Some methods used to represent crack growth due to repeated loads, for instance Paris-Erdogan law, Foreman equation, Walker equation, or McEvily equation; other methods consider the temperature as cause of failure, as is the case of Coffin-Manson model, Arrenius equation or Eyring equation.

3 MACHINE TOOLS CONDITION MONITORING

Production systems deteriorate with the age and usage. Preventive maintenance practices is the normal strategy to mitigate the consequences of this deterioration, although not always can be deployed, what leads to carry on a supportive workforce reactive in the case of clearly detected malfunctions or machine breakdowns. Quality, cost and in general productivity are principles that may be affected by the maintenance strategies. Furthermore, another issue that may cause a big impact on product production, or delivery times, is the uncertainty of the machine reliability. For instance, it is known that a worn-out or incorrectly assembled mechanism produces higher energy consumption. There is a great pressure for achieving a better equipment management; a full life cycle strategy to preserve equipment functionalities, maintain the quality of produced goods, ensure the productive capacity and avoid the consequences of minor and substantial failures. The deployment of intelligent predictive technologies can detect malfunctions or potential breakdowns, and provide an anticipated solution.

Condition based Maintenance (CbM) includes obtaining data (see figure 1) from sensors coming from the machine for its further analysis, giving extra information about the machine tool performance. Classical monitoring techniques on machine tools implies acoustic and vibrations techniques, but these Condition Monitoring (CM) methods involve a heavy setoff, the requirement of costly transducers installation and signal analysis equipment, which must be handled by skilled personnel. Consequently, the research trends have been focused on methods based on available operating data that do not require costly equipment or skilled personnel. Within the industry, it takes a relevant importance in areas where there is available a fleet of similar units. Manufacturers and owners of packing machines, windmills, airplanes, ships or machine tools are able to reuse the methods and experience gained from their historical data.

Current analysis for machine health assessment is a non-intrusive monitoring technique affordable in terms of cost. Based on the signature analysis results, the health indicator of a component may be computed and related to a degradation model [9]. Power monitoring with a torque sensor is evaluated in [10]. Power analysis to detect production machine failures with current signals can be

