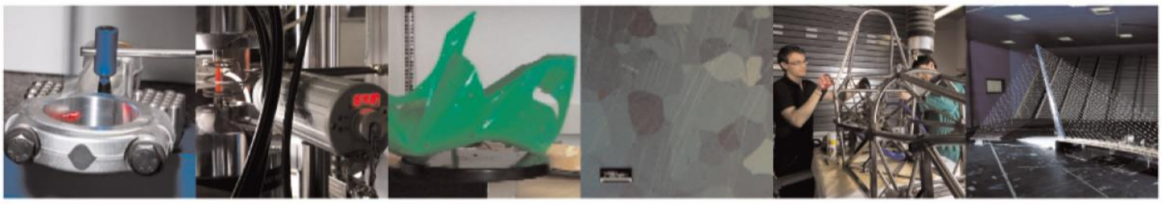

A review of prognostics and health management of machine tools

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A review of Prognostics and Health Management of Machine Tools

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Abstract This paper presents a survey of the applications of Prognostics and Health Management maintenance strategy to machine tools. A complete perspective on this Industry 4.0 cutting-edge maintenance policy, through the analysis of all its preliminary phases, is given as an introduction. Then, attention is given to prognostics, whose different approaches are briefly classified and explained, pointing out their advantages and shortcomings. After that, all the works on prognostics of machine tools and their main subsystem are reviewed, highlighting current open research areas for improvement.

Keywords PHM · Predictive Maintenance · Industry 4.0 · Machine Tool

1 Introduction

Degradation is an unavoidable natural phenomenon, which not only affects living beings but also engineering systems. Technicians counteract it by means of maintenance activities, which aim either at preserving the health status of the system, if they are done in advance with respect to a failure, or to restore it, when they are performed after the system has experienced a breakdown.

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Maintenance policies have evolved over time: starting from the elementary reactive maintenance policy (fail and fix), through the preventive maintenance policy, in which maintenance activities are performed at regular intervals determined on the basis of statistical reliability tests, this evolution process has come firstly to condition based maintenance, in which repair is done when a monitoring indicator goes over a predefined threshold, and finally to Prognostic and Health Management (henceforth referred to as PHM) maintenance policy, which is the most advanced today available maintenance strategy [46]. Table 1 summarizes the main characteristics of the aforementioned maintenance policies. So far, Condition Based Maintenance CBM has been the most investigated maintenance strategy both by the research community and by industries. Several important review papers on CBM can be found in the specific literature. For instance, Goyal and Pabla [29] focused their attention specifically on machine tool sector. Although, in this paper, the authors made a comprehensive review of the most suitable sensors for monitoring the vibrations in machine tools together with some available data analysis methodologies, no considerations on how to estimate the machine tool components health were reported. In [40], although it does refer to machinery in general, some additional considerations on the available techniques for reasoning and for supporting the maintenance decisions were carried out. PHM encompasses the estimation of the current health status of the system or component under analysis along with the prediction of its Remaining Useful Life (RUL) [57]. The main objective of PHM is the reduction of maintenance associated costs, through the elimination of unnecessary inspections, components re-

Table 1 Different maintenance strategies: an insight on their main characteristics (this table is a rearrangement of the one proposed in [46])

Maintenance strategy	**Reactive**	**Preventive**	**Condition based**	**PHM**
Maintenance interval	Determined by component failure	Fixed (determined upon statistical reliability tests)	Based on system condition	Based on system health status and remaining useful life
Severity, or impact, of the typical associated fault	Low	Low-medium	Medium-high	High
Technological requirements and complexity	Low	Low	Medium-high	High
Human interventions required	High	Medium	Low	Low

placements and system failures [100] Moreover, it is a significant tool for the reduction of the risk of catastrophic events [89]. PHM maintenance policy belongs to Industry 4.0 paradigm [119,118], as they share several technological enabling factors [109]:

- the wide range of sensors today available, which can register every source of information coming from the machine (vibrations, acoustic emissions, temperature etc) at, most of the times, a relatively small cost and size [118,21];
- the increased computational resources made available in embedded computer, which can be installed close to the system to perform some initial processing tasks on data, such as cleaning, interpolation and feature extraction [56];
- the connectivity or Internet of Things (IoT), which allows to connect each system to a network of interconnected assets [25,118]. Research in open standards can potentially foster and ease the exchange of maintenance data [104,54,102];
- big data technologies, which allows to store, manipulate and access all the data collected from each machine, for a real-time update of system health status and remaining useful life estimate [55,119,96].

Despite the ease with which companies nowadays have access to these enabling technological factors, small, medium and large enterprises are still facing several challenges when trying to implement a PHM maintenance policy, such as costs and availability of sufficiently skilled human resources [46].

This paper focuses on the application of PHM maintenance strategy to machine tools and their subsystems and components. For the first time to the best of authors' knowledge, PHM works dealing with this kind of machinery equipment are reviewed, while also highlighting current open research areas for future improvements. Another novelty aspect of this article lies in the comprehensive introduction to PHM, which covers in details its preliminary phases, namely preliminary analysis, monitoring and diagnostics, to give a global perspective on PHM to a maintenance manager interested into it. In fact, several PHM review paper have been published so far, but none of them considered all these phases together, as for example [40,79,93,64,58,127], while [100,109] concentrated on technological and economical aspects.

2 PHM preliminary phases

PHM is made of several consecutive phases, as illustrated in Fig. 1. In the following, PHM maintenance strategy preliminary phases are presented, before diving into the analysis of health assessment and prognostics, the core of a PHM maintenance strategy.

2.1 Preliminary analysis

An analysis preliminary to the application of a PHM maintenance policy is necessary to establish:

- the components, or subsystems, for which it would be possible to apply a PHM maintenance strategy. In fact, not all the components are suited for the application of PHM maintenance policy: only components which deteriorate over time emitting signals of the deterioration can be maintained with a PHM strategy. So, for example, an electronics component, whose failure rate is usually assumed to be constant over time (apart from infant mortality), may not be suited to PHM if its degradation is not progressive

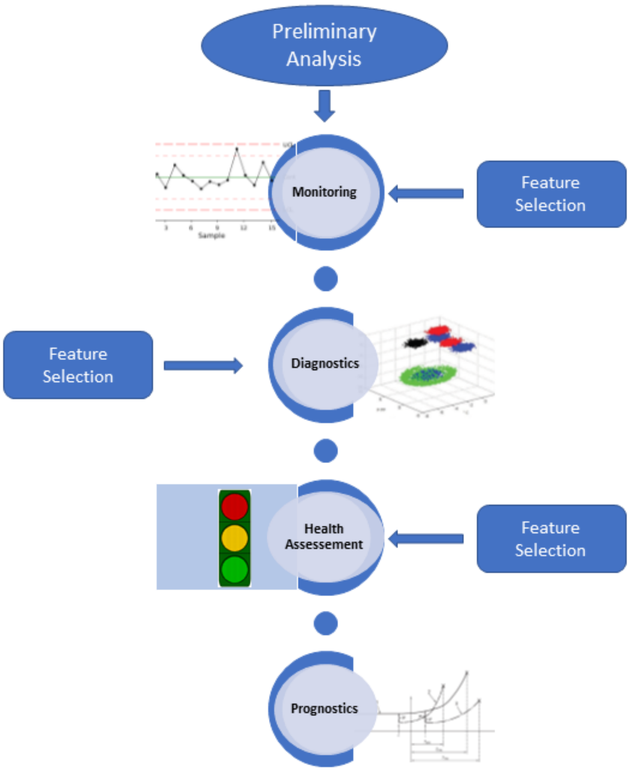

Fig. 1 General scheme of a PHM maintenance strategy, which highlights its constitutive phases. Diagnostics and prognostics thumbnails have been taken from [36] and [37]. respectively

