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# System-level failure prognostics: Literature review and main challenges

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## Abstract

This paper reviews methods and practices for addressing the concepts of system-level prognostics (SLP) and system remaining useful life (SRUL) estimation applied to multicomponent systems. A precise definition of SLP is provided, emphasizing the advantages of its use in terms of identifying the scope of SLP applications. In addition, a comprehensive review of the literature is provided to properly classify and compare the findings of previously published studies in the field of SLP and evaluate the effectiveness of the available methodologies within the different stages of prognostic development. Finally, and considering that SLP is still a relatively recent research field, we also provide a thorough discussion on the main challenges that remain to be solved before achieving complete technology transfer, as well as future research directions.

## Keywords

System-level prognostics, complex systems, heterogeneous systems, interdependencies, system remaining useful life, uncertainty.

## Introduction

Over the most recent twenty years, failure prognostics has turned into a discipline by its own doing with an abundance of papers covering a large number of scientific issues and different industrial applications (1; 2). Its introduction into the industry accelerated with the emergence of the concept of PHM (Prognostics and Health Management), which integrated fault detection, failure diagnostics, prognostic, and maintenance decision support. This saved a large part of the costs allocated to maintenance. For example, a study that surveyed 5 industrial members of the Center for Intelligent Maintenance Systems reported savings of over 855 Million U.S dollars based on the successful implementation of the predictive monitoring and PHM solutions (3).

As industrial systems are increasingly complex (such as aircraft, power plants, etc.) and consist of several interdependent and mutually influencing components, prognostics at the system-level becomes the most appropriate level for predicting a system's future behavior and determining its time of failure. However, due to large-scale engineering systems' complexity, prognostic studies have been limited to the component-level. Yet, the output of these prognostic algorithms can be practically useful for the system managers, operators, or maintenance personnel, only if it helps them make decisions based on system-level parameters. Therefore,

there is an emerging need to build health assessment methodologies at the system-level.

Several reviews exist about the topic of failure prognostics in general, summarizing, structuring, and organizing the literature. However, the majority of these reviews did not report studies concerning system-level prognostics (SLP). In contrast, the works concerning this theme are growing more and more. Therefore, this paper aims to provide state-of-the-art, as exhaustive as possible, of the existing SLP literature. This includes:

- Framing and positioning of the SLP topic about component-level prognostics (CLP) and PHM in general;

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- Advantages and benefits of utilizing SLP approach and methodology to choose an adapted prognostic approach for multicomponent systems;
- Classification of the work carried out so far based on the granularity of the modeling ;
- The different applications of SLP in the current literature;
- Presentation of an approach to use a realistic benchmark, which is the Tennessee Eastman Process, for system-level prognostics purposes;
- Challenges that need to be addressed to have an effective and applicable SLP methodology at the industrial level.
- Some recommendations and directions for further research to go beyond state of the art.

The paper is organized as follows. In Section 2, the background on component-level prognostics is introduced. Section 3 is concerned with defining the system-level prognostics, and Section 4 by presenting its advantages and benefits. Section 5 reviews SLP approaches and methods. Section 6 contains the different applications of SLP in literature and an introduction to the use of the Tennessee Eastman Process for SLP. Section 7 detailed the challenges related to SLP. Finally, Section 8 concludes the article by providing a discussion of recommendations and future research directions for this field by delivering a discussion on recommendations and future research directions for this field.

## Background on component-level prognostics

Failure prognostics is one of the principal added values provided by the PHM (4). Indeed, with prognostic, system failures are proactively prevented from limiting their consequences and taking them into account in future decision-making. The interest for this discipline is primarily due to the proliferation systems where failure is considered financially, humanly, and/or environmentally dramatic. Hence, the maintenance of these systems must anticipate failure patterns through the implementation of prognostic algorithms.

To formally introduce failure prognostics, let us consider a system with a nominal functioning state before its utilization, and no maintenance is necessary (Figure 1). During the early stages of its exploitation, it operates with a specific health level that is broadly stable until a particular stage, where an early incipient disruption occurs, and then the failure risk increases with time. Therefore, prognostics can

be defined as the process of this failure time prediction: i.e., the end of (useful) life (EOL) and/or the remaining useful life (RUL). This estimation is forecasting an event in the future, which is, by definition, uncertain. This is based on the fundamental notions of systems' deterioration, monotonic damage accumulation (called *soft failure* process in reliability studied in contrast with *hard failure*, which are due to random shock process), pre-detectable aging symptoms, and how it correlates with the system degradation model. Hence, prognostic implementation aims to detect, diagnose, and analyze system deterioration in order to estimate the remaining useful life (RUL) (5).

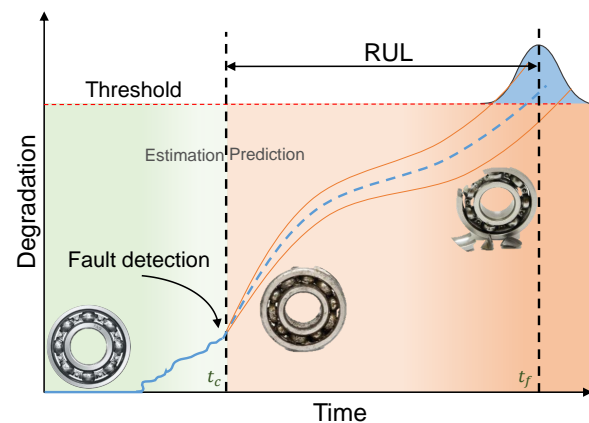


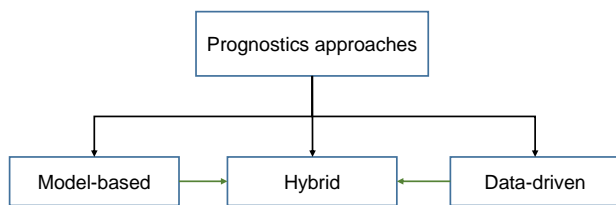
Figure 1. Prognostics illustration.

A component RUL (in the framework of component level prognostics, CLP) is given by the difference between the failure time  $t_f$  where the system will reach the failure threshold and the current instant  $t_c$ .

$$RUL = t_f - t_c \quad (1)$$

Generally, the research conducted in failure prognostics of assets with the CLP approach is classified into three main approaches: data-driven, model-based (also called physics of failure), and hybrid prognostics (Figure 2). The first approach uses the data provided by sensors (monitoring data), which capture the system's degradation evolution. The data are then pre-processed to extract features, which are used to learn models for health assessment and RUL prediction (6; 7). Different tools and models can be used for data-driven approaches, among them we can mention: neural networks (8), regressions (9), hidden Markov models (10; 11) and support vector regression (12). The second approach requires a deep understanding of the system's physical phenomena, including the degradation evolution. This approach uses physical laws or principles to build the degradation model, which is tuned using the monitoring data in order to compute the RUL (13; 14). Examples of

degradation models are those related to crack by fatigue, corrosion, and wear (15; 16). Finally, the third approach combines both previous approaches and benefits from their advantages, such as precision and applicability, but can also inherit their drawbacks, such as important modeling efforts and the need for a lot of representative data.



**Figure 2.** Component-level prognostics approaches.

The reader is invited to consult these comprehensive reviews on the topic of component-level prognostics (4; 17).

As industrial systems are increasingly complex, CLP is no longer sufficient to ensure accurate results. Thus, prognostics at the system-level becomes the most appropriate way to conceive the implementation of methodologies that aim to predict the system's future behavior and determine its time to failure. The following section aims to properly introduce this topic and provide a precise definition of system-level prognostics.

## Definition of system-level prognostics

There is no consensual definition of the systems-level prognostics in the literature yet. In (18), the authors inventoried the papers published before 2011 that propose a definition of prognostics in a general way. Among these papers, partial definitions of system-level prognostics were proposed. It was found that, collectively, these definitions state or imply, among others, that prognostics is, or should be, performed at the component or sub-component level. In (19), the system-level prognostics was defined in contrast with the cellular-level one in relation to battery health state problem. In contrast, the system level refers, in this case, to a single component, which is the battery made up of several identical cells. However, this definition cannot be applied to complex systems where we have several heterogeneous components. In (20), it was stated that *SLP "combines degradation models for individual system components and information about how components interact to define the system behavior"*. This definition considers the interactions between components but only considers degradation models of components without referring to the nominal models. Nevertheless, prognostics is not only

concerned with determining the system's behavior but seeks its evolution to predict failures.