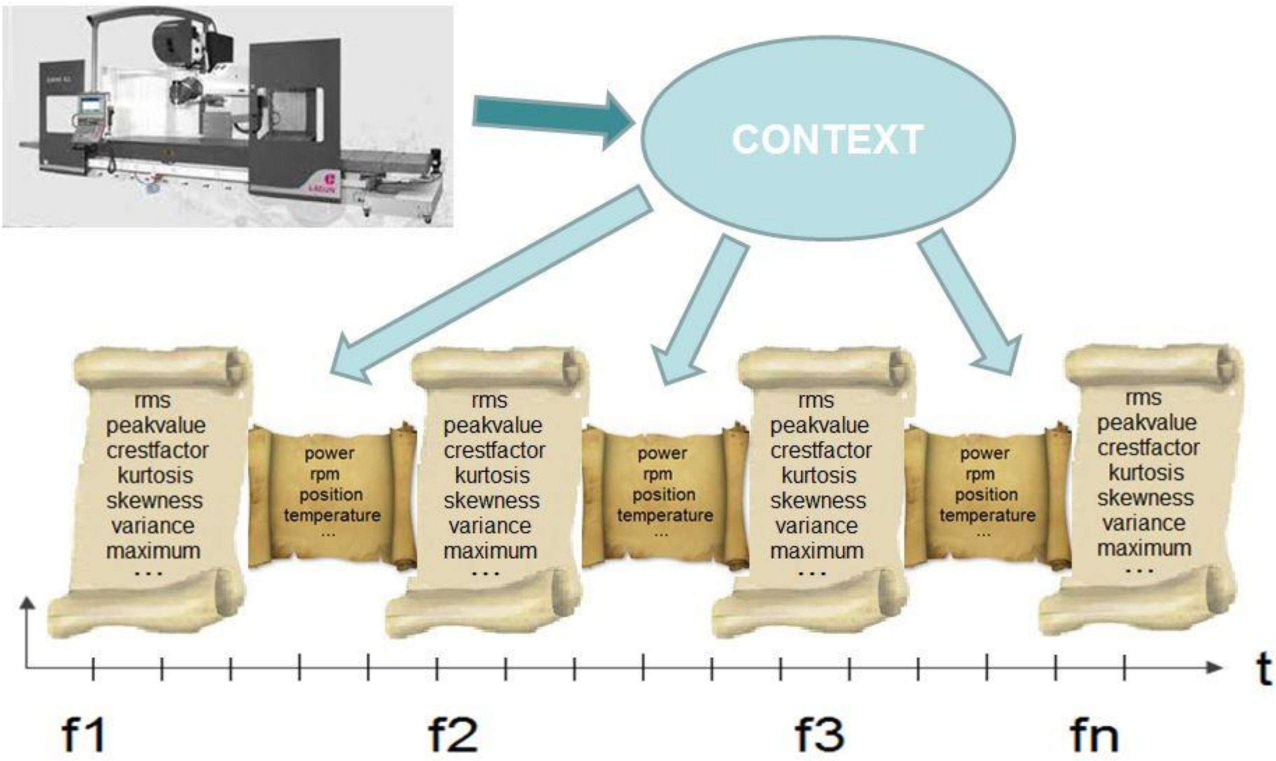

Figure 1 Fingerprint and Operational Data Fusion

consulted in [11, 12] and machine internal signals in [13]. As can be learnt from [14, 15], different failures may be detected deploying an induction motor current analysis. The controlled values, for example, of a gearbox failure, can be compared in the stator current spectrum, because several peaks are related to shaft and gear speed. Current-based diagnosis of mechanical faults, such as imbalance and misalignment, can be performed in the same way. It is also possible to control the rotating movement of the machine; in addition, some work has been done on linear movement. For example, Electro Mechanical Actuators (EMA) is widely used in aeronautic systems; the use of Health Monitoring is widespread [16, 17, 18] as well and similar actuators are used in machine tools.

3.1 Disparate source data fusion

The main technique for detecting mechanical and electrical problems uses vibration analysis or Motor Current Signature Analysis (MCSA) in combination with context data.

MCSA uses the electric motor as a transducer, allowing the user to evaluate the electrical and mechanical condition of the motor control and, by extension, of the machine. To obtain the main fingerprint features, machines are run in a pre-defined test cycle in no-load condition to achieve better failure detection and to remove any noise that could affect the normal machine process load. Condition monitoring data are based on the fingerprints obtained from the machine. In the first stage, data analysed during the experimentation phase may help in the selection of the type of sensors, acquisition rates and tests to be performed on the machine in the production plant. The aim behind this type of studies is the analysis of the variations produced in current and voltage by any load or speed variation within an electromechanical system.

The resulting time and frequency signatures reflect loads, stresses, and wear throughout the system. Comparing a reference, electric signature of equipment in good or healthy condition, from now on called fingerprint, and equipment under monitoring supports fault identification. Fingerprint raw data is collected periodically under a non-stress situation using a test procedure with a considerable sample rate (range of KHz), since some frequency signatures are placed on a high frequency interval.

Typical data collected and synchronised in time are vibration, motor power, position and speed for different component (spindle head, linear axis, etc.). The data can be analysed in both time and frequency domains [1]. Several features in the time domain (for instance: peak value, root mean square, standard deviation, kurtosis value, crest factor, clearance factor or shape factor) can be calculated for each signal. In the frequency domain, the system follows the vibration levels on known frequencies and its harmonics like gear mesh frequencies, bearing frequencies, rotational speed etc. Then it is processed and the most sensitive signal features are extracted which are used to compare their evolution over time providing the health assessment of the machine.

Determining the usage of the machine by the end user yields a more holistic understanding of the real status of a machine's critical components. The historical use of the machine is found in the operational data, which comprises the contextualization of the machine usage. The main motivation to retrieve operational data is to determine the operating environment of the machine, with the purpose of finding possible reasons for malfunction or failure and optimising reliability through the proper set up of component or machining parameters. Depending on the already installed or optional sensors, the solution may vary, but in any case, the required data rate should not be high (tens of Hertz). Some processing is done to extract all the information from the data, using it to build a historical register of the use of the machine (several profiles must be identified) and to obtain the data required for further service implementation.

This characterization of operational conditions helps to understand the relationship between the health status and the

Figure 2 Fingerprint and Operational data in Human´s Life

usage of the machine and the impact of the operational conditions on the evolution of the degradation model. A comparison with the human´s life is depicted in figure 2. The fingerprints represent the periodically health status checking and the operational data retrieved between fingerprints can be gathered in different usage profiles that will impact in the fingerprint evolution.

