State of the art and taxonomy of prognostics approaches, trends of prognostics applications and open issues towards maturity at different technology readiness levels

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Abstract

Integrating prognostics to a real application requires a certain maturity level and for this reason there is a lack of success stories about development of a complete Prognostics and Health Management system. In fact, the maturity of prognostics is closely linked to data and domain specific entities like modeling. Basically, prognostics task aims at predicting the degradation of engineering assets. However, practically it is not possible to precisely predict the impending failure, which requires a thorough understanding to encounter different sources of uncertainty that affect prognostics. Therefore, different aspects crucial to the prognostics framework, i.e., from monitoring data to remaining useful life of equipment need to be addressed. To this aim, the paper contributes to state of the art and taxonomy of prognostics approaches and their application perspectives. In addition, factors for prognostics approach selection are identified, and new case studies from component-system level are discussed. Moreover, open challenges toward maturity of the prognostics under uncertainty are highlighted and scheme for an efficient prognostics approach is presented. Finally, the existing challenges for verification and validation of prognostics at different technology readiness levels are discussed with respect to open challenges.
Keywords: Applicability, data processing, modeling, prediction, prognostics, robustness, reliability, uncertainty.

1. Introduction

Availability and maintainability of critical engineering assets is of great concern for a modern industry to ensure proper operation and to prevent undesirable situations. The optimization of service and minimization of risks/ life cycle costs demands continuous monitoring of degrading behavior, and accurate prediction of lifetime at which the equipment will be unable to perform required function. According to [1], the barriers of conventional Condition Based Maintenance (CBM) for a widespread application, identified at a workshop organized by National Institute of Standards and Technology (USA): 1) inability to continually monitor; 2) inability to reliably predict remaining useful life; 3) inability of maintenance systems to learn and identify impending failures and recommend actions. We can further define these barriers as deficiencies in sensing, prognostics and reasoning. In addition, over the last decade, CBM has evolved into a discipline Prognostics and Health Management (PHM), which links the studies of failure mechanisms (corrosion, fatigue, etc.,) and life cycle management [1, 2]. Basically, PHM is acting on a higher level than CBM with a strong focus on prognostics for managing health of an equipment. Since, it aims at extending the service life of an equipment, while minimizing exploitation and maintenance costs. The details about commonalities and the difference between CBM and PHM are given in [3]. The acronym PHM has two elements [1, 4].

1. Prognostics refers to prediction/ extrapolation/ forecasting of process behavior, based on current health state assessment and future operating conditions.

2. Health management is decision process to intelligently perform maintenance, logistics and system configuration activities on the basis of diagnostic/ prognostics.

The overall aim of PHM is to produce actionable information to enable timely decisions. PHM is accepted by the engineering systems community in general, and the aerospace industry in particular, as the future direction [5]. Also it is a present-day strategy to benefit vendors, integrators and operators to dynamically maintain their equipment in different domains: manufacturing, aviation, automotive, energy, defense, health care, etc., Fig. 1.

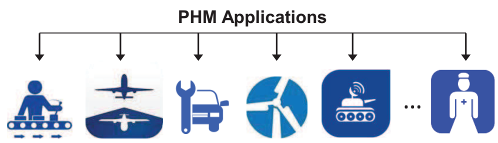

Figure 1: PHM a present-day strategy in different domains

PHM use past, present and future information of an equipment in order to assess its health, diagnose faults, predict

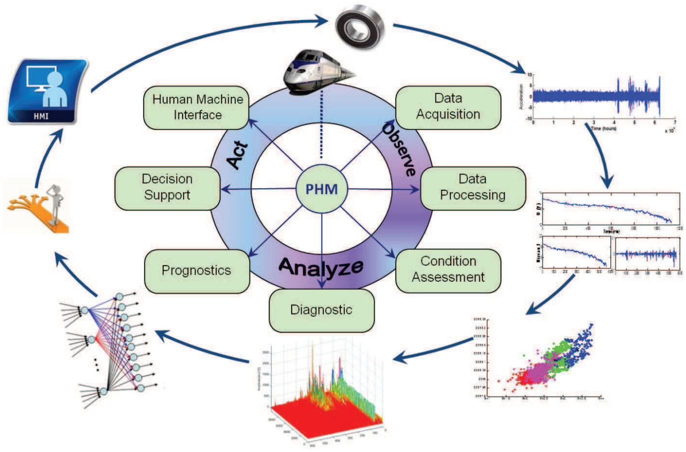

Figure 2: PHM cycle (adapted from [6])

Observe	1.Data acquisition: collect condition monitoring data records using digitized sensors. 2. Data processing: perform data cleaning, denoising, relevant features extraction and selection.
Analyze	3. Condition assessment: assess current condition of monitored machinery and degradation level. 4. Diagnostic: perform diagnostic to detect, isolate and identify faults. 5. Prognostics: perform prognostics to project current health of degrading equipment onto future to estimate RUL and to associate a confidence.
Act	6. Decision support: offline recommend actions for maintenance and online system configuration. 7. Human Machine Interface: interact with different layers and display warnings etc.

Table 1: 7 layers of PHM cycle

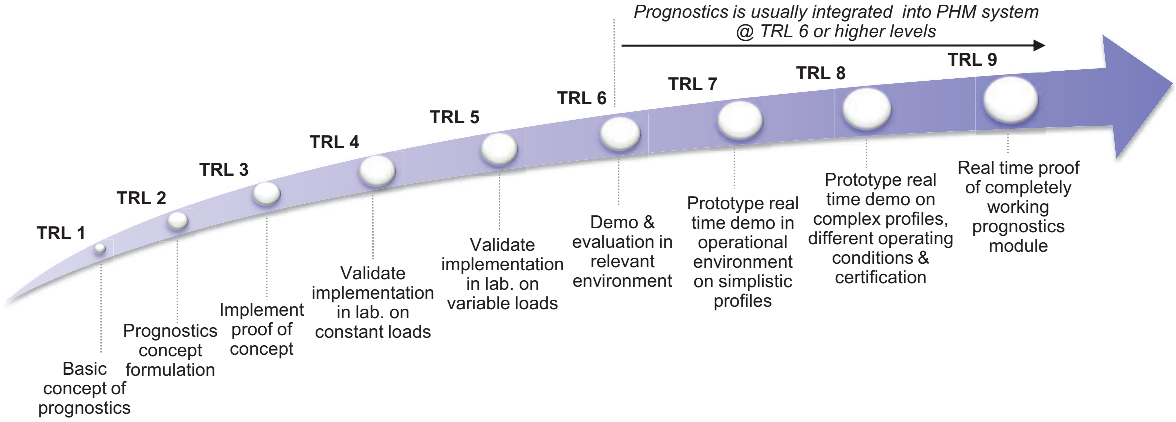

Figure 3: Concept of TRLs adopted to represent prognostics maturity (adapted from [8])

and manage failures [4]. Considering such activities, PHM is described as the combination of 7 layers adapted from Open System Architecture for CBM [6, 7], that all together enable linking failure mechanisms with life management (Fig. 2). We can group these layers into three phases: 1) observe, 2) analyze & 3) act. Brief description of each layer is given in Table 1. Within analysis phase, prognostics is a key step with future potential, which estimates Remaining Useful Life (RUL) of an equipment. The maintenance managers require RUL to be greater than cumulative time of decision, scheduling, and maintenance tasks Fig.4.

Therefore, prognostics must be achieved efficiently for timely decisions for maintaining the equipment offline, changing mission profiles or configuring it online. This requires *verification* to ensure that prognostics observes testable constraints imposed by the requirements and *validation* to evaluate that prognostics accomplishes the intended function. In other words, *verification* of prognostics is for the current point in time and it doesn't give any confidence going forward, whereas *validation* establishes a confidence and gives the ability to expect to know future outcome. This enables prognostics to attain a certain "maturity level" for a real application [10].

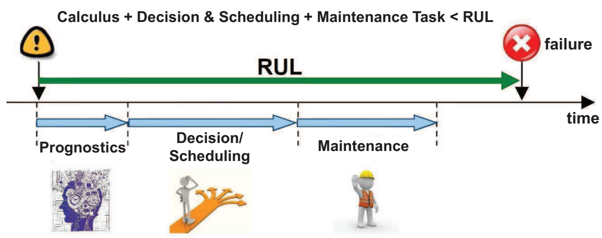

Figure 4: Useful prognostics must enable maintenance [9]

According to authors knowledge, there is only one paper that partially addresses maturity of prognostics (from a lower to higher level) by adapting the concept of technology readiness level (TRL), where *verification* and *validation* activities at each level are discussed as key factors linked to maturity of prognostics [8]. Basically, the study highlighted different components of prognostics and showed that like other PHM components, prognostics follows its own TRL development stages and its usually integrated into PHM system at TRL6 or higher levels Fig. 3. The components of prognostics algorithm are follows [8].

1. Core prognostics algorithm: flow chart/ pseudocode.
2. Implementation aspects: coding and hardware.
3. Data source: sensor measures & operating conditions.
4. Domain specific entities: features & model.

Leaving aside first two components, maturity of prognostics algorithm (at different TRL's) is closely linked to data sources and domain specific entities, for which some issues can be pointed out.