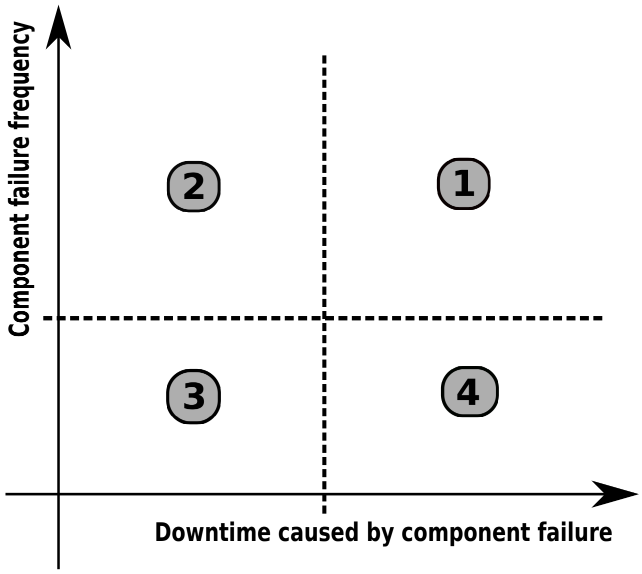

Fig. 2 Chart, adapted from [57], to ease the identification of components worthy of PHM maintenance policy

and observable in some way. Indeed, prognostics and health management of electronic components is at its infancy [100]. In these cases, the best estimate of the remaining useful life of the component or system is given by fleet wide statistics, as the MTTF [26];

– if a PHM maintenance policy would be able to bring effective results, savings and improvements with respect to other less complicated maintenance policies. To understand these effects, [57] presented the chart reproduced in Fig. 2, which should assist the maintenance manager in the maintenance strategy decision making process. This chart clusters failures into four classes, whose boundaries have to be selected based on the component or subsystem under analysis:
  1. the first quadrant in Fig. 2 comprises the components who experience a lot of failures with large downtime. Instead of thinking about a change in the maintenance policy, the authors of the picture suggest that resources should be allocated to the design process, to improve the reliability of this component;
  2. the second quadrant in Fig. 2 is the group of components whose faults are frequent but not expensive, so simply more spare parts are needed without changes to the currently implemented maintenance strategy;
  3. the third quadrant in Fig. 2 makes reference to components which are almost not failing and whose associated downtime is small. No action is needed;
  4. the fourth quadrant in Fig. 2 is the one devoted to components suited to PHM, namely components which seldom fails but with large associated downtime, as already suggested by Table 1.

– for each critical component worthy of a PHM maintenance policy, as more information as possible on its failure modes should be gathered, as suggested by the international norm on prognostics [37]. Tools traditionally adopted for risk assessment of safety critical systems, can be utilized, as for instance:
  1. Failure Mode and Effects Analysis [34] (FMEA) is an analysis which basically aims at identifying all the single failures associated to a system and for each of them their root causes, the sensors which can detect the presence of the fault and the suggested maintenance actions. In practice, the maintenance manager has to fill in a table as the one presented in [106,14,19]. The main shortcoming of this analysis tool lies in not being suited to multiple concurrent and interacting faults, as it is not able to highlight the interactions among different faults. Alternative versions of this tool have been proposed in [45] and in [13], which specifically addresses PHM needs;

2. Fault Tree Analysis [35] (FTA) is complementary to the FMEA since its strength is the shortcoming of FMEA: being able to convey a simple graphical representation of the interactions among the different faults which can affect the machine;
3. root cause analysis aims at the identification of the root cause of a fault. It is particularly suited for complex assets affected by multiple and interacting faults. The output consists of a causal graph, called causal tree, which portrays the sequence of events which leads to a determined fault, as illustrated in Fig. 3.

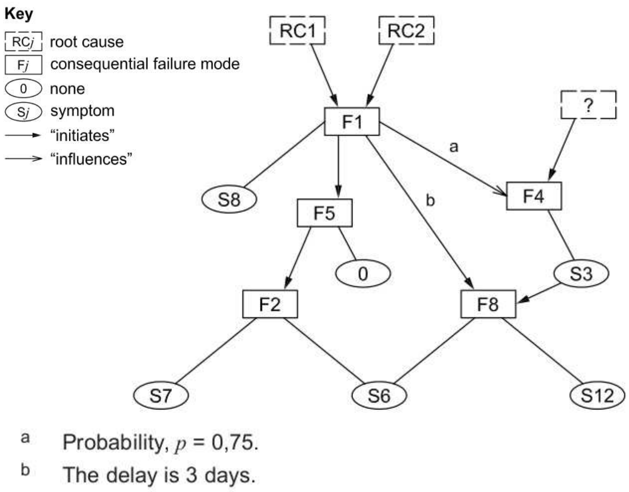

Fig. 3 An example of causal tree [35]

2.2 Monitoring

Monitoring, also referred to as anomaly detection, is the act of constantly verifying that the machine or asset is performing as expected and triggering an alarm if it is not. Basically, monitoring translates into a comparison between the normal asset behavior (which constitute the so-called baseline data [38]) with the current machine behavior. The difference between baseline and current data is called residual. When the monitoring algorithm detects an anomalous system behaviour, it sets an alarm, which in turn triggers the diagnostic module, which is in charge of establishing which failure mode has appeared. For instance, statistical process control is the most known and suitable monitoring tool [40, 71]. One of the main challenges encountered in the monitoring phase are false alarms, which can be caused by [65]:

- the intrinsic difference between different machines, even of the same model. Indeed, each machine is different from the others, therefore it may call for a dedicated baseline;
- a variation of operating conditions;
- the dynamics during machine warm-up time. For example, data collected during warm-up time may be misleading due to thermal expansion;
- a baseline shift due to either maintenance adjustment or replacement. As a consequence, baseline may be recorded again.

As for diagnostics and prognostics phases, monitoring is not performed over the raw signals but on features, which are essentially synthetic information carriers. In other words, information contained in the collected and cleaned raw signals are usually mapped to a low dimensional feature space for an easier and more tractable match and comparison process [68]. Features can be extracted from different sources. In particular, they can be:

- computed directly from raw signals. It must be noticed that with "raw" we are referring to signal acquired with a sufficient sampling rate, and without data losses due to compression algorithms [36]. In addition to this, raw data are cleaned to get rid of data errors, in order to avoid the so-called "garbage in garbage out" situation. Data errors can be traced back to typing or insertion errors, for event data entered manually (as, for istance, maintenance intervents), and sensor faults, for condition monitoring data [40]. In particular, errors which fall inside the expected region of operation are the most dangerous ones, because they cannot be easily detected, while outliers can be more easily and automatically removed [36];
- computed from residuals, to be independent from operating conditions.
- parameters of a model, which are recursively estimated in real time, as for example in [11].