4 HYBRID MODEL FOR DATA INTEGRATION

A hybrid methodology can employ symbolic, data-driven, and phenomenological models. Combination of three models can provide better information that facilitates identifying the fault state more accurately. While most models incorporate some prior knowledge, little work has been done on explicit hybrid modelling for fault diagnostics and maintenance decision making [19]. Therefore, there is a knowledge gap in understanding the overall relationships between production and reliability for systems that vary with time. The goal of system reliability (indeed, any classification exercise) is to minimize Bayes risk. In other word, to choose the lowest risk option based on the observed system outputs and conditional probabilities of what state the system is in, given the observed data. Minimum Bayes Risk decision making relies on conditional probabilities, which rely on a posteriori probabilities and prior probabilities of states of the system (in this case, fault modes) [20].

Thus the implementation of a hybrid prognostic allows taking benefit from both model-based and data-driven approaches [21]. The advantages of the physics-based model are: intuitive prediction results, based on modelled case-effect relationships; any deviation may indicate the need to add more fidelity for unmodelled effects or methods to handle noise; once a model is established, only calibration may be needed for different cases; clearly drives sensing requirements; and it is highly accurate if the physics of models remains consistent across the systems. However this physics-based model requires assumptions regarding complete knowledge of the physical processes; parameter tuning may still require expert knowledge or learning from field data; and high fidelity models may be computationally expensive to run. On the other hand, when using data-driven approaches the variety of generic data-mining and machine learning techniques are available; it helps gain understanding of physical behaviours from large amounts of data; and represents facts about what actually happened, not based on theoretical assumptions. But this approach may require large amounts of data; learning what happened to several units on average may not be good enough to predict for a specific unit under test; and hauls difficult to balance between generalisation and learning-specific trends in data [6].

Once stated the benefits of using a hybrid model, the aim of this research can be particularized as the integration of both, operational (providing a context awareness aspect to improve the accuracy of the forecasting) and fingerprint data, by means of different prognostic techniques, either data-driven models or physics-based model; in order to enhance the RUL estimation on machine tools components under the context driven prognosis discipline (see figure 3).

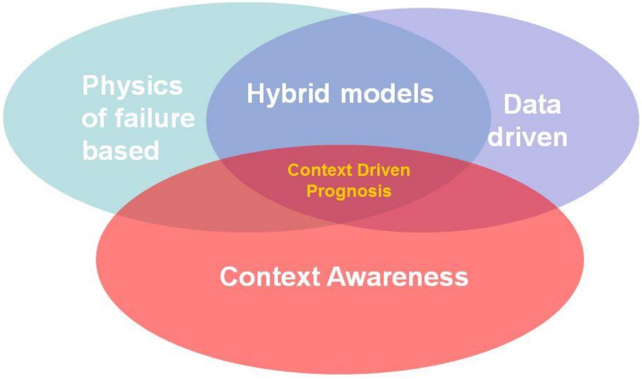

Figure 3 Context Driven Prognosis intersection

The first step to carry on such integration, deals with the fingerprint data preprocessing. In order to extract the different features in time and frequency domain a processing of the raw signal is needed. Then, classification methods are used for feature selection. These fingerprint features should show a strong relationship with the degradation of a machine tool component. The evolution of the fingerprint feature trajectory may be analysed within the contextual conditions given by the operational data. Through data-driven techniques, the impact of the operational conditions over the trajectory of the fingerprint feature leads to a more accurate estimation of the potential further point on the trajectory. This is achieved through the identification of machine usage profiles and its impact in the degradation curve. The key point is to reduce the uncertainty inherent of the physics-based model based on the results from the data-driven techniques that provide the usage profiles. The total uncertainty is now divided in several uncertainty intervals and each one has associated different machine usages.

Based on the results of this analysis, the calibration and tuning of the parameters of a physical model equation or set of equation would represent a better approximation of the real behaviour of the components of the machine.

4.1 Case Study

For a better understanding of the proposed model a case study is detailed coming up next.