- Data are an important source of information to build a prognostics model. However, the accuracy of prognostics suffers from inherent uncertainties associated with data. Therefore, it is required to address data related uncertainties that impact prognostics. For e.g. uncertainties associated to deterioration process, lack of sufficient data, sensor noise, form of extracted features, unknown environmental and operating conditions and engineering variations, etc.
- In recent years, a vast number of prognostics methods have been proposed. Choice of a prognostics approach has its own importance, because, lack of understating about complex and non-linear behavior of degrading equipment under dynamic environment prevents practitioners from developing precise models for prognostics. Such issues require verification of different factors related to ease of application of a prognostics approach.
- The validation of prognostics is essential to ensure that its long-term prediction performances are within allowed limits. However, the major problem is: how to assess the level of prognostics performances (like accuracy and precision) in the absence of ground truth and under uncertainty?
- For the verification and validation of prognostics, no thorough procedure exists.

Above issues prevent integration of a prognostics model to a real application and for this reason there is a lack of success stories about development complete PHM system. Thus, maturity of prognostics require great attention. This paper intends to give a view on state of the art of prognostics and issues toward maturity, for which the contributions are:

- state of the art and taxonomy of prognostics approaches is given, including their application perspective;
- factors for selecting a prognostics approach are highlighted;
- open challenges toward maturity of prognostics under uncertainty are discussed and defined;
- existing challenges of prognostics validation are elaborated for different TRLs.

The remaining paper is organized as follows. Section 2 elaborates the importance of condition monitoring data and associated uncertainties. Further prognostics and RUL estimation tasks are discussed and the essential steps for handling uncertainty are summarized. Section 3 presents a thorough survey of prognostics approaches and discusses the application point of view for each category. In section 4, a clear taxonomy of prognostics approaches is given and important factors for selecting a prognostics approach are highlighted. Recent case studies of prognostics from a component level to a system level and their maturity is discussed in section 5. Open issues towards maturity of prognostics are discussed in section 6 and new definitions are given. Finally, section 7 concludes this work in detail.

2. Backgrounds

2.1. Condition monitoring data & uncertainties

2.1.1. From critical equipment to data acquisition

The main objective of condition monitoring (CM) is to provide useful information about the current and future health states of an equipment under operation (e.g. component, sub-system or system) [11]. Note that, in context to PHM, in order to identify critical components it is suggested to use Failure Mode and Effects Analysis (FMEA) and Fault tree [12]. The CM from an equipment are fundamental to implement a right health assessment and prognostics model, estimate its parameters and to verify/ validate its maturity. Such data are collected at regular intervals through a procedure of monitoring (carefully selected physical) parameters which indicate health condition/ state of the equipment under given load profiles. Those parameters can be force, vibration, temperature, voltage, etc., for which appropriate sensors are used to collect the data, e.g. accelerometer sensor measures vibration and dynamometer sensor measures force Fig. 5.

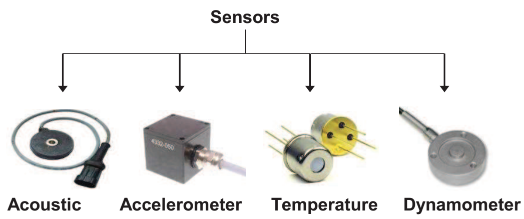

Figure 5: Types of sensors for acquiring measurements data

The acquired data are usually uncertain due to initial damage state and engineering variations like: material properties, manufacturing variability, sampling rates, sensor failures, etc. These uncertainties come from inherent variability in the process, and can be called as *input data uncertainty* [13].

2.1.2. From data acquisition to data pre-processing

The quality of data is important, because raw data are redundant and noisy, therefore they cannot be directly used for prognostics. The relevant information linked to degradation process is usually hidden in raw data, which should be processed to extract/ select health indicators (or features), preferably monotonic and trendable features [14]. For understanding, consider Fig. 6, where features with different characteristics and their effect on prognostics is presented.
Moreover, it is suggested that features selection phase of prognostics should be performed accordingly to the predictability of features, since there is no interest in retaining features that cannot be predicted [15]. Therefore, the uncertainty in case of data acquisition and data processing can be due to sensor noise, loss of information during processing step , etc., and called as *measurement uncertainty*, which can be managed to a better level. A survey of data processing techniques is given in [14]. Moreover, CM data are open to high variability due to *operating environment uncertainties* like future loads or environments [13, 16].
Nevertheless, CM data are also essential source of information from an equipment, that can not be allowed to run until failure due to their consequences. In this view, not only the quality, but also the quantity CM data is important, which can significantly affect performances of the prognostics model.

2.2. Prognostics, Remaining Useful Life & Uncertainties

According to International Organization for Standardization [17]: prognostics is defined as *"the estimation of time to failure and risk for one or more existing and future failure modes"*. This task is composed of two steps.

- The first step is current health state assessment, which can be considered under detection and diagnostic. Different pattern recognition methods can be applied to this step [18, 11].

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- The second step is predicting degradation indicators to estimate RUL. That is to project, current (fault) condition up to the failure threshold (FT). This task is usually achieved by time series methods [19].

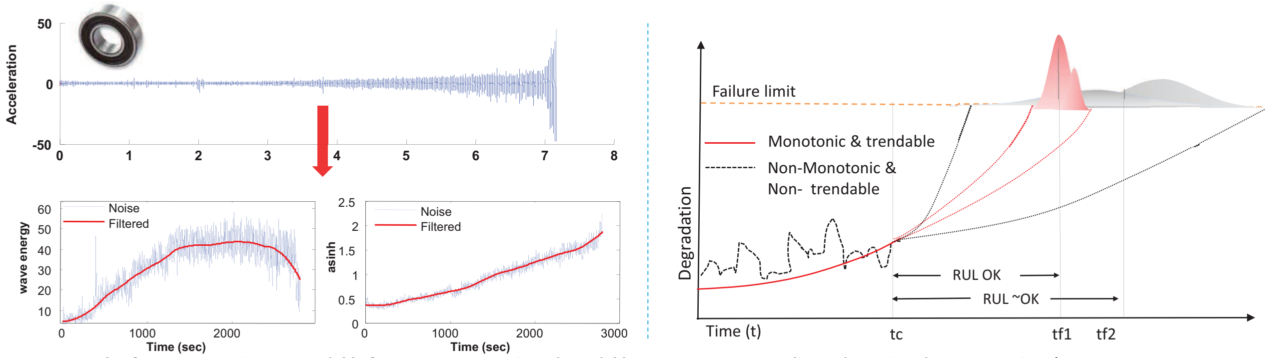
Therefore, for a real-time application, it is essential to accurately assess current health state and precisely estimate the RUL of the equipment (i.e., component, subsystem or system) [20]. The RUL is expressed by units corresponding to the primary measurement of use for an overall system. As for illustration, consider upper part of Fig. 7, where for simplicity the degradation is considered as a one-dimensional signal. RUL can be computed between current time **tc** after degradation has been detected **tD**, and the time at which predicted signal passes the FT, i.e., time **tf**, with some confidence to show uncertainty of the prediction. In general, RUL can be defined by Eq. (1):

$$RUL = tf - tc \tag{1}$$

where **tf** is a random variable of failure time, and **tc** is the current time. Basically, due to inherent uncertainties of degradation process, measurements, operating/ environmental conditions and modeling errors, it is necessary to quantify/ propagate different sources of uncertainty and to provide confidence to predictions and RUL estimation. The decisions are based on the bounds of RUL confidence rather than a single value [21]. A narrow confidence indicates better performances in terms of precision/ accuracy over wide confidence that show large uncertainty, thus risky decisions should be avoided.
In PHM context, it is generally desirable to have early RUL rather than late RULs, since the main aim is to avoid failures. The RUL estimates can be inaccurate due to modeling error. For instance, this can be due to lack of understanding about degradation process behavior, insufficient knowledge or incomplete coverage of data to tune prognostics model parameters to fit the changing observations for health assessment and prognostics. As a result predicted response of the model is different from true response and thus the prognostics is uncertain. The uncertainty in the case of health assessment (at current time) and prognostics is called as *modeling uncertainty*. However, the modeling uncertainty can be reduced by improved methods [13]. In addition to that, the combined uncertainty of modeling include the FT as well, which can also limit the applicability of the prognostics. Note that, the FT does not necessarily indicate complete failure of the machinery, but a faulty state beyond which there is a risk of functionality loss [22], and end of life (EOL).
The lower part of Fig. 7 shows a situation, where RUL is updated when new data arrives at each time interval. It means that the frequency of RUL updation should be synchronized with preceding steps, i.e., data acquisition/ processing and health assessment. Lastly, the evolution of RUL probability density function (pdf) is shown with respect to time, which indicates the increase in accuracy and precision of RUL estimates, as more data are available.