Finally, when dealing with large feature spaces, multivariate analysis tools, as independent component analysis (ICA) and/or dimension reduction techniques, as for example principal component analysis (PCA), are used to handle data with complicated correlation structures [40], and to reduce the dimension of the feature space [15], respectively. It must be stressed that the feature selection phase is of paramount importance for obtaining meaningful monitoring, but also diagnostic and prognostic results. Moreover, the set of features which yields the best monitoring (or diagnostic, prognostic) results is heavily dependent on the specific characteristics of the system under analysis.

2.3 Diagnostics

Diagnostics is the act of tracing back the evidence of anomaly behaviour to their respective causes, i.e. their faults. In particular, taking inspiration from [90], [24] defines a fault as "*an unpermitted deviation of at least one characteristic property or parameter of the system from the acceptable condition* (or baseline). Usually, diagnostics is performed after the machine has experienced a breakdown, i.e. it has been conceived as a posterior analysis. Therefore, in the context of PHM, it is more appropriate to think to the diagnosis phase as the diagnosis of early fault signs [57], which basically is needed to trigger the prognostics module.
While monitoring translates into a comparison between baseline and current machine data, diagnostics translates into a comparison between current operating data and a faults database. From a more technical perspective, diagnostics is a pattern recognition and classification problem:

- **pattern recognition** because the dataset collected with a faulty machine are used to search for patterns among the extracted features, to be able to distinguish among the different faults. It is worthy to elaborate a bit on this statement. Pattern recognition is a preliminary phase, which comes before classification, only when supervised learning algorithms are used [8]. In this case, a training dataset with already recognized faults is needed. When using unsupervised learning algorithms, pattern recognition is called clustering [2]. Unsupervised learning algorithms are useful for detecting new faults. For instance, faults that could not be inferred neither in the preliminary analysis nor analyzing the training data-set. The event in which a technician did not fixed correctly a screw while reassembling the asset and this caused unexpected machine vibrations can be considered as a realistic example. These issues could even happens when the faults contained in the recorded data are not known a priori that demonstrates that there is a very limited knowledge of the system;
- **classification** because, once the fault database has been built, the current machine data have to be classified to decide which faults are affecting the system.

Several algorithms can be used for pattern recognition and classification. A review of their application to the diagnostics problem can be found in [40]. See [57] for a table which sums up the strengths and shortcomings of the main diagnostic algorithms today available.
As for monitoring, the feature selection step is crucial. There are currently two methods for diagnostic feature selection [50,60]:

- **filter based method**, which ranks the features based on a pre-selected criterion. One of the most used index for feature ranking is Fisher score;
- **wrapper based method**, which selects the best features by using the chosen classification algorithm along with search methods as for instance forward and backward search [60]. Basically, the feature set which yields the best classification results is elected as the diagnostic feature set;

Finally, it must be kept in mind that it is not true that the more features are used, the better classification results are obtained. The best accurate diagnosis are obtained when the smallest number of relevant feature is used, as proven for instance in [60].
A benefit of an accurate and reliable diagnostic system is shown in [39], in which an artificial intelligence based automatic fault detection algorithm has been tested on Columbia space shuttle data and has proven to be able to detect the fault on shuttle wing minutes after it happened rather than during re-entry; such a system would have, probably, saved the life of the whole shuttle crew.

3 Prognostics and Health Assessment

3.1 Health assessment

Once the diagnosis has been performed and therefore the faults affecting the system have been identified, the current health status of the machinery equipment has to be assessed. System's health status is generally expressed as a numerical index, which varies from 1 (healthy component) to 0 (broken component). Component End of Life (EoL), i.e. health index value at which system is shutdown in order to prevent failure, is suitably selected based on experience. Sometimes, a degradation index (ranging from 0 to a previously determined EoL) is used in place of a health index to quantify the extent of the degradation process. Health and degradation index time profiles can follow different degradation patterns, as represented in Fig. 4 and 5, depending on the degradation mechanism being involved. In particular:

- a **single stage degradation pattern**, as for example a linear or an exponential trend, is associated to a not reversible (or monotonic) and continuous degradation process, as for instance the degradation of a machine tool cutting insert;
- a **two stage degradation pattern** is characterized by an healthy stage, with no evidence of fault, and an unhealthy stage, in which the degradation process starts and proceeds until machine failure or stop. The prognostics algorithm has to be started at

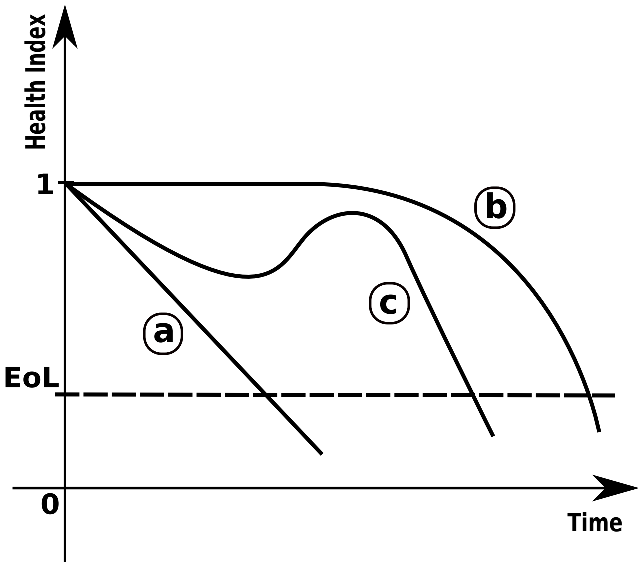

Fig. 4 An example of typical health index time profiles: circles a, b and c denotes a single stage and monotonic degradation pattern, a two stage degradation pattern and a three stage degradation pattern, respectively

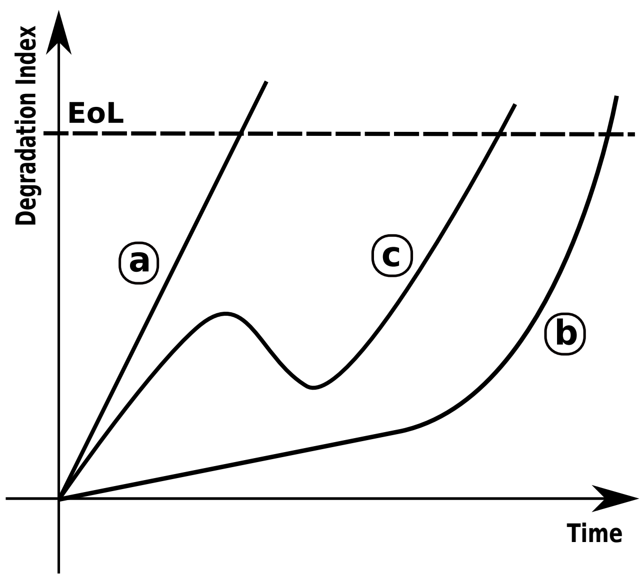

Fig. 5 An example of typical degradation index time profiles: circles a, b and c denotes a single stage and monotonic degradation pattern, a two stage degradation pattern and a three stage degradation pattern, respectively

the beginning of the unhealthy stage, triggered by the monitoring and diagnostics systems;
- a **three stage degradation pattern** is the case, for example, of rolling element bearings inner race surface fault: initially the impacts of the rolling elements on the surface fault produce a lot of vibrations. Then, the defect is smoothed by the continuous impacts before increasing again in size. Consequently, an increase-decrease-increase degradation trend is observed;
- in a **multi-stage degradation pattern** component, or system, degradation process goes through multiple stages. This is often the case of a complex systems affected by multiple, interactive, concurrent faults.