Let suppose that a machine tool formed by several linear axes (X, Y and Z, one for each Cartesian dimension) and one spindle head is the target of our analysis. The three lineal axes place the spindle head along the spindle working space. The spindle head is the subsystem of the machine tool that is under analysis. The operational data set monitoring the operational context that the machine has been performing on includes: power, actual speed, torque, and head temperature, all of them referenced to the spindle head; but also ambient temperature of the machine and the current and position of the different axis is collected as well. By means of CbM and CM techniques and its further analysis the data is retrieved from the machine and stored for computation. Three different usage profiles are identified: Soft, Medium and Hard machining. These profiles are defined by combinations of several operational data variables, where the power consumption plays a crucial role, using clustering techniques. It must be remarked that this data set may be completed by means of the internal information provided by the Computer Numerical Control (CNC), which most of the present machines tools have.

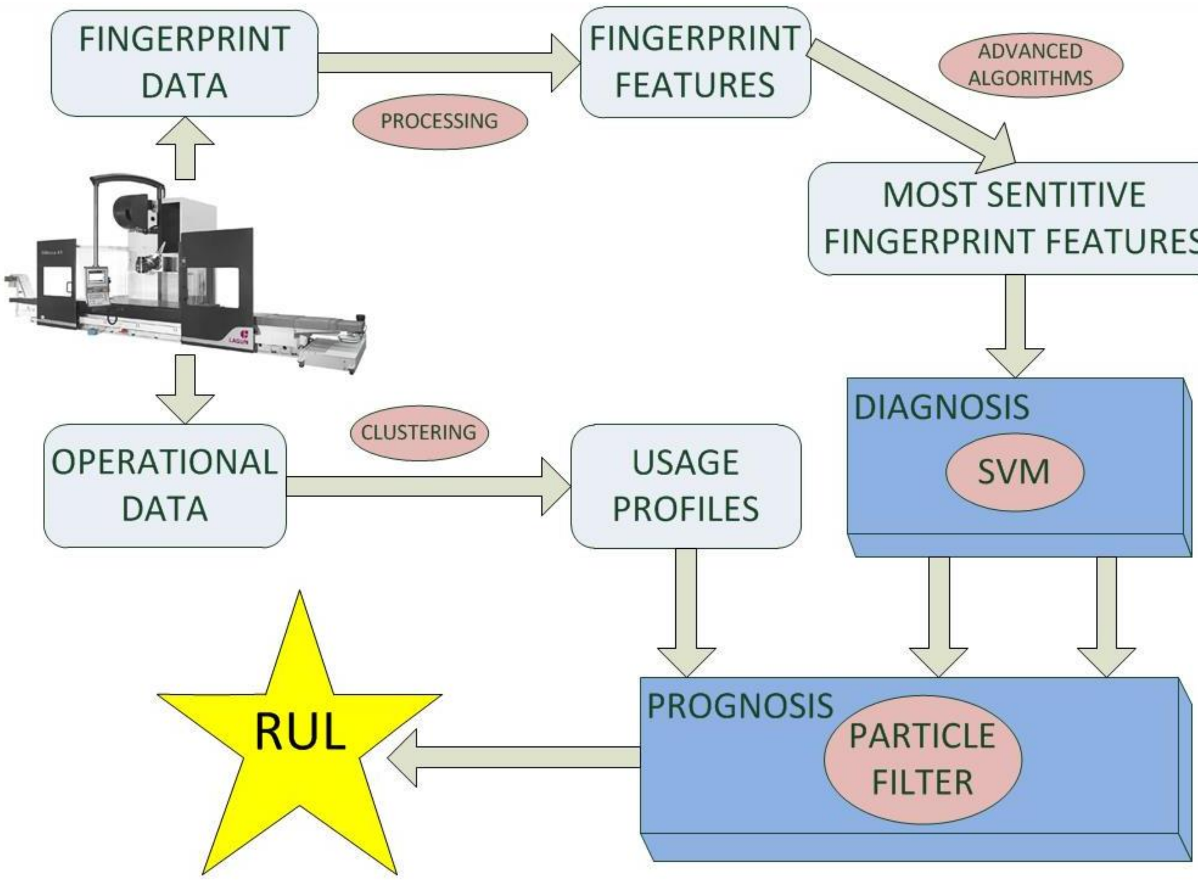

Figure 4 RUL System

On the other hand, fingerprint data is collected periodically along the test time span. The data needed for the fingerprint is collected by a current sensor, a tachometer of speed and accelerometers, subjecting the machine to different test: constant speed test at different speeds; waterfall test, i.e. a constant acceleration between a speed interval; and a fast acceleration between different speeds to test the transients. These tests have been deployed firstly in spindle test benches proving that its outputs are sensitive enough for the aim of this study. Then, the fingerprint data is processed and the most sensitive features that are related to the degradation of the component are extracted.