To give a general definition of SLP, the authors proposed transposing the definition accepted in the PHM community of component-level prognostics at the system level by outlining the system's meaning. This results in the following definition: *system-level prognostics corresponds to the estimation of a system RUL (SRUL) knowing its current health state and future conditions of use (21)*. A system is defined as a set of elements (components or subsystems) interacting with each other and the environment to perform one or more tasks (22). As a result, mainly due to interactions, the system's behavior is not the direct sum of the behaviors of its components due to new emergent phenomena. Consequently, the prognostics at the systems level will allow taking into account:

- system failure due to the degradation of one of its components,
- system failure due to degradation of several interconnected components,
- system failure due to performance below the required thresholds,
- system failure due to mission profile interruption.

In the literature, it is referred to SLP with different terms: system-level prognostics (23; 21), system approach of prognostics (24), multi/multiple components prognostics (25; 26) and prognostics of complex systems (27).

## Advantages and benefits of adopting SLP approach

The prognostics at the system-level stems from the desire to maximize the systems' lifespan either through maintenance actions or by modifying the mission profile to reduce the degradation rates. Indeed, CLP is only an approximation of the system's behavior, while SLP considers the maximum number of factors influencing the degradation of a system. Besides, some of the reasons that encourage shifting to system-level prognostics include, among others, the following arguments.

- For system users and operators, it is important to know whether a system as a whole can provide its designated services(28).
- In practice, a slight degradation in several components can concur to have a more significant impact on system performance. This is due to the interdependence between components. Therefore, system end-of-life calculation is not just a simple combination of single

component failures. The direct extrapolation of the component RUL to the system RUL will lead to overestimation or underestimation problems (20).

- In redundant systems, knowing the component RULs is insufficient to determine the impact of degradations or failures on the system's operability. In this case, it is more relevant to use the RUL of the whole system.
- To maintain systems or extend their life, information on its whole future behavior is needed: e.g., to schedule system-wide maintenance.
- Applying system-level prognostics allows localizing the most vulnerable/critical components of the system in order to monitor them more.

As a result, system-level prognostics can benefit all stages of the system life-cycle by improving system reliability and availability, increasing safety, and making systems more sustainable (29) while reducing the maintenance costs. Also, SLP can help localize the components to be monitored even if they do not represent a low RUL, which can influence other components and accelerate their degradation. Many studies have looked at optimizing the costs of maintenance of multiple components (30; 31), based on the individual component prognostic. These studies will gain precision if the structural and degradation relationships between components are considered.

System-level prognostics can also help locate the root causes of a failure and improve the diagnostic function (32). It can also improve the maintenance function organization: schedule system-wide maintenance, reduce the number of interventions, etc.

### How to choose the right level for prognostic

Adopting a system-level approach is very likely to yield more accurate prediction results. However, implementing such an approach is likely to generate higher implementation costs in terms of monitoring (detection, bandwidth, etc.), computing capacity, and expertise needed.

To choose the prognostic level to be taken into account for the study of a multicomponent system, we propose a scheme (Figure 3) inspired by the scheme proposed in (33) and to which the costs related to failure and system-level prognostics implementation are integrated.

Once the prognostics at the system level has been determined as the appropriate level for monitoring a system's health state, an important question posed here is how to choose an appropriate approach for a considered problem. Hence, a comprehensive review of different approaches used to implement SLP will be presented in the next section.

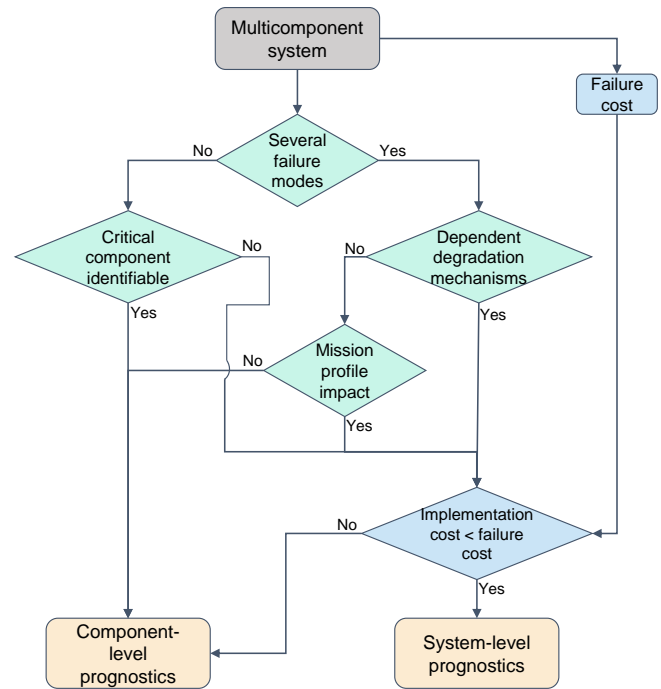


Figure 3. Choice of the level of study of the prognostic system.

## Literature on system-level prognostics

Several literature review papers have been published on prognostics in general and have focused on system-level prognostics broadly through a few paragraphs. We can mention for example (4; 1; 34). These reviews conclude that there are not many studies on system-level prognostics. However, more and more works have addressed the SLP problem for many years. The purpose of this subsection is to exhaustively as possible introduce the literature on SLP.

In order to report the different works addressing SLP issues, a classification based on the system modeling point of view is proposed (Figure 4). This choice was motivated by the fact that one of SLP's most significant issues is the whole system modeling degradation (40; 35) According to the proposed classification, we can distinguish two categories regarding the granularity of the modeling used: simplified modeling and holistic modeling. The classification is refined in each category regarding the using approaches and tools. This classification is presented in Table 1 with some tools used in each category as illustration.

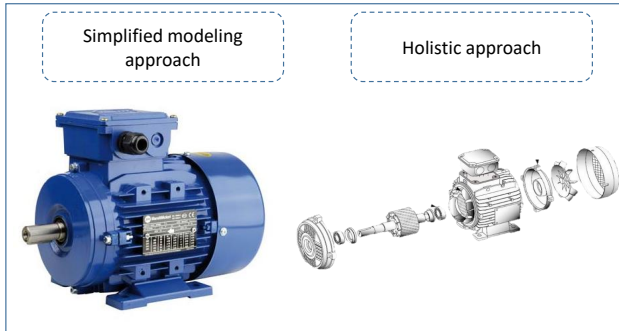
### Simplified modeling

The studies in this group usually simplify the system modeling when evaluating the SRUL. These methods can be divided into two categories: Construction of input-output relations and Critical component selection.

*Construction of input-output relations* In this case, the system can be considered as a black box (as illustrated in

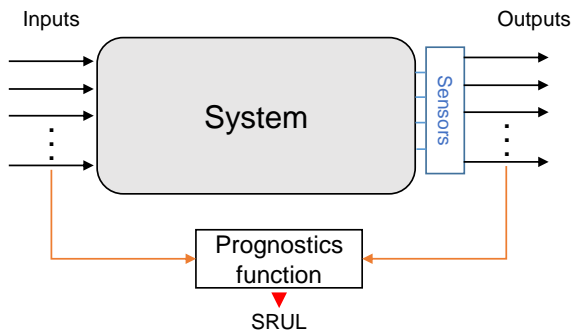
**Table 1.** Classification of system-level prognostics main works.

Modeling type	Approach	Tools and methods
Simplified modeling	Construction of input-output relations	Black box: ANN (35), SVM, etc.
	Critical component selection	FMEA (36), PRA, etc.
Holistic modeling	Model-based approach	System decomposition model (28), equivalent circuit, etc.
	Data-driven approach	<i>Reliability data:</i> Fault tree (37), PDMP (38), etc. <i>Monitoring data:</i> Kalman filter (39), ANN, etc.



**Figure 4.** Illustration of granularity modeling.

Figure 5), and the SRUL is estimated based on the input-output data using machine learning methods (35), statistical methods (41), or similarity-based methods (42). The main tools used for this approach are sophisticated neural network (8) (e.g., LSTM), Levy-based process (e.g., Wiener process), stochastic filtering-based models (e.g., Particle Filtering or Kalman filter), SVM-based methods.



**Figure 5.** Prognostics based on input-output relations.

The advantage of this approach is that it is easy to apply even without extensive system knowledge. On the other hand, this approach requires many monitoring data that are not easy to acquire in practice, resulting in a more extended model training period, which may not be acceptable for expensive systems that cannot remain non-operational for long or risk of substantial margin. Also, because we are not interested in what is actually happening inside the system, we may lose the modeling’s physical meaning. The health indicator used will be difficult to monitor because of nonlinearity and non-stationarity (43). In fact, the variation of the system health indicator of a complex system results

from all the changes that occur inside the system. Yet, the changes can be the result of many combinations, and thus the evolution of these changes could be unpredictable.