2.3. Uncertainty related tasks in prognostics

As discussed in previous topics, that prediction of the future behavior of an equipment is affected by different types of uncertainty that come form different sources (Fig. 8), that are: input uncertainty from system, measurement



Example of non-monotonic, non-trendable feature vs. Monotonic and trendable feature from vibration signal

Feature quality and associated RUL uncertainty (tc=current time, tf=failure time)

Figure 6: Impact of features/ health indicators quality on prognostics

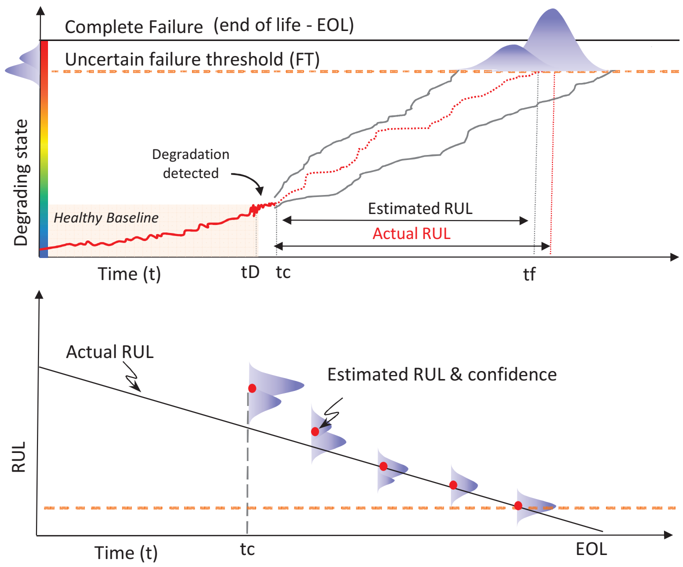


Figure 7: Illustration of prognostics and RUL estimates

uncertainty from sensors, operational environment uncertainty from usage conditions, and modeling uncertainty from degradation model. Whatever the type of uncertainty, it will impact the RUL accuracy a prevent timely decisions (section 2.1 and 2.2). Therefore, RUL must provide the level of confidence to enable offline/ online decisions. According to literature [13, 23], for prognostics algorithm development, four tasks are essential to encounter uncertainty from different sources, without that a prognostics is not useful for a decision maker.

1. Represent uncertainty: is guided by the choice of modeling and simulation. Some common theories include, fuzzy set theory, probability theory, etc. However, in PHM domain the probability theory has been employed widely for uncertainty representation.

2. Quantify uncertainty: to identify and include different sources of uncertainty into modeling and simulations as correctly as possible. The common sources of uncertainty for a real-time prognostics application discussed before can be sensor noise, modeling errors, model parameter initialization, future operating conditions, etc.

3. Propagate uncertainty: accounts for propagation of previously quantified uncertainties and uses that information to predict, 1) the future states and their uncertainty and to estimate, 2) the RUL and its uncertainty.

4. Manage uncertainty: to reduce uncertainty of future states and RUL estimates. This can be achieved by improving by quality/ choice of sensors, by processing data and by improving modeling for health assessment and prognostics.

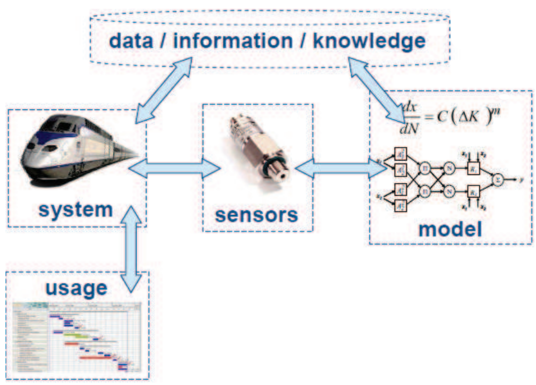


Figure 8: Illustration of different sources of uncertainty

3. Prognostics approaches

An accurate prognostics enables safe operation of an equipment as long as its healthy. Due to importance of such aspects, study on PHM has grown quickly in recent years, where several review papers on classifications of prognostics approaches have been published [24, 25, 26, 27, 28, 29, 21]. In spite of divergence in literature, we bring discussions on common grounds, where prognostics approaches are classified as follows: 1) physics based, 2) data-driven and 3) hybrid. However, this classification is still not explicit in literature and requires a detailed survey.

3.1. Physics based prognostics

3.1.1. Overview

The physics/ model based prognostics approaches use explicit mathematical representation for formalizing physical understanding of a degrading equipment [30]. RUL estimates with such approaches are achieved on the basis of acquired knowledge of the process that affects normal operation of the equipment and mechanisms that cause failure. They are based on the principle that failure occurs from fundamental processes: electrical, chemical, mechanical, thermal, radiation [31]. As an example, common approaches of physics/ model based approaches are spall progression models, crack-growth models or gas path models for turbine engines [32, 21, 2]. To identify possible failure mechanisms, such approaches use knowledge like loading conditions, geometry, and material properties of a system [27]. The main steps to implement physics based approach are failure modes and effects analysis (FMEA), feature extraction and RUL estimation [27].

The behavior physics based model depends on parameters of the model, which are obtained from laboratory test or estimated real time using measured data up to time **tc**, using data-driven approaches [33]. In context to that, In literature, different works categorize physics based prognostics as physics of failure (POF) or system modeling approach [30, 34]. However, such methods should be limited to POF [35], because system modeling is dependent on data-driven approaches to tune parameters of the model and should be classified as hybrid prognostics (section 3.3).

3.1.2. Application perspective

In general, physics based prognostics is application specific. Such methods are based on assumptions that system behavior can be described analytically and accurately. They fit for a situation when accuracy outweighs other factors e.g. air vehicles [36]. Physics based models are usually applied at component or material level [35]. However, physics based methods might not be a good choice for most industrial applications, as fault types can change from one component to another and are hard to identify without interrupting equipment operation [32]. Moreover, system specific knowledge may not be always available [30], and future operating conditions can affect fault propagation as well. In such situations a mathematical model may not be accurate choice [35]. Therefore, physics based model is combined with data-driven approach to tune model parameters online, which known as hybrid approach.

3.2. Data-driven prognostics

Data-driven prognostics approaches are black box models that learn equipment behavior directly from CM data (to fit changing observations). They are low cost approaches and have the advantage of better applicability. They require data to gain knowledge internally, instead of detailed external knowledge from experts. Several studies are performed to classify data-driven approaches. [19] grouped data-driven approaches as machine learning and statistical approaches. [24, 28] classified data-driven approaches as artificial intelligence (AI) techniques and statistical techniques. A survey on AI approaches was presented by [38], where data-driven approaches were grouped as machine learning and conventional numerical methods. [34] classified data-driven methods as machine learning/ AI, evolutionary and state estimation techniques. According to literature, we classify data-driven approaches as machine learning and statistical learning approaches and also elaborate their close links.

3.2.1. Machine learning approaches

The branch of AI that attempt to learn by examples and are capable to capture complex relationships among collected data that are hard to describe. They have the advantage of low implementation cost and can be deployed quickly. Also, they can give system-wide scope. Depending on the type of data, learning with such data-driven methods can be performed in different ways. 1) Supervised learning can be applied to labeled data, i.e., inputs and the desired output is known. 2) Unsupervised learning is applied to unlabeled data, i.e., only inputs. 3) Semi-supervised learning that involves both labeled and unlabeled data (see Fig. 9). Machine learning approaches are categorized as follows with examples.

- Connectionist methods
  1. Artificial neural networks (ANN) [39, 40].
  2. Neuro-Fuzzy systems [39].
- Bayesian methods
  1. Markov Models and variants, e.g., Hidden Markov Models (HMM) [41].
  2. State estimation methods, e.g., kalman Filter, particle filter & variants [42, 21].
- Instance Based Learning methods (IBL)
  1. K-nearest neighbor algorithm [43]
  2. Case-based reasoning [35].
- Combination methods
  1. Connectionist & state estimation techniques [44].
  2. Connectionist & clustering methods [15, 45].
  3. Ensemble to quantify uncertainty/ robust models [46].

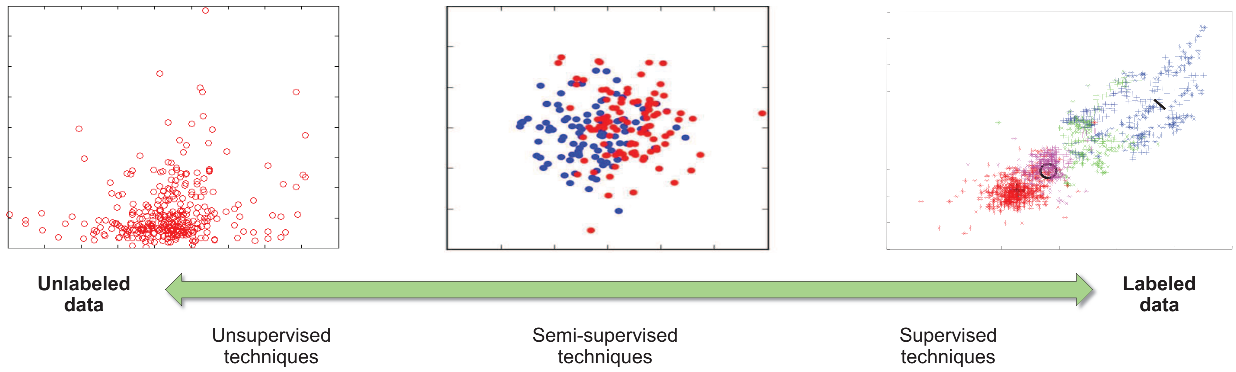


Figure 9: Data and learning (adapted from [37])

3.2.2. Statistical learning approaches

RUL is achieved by fitting the empirical model (a function) as close as possible to the collected data and extrapolating the fitted curve to failure criteria. Such models can be regression methods for trend extrapolation for e.g linear, exponential and logarithmic functions. Like machine learning approaches they are simple to conduct. Also they require sufficient data to learn behavior of degrading equipment. [29] presented a review of statistical methods, where the taxonomy was mainly based on nature of CM data. From this systematic review paper, some commonly known prognostics approaches are: stochastic filtering (or state estimation) methods like kalman filters, particle filters and variants, hidden markov models and variants etc. The details about this taxonomy are give in [29]. Note that, Bayesian techniques mentioned just above can also be called as machine learning approaches. Other methods in this group can be classical time series approaches like auto-regressive moving average and variants [21]. Lastly, this category also include combination models for example using a particle filter to tune the parameters of the empirical model (i.e., exponential/ logarithmic, etc.,) [47].