In addition to these, one has to consider that for each failure mode affecting the system, a dedicated health index must be computed. The overall system health status can be displayed with, for example, a radar chart, as in [57].
Health index selection is a key moment in the set up of a PHM maintenance policy. It is performed based on a set of metrics, as for istance monotonicity and robustness to noise, which are estensively reviewed in [58]. For example, a monotony metric has been used in [63] along with a genetic algorithm, to return the combination of features characterized by the best monotonic trend. It is important to stress that the characteristics of the degradation pattern heavily affects the choice of the prognostic algorithm, making the health assessment and prognostic phases strictly connected to each other. Indeed, only a few prognostic approaches, as for example Hidden Markov Models (HMM), can deal with multi-stage degradation processes, while a wider range of prognostic techniques are suited for single stage monotonic degradation patterns.

3.2 Prognostics

The prognostic module is activated after an estimation of the current system's health has been computed. Its purpose is to either predict system's RUL or, for catastrophic failures, the probability that the system operates without fault(s) or failure up to some future time (for example, the next inspection or planned maintenance) [40].
Ideally, a prognostic algorithm should be able to:

- work in all the different operating conditions, which include varying working parameters and environmental factors. Interestingly, to cope with very different working conditions, in [57] only data collected during transients (which are executed on purpose at the end of each day of work) are used for PHM;
- integrate event data coming from machine tool Programmable Logic Controller (PLC) with condition monitoring data acquired by sensors;
- take into account component aging;
- provide an estimate of RUL of multiple components with concurrent faults (each with a different speed, which must be taken into account) and fuse these

estimates into a unique prediction of RUL, with a certain confidence level;
- automatically identify new fault types;
- use as feedback of machine current health status observations and measurements coming from machine inspections;
- provide a suggested maintenance action and a corresponding RUL estimate.

From the technical point of view, prognostics is a time series forecasting problem, also referred to as a prediction problem [33,50]. In particular, the variable whose future evolution is predicted is the health or degradation index, which corresponds to the prognostic feature. The prediction of the evolution of the degradation process is carried out based on past recorded run-to failure data, taken from other similar components and on an estimate of the current health status of the machinery equipment.
When the quantity to be estimated is system's RUL, it is computed as the difference between the time at which the health or degradation index crosses a threshold level which corresponds to the selected component's end of life, t_{EoL}, and the current time instant t [37], as exemplified in Fig. 6. The Failure Threshold FT does not necessarily indicate a complete failure of the system, but beyond which risk of functionality loss. Indeed, sometimes a hazard zone is even considered for the threshold, [73,32]. Specification of FT is a critical issue. Although the FT is often chosen according to experience (data) or requirements there is lack of standard approaches to support this important choice, [51, 83]. In some applications discrete states were used. In such cases the use of the classical thresholding techniques is not necessary but the number of faults need to be known a priori and this is not common in real machinery. According to this scenario, some research works (i.e. Javed et al. [42]) developed methodologies that allow setting the FT dynamically and managing multi-dimensional data.

Component's RUL must be thought as a statistical variable, hence not only its mean value, but (ideally) its probability density function should be estimated. In other words, a good prognosis is characterized by an estimation of the RUL along with its associated confidence interval (C.I.), as suggested by the international norm on prognostics [37]. It must be taken into account that, as [89] reports, RUL probability density function is seldom Gaussian, hence the estimation of its mean and variance may not be sufficient. In addition to this, if the confidence associated to the predicted RUL is too small (or, conversely, the RUL for which the associated uncertainty is sufficiently large is very short), prognostics is not providing meaningful information for

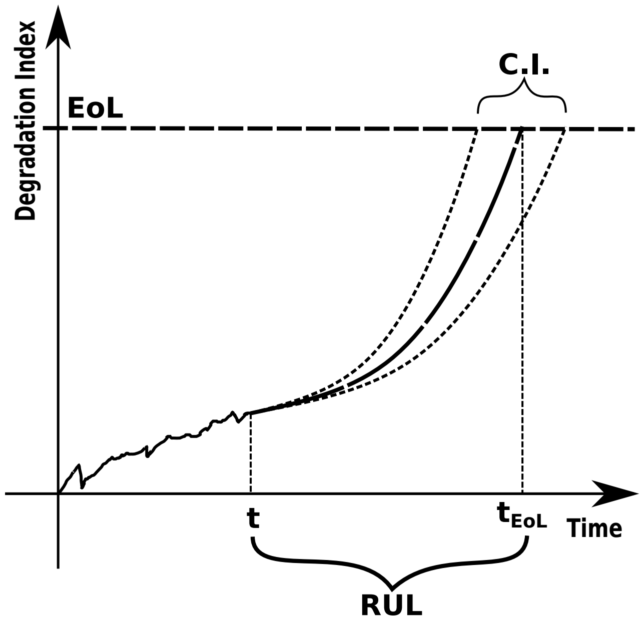

Fig. 6 Graphical representation of the computation of the RUL and of its confidence interval (C.I.)

taking maintenance decisions [26,37]. Fig. 6 depicts an example of confidence interval, which not surprisingly becomes larger as the length of the prediction horizon increases.
In general, more than one fault simultaneously affect a system. For each concurrent fault, a prognostic algorithm should give an expected RUL with an associated confidence level. Then, RUL of all the components have to merged into the RUL of the global system. Therefore, data fusion techniques which can handle confidence level associated to each prediction, are of interest [40].

In general, the forecasting of the future health index values is done by identifying a model which can predict with a sufficient accuracy, which must be specified as well, the future evolution of the monitored variable. This model can be:

- a *rule based model*, in case in which the model is built upon expert knowledge. This is the case of the so-called [37] **knowledge, or experience based prognostic approach**;
- a *white box model*, in case of a physics based model of component degradation process. In this case, only some model coefficients have to be determined based on experimental data (model tuning process), while the structure of the model is known a priori, since it is determined by the underlying degradation mechanism, whose dynamic equations are known, i.e. derived from first principles. This is the case of the so-called **model based prognostic approach**;

– a *grey box model*, in case in which there is not a physical based model describing the degradation phenomenon, but a user-selected dynamic model, whose coefficients have to be determined based on available empirical data. In this case, both model structure and model coefficients have to be determined. This is the case of **statistical based prognostic approach**;
– a *black box model*, in case nothing is a priori known about the model, which is completely identified from experimental data. This is the case of **data-driven prognostics approach**, such as artificial neural networks and deep learning;
– a *combination* of the previously mentioned models, yielding the so-called **combined, or hybrid prognostic approach**, to leverage on their respective advantages to outweigh their limiting assumptions, constraints.

In the following, we're looking more closely to these families of prognostics approaches.