In (44), a combination of SVM and ARIMA methods is proposed to estimate the RUL of an aircraft engine from different variables. In (35), a review of tools and methods considering rotating machinery as one component is proposed.

In a nutshell, this approach can be assimilated into component-level prognostics for complex systems. However, for CLP, degradation mechanisms concern one component with a few degradation modes. Whereas, in SLP, degradations can occur in all the components with propagation effects.

*Critical component selection* From this perspective, the system prognostics is simplified to the prognostics of the critical components determined by using risk analysis and reliability methods (36; 45; 46). The standard (47) provides a series of methods to support engineers in evaluating the reliability of a given system. These methods can be divided into two main groups, namely qualitative and quantitative techniques. Qualitative and semi-qualitative methods rely on expert judgments on available data to identify and evaluate potential failures to make reasonable judgments about risks. These techniques can be based on decisions or experiences and provide a qualitative assessment of risks (low, medium, and high). Qualitative methods are usually performed using techniques such as Checklist, Failure Mode and Effects [Criticality] Analysis (FMEA/FMECA), Preliminary Hazard Analysis PHA, and Hazard and Operability Study (HAZOP).

The quantitative methods can be probabilistic or deterministic. The probabilistic methods use statistical tools to estimate measures such as failure rates, mean time to failure (MTTF) and Mean time between failures (MTBF) to evaluate the reliability of a system (47). The most commonly used tools are the Fault Tree Analysis (FTA) and the Event Tree Analysis (ETA). Moreover, the above-mentioned methods can be combined for system reliability and risk analysis (48). The deterministic methods typically rely on different approaches to determine which

component-specific parameters most impact the system-level degradation determined by an overall health indicator. These approaches can be physics-based (49) or data-driven (50; 51; 52).

The critical component identification approach was applied in several cases, such as identifying the contact wire as the most critical and impacting component of the Overhead Contact System of railway infrastructure (45), bearings in rotating machines, lithium-ion batteries, and turbofan engines in commercial airplanes (46), etc.

However, this approach may be insufficient to ensure the availability of a system whose components interact. In this case, the identification of critical components is not an adequate solution.

### Holistic modeling

The aim of the second group of system-level methods is to provide a holistic view of the system under study, i.e., considering all its components and the underlying degradation mechanisms, including degradation propagation and environmental effect, when evaluating the SRUL by using data-driven or model-based approaches. In Table 2, studies that addressed SLP, as stated in the definition given above, are presented concerning the tool used and their capacity to consider component interdependencies, uncertainty, mission profile effects, and non-linear degradation mechanisms. The references presented in this table are detailed in the remaining of the paper.

**Model-based approach** The model-based approach (i.e., physics-of-failure, PoF) of the holistic modeling utilizes knowledge of the life cycle loading, failure pattern models, control models, or other phenomenological descriptive models of the system. These models are usually mathematical aggregations of component failure models with additional equations describing how they interact within the whole system.

According to (70), model-based approaches better suit system-level prognostics as it is challenging to use the monitoring data directly to represent and get a physical interpretation of the component interactions. The advantage of PoF-based methods is, often, their ability to isolate the root cause(s) that contribute to system failure (71). However, sufficient information about the product is needed, and it is challenging to analytically describe complex systems. For instance, in PoF models, geometry, materials, and operational and environmental conditions are required, although finite element models can help. However, in

complex systems, these parameters may be difficult to obtain. The development of models involves some knowledge of the underlying physical processes that lead to system failure. Therefore, it is difficult for complex systems to create dynamic models representing the multiple physical processes occurring in the system (72).

Currently, one of the most used models in prognostics is the state-space representation (73), which is formulated as follows:

$$\begin{aligned} x &= f(t, x(t), \theta(t), u(t), v(t)) \\ y(t) &= h(t, x(t), \theta(t), u(t), n(t)) \end{aligned} \quad (2)$$

where  $x(t) \in R^{(n_x)}$  is the state vector,  $\theta(t) \in R^{(n_\theta)}$  is the unknown parameter vector,  $u(t) \in R^{(n_u)}$  is the input vector,  $v(t) \in R^{(n_v)}$  is the process noise vector,  $f$  is the state equation,  $y(t) \in R^{(n_y)}$  is the output vector,  $n(t) \in R^{(n_n)}$  is the measurement noise vector, and  $h$  is the output equation. This model describes both the nominal behaviour and faulty behaviour, including the fault progression function.

The use of this model in CLP allows taking into account different parameters that influence a component's degradation. However, for SLP, the state-space model has several limitations: the inability to model heterogeneous components, the no-modeling of component interactions, and the computation time.

Otherwise, another approach consists of building system models by integrating the simpler behavioral equations with experience-based models or utilizing data fusion techniques (18). In (28), the authors propose a method to decompose the system state-space model into independent sub-models and then derive the SRUL based on the RUL calculated from each sub-model. However, this approach assumes subsystem independence. Moreover, its practical application is limited due to the complexity of the proposed analytical models. In (23), the same authors applied this approach to the United States' Airspace Management. In that perspective, an aircraft is viewed as an independent component of a system that is the airspace. The risks of "loss of separation" (two planes becoming very close) and dry breakdowns are assumed to be reversible progressive degradations. Then, the aim is to determine the time before these risks exceed a certain probability. The prediction was conducted using Monte Carlo simulation algorithms.

In order to model the interdependencies, the authors of (56) used the state-space-based modeling where the dependencies among different degradations are captured in the matrix of diffusion coefficients. Then, by using the sequential Kalman filtering, the hidden degradation states are identified

**Table 2.** Literature review of system-level prognostics holistic approaches.

Holistic approach	Tool/model	Paper	Interdependence	Uncertainty	Mission profile	Non-linearity	
Model-based	Input-output Model	(53)	✓	✓	✓	✓	
	First ordre model	(54)	✓	✓	✓	✓	
	Petri Nets	(55)	×	✓	×	×	
	State-space model	(28)	×	✓	✓	✓	✓
		(56)	✓	✓	×	×	
	Stochastic filtering theory	(57)	✓	✓	×	×	
	Stochastic differential equations	(58)	✓	✓	×	×	
	First order reliability method	(20)	×	✓	×	✓	
Bond graphs	(59)	×	✓	✓	✓		
Data-driven	Fault tree	(25; 60)	×	✓	×	✓	
		(61)	×	✓	×	×	
	Piecewise Deterministic Markov Process	(38)	✓	✓	×	✓	
		(62)	✓	×	✓	✓	
	Multi-Agent Systems	(63)	✓	✓	×	×	
	Wiener process and Frank Copula function	(64)	✓	✓	×	×	
	Linear regressive model	(40)	×	×	✓	✓	
	Fuzzy logic	(65)	×	✓	×	×	
	Graph Convolutional Network	(66)	✓	×	×	✓	
	Artificial Neural Network	(67)	✓	×	×	✓	
	Bayesian networks	(68)	✓	✓	×	×	
	Extrapolation	(25)	✓	×	×	×	
Expectation-maximization algorithm	(69)	×	✓	×	✓		

based on multi-dimensional observations. Meanwhile, the model’s unknown parameters are updated iteratively by the expectation-maximization (EM) algorithm. However, this approach was applied to simplistic systems where homogeneous components are involved. To address the limitation of state-space modeling regarding the heterogeneous system, in (25), the calculus of the SRUL is made on one global performance indicator. This later is derived from the aggregation of the individual component performance indicators calculated using independent individual component state-space modeling while taking into account system architecture. However, it is assumed that the relationship between the deterioration of health indicators and system performance is known.

Furthermore, one of the main challenges when applying the model-based prognostics approach is the uncertainty quantification that slows the involved calculation of the SRUL. Khorasgani et al. presented a prognostics methodology for system-level RUL prediction that considers different sources of uncertainty such as model uncertainty, measurement uncertainty, and output uncertainty (20). Two methods were developed to model the uncertainties: stochastic simulation and inverse FORM (First-Order

Reliability Method) approaches. The authors presented an analysis of the computational complexity of the two developed methods and showed that the inverse FORM approach was faster than the stochastic simulation approach. In (57), the uncertainty related to component dependencies and their effect on system RUL was tackled using stochastic filtering theory.