3.2.3. Application perspective

Data-driven approaches encounter a common criticism that they need more data as compared to physics based modeling, which is not surprising. Obviously sufficient run-to-failure data are necessary to train data-driven models and to capture complex relations among data. According to [2], sufficient quantity means that data have been observed for all fault modes of interest. The machine learning prognostics could be performed with an ANN [39] to recursively predict the continuous state of degradation, until it reaches the defined FT. Bayesian techniques can be applied to manage prognostics uncertainty [13], but, again RUL estimation rely on FT. In contrast, instance based learning does not require FT and can estimate RUL directly by matching similarity among saved examples and new test instances [43]. They are also known as experience based approaches [35]. A combination of different machine learning methods can be an appropriate choice to overcome the drawbacks of an individual method [45]. But, whatever approach is considered for prognostics modeling, it is necessary to integrate operating conditions and actual usage environment. Lastly, in some cases the statistical learning approaches for prognostics do not consider operating conditions, failure mechanism and actual usage environment [48].

3.3. Hybrid prognostics

A hybrid approach is a combination of physics based and data-driven prognostics approaches that attempts to leverage the strengths from both categories. According to literature, hybrid prognostics is performed in two ways [49]: 1) series and 2) parallel approaches.

3.3.1. Series approach

In PHM literature, series approach is also known as system modeling that combines physics based model having *prior* knowledge about the process, and a data-driven model which serves as a state estimator of unmeasured process parameters that are hard to model by first principles [50]. In other words, for series hybrid, a physics based model is combined with online parameter estimation technique to update model parameters when new data are available. Different publications in recent literature label series approach as model based prognostics [30, 34, 51]. However it cannot be considered as model based, because, the mathematical model is dependent on a data-driven method to tune its parameters (Fig. 10). As for example from recent literature, [52] presented a Matlab based tutorial that combines physics based model for crack growth and particle filter that uses the observed data to identify model parameters. An approach to RUL estimation of power MOSFETs (metal oxide field effect transistor) was presented by [53], which used an extended Kalman filter and a particle filter to accomplish prognostics.

3.3.2. Parallel approach

A parallel integration can benefit from advantages of physics based model and data-driven model, such that the

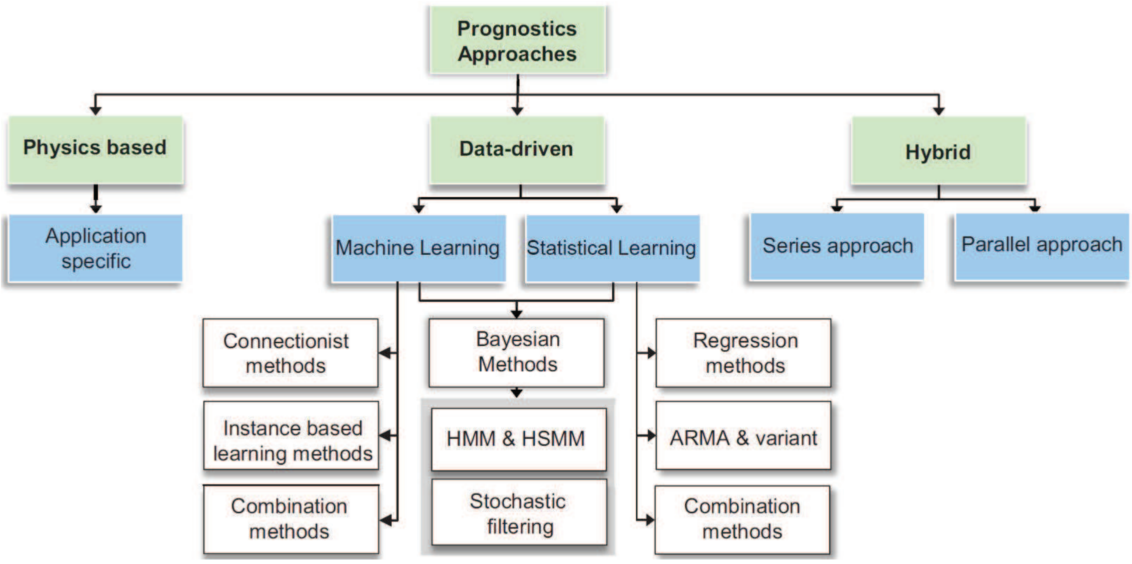


Figure 11: Classification of prognostics approaches

output of resulting hybrid model is more accurate (see Fig. 10). According to literature, with parallel modeling, the data-driven models are trained to predict the residuals not explained by the first principle model [54, 55]. In PHM discipline different terminologies are being used for parallel modeling. [56] called it as parallel hybrid, for an application of choke valve. In some works, such combination of physics based and data-driven models is called as fusion prognostics [57]. A hybrid model to fuse outputs from physics based and data-driven model was proposed by [58]. As for some examples, [59] proposed a fusion approach for prognostics of multilayer ceramic capacitors. [30] proposed a road map for information and electronics-rich systems.

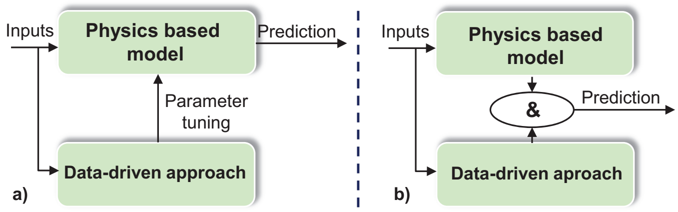


Figure 10: a) Series & b) Parallel approaches (adapted from [54])

3.3.3. Application perspective

Series hybrid prognostics require detailed knowledge of degrading process. However, for the complex systems, it is hard to achieve accurate mathematical model. Also, precise FTs for RUL estimation are required.

The requirement for implementing parallel hybrid prognostics lies in the limitation of building model with an individual approach i.e., physics based or data-driven. Thus, accuracy of parallel hybrid should be higher. Nevertheless, implementing such models require several steps, which can limit their applicability [57]. In brief, the key steps to achieve prognostics with parallel hybrid are: parameter identification and monitoring, feature extraction and healthy baseline creation, anomaly detection, parameter isolation, POF models, failure definition, parameter trending and RUL estimation [59]. Therefore, parallel hybrid has higher modeling complexity and computational time than series hybrid.

4. Classification, Usefulness evaluation & Data-driven prognostics strategies

4.1. Proposed classification of prognostics approaches

According to discussions above, prognostics approaches can be broadly classified as physics based, data-driven, and hybrid approaches. Note that, the classification does not include statistical/ stochastic approaches that use event data rather than direct CM data to project the current condition of the equipment [29], see Fig. 11). Among these classes, physics based methods need modeling POF progression, and can produce accurate results. In contrast to data-driven approaches, they require less data, yet, they are component or defect specific [19]. As for higher system level, physics based model can be hard or even impossible to achieve. However, data-driven methods are considered model free, as they do not need mathematical formulation of the process and solely depend on run-to-failure data. Data-driven are good choice when it is hard to build physics based model for a complex system. But, collecting sufficient CM data is not always possible.

A hybrid of data-driven and physics based methods could benefit from both classes. With hybrid prognostics, reliability and accuracy of model is gained significantly [4], however, it can result higher computational costs which restricts its applicability. In spite of various efforts, real prognostics systems are still scarce, because whatever the prognostics method either physics based, data-driven or hybrid, they are subject to particular assumptions [21]. Moreover, each method has its own advantages and disadvantages, which limits its applicability. Therefore, for a particular application prognostics approach should be selected by considering two important factors: 1) performance and 2) applicability.

4.2. Usefulness evaluation criteria

4.2.1. Performance metrics

In general, prognostics discipline lacks in standardized concepts and still evolving to achieve certain level of maturity for industrial applications. To approve a prognostics approach for a critical equipment, it is necessary to evaluate its performance *a priori* for issues that are inherent to uncertainty from different sources. Still, there are no universally accepted methods to quantify a prognostics method [2]. Also the desired set of metrics for prognostics is not explicit and less understood. In recent years, methods to evaluate prognostics performances have acquired significant attention. From a survey, [22, 60] classified performance metrics into four classes.

1. Algorithm performance: selection among competitive models is performed by considering different accuracy and precision criteria, e.g. Mean Absolute Percentage Error (MAPE), standard deviations, etc.

2. Computational performance: metrics highlight the importance of computational performance that can be easily measured by CPU time or elapsed time.

3. Cost Benefit Risk: metrics are influenced by accuracy of RUL estimates. This will result in replacement of fewer components and also potentially fewer costly failures.

4. Ease of algorithm Certification: metrics are related to assurance of an algorithm for a certain application.

From the above classification, cost benefit risk metrics have a broad scope, and obviously it is difficult to quantify probable risks that are to be avoided. Ease of algorithm certification metrics are associated to algorithm performance class. Because if prognostics model error/ confidence is not mastered, it cannot be certified. In addition to classification above, in literature offline and online metrics for prognostics are also proposed, which are again associated to prognostics algorithm performance. In brief:

- offline metrics: of prognostics are accuracy and precision, prognostics horizon, prediction spread, horizon-prediction ratio, for e.g. see Fig. 12a [22, 60].