3.2.1 Knowledge or experience based prognostics approaches

In knowledge, or experience based approaches intelligence is put in by human experts [15]. Their main strength is a relatively simple implementation, while their main shortcoming lies in being applicable only in cases in which expert knowledge exists. The main families of algorithms are the following:

– **expert systems (ES)**, whose adoption for diagnostics dates back to the 1960s, are used to insert explicit knowledge from experts into the PHM algorithm by means of human coded (qualitative) rules[15], typically in the form of IF-THEN rules, which closely resemble the way a human specialist solves a problem [64]. The advantages are that they don't rely on a physical model of the system, ease of development, transparent reasoning, the ability to reason under uncertainty, the capability to explain the solution provided [15]. On the other hand, they do not perform well when a huge number of rules is needed (for the combinatorial explosion problem, with the number of rules which grows exponentially with the number of variables [40]) and cannot handle new situations not explicitly coded [79]. In addition to this, expert system cannot directly deal with continuous variables [64]. Moreover, this approaches are usually not reconfigurable, meaning that the given rules cannot be used for another kind of machinery equipment, even if object oriented rules have been introduced to adapt to different systems [15];
– **fuzzy logic (FL)**: a human expert gives a linguistic description of the system. Fuzzy logic based methods are particularly robust against noise and disturbances, and can be used to define fault classification and prognostics rules. Compared to ES, they can handle the uncertainty intrinsic to human experts knowledge [40] and they can treat continuous variables [64]. Typically, they are used in conjunction with artificial neural networks, which optimize membership functions, yielding the so-called neuro-fuzzy (NF) systems, whose main drawback lies in being dependent on a huge number of training data [58], as any other data-driven method.

3.2.2 Model Based prognostic approaches

Model based prognostics approaches leverage on a detailed mathematical model of system degradation process. Models are obtained starting from first principles, and draw on system identification and state estimation techniques for parameters estimation and unmeasureable variables estimation, respectively [24]. Additionally, model parameters can be estimated with the help of a FEM model [58]. Among the advantages of model based prognostic approaches, the following characteristics can be mentioned:

– model based prognostic approaches can be more effective than model-free, or data-driven approaches when a correct and accurate model is built [40];
– a physics based model can account for different operating conditions, making the prognostic algorithm more robust and versatile;
– less data, compared to a data-driven method, can be needed to tune a model based prognostic algorithm [15,11];
– a prognostic model may help the adaptation of the algorithms to a new machine of the same type [11].

The main disadvantages of model based prognostic approaches are:

– a model of the system is not always available, due to either the lack of modelling approaches for the system of interest, or to the too high cost involved in modelling, which is tied to the complexity of the system [64]. This is due to the fact that prognostic models are degradation models, which rely on the understanding of physics-of-failure mechanisms [31];
– their performances are strongly dependent upon the accuracy of the model;
– the impossibility of reusing the model for a different kind of machine (reconfigurability issue).

In general, a model based PHM strategy has been employed to predict [64,40] crack growth, creep evolution, pipeline tube degradation, battery state of charge, gearbox, roller bearing deterioration as in [81].

3.2.3 Statistical based prognostic approaches

In statistical based prognostic approaches, the degradation process is seen as a stochastic process subjects to different sources of variability and uncertainty. Stochastic models are therefore used to perform prognosis [58]. RUL is considered a random variable, whose probability density function is estimated, yielding a considerable advantage for risk analysis and maintenance decision making [93].
Several stochastic models have been used to model the system degradation process. Interestingly, [93] classified them into two categories:

- **stochastic models based on directly observed state processes**: these models are based on direct condition monitoring data or features, i.e. data or features that can describe the underlying degradation state of the system directly, as for example the length of crack when it can be measured or a feature which can directly represent system's health status. In these cases, the prognosis translates into the prediction of the time at which a predefined threshold will be reached. The following stochastic models fall into this category:
  - **regression based models** model state evolution as a continuous process.
    The most used ones are Auto-Regressive (AR) time series models, as Moving Average Auto-Regressive models (ARMA), which assume that the future evolution of the predicted variable is a linear function of both past observations and normally distributed random noise, under the assumptions of stationary data and statistical independence of the errors. Their advantages are that they are easy to be implemented, they don't require a lot of computational resources for computation and the results can be easily explained [64]. On the other hand, their performance are heavily affected by the quality of past observations [58]. Moreover, they are usually effective for short-term prediction and unrealiable for long term prediction. Finally, they don't perform well under variable load and operating conditions, and during fault initialization stage, as in this phase the health index indicator is typically non-monotonic and noisy [64]. However, [67] proposed an extension of an AR model, which took into account the nonlinear aging of the component;
  - **Markovian based models** represent state evolution as a discrete state space process. In other words, they assume that the degradation process of the system is represented by a series of transformations in a finite state space, which obey to the Markov property and hence to a memory-less assumption. Markovian based models are prone to describe a multistage degradation process [58]. In addition to this, they have been used quite often in condition based maintenance and monitoring approaches, thanks to the fact that model's states can be selected to be very easy to understand, as for example "Good", "Maintenance required" etc. In addition to this, they have a strong theoretical background. Their main limitations are:
    - memoryless assumption is not always valid in degradation processes, even if it is worthy to mention that there is no any method for testing Markov property for a generic process [93];
    - transition probability among system states is determined either by empirical knowledge or by large datasets, which are not always available [93].
- **stochastic models which are based on indirectly observed state processes**, also referred to as partially observed state process models since there is a stochastic relationship between the observed condition monitoring data and the unobservable degradation state. These stochastic models are based on indirect condition monitoring data, i.e. data that can only indirectly or partially indicate the underlying (degradation) state of the system, as for example vibration data. The following stochastic models fall into this category:
  - **stochastic filtering based approaches** model the degradation process as a state which has to be estimated based on observations of output variables. Examples of filters are Kalman filter (which provides a point estimate of RUL), particle filter (which estimates RUL probability density function (see [113] for a coincise but clear introduction), Benes filter, multiple model filter. The limitation of these approaches is that they need a threshold level for the estimated state, which is not easy to obtain [93]. Another aspect which may be troublesome is that these approaches need a pre-defined model of health dynamics. If this model is linear, and the noise is Gaussian, then Kalman filter can be used. Otherwise, particle filter is the most suited approach

for nonlinear dynamic models, as for instance exponential models.

– **Hidden Markov model (HMM)** is a stochastic, parametric process model, easy to realize in software and with a well-constructed theoretical basis, which can be trained with both event and condition monitoring data. More in details, it consists of two stochastic process: a Markov chain with a finite number of states describing an underlying mechanism, and an observation process depending on the hidden state. HMMs have been adopted for this kind of prognosis since the beginning of the 21st century [93]. [9] has been the first to apply HMM to prognostics: the RUL of a helicopter gearbox was analyzed, where vibration measurements were treated as realizations of the observation process. The limitations of this approach are the difficulty encountered in the HMM parameters estimation (large computational resources and memory required) and state transition probability estimation. In addition to this, the Markov property limits the ability of the HMM to model the temporal structure of prediction problems. Finally, only RUL mean and variance can be estimated with this approach [93].

Other statistical approaches, which can be used with both the previously mentioned categories, can be found in the literature, as for example:

– **gaussian process regression (GPR)** model cumulative damage processes of random variables with joint multivariate distribution, which are then used to predict future values. This approach works well with both small and large sample datasets. Its drawback is the need of large amounts of computational resources [58];
– **similarity based pattern matching methods** can be used when abudant run-to-failure data are available, which is not always the case in machinery field, to yield very accurate predictions. These methods match health index degradation pattern to the historical run-to-failure dataset which closely resemble its trend [64].