A more phenomenological approach to system degradation is addressed in (54), where authors developed an approach to decompose an electronic system into circuits instead of components. Because of the difficulty of monitoring miniaturized electronic components, this approach presents obvious interest. The circuit-level faults are merged to obtain a global fault indicator of the system. In this work, the assumptions of monotonically increasing degradation and component independence are explicitly taken. Also, one can reveal the problem of determining how to decompose a system in circuits, which can be challenging in complex architectures. Although, in this study, the application was made on a simplistic system consisting of a bandpass filter (BPF), mixer, and low pass filter (LPF) circuit, respectively, in series. In (58) and (39), the authors investigated the

stochastic dependencies of multiple components through stochastic differential equations, which are developed based on the physical understanding of the system.

In contrast to the state-based modeling of state-space models, in (74), component deteriorations can be regarded as a time-dependent stochastic process. The author assumed that the deterioration process could be modeled as a gamma process, and a Poisson process generates the stochastic process of the load. Then, the component failure is defined as the event at which stress exceeds a strength that is liable to deterioration. However, since real systems are generally non-linear and sometimes non-stationary over time, it is not possible to model their degradation over time (75).

Other models are discussed in the literature, such as bond graphs or Petri nets. In (59) using bond graphs, multiple degradation models are suggested and are adapted with new information about the monitored system's degradation states. In (32), a new model brought back from economic studies was introduced as a unified framework for SLP, namely the Input-output Inoperability Model (IIM), which can take into account inner component degradation, dependencies between components, and the effect of mission profile. Based on the IIM, an online methodology for SRUL calculation based on particle filtering for health state estimation and prediction and gradient descent for model parameter estimation was presented and applied for the Tennessee Eastman Process (76). In (77; 78; 55), based on Petri nets, a generic online health monitoring architecture was proposed; this architecture is capable of using several prognostic methods for the different components depending on the available models. But it does not consider the operating conditions (mission profile) during the system's utilization.

*Data-driven approach* Holistic data-based approaches, even if they do not describe the phenomenology of system degradation, can account for their evolution through the monitoring of health indicators by sensors. One of the most widely used methods in this category is neural networks with multiple inputs to account for the correlation between different system variables. This can correspond roughly to the degradation interdependence between components. The authors in (67) presented an architecture where the prognostic process is defined at the component and global levels; each local agent uses specific prognostic methods according to the knowledge available on the monitored component, and the global agent feeds a neural network with data collected from local agents. This network of neurons is presented as a global prognostic tool to aggregate local prognostic. The weights in the networks can be

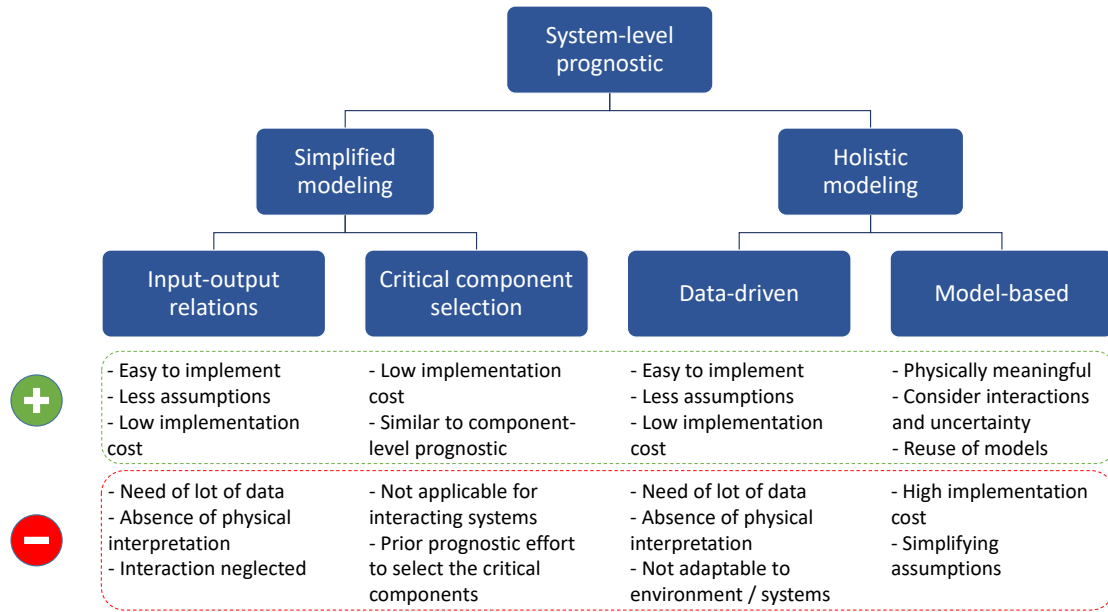
determined using monitoring data and expertise. In (66), a graph convolutional neural network is used, where system components, sensor data, and interactions are represented and analyzed as a graph.

Other methods, such as the Bayesian network and its extensions, have been used from the same perspective. For instance, in (68), causal Bayesian Networks (BNs) are used to model the dependencies existing between component degradations to improve the decision-making on system troubleshooting. A method is presented for the integration of information from multiple levels, such as prior knowledge and direct experience data, in order to characterize the fault propagation in an electromechanical actuator.

Regression methods based on run-to-failure or seeded fault experiments are also used for SLP. In (40), a linear regressive model was used to estimate the SRUL of a system with redundant components. The main feature of the method presented in this study is the re-computation of the component RULs due to system reconfiguration after a component failure. Nonparametric regression of the system health state evolution was proposed for SLP through extrapolation (25) and expectation-maximization algorithm (69).

To handle the data uncertainty, multivariate distributions were explored through gamma distributions (79) and Copula (80; 81). The paper (38) provides a framework for evaluating the reliability and the RUL of a system with two components: a pump degrading following a discrete process and a valve with a continuous degradation process. The authors of (26) proposed a statistical approach for prognostic to estimate the RUL of a system by considering the degradation rate interactions between its components. A probabilistic Weibull model is used to establish a common prognostic approach for each component. This model enables representing the failure probability of each component in the system. Still, each component can only be the "initiator of" or "subject to" degradation on another component (uni-dimensional degradation relationship). Another way to consider data uncertainty is the use of fuzzy logic, especially for expertise data. In (65), the fuzzy analytic hierarchy process was used to evaluate the satellite power system-level health state.

Data aggregation methods have been used through multi-agent methods in (82; 63) and fault trees (25; 60; 37). In (82), the authors proposed a distributed architecture composed of several agents coordinated to monitor a given component or subsystem through a diagnostic algorithm. The agent switches to the prognostic mode, and when a critical condition is detected, it informs the base station. This latter works as a manager of resources and agent



**Figure 6.** System-level prognostics approaches and their advantages and disadvantages.

control. Recently, (63) proposed a new approach for system-level prognostics based on Multi-agent systems (MAS) applied to the lorry system. MAS is an approach derived from distributed artificial intelligence based on an ensemble of individual autonomous and cooperative entities called agents. This approach is a time-dependent degradation one with the system states' discretization, which reduces its applicability. Also, only linear independent degradations are accounted for in this study. In a series of papers (25; 60), the authors used the functional architecture of a system described by a fault tree to calculate the SRUL from component RULs. From the system minimum cut sets, the probability of system failure is obtained using logic gates and each component's probability density function. In this study, SRUL is determined regarding the time remaining for the probability of system failure to reach a certain threshold. Fault trees are effective tools, but their disadvantage is that the basic events must be independent. In (37), the structural dependencies are considered using a fault tree to improve the scheduling of inspection periods without considering the system mission profile.

Recently, research (83) has considered the problem of system-level prognostics in the cloud. This research has considered applying system-centric architecture to cloud-based systems that leverage shared computational resources to reduce cost and maximize reach.

So far, we have discussed the different approaches used to implement system-level prognostics. A summary of the advantages and disadvantages of each approach is presented

in Figure 6. The next section will examine the SLP applications for various systems.

### Applications of system-level prognostics in industry

Any multicomponent system subject to degradation mechanisms that can lead to damageable failures can be applications for prognostics at the system level. Transportation, aerospace, automotive, manufacturing systems, (nuclear) energy production and storage, chemical processes, and smart grids are some examples. Table 3 gives an introductory summary of some systems that had been treated with a system-level prognostic approach and the degradation/failure mechanisms considered.

Because of the scarcity of in-field data and benchmarks that would permit the SLP approach evaluation, the number of SLP approaches proposed in the literature remains far below its importance and possible contributions. Indeed, in practice, it is difficult to convince an end-user to let his/her system operate until its complete failure to gather representative data for prognostics.