- online metrics: of prognostics are RUL precision index and RUL steadiness index, for e.g. see Fig. 12b [61].

Analyzing the performance of prognostics is necessary not only to evaluate its (offline/ online) prediction accuracy or precision, but also to make a right choice (of algorithm) among available options. Thus, discussions in the following section are limited to algorithm performance classes for prognostics validation.

4.2.2. Applicability requirements

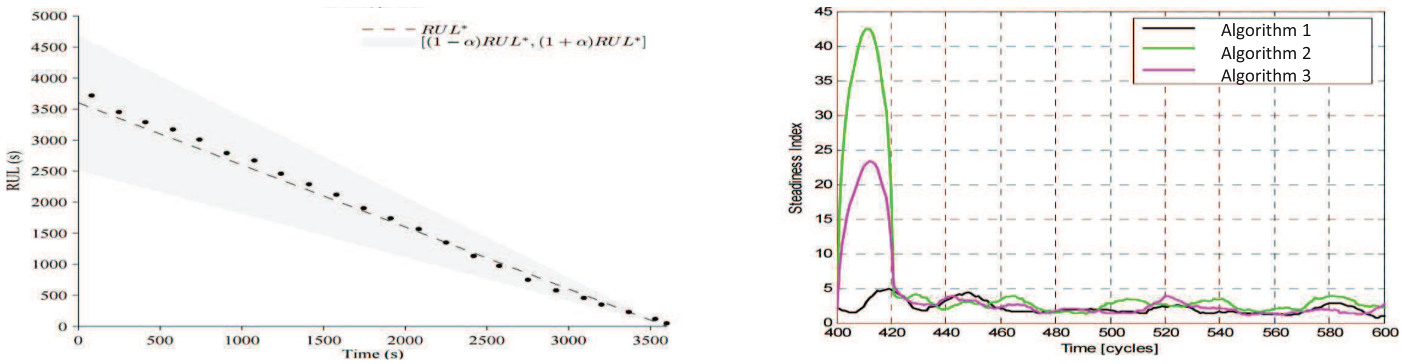
Although in recent years, performing prognostics using traditional physics based approaches have been emphasized, but still data-driven techniques serve powerful techniques to ensure safety and availability of the equipment. Obviously, a major criteria for applicability of physics based prognostics or their hybrid is building a behavioral process model including degradation. This requires a good knowledge of underlying physical phenomena, their dynamics and principal factors that influence i.e., mission profiles, operational conditions, which is not always possible. Also, physics based and hybrid prognostics approaches are based on certain physical and mathematical assumptions. Due to such issues, and with the advance of modern sensor, data storage and processing technologies, the data-driven prognostics have been widely used and become popular [20]. Therefore, excluding data-driven prognostics, other classes have limited scope or generality, where as data-driven prognostics can be applied to system level.

In context of prognostics applicability, one can point out key criteria for selecting a prognostics approach based on discussions from application point of view (sections 3.1.2, 3.2.3, 3.3.3). Table 2 shows the mapping of applicability requirements that must be verified to select a prognostics approach. Considering the importance of such broader aspects, following topic further elaborates the main strategies for data-driven prognostics. Note that, the applicability requirements of each data-driven strategy are also included in Table 2.

4.3. Data-driven prognostics modeling strategies

In recent years, there are rapid advances in research on data-driven approaches to achieve accurate prognostics for complex equipment. According to authors knowledge, the data-driven RUL estimation strategies are classified into three groups: 1) univariate degradation based modeling, 2) direct RUL prediction and 3) multi-variate degradation based modeling Fig. 13.

- Univariate degradation modeling: rely on the prediction of continuous degrading state (or degradation trajectory) followed by a failure criteria. RUL is estimated when degrading signal intersects a pre-defined FT. The requirements of this method are: 1) to identify degradation indicator and 2) to set the FT. However, it is often very difficult to define (or fix) FTs. It should be noted that, with this strategy it is not always required to have run-to-failure data. This advantage has been shown in recent publication, where



a) Alpha-Lambda metric for prognostics accuracy

b) RUL On-line Steadiness Index

Figure 12: Illustration of prognostics algorithm performance metrics, a) offline & b) online

Table 2: Mapping applicability requirements of prognostics approaches

Applicability	**Physics based**	**Data-Driven**			**Hybrid**	
		Univariate	*Direct RUL*	*Multivariate*	*Series*	*Parallel*
Degradation process model	Required	Not required	Not required	Not required	Required	Required
Failure Threshold	Required	Required	Not required	Not required	Required	Required
Generality & scope	Limited	Broad	Broad	Broad	Limited	Limited
Learning experience	Observations	Observations	Run-to-failure	Run-to-failure	Observations	Observations
Operating conditions	Required	Beneficial	Beneficial	Beneficial	Required	Required
Assumptions (Phys./math.)	Yes	No	No	No	Yes	Yes
Knowledge	Detailed	Few	Few	Few	Detailed	In-depth
Transparency	High	Low	Low	Low	Medium	Medium
Modeling Complexity	High	Low	Low	Low	High	Very high
Computational Time	Low	Low	Medium	Medium	Medium	High

the univariate approach using a connectionist tool has been applied to prognostics of a fuel cell stack by using CM data from few hours of observations, see [62] for details.

- Direct RUL prediction: prognostics model learns from the data, the relation between observed trends and equipment end of life. RUL is derived from data-driven model by a pattern matching process between the current observation and the knowledge of equipment RUL [63, 64]. This method does not require FTs, but rely on smooth and monotonic features for pattern matching [43]. However, even a small deviation from matched history case, either due to uncertain operating conditions or non-linearity due to noise phenomena can lead to large RUL errors. In addition, it is also necessary to have sufficient knowledge on RULs available in training dataset. Lastly, the similarity search procedure can be costly as well, in terms of modeling complexity and computational time [35].

- Multivariate degradation based prognostics: model is composed of two complementary modules, 1) a prediction engine that forecasts observations in time i.e., continuous states, 2) a classifier that sets precise FT and estimates the most probable states of degradation, i.e., discrete states [65]. RUL is the estimated time to reach the faulty state from the time when prognostics is initiated. This idea was initially proposed in [66]. A complete illustration of this method is given in [45].

Obviously no model is perfect, however, among data-driven prognostics modeling strategies, the multivariate degradation prognostics is relatively new and realistic as compared to former methods. In addition, its closely aligned with engineering reasoning for prognostics, i.e., with degradation phenomena, fault modes or severity of defect, failure definition, etc. Also, to improve RUL accuracy, the use of multidimensional degradation indicators is preferred rather than one-dimension signal [67]. Note that, from the above mentioned strategies some works also use a combination of univariate degradation modeling and direct RUL prediction approach for prognostics, for e.g. see [68] for further details.

5. Case studies: form component to system level

According to literature, the prognostics applications can be grouped into three categories: 1) components level, 2) sub-system level and 3) system level Fig. 14. However, with the increase of application level, that is form a component to a system the complexity prognostics increases.

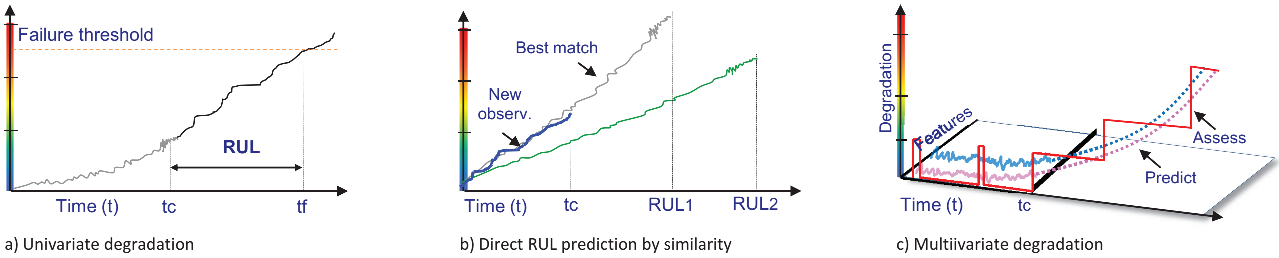


Figure 13: Data-driven RUL estimation strategies

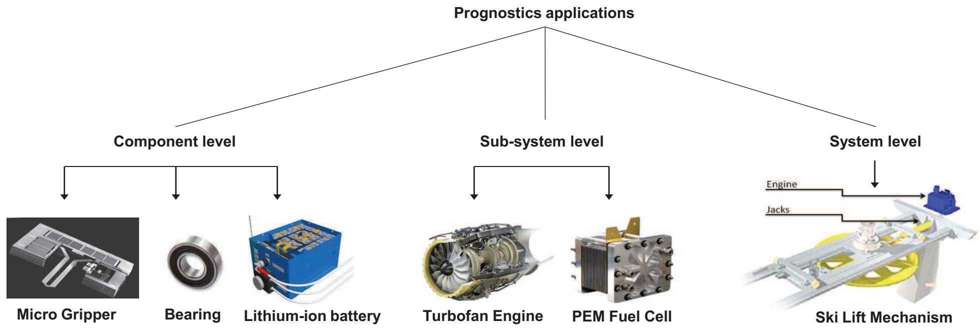


Figure 14: Prognostics application levels: from a component to a complex system

This complexity can be due to several reasons for instance: lack of knowledge, quantity and quality of data, assumptions, modeling complexity, operational environment, increasing sources of uncertainty, validation or verification issues, etc. For such reasons in practice, it is suggested to perform prognostics at component or sub-system level. Moreover, in the case of complete system, critical components or sub-system should be monitored or maintained individually rather than prognostics of system, which can be quite challenging to achieve [69]. Nevertheless, new case studies of prognostics applications (Fig. 14) at different levels and their maturity is discussed for the main categories of prognostics approaches given in Fig. 11.