3.2.4 Data-driven prognostic approaches

Data-driven prognostics approaches are built on the assumption that failure prediction can be inferred directly from data, rather than from a stochastic, experience or physical model of the analyzed system. More specifically, data-driven algorithms are not applied directly on sensors' signals, but on extracted features, which reduce data dimensionality [68]. In general, the main shortcoming of data-driven methods is that their efficacy is highly-dependent on the quantity and quality of the data used [69]. In addition to this, the lack of efficient procedures to obtain good training dataset (so, usually, experimental dataset are used) represents another limitation of these approaches [40]. Finally, data-driven methods cannot generally estimate the probability density function of RUL, since they do not have a probabilistic orientation [93]. However, some approaches to estimate RUL probability density function have been proposed, as in [20]. Their advantage lies in not needing any prior physical or statistical model or knowledge of the analyzed system or components. In addition to this, they are able to analyze big datasets (also of different data types) and find unforeseen data relations [79]. Several machine learning algorithms can be used for data-driven prognostic methods, as for example:

– **Artificial Neural Networks (ANN)** are built by three (input, hidden, output) layers and aim at reproducing the way a human brain works.
  They are considered good approximators of nonlinear functions and complex and unstable systems [64]. For this reasons, they have been mainly used to learn the relationship between health indexes and RUL [58].
  Their limitations lie in being a black-box approach, so output cannot be physically explained, in the complexity of the training procedure, which requires a large amount of data, and in the difficulties which have to be faced when selecting network layers and nodes number [79, 64]. Several ANN variants can be found in the literature, such as dynamic wavelet neural networks (DWNN), Elmann Recurrent NN (ERNN) to model non-stationary processes [64];
– **support vector machine (SVM)** is a supervised learning tool, built on statistical learning theory [15]. They non-linearly map an input set into a higher dimensional set, in which a linear classifier separate classes [35]. Compared to artificial neural networks, they usually perform better on small datasets. In addition to this, their computational complexity does not depend upon the dimensionality of input data and they provide a unique solution to a given problem, while ANN are prone to local minima [35]. However, they suffer from several limitations:
  – they can provide only a single-value (deterministic) prediction, rather than a probabilistic prediction or probability density function. To overcome this limitation, relevance vector machine (RVM) has been proposed [64], which is based

on Bayesian inference[1] and hence can incorporate prior knowledge. RVM features also other advantages over traditional SVM, as less computational resources needed and a mechanism for avoiding over-fitting [31];
  - their performance is highly dependent on their kernel function, whose selection, along with their parameter estimation, has no standard methods[58,64], so human expertise is needed.
- **deep learning** is an unsupervised learning algorithm which has received great attention in these years, thanks to its achievements in the fields of object recognition from images and speech processing. The need of a huge amount of training data to provide meaningful results is its main shortcoming [40]. We can distinguish between several architectures of deep learning networks [68,127], such as autoencoder, restricted Boltzman machine,deep belief network.

3.2.5 Combined prognostic approaches

Usually, more than one fault affect simultaneously a component or system. This naturally calls for the adoption of a combined, or hybrid [58,37], prognostic approach, given the fact that it is unlikely that a single approach can account for all the possible faults and failure modes of the analyzed system. In addition to this, each approach has its strengths, which a combined approach aims to foster, and shortcomings, whose effects are in principle minimized by a combined approach through redundancy and compensation. In [64] a panoramic of combined prognostics approaches has been presented. As an applicative example, in [26], a model based prognostic algorithm for avionic roller bearings has been designed to fuse competing RUL estimates, one coming from a physics based model of fault propagation and one coming from experimental data, collected in run-to-failure experiments. Experimental data collected from a bearing test rig showed that a fused RUL estimate better reproduces system real degradation behaviour compared to either a physical based model, which underestimate damage, or an experience based model, which overestimate damage.

3.2.6 Metrics used in Prognostics

One of the challenges in PHM, as in other forecasting disciplines [87], is to conceive suitable standardized metrics for evaluating different prognostic approaches, [89]. Prognostic algorithms, as already deeply discussed, generally compute different output quantities such as HI (health index), PoF (Probability of Faiulure) or RUL (remaining using life) . In order to meaningfully deal with prognostics, the involved algorithms should deal with the Uncertainty Representation and Management (URM), [85]. The main steps of URM are: uncertainty representation (frequentist (classical) or Bayesian), uncertainty quantification linked to different sources (modelling errors, model parameters, sensor noise, measurement errors (outliers), state estimates, future load and operating and environment conditions), uncertainty propagation and uncertainty management. For what concerns the propagation, it is important to understand that RUL estimations are simply dependent upon the various uncertainties characterized in the previous step, and therefore, the distribution type and distribution parameters of RUL should not be arbitrarily chosen. Sometimes, a normal (Gaussian) distribution has been assigned to the RUL; such an assignment is erroneous and the true probability distribution of RUL needs to be estimated though rigorous uncertainty propagation of the various sources of uncertainty through the state space model and the EOL threshold function, both of which may be non-linear in practice, [99,98] . In many of the previous research works, a probabilistic representation of the uncertainty was adopted, [103]. So far, most of the research has been using metrics based on precision and accuracy. For instance, MSE (means square error), SD (standard deviation), MAD (mean absolute deviation), $MdAD$ (median absolute deviation) and MAPE (meas absolute percentage error). In some other applications, metrics more related to business have been adopted: ROI (return of investment), $MTBF$ (mean time between failure), etc. [87,116,53]. These metrics takes into account, from the statistical perspective, the variation of the prognostic algorithm output quantities (i.e. RUL). Develop a proper URM is surely a future research challenge for experts in prognostics, [108,70,18,76,103]. The commonly adopted metrics were not specifically conceived for applications where the prediction is typically updated as more data becomes ready to be used. Another important limitation is related to the incapability of assessing the enhancement of the prediction, both in terms of accuracy and convergence speed, when new data are available. In order to bridge this gap, several research works were developed, [108,88,89] . In particular, Saxena et al. in [89], conceived a hierarchical framework of four metrics for off-line prognostic applications. The first metric (prognostic horizon PH) provides the time index when the predictions first meet the performance index in terms of accuracy. High values of PH means more time avail-

[1] see [23] for a historical-perspective clear introduction to the different inference paradigms today existing

able to act. The second one is the $\alpha - \lambda$ metric. It assesses if the quality of the prediction fulfills the performance specification over time λ. The third one is the relative accuracy RA that measures the accuracy of the prediction over the time. The last metric Convergence quantifies the rate at which any metric improves as new data become available. Although in [88] the use of such metrics in some real cases (not connected to machine tools) was discussed, the development of improved standardized metrics, suitable even for on-line applications, still represents a stimulating topic for the research community. Indeed, even the computational burden of the algorithms has to be considered if the deployment of the code on hardware platform is requested. Indeed, this aspect is very important especially if safety-critical decisions need to be performed in real-time. Saxena et al. in [87], Roemer et al. in [84] and [6] defined metrics for comparing algorithms even from the computational perspective. Since prognostic parameters are used to estimate the RUL of a specific component in its specific environment, the identification of appropriate parameters is vital for an accurate and precise estimation. Optimization strategies could be used to select the most suitable parameters for maximizing/minimizing the considered metrics, [17]. Even the adopted prognostic algorithm can be selected according to an optimization process, [107]. The meta-herustic algorithms (nature inspired), used even in other fields, could be particularly suitable for this purpose since the high-complexity of the task, [80,72].

4 PHM of machine tools

To the best of authors' knowledge, here works on prognostics of machine tool subsystems are presented, to shed a light upon their shortcomings and limiting assumption and hence highlight open research areas.