In order to encourage the proposal of approaches to address the SLP problem, we present hereafter a realistic benchmark of a real industrial system, namely the Tennessee Eastman Process (TEP). We believe that the TEP could be a relevant alternative for testing scientific developments about SLP as it contains all the points present in the SLP definition. However, as this system was not intended for prognostics

**Table 3.** Applications of system-level prognostics in industry

Field/Industry	Systems	Degradation/failure mode
Transportation	Underground Aircraft bleed system Aircraft electrical system  National Airspace System Planetary rover Ski lift Braking system of rail vehicles Environmental control system in an aircraft Helicopter gearboxes Lead acid and li-ion batteries in hybrid vessel	Multiple failure modes (53) Loss of air flow due to valve failure (40) Power loss due to generators or switches failure (37) loss of separation (23) Friction damage (28) Degradation of Jacks strength (26) Demagnetization fault mechanism (84) Pressure loss of the control valves (85)  Tooth crack (86) The fade of capacity (87)
Manufacturing systems	Chemical plant (Tennessee Eastman Process) Chlorine dioxide generation system Petrochemical plant HVAC Production and maintenance scheduling Tank system Milling machine Pump and valve system Blast furnace	System shutdown due to parameter drift (88)  Multiple failure modes (66) Tube fouling (89) Multiple failure modes(90) Production downtime (91) Pump failure (62) Tool worn-out and breakage (92; 93) Valve failure (38) Thermal wear (56)
Electronics	Rectifier MOSFETs/IGBTs and ECaps Electrical hybrid system Radio frequency receiver system	Electrolytic evaporation (20) Multiple failure modes (thermal, fatigue, etc.) (94) Multiple failure modes (59) Gain reduction (54)
Energy production and storage	Hydrogenerator  Gas Turbine Engine Turbofan engine Transmission substation in power grid Lithium-ion cells in a battery pack Wind turbine Satellite Power System	Multiple failure modes (Thermal aging, wear and erosion) (77) Erosion and fouling degradation (95) Creep rupture in the turbine blades(27) Multiple failure modes (61) State-of-Charge (96) Multiple failure modes (97) Multiple failure modes (65)
Miscellaneous	Cloud health care monitoring Bearings	Service loss(83) Crack (31)

purposes, an adaptation and a paradigm shift should be made as proposed in (98).

### Benchmark: Tennessee Eastman Process

The Tennessee Eastman Process (99) is used in the literature as a realistic benchmark for process control optimization (100), fault diagnostics (101) and, to a lesser extent, for component-level prognostics. The TEP comprises five major units (working in an open-loop): a reactor, a condenser, a separator, a stripper, and a compressor. The piping and instrumentation diagram (P&ID) of the TEP is given in Figure 7.

The aim of the TEP is the synthesis of two liquid products from gaseous reactants. The process is monitored by 53 measured variables. There are, in total, 28 faults that can be

injected in the process (102). These faults are related to step changes, drifts, and random variations of some variables.

### SLP in the Tennessee Eastman Process

For this benchmark, an interruption of the operational continuity resulting from the violation of the variables shutdown limits is considered as a system failure. Therefore, only the components having shutdown constraints are considered, i.e., the reactor, the stripper, and the separator. A single parameter is used to monitor each of these components: gas pressure for the reactor and liquid level for the stripper and the separator. These parameters should respect the operational constraints listed in Table 4 in order to

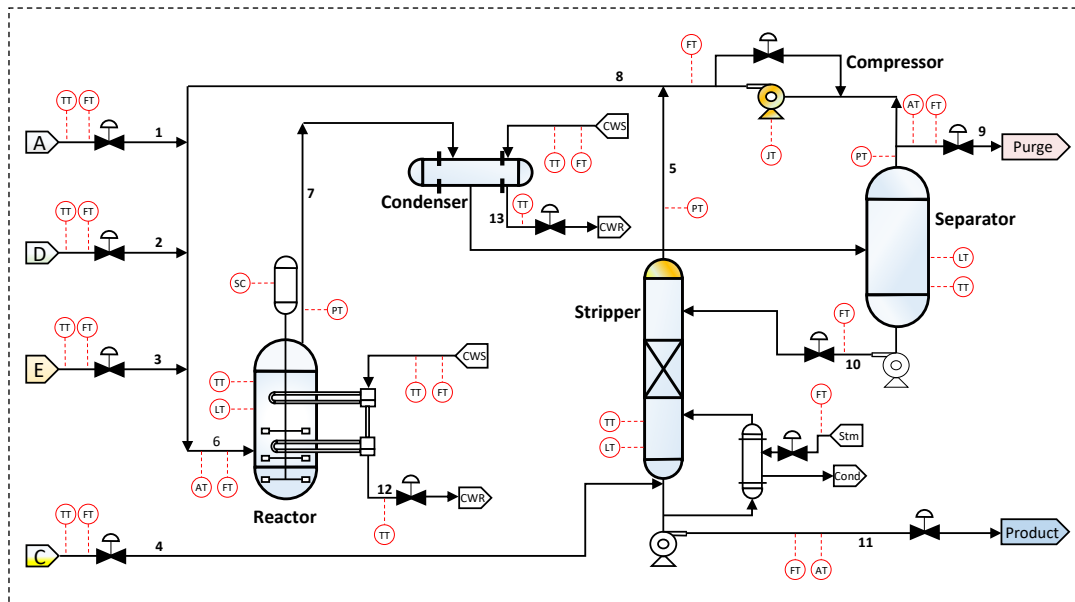


Figure 7. PI&D of the Tennessee Eastman Process.

Table 4. Process operating constraints in the TEP (99).

Process variables	Normal operating limits		Shutdown limits	
	Low limit	High limit	Low limit	High limit
Reactor pressure	none	2895 kPa	none	3000 kPa
Separator level	3.3 m	9.0 m	1.0 m	12 m
Stripper level	3.5 m	6.6 m	1.0 m	8.0 m

avoid the system shutdown. However, several parameters can be used/fused to infer the system components' health state.

The Tennessee Eastman Process simulation originally includes 21 pre-programmed faults (99). In (102), the authors added 7 faults, bringing the total to 28. These faults are related to setpoint changes (IDV (3) and (25)), drifts (IDV (13), (16) and (17)), and random variations (IDV (11)) of some variables (as shown in Table 5). The simulation program allows the faults to be injected either individually or in combination with another.

The simulation code for the process is available in FORTRAN and can be implemented in Matlab®, and a detailed description of the process and the simulation is presented in (99; 102).

Table 5. Examples of process disturbances in the TEP (99; 102).

Fault number	Description
IDV (3)	Step in <i>D</i> feed temperature (Stream 2)
IDV (11)	Random variation of the reactor cooling water inlet temperature
IDV (13)	Reaction kinetics deviation
IDV (16)	Heat transfer deviation of the heat exchanger of the stripper
IDV (17)	Heat transfer deviation in reactor
IDV (25)	Step in <i>E</i> feed flow (Stream 3)

There are six modes of process operation (i.e., the system mission profiles) corresponding to various product mass ratios and their hourly production rates. The product mix is typically dictated by product demands, and the production rate is set by market demand or capacity limitations.

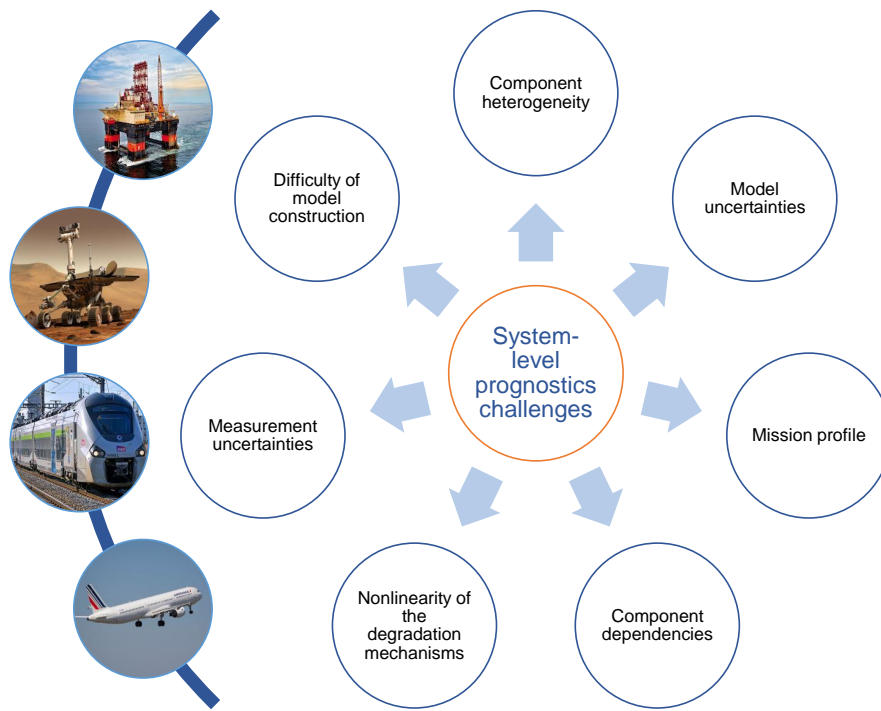
Depending on the approach to be developed, the system can be put on a closed- or an open-loop, allowing to take into account or not the effect of the control signals.