In the time domain, the statistical parameters used are: root-mean-squared (RMS), peak value, crest factor, kurtosis, skewness, clearance, impulse and shape factor, average, median, minimum, maximum, variance and deviation. They attempt to capture unusual behaviour and/or impacts associated to early degradation stages and faults.

Related to frequency analysis different frequency bands are checked depending on the design of the machine. Bearings produce a series of force impacts. The impact rate is determined by the rpm of the shaft and the geometry of the bearing. These are the ball or roller spin frequencies, the ball pass frequency on the inner and outer races, and the cage rotational frequency. For gears, gear mesh frequencies and sidebands associated to frequencies/harmonics can be indicative of faults. Similarly, motor current analysis is used to detect motor failures. The electric motor is used as a transducer, and the current spectrum or signature is monitored to give an idea of the electrical and mechanical condition. The current signal is modulated due to vibration, as it causes pulses in torque and appears in harmonics. Thus, current spectrum analysis can be used to detect failures in the driven loads. Then, the use of more advance algorithms (genetic algorithms, neural networks) is needed to determine the most sensitive features. Up to this point, only data-driven techniques are required for the information extraction from the raw data.

At this stage, the most sensitive fingerprint features that can show the degradation of the component of the machine are identified, and also, different usage profiles are determined from the operational data. In order to provide an accurate and enhanced RUL estimation, what is the main goal of this research, a first diagnostic step is mandatory. The diagnostic process allows establishing the different thresholds that are the outputs of our RUL estimator. Semi supervised learning techniques (support vector machine, for instance) are a proper tool to generate these thresholds. In addition, this methodology allows working in the feature space, and then tracking these trajectories the most critical feature is selected for its further study over time.

After the diagnostic phase, where the current state of the component and the threshold are stated, the prognostic stage closes this approach. The strategy chosen to perform this phase is the use of a particle filter. The particle filter needs some inputs that can be extracted from the data that has been obtained from the previous steps. Basically, the degradation equation with the initial distributions of its parameters and the thresholds are the inputs of the system. The equation and the performance limits are extracted from the fingerprint data analysis, and the variability in the equation parameters, which provide the final accuracy of the result, are determined by the different usage profiles defined from the operational data.

In [22], this type of implementation can be consulted in detail. The result of RUL estimation includes the usual uncertainty inherent of these type of systems that can be associated with the previously usage profiles (see figure 5).

The harder the machine is used, the shorter is the RUL estimation.

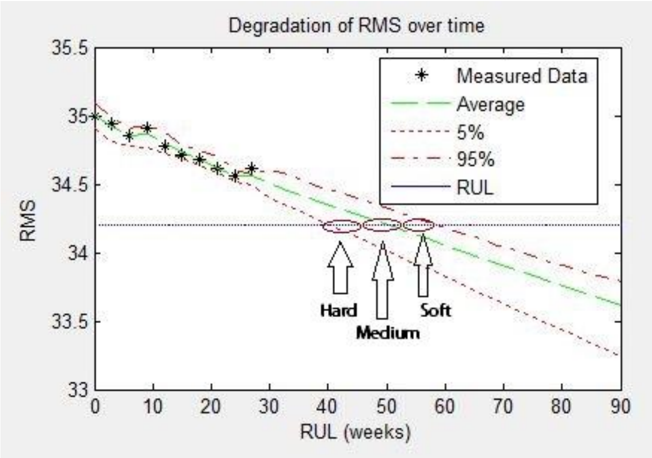

Figure 5 RUL Estimation

5 CONCLUSIONS

The capabilities of using data from different sources in the CM phase helps to define a better working environment, which integrated with degradation data over time of the machine tool, provide a more complete scenario. This situation is conducive to expand the functionalities of the prognostics methods; stressing upon the advantages of merging different kind of techniques generating a hybrid model able to improve the uncertainty of the results.

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