5.1. *Component level prognostics*

5.1.1. *Micro Gripper application*

The microelectromechanical systems (MEMS) offer several applications in different domains like automotive, communication, aerospace, etc., to perform sensing, actuating or controlling functionalities. The failure of MEMS can be due factors like temperature, humidity, etc. To improve the reliability of MEMS, Skima et al. [70] presented a new work on prognostics of a micro-gripper using parallel hybrid approach (Fig. 10).

To achieve prognostics of considered MEMS, in the first step a physics based model of a micro-gripper is derived, which can also be called as nominal behavior model. Following that, accelerated life testes are performed on the micro-gripers under constant operating conditions and measurements are obtained from the fingers of three micro-grippers. Fig. 15a, shows the measurements of the stiffness from the fingers of those different micro-grippers. In the final step, a degradation model (using polynomial fitting) is obtained from accelerated lifetime tests to project the health state of the targeted micro-system. An illustration of variation of RULs from the micr-grippers is given in Fig. 15b.

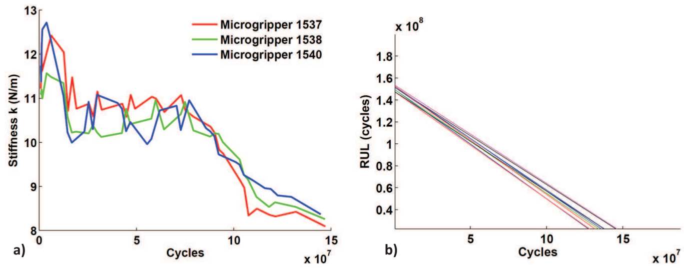


Figure 15: Micro-gripper: stiffness measurements & RULs

5.1.2. *Bearings application*

Bearings are the key components of rotating machines and therefore an area of research for several year. However, there is no clear rule about the degradation of bearings and prognostics of bearings is closely dependent on form, and trend of extracted features. Recently, Javed et al. [14] proposed a new framework for extraction and selection features from vibration data to achieve accurate prognostics.

The extraction is based on trigonometric functions and cumulative transformation, and the selection is performed by evaluating feature fitness using monotonicity and trendability characteristics to manage the uncertainty of monitoring data (section 2.1). This proposition is applied to the time-frequency analysis of non-stationary signals using Discrete Wavelet Transform. A comparison of classical features vs. cumulative features on different bearings (*Ber*) is given in Fig. 16. The main idea is to map raw vibration data into monotonic features with early trends, which can be easily predicted. The selected features are used to predict the degradation of bearing using a rapid learning connectionist approach namely, the Summation Wavelet-Extreme Learning Machine (SW-ELM). The prognostics approach using SW-ELM algorithm is known as univariate degradation based modeling, which is based on a single feature to project the condition of the critical equipment (Fig. 13). An illustration of long-term prediction of bearing condition up to 757 steps horizon is shown in Fig. 17.

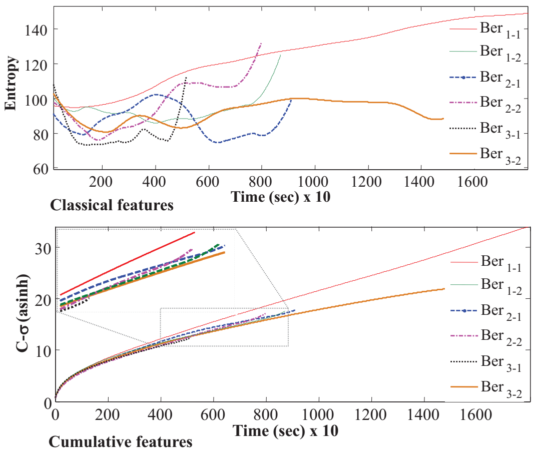


Figure 16: Classical features vs. cumulative features

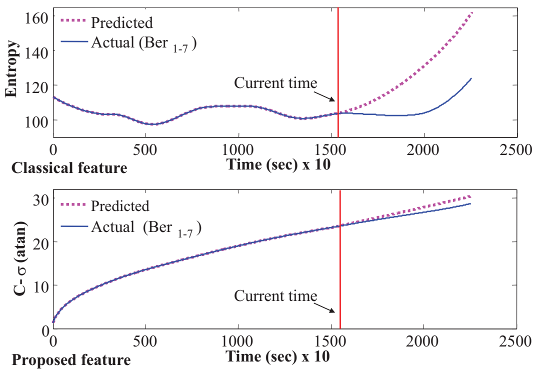


Figure 17: Long-term predictions (classical vs. cumulative features)

5.1.3. Lithium-ion battery application 1

Lithium-ion battery is a commonly used battery type for which several works are published on prognostics, for details see review paper [71]. Recently, Mosallam et al. [69] proposed a direct RUL prediction approach for prognostics of Lithium-ion battery. Note that, in this work only charge and discharge cycles of the battery are used. The key features of the proposed approach are as follows. The direct RUL approach is based on offline and online steps. For the offline step, a health indicator (HI) construction method is proposed using monitoring data to reflect the condition of the degrading battery. Those HIs are considered as offline models, which are stored in the model base. In the online step, similar HIs are obtained from the sensor data and a Bayesian filter is applied to estimate the current health state of the new battery. Finally, the model base is searched for the closest match with the health indicator of new battery and the life span of the matched HI considered as the RUL of the new battery (Fig. 13). An illustration of RUL estimates at frequent intervals is shown in Fig. 18.

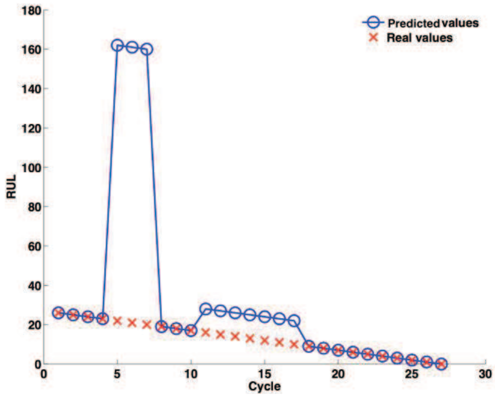


Figure 18: Battery RUL estimation results

5.1.4. Lithium-ion battery application 2

The second application Lithium-ion battery discussed here is proposed by Saxena et al. [51, 72]. The proposed approach is based on series hybrid prognostics to estimate the RUL of degrading battery Fig. 10. In brief, the prognostics is achieved by a physics based discharge model of battery cells and a particle filter to tune the model parameters online, and to quantify and propagate uncertainty of prognostics. The proposed approach is used under variable loading profiles for predicting the end of discharge (EOD) Fig. 19, and the prognostics performances are compared with a classical ANN and polynomial regression models using offline metrics (section 4.2), see Fig. 20.

5.2. Sub-system level prognostics

5.2.1. Turbofan Engine application

To improve the accuracy of RUL estimates the use of multidimensional signals is preferred for prognostics rather than one-dimension signal [67]. In this context, a new data-driven approach for prognostics is proposed Javed

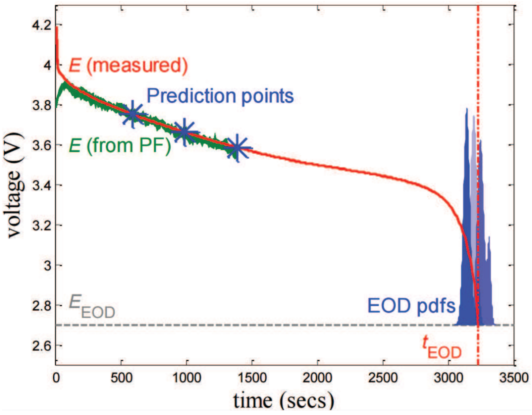


Figure 19: EOD prediction results

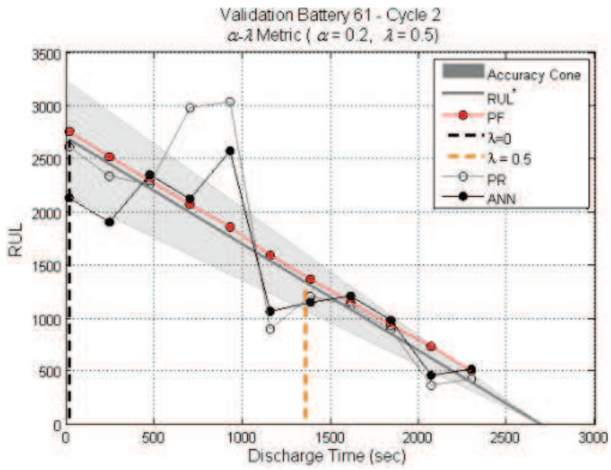


Figure 20: Alpha-Lambda metric to compare performance

et al. [45], namely an enhanced multivariate degradation modeling (Fig. 13).
The proposed prognostics model is achieved by integrating two new algorithms namely, the SW-ELM and Subtractive- Maximum Entropy Fuzzy Clustering to show evolution of equipment degradation by simultaneous predictions and discrete state estimation. The prognostics model is equipped with a dynamic failure threshold assignment procedure to stop the prediction process and to estimate RUL in a realistic manner. For validation the proposed approach is applied to 200 turbofan engines data. An illustration of RUL estimation multivariate degradation prognostics is given in Fig. 21.