### Challenges related to system-level prognostics and future research directions

In light of the literature review in the previous section, it can be concluded that system-level prognostics present some challenges not yet faced when dealing with prognostics at the component-level. In what follows, we have compiled the various obstacles to be addressed by future SLP studies (Figure 8), as well as some possible solutions.

#### Interdependencies

Interactions between component degradations have been intuitively felt since the first works on component wear and reliability of systems (103). This has resulted in a large literature in the areas of condition-based maintenance (CBM) and reliability. For instance, maintenance policies of



**Figure 8.** Challenges related to system-level prognostics.

multicomponent systems have been widely reviewed in the following papers (104; 105; 103; 106). However, in CBM, these dependencies are merely being studied as a stepping stone to maintenance optimization. Hence, an exhaustive classification of the component interactions from PHM point of view (Table 6), inspired by (107), is proposed in this subsection. This classification is divided as follows.

1. **Structural interdependencies** concern the structural and static relationships between components. First, they can be related to situations where one component replacement requires the dismantling or the replacement of other components (105; 108; 30). Second, components can be dependent on the system's physical or functional structure, influencing how it fails. Indeed, a system with a series configuration is more sensitive to the failure of one component than in a parallel configuration or with a  $k/N$  architecture (37; 21). Moreover, the failure of a system with parallel architecture is influenced by the switching strategy between redundant components. Thus, a system with hot redundancy degrades less quickly than a system with warm or cold redundancies (109).
2. **Stochastic interdependencies** refer to the (partial) dependence between component degradation or failure processes. We can distinguish four types of stochastic interdependencies:
  - Degradation interactions. A degradation of one component influences (generally by accelerating) other component degradations (38; 21; 63). Wind turbines are an example of a typical mechanical system where, for example, the degradation of hydrodynamic bearings may result in increasing looseness of the primary transmission shafts, which in turn may increase the vibration levels in the gearbox (58).
  - Failure induced damages. Failure of one component leads to an immediate increase of the degradation level or even immediate loss of other components (30). For example, the failure of a computer fan will induce processor degradation or failure.
  - Load sharing, which can be induced by a component failure or degradation. Indeed, one or more components' failure increases the load on the functioning ones, hence deteriorating faster. This fact can be observed in a set of pumps used to distribute the same amount of gas/liquid (40). A component deterioration can also increase the load on the other ones, as outlined in (89) for the fouling of tubes in a distribution network.
  - Common mode deterioration. Several components can fail or deteriorate simultaneously due to similar mission profile (53) (e.g., components

**Table 6.** Component interdependencies classification.

Structural	Technical	<ul style="list-style-type: none"> <li>• Maintenance restrictions (105)</li> <li>• Usage restrictions (30)</li> </ul>
	Architecture	<ul style="list-style-type: none"> <li>• Series configuration (21) <ul style="list-style-type: none"> <li>• Parallel configuration (hot (37; 110), warm (111), and cold redundancy)</li> </ul> </li> <li>• k/N configuration (112)(79)</li> <li>• Arbitrary configuration</li> </ul>
Stochastic	Load sharing	<ul style="list-style-type: none"> <li>• Failure load-based sharing (40)</li> <li>• Degradation load-based sharing (89)</li> </ul>
	Common mode degradation	<ul style="list-style-type: none"> <li>• Environment (113)(114)</li> <li>• Mission profile (53)</li> </ul>
	Failure induced damages (30)	
	Degradation interactions (38; 21; 63)	
Resources	Workers (115), spares (116; 117; 60), tools and transport sharing	
Economic	Negative (118) or positive (106; 31) economic dependencies	

sharing a common power supply) or environmental conditions (113) (e.g., wind turbines in an offshore field under weather conditions).

3. **Resources interdependencies**, which arise when several components are connected through a shared limited set of spares (116), workers (115), tools, or budget. Consequently, maintenance optimization is required on the system level rather than on the component level.
4. **Economic interdependencies** refers to the situations where maintaining several components at a once is either more expensive (negative economic dependence) (118) or less expensive (positive economic dependence) (106; 31) than maintaining components separately.

In practice, not all of the above-mentioned interdependencies are investigated in SLP. Indeed, only stochastic interdependencies directly influence the system health state evolution and, therefore, its SRUL. The other interdependence types concern post-prognostic decision-making regarding maintenance actions.

### Uncertainty

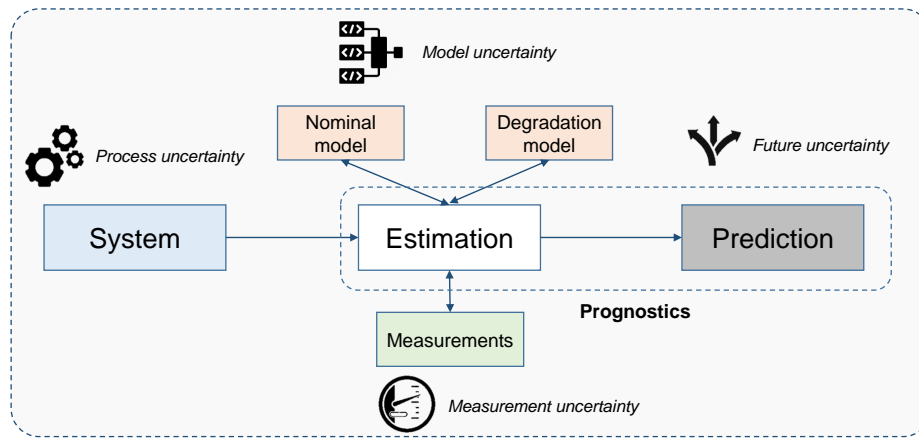
Uncertainty is intrinsically related to any prediction (119) and, therefore, to failure prognostics. The main types of uncertainty (Figure 9) that affect both the current and future degradation state are process uncertainty, model uncertainty, measurements uncertainty, and future uncertainty.

First, process uncertainty relates to the variability in the behavior of a process due to operating conditions and the environment. In detail, this uncertainty translates into the variation of the system’s physical parameters (resistance, inductance, stiffness, capacitance) (4). To alleviate this uncertainty, new systems should be robustly designed to have

minimal sensitivity to material, manufacturing, or operating variations (120). For systems already in operation, the uncertainty related to the system parameters can be tackled by using adequate methods such as interval ones (121).

Second, the uncertainty related to modeling greatly affects the prediction accuracy in prognostics (122). For the nominal model of a system, the uncertainties can result from a set of assumptions used during the modeling process and lead to models that do not fit precisely the real behavior (4). Indeed, either for the nominal model or the system’s degradation model, it is only an approximation of the real behavior, which does not consider all the involved parameters. The degradation model is generally obtained from accelerated life tests conducted on different samples of components (72). However, data resulting from accelerated life tests conducted under identical operating conditions may exhibit different degradation patterns because of the degradation stochasticity. To handle this type of uncertainty, the system state modeling and estimation problem has been approached in a probabilistic form and by using tools derived from possibility theory (fuzzy logic) (123; 124) or Dempster-Shafer theory (evidential theory) (86). The probabilistic representation of uncertainty is often used in filtering methods (Particle filter (125), Kalman filter (126), etc.) to estimate the system state by combining imprecise models and noisy measurements.

Third, whatever the approach used for prognostic, considering measurement uncertainty is of utmost importance in the prediction process. Indeed, sensor data are used to learn algorithms in data-based approaches and estimate model parameters in model-based ones. However, sensors are also affected by uncertainty. Indeed, sensor noise can result from a variety of sources like electrical interference, digitization error, sensor bias, dead-band, backlash, and nonlinearity in



**Figure 9.** Sources of uncertainty in the prognostic.

the response (127). Therefore, it is necessary to consider this noise when estimating the system's health state.