4.1 Reliability of machine tool subsystems

As stated before in Section 2.1, as more information as possible on the system being maintained have to be gathered, especially to establish subsystems and components suited to the application of a PHM maintenance policy. From our analysis, it immediately emerged that literature lacks of a large number of works dealing with the collection of data regarding machine tool failure rates. We formulated three explanatory hypothesis:

- firstly, often machine tools are customized systems, produced in small batches. This severily hampers the collection of large failure datasets [121,123,48];
- secondly, machine tool manufacturers have generally not extensively and systematically collected failure data, mainly due to the fact that reactive and preventive maintenance policies have been preferred so far over condition based maintenance strategies;
- last but not least, not a lot of time has elapsed since the introduction of IoT devices, one of the enabling technologies which allow to collect large datasets from remotely connected machines.

In [16] failure data from a numerically controlled lathe were collected for a 5 years period. Hydraulic and electric subsystem were found to be the most faulty machine tool subsystems. [78] adds the chunk system as a reliability critical component, based on failure data gathered from 50 numerically controlled lathe machines working three different materials for 7 years. In [120] failure data from twelve machining centers are analyzed. Hydraulic system emerged as the most faulty subsystem, accounting for 18 % of the total number of experienced machine breakdowns, followed by the electrical system, the tool magazine and the tool clamping mechanism. Spindle system failures constituted 9.2 % of the total number of failures; however, they were considered as critical faults, as their repair time (2.65 hours) was the second longest of the whole machine. Among spindle subsystem, in [122] spindle's bearings were discovered to be far the most faulty component, based on failure data collected from 500 numerically controlled machining centers. Bearings failures, together with motor system and tool clamping mechanism failures, accounted for 92 % of the total number of spindle system breakdowns. However, these results may be influented by human errors, which strongly affects reliability results by representing a consistent source of uncertainty. In fact, [12] reports that the majority of spindle bearing failures are due to accidental tool impact.

4.2 Feed axis

Although feed axis failures are not so frequent, as explained in Section 4.1, their repair time is often the larger of the whole machine tool [120]. In addition to this, it must be remembered that the deterioration of machine tool feed axis hamper the quality of the worked piece, since the accuracy of axis positioning decreases and vibration increases. Hence, machine tool feed axis is a subsystem suited to the application of a PHM maintenance strategy. Nevertheless, works on prognostics of machine tool feed axis are very scarce. Moreover, they focused entirely on ball screw degradation, as summarized by Table 2; so, other transmission layouts, as for example linear electrical motors or rack and pinion have been completely neglected. Beside this, all the prognostic approaches presented took advantage of vibration signals acquired at ball screw nut to track and predict ball screw degradation process, which is generally observed to be monotonic. However, attention must be paid since the installation of an accelerometer at screw nut may not be always easy or even feasible, due to tight space constraints in this region of the machine tool.

4.3 Spindle

Although spindle plays a fundamental role in machining, being partially responsible for the quality of the worked piece, for machine's maximum achievable removal rate, and being arguably one of the most critical subsystems for machine tool's reliability as explained in Section 4.1, to date, just a few works explored prognostics of spindles, as illustrated by Table 3. Moreover, all these works dealt with the prediction of spindle bearings failure, the most faulty component of the spindle assembly, either due to accidental tool impacts or simply to wear and aging effects [12]. Both the cited works took advantage of spindle vibration measurements acquired with accelerometers mounted close to spindle bearings to compute the features used for prognosis. Finally, it is worthy to highlight that only in [94] tests have been carried on a machine tool during milling operations, while in [66] and in [86] tests have been performed on a dedicated test bench which did not feature a working cutting tool.

4.4 Hydraulic system

Hydraulic system plays a crucial role in the assessment of whole machine tool reliability. In section 4.1 it has been shown that hydraulic system is on the most faulty subsystem, so the ability to foresee an incipient failure would certainly be a significant advantage for any customer.

In machine tools, several hydraulic circuits are present. Typically, a high pressure circuit is dedicated to the automatic tool changing mechanism, while a lower pressure circuit is in charge of lubrication. Moreover, other middle or low pressure circuits can be present for other auxiliary tasks. Finally, machine tools also feature a refrigerant hydraulic circuit and one for the addition of lubro-refrigerant cutting fluid.

Table 4 lists all the to date available works on the prognostics of hydraulic circuits and their components. It is evident that literature still lacks of prognostics approaches devoted to machine tool hydraulic systems, which is made of several different components, as pumps with their motor, pipes, valves, accumulators and actuators. Only a few works, from the aeronautic field, dealt with hydraulic circuit leakages. For hydraulic oil, while a large number of works on monitoring is available [110], works on prognosis are scarce. A slightly more large bunch of paper is available on pump prognostics, which is commonly referred to as the most faulty hydraulic component [10]. However, not all the different kind of pumps have been treated. For example, prognosis of gear pumps, which are traditionally installed on machine tools, has not been investigated yet.

4.5 Tool

The prognostics and health management of cutting tool is an opportunity made available by the fact that the well-known Taylor formula [47] and its more recent variants, as the one presented in [75], cannot take advantage of real time measurements to compute a more accurate, actual condition based RUL estimate [22].

Tool is machine tool component whose prognostics has been studied more extensively, as confirmed by table 5. The attention given to this machine tool component may be explained by the benefits obtained if changing the tool at the right moment: [97] stated that up to 40% of savings on tools cost could be achieved by monitoring the health of the tool and by consequently changing it at the right moment, to avoid to damage the piece being worked (consider that the quality of the worked piece is affected by tool wear). In addition to this, [52] reported that approximately 20% of machine tools downtime is statistically due to tool failure.

However, several shortcomings hamper the results of the so far published researches on tool PHM . Firstly, in almost all these works a load cell, or dynamometer, has been used to measure cutting forces, which are the variables carrying the largest information content on tool wear [114]. But this is not a sensor which can be used in a real production environment [22], because is it not sufficiently robust and because it modifies machine tool natural frequencies due to its not negligible mass and to the reduction of system stiffness which introduces. Recent research works demonstrated the possibility to correlate cutting forces to tool displacements or tool strain, Wang et al. [111,112] . Cutting forces should be instead estimated online with dynamic estimators which take advantage of more easily obtainable measurements, as vibration and spindle motor current, see for example [3, 4,49,77,44]. Secondly, a few of these researches tested the robustness of their respective prognostic algorithm under varying cutting parameters and cut materials, a common scenario in a real production environment. For these reasons, we believe that the prognostics of the

Table 2 Works on prognostics of feed axis

Ref.	Failure modes	Sensors installed	Health Index (HI) selection strategy	HI	Prognostic algorithm
[60]	Ball screw preload loss	Motor torque and current sensor, accelerometer mounted at ball screw nut	Maximization of signal to noise ratio and display of a monotonic trend	Features set extracted from vibration signals	Gaussian process regression
[115]	Pitting on screw surface (as a result of accelerated life tests)	Accelerometers, one mounted on ball nut and one on bearing housing	Ranking based on trendability index; then correlation clustering to group features with the same information content and extract a representative feature from each class	Weighted Mahalanobis distance	Particle filter, based on an exponential Wiener process model, whose parameters are iteratively updated drawing on Bayesian theory
[126]	Ball screw degradation	3 accelerometers, of which 2 mounted on bearings housing and one on screw nut	Principal Component Analysis	First five principal components	Dynamic fuzzy neural network, whose parameters have been tuned with a quantum genetic algorithm

Table 3 Works on prognostics of spindle

Ref.	Failure modes	Sensors installed	Health Index (HI) selection strategy	HI	Prognostic algorithm
[66]	Balls, cage and races failures as a result of insufficient lubrication and salt water put on races to accelerate wear	Bearings and motor vibration and temperature	Fisher criterion	Minimum Quantization Error	Particle filter, operating on an exponential model identified with Bayesian statistics
[86]	Not specified	Bearings vibration and temperature, motor temperature and current	Correlation		Polynomial regression
[94]	Failure as a consequence of either cage, inner race or outer race defect	Spindle vibration and temperature	Highest signal to noise ratio	Mahalanobis Distance (MD)	Linear approximation of MD evolution over time for RUL prediction

tool, despite been already covered quite extensively, is still not enough mature to be adopted in industry.