5.2.2. Proton Exchange Membrane Fuel Cell application

Fuel cell (FC) technology is promising source of renewable energy, which has a great potential to take over existing technologies in future, for example batteries in transport applications. PHM of FCs is a new discipline to enable improvements in the life management, use and support [73].

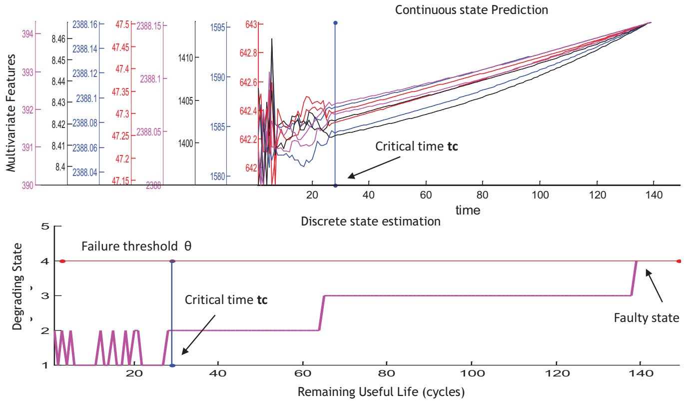


Figure 21: Multivariate degradation prognostics (Engine 1)

A physics based approach for prognostics of Proton Exchange Membrane Fuel Cell application (PEMFC) stack is proposed by Lechartier et al. [74]. The proposed physics model is composed of a static part and a dynamic part to represent the behavior of PEMFC stack. In addition, in this work a parametric sensitivity analysis is performed to identify those parameter which have the most influence on the physics based model. The proposed approach is applied to a commercial PEMFC stack to perform prognostics under constant load current. Fig. 22 illustrates the PEMFC stack voltage prediction results by the prognostics model using few observations from the stack.

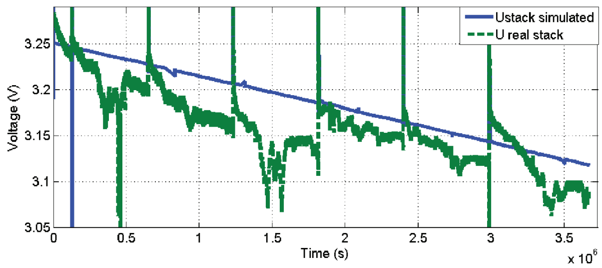


Figure 22: Actual & predicted stack voltage

5.3. System level prognostics on ski lift mechanism

The prognostics of a multi-component system is a less explored area in the PHM community. This is mainly due to the complexity and inter-dependencies among the components, therefore predicting the behavior of a complex system is not an easy task. To this aim, Wael et al. [75] proposed a statistical approach for prognostics to estimate the RUL of a system by considering the degradation rate interactions between its components. In order to establish a common prognostics approach for each component, a probabilistic Weibull model is used. This model enables representing the failure probability of each component in the system.

Table 3: Summary of recent case studies and their maturity (Fig. 3)

Application	Equipment	Prognostics	Performance metrics	TRL	Online	Uncertainty task
Component	MEMS	Parallel hybrid	N/A	TRL 3	No	No
	Bearing	Univariate degradation	Accuracy	TRL 4	Yes	Yes
	Battery 1	Direct RUL prediction	Accuracy	TRL 4	Yes	No
	Battery 2	Series hybrid	Accuracy, Prognostics	TRL 5	Yes	Yes
Sub-system	Turbofan	Multivariate degradation	Accuracy,Time, Prognos.	TRL 4	Yes	No
	PEMFC	Physics based	Accuracy	TRL 4	Yes	No
System	Ski-lift	Statistical	N/A	TRL 3	No	No

The proposed prognostics approach is applied to a ski lift mechanism for which the jacks and the engine are considered as critical components of the ski lift system. In this case study, the jacks are identified as the main components that influence the RUL of the ski system. Fig. 23 shows the change in jacks failure probabilities with a cumulative density function, where r represents the degradations rate.

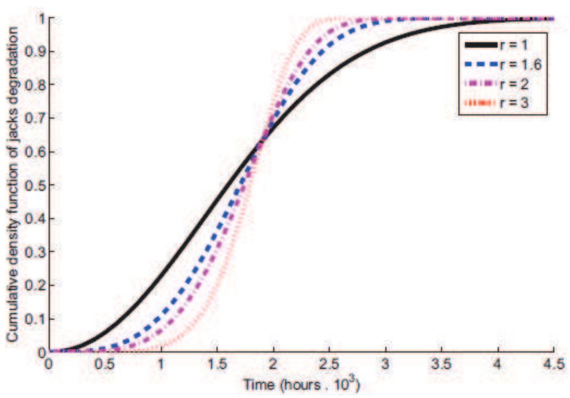


Figure 23: CDF of jacks degradations

Although there is diversity in the prognostics literature, which can be understood by the newly developed case studies. However, prognostics is still not mature as indicated by the Technology Readiness Level (TRL) of those applications in Table 3. Moreover, most of the case studies do not consider uncertainty related tasks (section 2.3), without that prognostics is not useful. Also there are validation issues, as few works consider only offline metrics to validate prognostics and there is no clear metric to ensure online prognostics performances. In this context, following topic highlights the open issues toward maturity of prognostics and the existing challenges.

6. Open issues toward prognostics maturity

According to discussions above, various approaches for prognostics exist, i.e., physics based, data-driven and hybrid approaches. However, real prognostics systems to meet industrial challenges are still scarce. This can be due to inherent uncertainties associated to deterioration process, lack of sufficient quantities of data, sensor noise, unknown environmental and operating conditions, and engineering variations, etc., which prevents building prognostics models that can accurately capture the evolution of degradation. In other words, highly complex and nonlinear operational environment of industrial equipment, makes it hard to establish efficient prognostics models, that are robust enough to tolerate uncertainty, and reliable enough to show acceptable performance under diverse conditions [76, 20, 33]. In addition, implicit relation between CM data and RUL makes it hard to know which prognostics algorithms give the best performances for a specific application [20]. Besides that, the applicability of prognostics approaches is also necessary to meet industrial constraints and requirements. Finally, prognostics approaches should be enhanced by handling simultaneously all three challenges, robustness, reliability and applicability, which are still open areas. However, practitioners still encounter difficulties to identify their relationships and to define them. The following topics will discuss, how maturity of prognostics is linked to validation of robustness/ reliability issues and to verification of applicability requirements.

6.1. Robustness of prognostics

Real industrial systems are intrinsically not "perfect" and the usefulness of gathered data are highly dependent on the variability of phenomena, sensor nonlinearity, etc. Also, the degradation of an equipment cannot always be directly measured, so that indirect observations must be imagined. This complicates understanding (and modeling) of complex and uncertain behavior of real systems. Following that, it is obviously difficult to provide a prognostics model that is insensitive to uncertainty of data, and is capable of capturing dynamics of degrading asset in an accurate manner. Robustness of prognostics appears to be an important aspect [77], and still remains a critical issue [78]. We define robustness as:

- Robustness is the *"ability of a prognostics approach to be insensitive to inherent variations of input data"*.

It means that, whatever the subset from the entire learning frame is used, the performances of a robust prognostics model should not impair (i.e., steady performance).

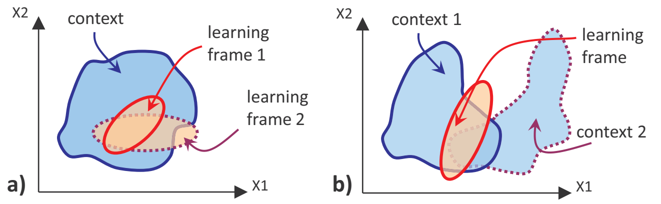


Figure 24: Illustration of challenges: a) robustness & b) reliability

In other words, robustness validates prognostics performance and addresses uncertainty of the prognostics model when exposed to variations in learning data having same context, i.e., operating conditions, geometrical scales, material, etc. An illustration is given in Fig. 24.

6.2. Reliability of prognostics

Even if the prognostics approach appear to be robust to tolerate uncertainty under same context, it should also be reliable enough to be used for the context that is different from the one considered during the modeling phase [79]. In other words, the prognostics should cope with the variations related to the context, such as, multiple operating conditions or materials differences of components, etc. Robustness and reliability [1] of a prognostics approach appear to be closely related [28], and both should be considered as important to ensure the accuracy of RUL estimates. We define reliability as:

- Reliability is the *"ability of a prognostics approach to be consistent in situations when new/ unknown data are presented."*

The reliability validates prognostics performances when data with different context are presented to the model i.e., operating conditions, geometrical scale, material, etc. In other words, a reliable prognostics model can adapt variations related to context and can deal with uncertainty when exposed to new data with small deviation from learned cases (i.e., context is partially known), or when totally unknown data with large deviations are presented (i.e., unknown context). An illustration is given in Fig. 24.