Finally, once the system's state is known and its uncertainty quantified, the purpose of prognostics is to predict the system's future evolution, which is inherently uncertain. In fact, future system usage and future operating conditions are unknown, which makes future state and RUL predictions highly uncertain. In this scope, Markov chains have been proposed to simulate the battery usage profiles in (128). Similarly, the authors in (72) reviewed some methods used to integrate the life-cycle loading profile in the degradation of electronic devices.

The above-mentioned uncertainty types involve numerous challenges for failure prognostics. Moreover, the transition from component-level to system-level prognostics increases the uncertainty source number, which causes more issues when predicting the SRUL.

### SRUL determination

The SRUL provides information related to the time when the whole system fails (i.e., when the combined failures of the individual components lead to a system failure) (25) or when the system reaches a performance that is considered unacceptable. It allows giving a unique measure of the possibility of a system to perform the task(s) for which it was designed. However, the consequence of the degradation of one or more components depends on the considered architecture. Hence, we have to calculate the SRUL according to the system configuration.

In a case of deterministic prediction and a system with a series configuration, the SRUL represents the minimum RULs of the components:

$$SRUL = \min_{i=1, \dots, M} (RUL_i) \quad (3)$$

whereas, for components in parallel, the SRUL corresponds to the maximum:

$$SRUL = \max_{i=1, \dots, M} (RUL_i) \quad (4)$$

In (56), a particular case of parallel architecture was presented, called summation structure. In this case, the failure mode results from a combination of multiple component degradations. For instance, a system is assumed to be failed if the sum of all the degradations hits the failure threshold. This architecture only concerns homogeneous systems.

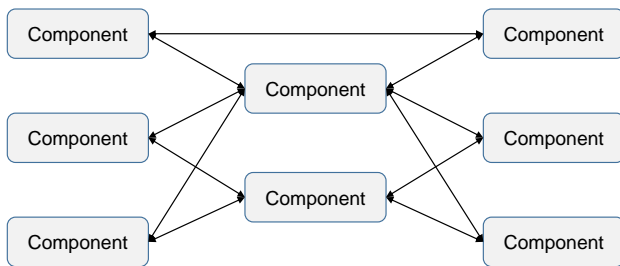
However, in practice, and given the complexity of industrial systems, it is important to consider the uncertainty. In (88), and based on the new paradigms proposed in (130; 131), a probabilistic SRUL calculation is proposed for series and parallel configuration. Many systems are made up of these types of configurations or with more complex compositions from these simple ones, e.g., parallel-series or series-parallel. However, there exist complex configurations that cannot be reduced to sub-configuration in series and/or parallel, such as networked structure,  $k/N$  architecture with active or passive redundancies, bridge configuration, or arbitrary configurations (Figure 10) (132). Assessing the SRUL of those complex systems is difficult and complicated, and it was not yet addressed in the SLP field. The solution for this issue could be relying on methods allowing the analysis and modeling of the functional operation using, for instance: network reliability, structured analysis and design technics (SADT), graph theory, reliability block diagram, or systems modeling language (SysML), etc.

### Components heterogeneity

Nowadays, systems are composed of several components with different characteristics. These components can

**Table 7.** General parameters which can be monitored in components (129).

Category	Parameter
Thermal	Temperature, heat flux, heat dissipation
Electrical	Voltage, current, resistance, inductance, capacitance, dielectric constant, charge, polarization, electric field, frequency power, noise level, impedance
Mechanical	Length, area, volume, velocity or acceleration, mass flow, force, torque, stress, strain, density, stiffness, strength, angular, direction, pressure, acoustic intensity, power, acoustic spectral distribution
Chemical	Species concentration, gradient, re-activity, mess, molecular weight
Humidity	Relative humidity, absolute humidity
Optical	Intensity, phase, wavelength, polarization, reflection, transmittance, refraction index, distance, vibration, amplitude and frequency
Magnetic	Magnetic field, flux density, magnetic moment, permeability, direction, distance, postition, flow



**Figure 10.** Example of an arbitrary configuration.

be electronic, mechanical, hydraulic, pneumatic, etc. Each component uses different energies, and the energy transformations within systems make them able to perform complex tasks (133). This heterogeneity of components poses a big challenge for SLP (134). Indeed, as shown in Table 7, regarding the component nature, its health indicator may be different in terms of dynamic or measurement, i.e., the sensor used to monitor it.

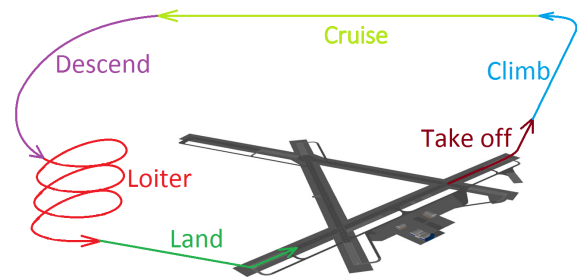
As shown in the following, some systems with serious degradation problems present totally different functioning mechanisms. This is the case for gears, which are one of the most common components used in mechanical transmission systems; lithium-ion batteries that are widely used in commercial products; liquid-crystal display (LCD); and light-emitting diode (LED), whose light intensity drops with usage (135). In (129), a review was made of the different parameters that can be utilized to monitor the state of health (SoH) of systems.

Several studies have been carried out in the literature on diagnostics of heterogeneous systems, but only a few addressed these systems' prognostic. Specifically, the problem here is how to design a single model for the degradation of an entire system. In (25), the authors proposed a performance function that links the parameter degradation of each component with the health indicator of the global system performance. However, this method suggests that the influence of the system performance component is known,

which is a strong assumption. In (21), it was proposed to normalize all the health indicators of a component to one parameter called inoperability. A distributed approach for prognostics on system-level is also proposed in (78; 28; 63). This approach addressed the problem of component heterogeneity so that different parameters and different models can monitor each component. However, it assumes that the component degradations are independent.

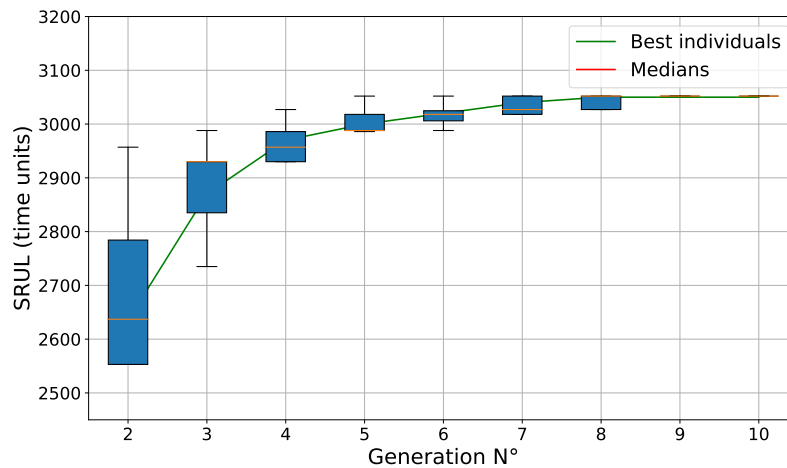
### Mission profile

How a system is controlled to perform its tasks under a given mission profile (MP) greatly influences its current and future degradation state; hence this reduces or extends its lifespan (53; 136). This MP can be a steady-state operating (such as in thermo-fluid systems) or have a particular cyclic pattern. This kind of pattern can be found, for instance, in an aircraft MP (Figure 11). Each step of this MP impacts the aircraft components differently.



**Figure 11.** Illustration of a standard aircraft mission profile.

In prognostic, future mission profiles and their impact on the system should be adequately characterized to perform efficient and accurate RUL/SRUL predictions. Indeed, future inputs are among the largest sources of uncertainty for prognostic algorithms (137). In prognostic literature, mission profile is referred to by usage profile, exogenous output, usage pattern, system inputs, etc. Some works have focused on characterizing future mission profiles based on their



**Figure 12.** SRUL evolution of the mission profiles population through generations of genetic algorithm.

past evolution through machine learning (138) or statistical methods (128). In (27), the mission profile is considered in the gearbox degradation by using Response Surface Methodology (RSM) to model the effects of the system's usage pattern on system-level health. Even if RSM is represented as a polynomial, RSM results are almost as accurate as the ANN results, resulting from a black-box method. In (53), the effect of the mission profile on an underground modeled by a mechatronic system is analyzed in relationship to the duration and amplitude of the MP. It was found that the SRUL can be decreased by up to 8% due to driver-induced.