5 Conclusions

This paper presented a panoramic of PHM and its preliminary phases in a brief but comprehensive way, to give to the reader a global picture of what this advanced maintenance strategy is about. Current available main families of prognostics algorithms were described. In particular, works on the prognostics of machine tools and their main subsystems were review. This analysis shed a light upon the current limitations (i.e. need of run-to-failure data, need to rely on robust approaches, manage the complexity of real system and multiple axes of information etc.) of these applications of PHM to this kind of machinery equipment. In general, just a few of the presented algorithms have been tested in realistic scenarios, while the robustness of the vast majority of these algorithms to varying working conditions and cutting parameters has not been assessed. This let us to believe that PHM of machine tools is still a topic under development, which will bloom in the next few years. Up to the authors' opinion the following aspects, being the main found limitations, need to be developed and further enhanced:

– Enhancement of condition based maintenance systems to collect accurate information, especially event information. This information would be useful for model building and model validation too. Moreover,

Table 4 Works on prognostics of hydraulic circuits and their components

Ref.	Failure modes	Sensors installed	Health Index (HI) selection strategy	HI	Prognostic algorithm
[28]	Circuit leakages	Liquid level (quantized degradation messages as output)		Liquid level	Particle filter, based on a discrete time state space exponential model, whose slope is online estimated
[128]	Oil contamination	Oil temperature, viscosity and dielectric constant		Particle contamination level	Particle filter
[74]	Servo-valve clogging	Actuator (motor) current and valve position	Sensitiveness and correlation with respect to clogging	Integral of motor current	ARMA model
[27]	Piston pump: looseness of regulator valve spring	Pressure	Not stated	average system pressure	Kalman filter; Montecarlo method for RUL confidence interval computation
[30]	Piston pump: wear between valve plate and cylinder barrel	Oil return flow	Empirical mode decomposition	Oil return flow	SVM
[101]	Piston pump: loose slipper	Vibration		Spectrum entropy, after discrete cosine transform and composite spectrum computation	Recurrent Neural Network
[95]	Centrifugal pump: seal and impeller failure and filter clogging	Vibration, temperature, flow, pressure	Highest signal to noise ratio	Mahalanobis distance	Linear dynamic model
[113]	Slurry centrifugal pump: impeller failure	Vibration	Expertise	Sum of the amplitude of the harmonics in the neighborhood of the vane pass frequency. Then, a moving-average wear indicator is used to extract the central tendency from the time profile of the previously defined feature	Particle filter, with an exponential model
[31]	Slurry centrifugal pump: impeller failure	Vibration	Expertise	Standard deviation	Relevance Vector Machine, which estimates the paramters of two exponential functions

it is particularly suitable when a great amount of data (big-data) are available. This is the case of modern machine tools that are equipped with several sensors and emerging Information Communication Technologies ICT (Industry 4.0 paradigm).
– Development of advanced sensor techniques for robust on-line data acquisition and development of methods for extracting, processing and interpretation of knowledge type information
– Development of efficient and fast on-line signal processing algorithms
– Development of fast and precise prognostic approaches. These would be particularly suitable for developing real-time maintenance systems. Moreover, as reported in section 3.2.5, prognostics craves for proper approaches for managing the estimation the linked uncertainty (*URM*).

Table 5 Works on prognostics of cutting tool

Ref.	Type of machining considered	Sensors installed	Health Index (HI) selection strategy	HI	Prognostic algorithm
[92]	Broaching	Cutting forces, strain, vibration	PCA	Principal components out of force covariance matrix	SVM
[5]	Drilling	Current	Fisher criterion	energy of wavelet packet signal node	ARMA model
[59]	Turning	Flank wear	Correlation with tool wear	Flank wear	A sort of similarity method
[125]	Milling	Vibration	Paerson correlation coefficient	A set of time-domain features	Neuro-fuzzy neural network
[105]	Milling	Cutting forces, vibrations, acoustic emissions	[1]	Rms, peak and standard deviation from dynamometer, rms and kurtosis from accelerometer, mean and standard deviation from acoustic emission	Dynamic Bayesian network
[61]	Milling	Cutting forces	Genetic algorithm	Cutting force peak, amplitude, average and standard deviation	Fuzzy inference
[62]	Milling	Cutting forces	Automatic Relevance Determination	Time-domain features	Multiple regression models
[43]	Milling	Cutting forces, vibration, acoustic emission	Genetic algorithm		Artificial neural network (extreme learning machine)
[7]	Milling	Cutting forces, vibration, acoustic emission	Expectation maximization,PCA and isometric feature mapping	Time-frequency domain features	Support Vector Regression (SVR) with gaussian kernel
[114]	Milling	Cutting forces	Experience	Energy features from time-frequency domain	Gaussian regression
[41]	Milling	Cutting forces, vibration	Genetic algorithm	Four time domain features	Extreme learning machine
[22]	Milling	Spindle power		Spindle power rms	Artificial Neural Network
[82]	Milling	Cutting forces, vibration, acoustic emissions (sensors installed onto workpiece)		Energy features from Wavelet transform and blind source separation	Nonlinear regression, with a different model for each cutting tool tested
[117]	Milling	Cutting forces	[91]	Time and frequency domain features	Bayesian multi-layer perceptron
[124]	Milling	Cutting forces, vibration, acoustic emissions	Expertise	Vibration signal rms	Weighted Hidden Markov Model

– Development of hybrid prognostic approaches that mitigate the limitations associated to each single methodology. For instance, it would be necessary to reduce the need of run-to-failure data.
– Develop specific prognostic solutions suitable for applications in which only limited data are available and, at the opposite, for applications in which big data are involved. For example, the increasing use of AI approaches is justified if a large number of high quality training data is available, [58]
– Development of methodologies capable of updating the prognostic model through on-line data in order to increase the precision of the prediction and to capture changes in operating conditions or transient behaviours
– Development of robust prognostic approaches for complex systems: for instance, single component with multiple faults or fault interaction of different components at the system level, [58]. Moreover, method-

ologies suitable for managing multiple axes of information are also requested.
- Establishment of efficient validation approaches using different metrics (see section 3.2.5 for performances evaluation approaches)

For what concerns specifically the machine tools, more attention ought to be devoted to PHM of hydraulic systems and spindle bearings, which represents two of the most faulty components of machine tools, and to automatic tool change and clamping mechanisms, for which no PHM works have been presented so far.

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