6.3. Applicability of prognostics

Besides robustness and reliability criteria, a prognostics model has to be chosen according to the implementation requirements and constraints that restrict the applicability of the approach. Mainly, these constraints can be related to the quality and quantity of data, the generalization capability that is expected, the complexity and computational time required by the model, the assumptions (physical or mathematical) that clearly impact accuracy of results, etc., [21]. The applicability problem still remains a technical challenge. We define applicability as:

- Applicability is the *"ability of a prognostics approach to be practically applied under industrial constraints"*.

The applicability verifies suitability or ease of implementation of a prognostics model for a particular application, i.e., requirements like failure definition, human intervention, model complexity, computation time, theoretical limits of the approach or any assumption. A scheme of robust, reliable, applicable prognostics under different types of uncertainties associated to CM data and prognostics modeling (section 2) is shown in Fig. 25. Note that, although it is practically not possible to achieve perfect prognostics that overcomes different sources of uncertainty. However, *validating* the robustness, reliability performances and *verifying* applicability of prognostics will enable practitioners to build the right model. Finally for decision making, the uncertainties from different sources should be quantified and propagated to show the reliability of RUL estimates (section 2.3).

6.4. Existing challenges

In general, handling uncertainty is a major hurdle while developing prognostics models. For instance, it is obviously almost impossible to accurately predicted the future unknowns, like operating loads and environmental conditions under which the equipment operates [23]. However, validating robustness and reliability will ensure the effectiveness of the prognostics model, establish a confidence, and give the ability to expect to know future outcome under uncertainty (according to the provided information). As discussed in section 4.2, the validation of prognostics performances require offline and online assessment for the real application and also for the development of complete PHM system.
In case of offline assessment, different error based prognostics metrics can be used for validating TRLs 1-5 Fig. 3 (see [8]) for details). The error metrics will facilitate in minimizing the prediction uncertainty, i.e., via improved data processing and prognostics modeling (Fig. 26). This task is mainly associated to the availability of ground truth. Therefore, whatever the prognostics approach is, either physics based, data-driven or hybrid, it requires sufficient data for validating prognostics performances (like robustness and reliability) against all possible faults. However, in some cases not all equipment provide such data, e.g. nuclear applications. Therefore, using simulation data is another option, which can be an added factor to overall uncertainty of prognostics.

[1] Note: classical definition of reliability "the ability of an item to perform a required function under given conditions for a given time interval" [80] is not retained here. Actually, the acception used in this work is according to the application of machine learning approaches in PHM, that do not consider reliability of prognostics model as dependability measure [81]. In this perspective, whatever is the approach for modeling prognostics, the model parameters have to tuned with input data in the learning phase (i.e., like machine learning).

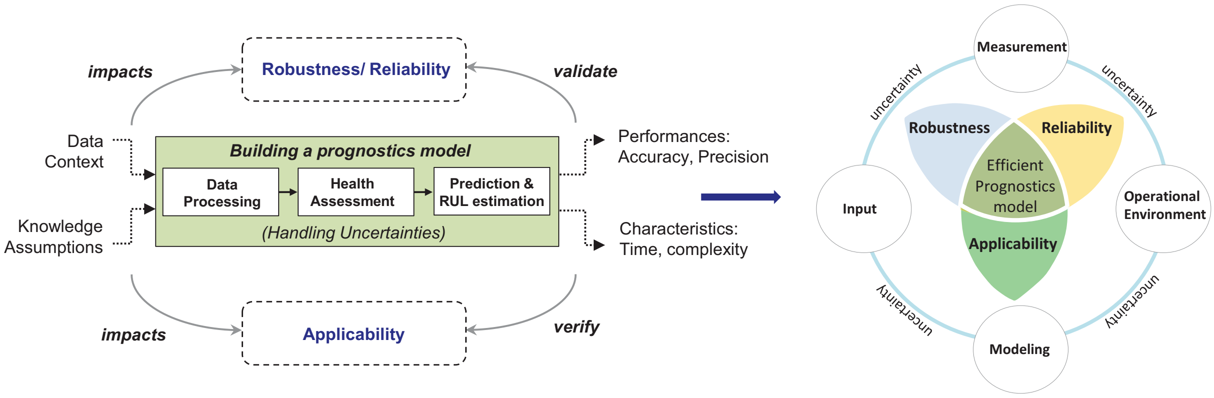


Figure 25: Scheme for robust, reliable, applicable prognostics under uncertainties

In case for online assessment like at TRLs 6-9 Fig. 3 (see [8]), due to the absence of ground truth and future operational conditions, validating the reliability of prognostics approach with real-time data is a major challenge that needs to be addressed by the PHM community. For example consider Fig. 26 for such a case, where the probability density function (pdf) of prediction error indicates precision and accuracy and enable the practitioner for further improvements (offline). However, for the online phase there is no such possibility and the error will accumulate with increasing prediction horizon. Also in such situation the RUL pdf is unknown. Obviously, decision-makers require indicators upon the evolution of degradation equipment to imagine adequate mitigation actions. Therefore, any assumptions on the RUL uncertainty or the future outcomes should be avoided.
According to discussions in section 4.2, online metrics like RUL steadiness can indicate the standard deviation of the RUL pdf for long-term prognostics. However, RUL can be precise but not accurate, which can impact the decision phase. This problematic seems necessary with regards to overall prognostics process. That is to say, the focus should be on mastering error of long-term prognostics, i.e., on the knowledge and the control RUL distribution such that the error is within allowed limits (which is linked to verification as well).
In addition to validation aspects, the requirements for applicability of prognostics model have to be verified at current point in time. Therefore, the robustness, reliability and applicability of the prognostics model will affect the overall efficacy of a PHM system. Finally, for a real application, it is required to develop an efficient prognostics approach that can estimate RUL with an acceptable performances under modeling challenges robustness, reliability and applicability.

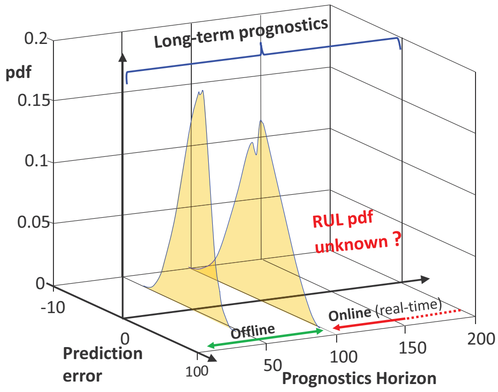


Figure 26: Long-term prognostics & prediction uncertainty

7. Conclusion

Within prognostics and health management system (PHM), prognostics is the key task with future capabilities, as it enables estimating the remaining useful life (RUL) of the in-service equipment. An accurate estimate of RUL allows timely decisions for offline maintenance, changing mission profiles or configuring operating conditions online. However, due to a dynamic operational environment, the deterioration process of an equipment is affected by different factors like engineering variances, failure modes, environmental/ operating conditions. Data acquired from such equipment are usually noisy and subject to high uncertainty/ unpredictability which affects RUL estimation and could lead to wrong decisions.
Therefore, a prognostics model must be *verified* and *validated* to ensure that it attains certain "maturity level" for a real application and thus the maturity of prognostics require great attention. To this aim, a thorough survey on the state of the art of prognostics is performed including a brief discussion on the technology readiness level (TRL) for prognostics algorithm. Moreover, the key components of a prognostics algorithm are discussed in detail, i.e., data source and domain specific entities like modeling. According to that, a clear classification of prognostics approaches is presented and application perspectives for each category

are discussed. Also key factors of selecting a prognostics approach are identified and new case studies of prognostics applications from component-system level are discussed. Finally, open challenges toward prognostics maturity are highlighted:

- robustness to encounter uncertain inputs, reliability to encounter uncertainty due to unknown data operating conditions, engineering variations, etc., to validate that prognostics accomplishes the intended function and to establish a confidence to expect to know future outcome.
- applicability to verify industrial constraints and requirements at current point in time.

According to discussions, authors believe that following points are vital for building an efficient prognostics approach.

1. Data are the key source of information that must be used intelligently to manage uncertainty.
2. Sufficient data and ground truth are required to correctly validate the prognostics model.
3. Before choosing prognostics approach its requirements must be verified for ease of application.
4. The use of multidimensional data are essential for prognostics.
5. Operating conditions that correlate equipment degradations should be used as prognostics model inputs.
6. Uncertainty of the prognostics must be quantified and propagated to show the reliability of prognostics.
7. Prognostics model should be capable of updating its parameters in real-time when new data are available.
8. RUL must be estimated at frequent intervals.
9. The frequency of RUL estimates should be synchronized with preceding steps, i.e., data acquisition/ processing and health assessment.
10. Accuracy and precision of RUL must be assessed under constant and variable operating conditions to validate the prognostics model performances.
11. Real-time RUL estimates should indicate correctness of long-term prognostics and confidence for decisions.

Prognostics is vital for a successful industry, however, this discipline is still evolving and there is a lack of success stories from lab experiments to real environment. The major challenge of prognostics either on a component level or system level would be to manage uncertainty of unknow future operating conditions, i.e., for a real-time application. Lastly, prognostics discipline lacks in metrics for real-time application for giving actionable information to ensure correctness at higher TRLs, which also facilitates in avoiding risky decisions.

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