As a mission profile can accelerate the degradation of some components more than others thus, it is necessary to evaluate which mission profile will maximize the SRUL while respecting operational constraints (139). For example, in (53), the authors used a genetic algorithm to optimize the underground mission profile. In the end, the SRUL of the system was extended by more than 22 % compared to the primary mission profile implemented in metros (Figure 12). In (140), it was proposed integrating the feedback loop of the effects of already made decisions on the monitored system in the process of prognostic process. Then, ant colony optimization is used to build future decisions about mission profiles.

### *Relationship between local and global health indicators*

In some cases, the SoH of the system is not sufficient to determine a system's ability to provide the services that are devolved to it. Indeed, in some cases, the SoH of the components may be "satisfactory", while some criteria of the system as a whole are no longer satisfactory. Thus, it can be

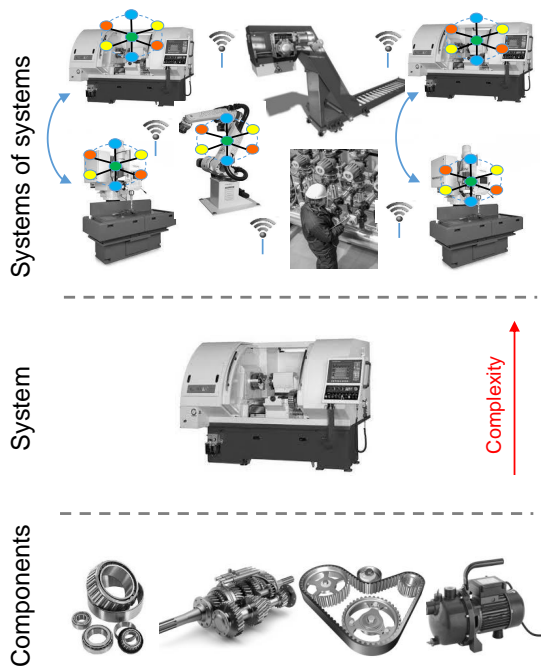
deduced that health status is not always correlated with its ability to provide the service for which it was manufactured.

The study (86) demonstrates how the system level variables can enhance prognostics at the component level. Indeed, as systems are generally conducted regarding the global system variables, those variables should be considered. It will be better to construct modeling that considers variables at different levels, using metamodel, for example. In (141), the relationship between different variables in a system is described based on a hierarchical architecture consisting of three layers; system-level, subsystem-level, and component-level. Based on this hierarchy, four types of variables are defined, i.e., system-level variables, subsystem-level variables, load variables, and stress factors.

### *Systems of systems*

Another area of future prognostic developments is the system of systems level (Figure 13). The latter concept defines a collection of systems (interacting or not) that pool their resources and capabilities together to create a new, more complex system that offers more functionality and performance than simply the sum of the constituent systems (142). A PHM policy at the level of a fleet of systems will allow better operational proactivity (91) and resource allocation. Prognostics can then be used to predict either the failure of this type of system or the loss of specific performance.

In general, what is called *system of systems engineering* is a critical research discipline for which frames of reference, thought processes, quantitative analysis, tools, and design methods are incomplete (143). However, some prognostic works are beginning to address large-scale systems. For instance, in (23), the risks of "loss of separation" (two



**Figure 13.** Systems of systems.

aircraft becoming very close) and dry breakdowns are considered as reversible progressive degradation, and the aim is to determine, by Monte Carlo simulation algorithms, the time before these risks exceed a certain probability. In (88), in a large-scale industrial system composed of several interconnected systems, a failure is considered as the interruption of the operational continuity resulting from the violation of the variables shutdown limits. In (63), the authors proposed a method based on multi-agent computing to update information on the health status of several components/systems. Each system is monitored separately, and a kernel is in charge of merging the various information to decide on the general SoH of the system of systems, on the condition that the different influences between the systems are known. The use of microsimulation models (144) could reduce this effort to model interactions between systems. Finally, it can be considered that work in CBM focuses on the economic ((118; 31)) and resource ((115; 116)) interactions between components/systems can be applied to a system of systems. An RUL prediction at the system of systems level will improve the results of these studies.

## Conclusions and perspective

### Conclusions on SLP

The purpose of this paper is to fill a gap in the literature regarding system-level prognostics. Indeed, the literature on prognostics, in general, has grown considerably over the last two decades, with works covering a wide

range of methodologies and applications. As a result, several literature reviews exist summarizing, structuring, and organizing the literature on the topic of prognostics. However, these reviews have a blind spot concerning the topic of prognostics at the system level, while the works concerning this theme are growing more and more.

In this literature review, we have tried to define a research perimeter for this theme and to give a clear definition. Then we have listed the advantages and benefits of choosing an approach at the system level and a diagram allowing us to select the best level for predicting the failure of a system according to its specificities and the means in work. After that, we reviewed the different works done until now through a classification based on the granularity of the representation of the system behavior and refined by the approaches used: data or models. In a nutshell, the insight that emerges is that model-based approaches are more accurate and interpretable but challenging to implement for complex systems. On the other hand, data-driven approaches are easy to implement but lack interpretability and uncertainty management. In addition, we have identified the different applications that have been done so far with the SLP approach. It reveals that the most currently studied systems are critical systems (in terms of safety or financial costs), which demonstrates the difficulty and cost of implementing a system-level approach. Finally, we have tried to identify the particular challenges that need to be addressed in order to reach sufficient maturity for the theme to be applied. Among these challenges that correspond to the current limitations of the literature, we can mention 1) the consideration of the interdependencies of the heterogeneous component degradation of a system and its mission profile (which are the most specific factors of the SLP compared to the CLP), the consideration of the expanding uncertainty in the case of the SLP because of the multiplicity of its sources, 3) the calculation of the SRUL for systems having functional and structural architectures other than the series and parallel, etc.

In the following, we will mention the perspective of SLP studies in light of Industry 4.0.

### Future research directions in SLP

Like other scientific fields of PHM, system-level prognostics will be an active field of research in the upcoming years with the potential to provide a safe and appropriate framework for the condition-based maintenance of complex systems. Some promising research directions for future studies are as follows:

*Explainable artificial intelligence for SLP.* Facing the challenges related to large-scale systems and the diverse interdependencies between their components, the model-based prognostic approaches become infeasible. Besides, data-based approaches, according to many researchers, may be the most appropriate to cope with the increasing complexity of systems. Of the many data-driven tools and methods, those related to artificial intelligence, especially deep learning, are the most promising. However, the latter methods suffer from a lack of interpretability. This characteristic becomes more crucial in PHM applications of critical equipment, e.g., transportation and nuclear. Indeed, companies show resistance to deploying AI-enabled PHM solutions because decision-makers and domain experts cannot correctly use predictive techniques without adequate explanation of the results, even though presenting performance levels that enable them for deployment. Until now, there is no clear way of understanding how and/or why deep learning models reach these positive results. Besides, as networks get deeper in terms of the number of layers, the tracking down of output towards its inputs becomes more unfeasible.

To remedy the working opacity of artificial intelligence methods, explainable artificial intelligence (XAI) is studied to see inside this black box and determine how and why a given model outputs some result. Several methods have been used to mitigate the "black box" effect of deep learning methods in recent years. These include Local Interpretable Model-Agnostic Explanation (LIME) and Shapley Additive Explanations (SHAP). Other methods are detailed in (145). All those methods allow increase the interpretability, explainability, and transparency of the AI approaches and permit better monitoring of the health state of complex systems. The studies of XAI approaches dedicated to SLP should be able to integrate the expert knowledge about system architecture and physics behaviors.

*Hybrid modeling approaches for SLP* Both model-based and data-driven prognostic approaches have their own merits and limitations, as was discussed earlier in this paper. Model-based approaches generally give accurate results and take uncertainty into account. However, despite the robustness of the results obtained with this approach, it is challenging for complex systems to obtain their degradation models since it is necessary to know all the underlying phenomena that cause this degradation. Data-driven methods are becoming popular due to their fast developmental cycle. Although these approaches do not require prior knowledge about fault mechanisms, they often require statistically sufficient

data and have difficulties learning the complex non-linear relationship in fault diagnostic and prognostic, and struggle to capture the stochastic nature of degradation phenomena.

Hybrid modeling approaches in SLP (4) aim to integrate the merits of model-based and data-driven methodologies while minimizing limitations for better system-level health state estimation and SRUL prediction. They should be able to model different component interdependencies and impact of mission profile to deal with the uncertainty propagation in SRUL determination.

*Digital twins* Digital Twins (DTs), also known as "device shadows", are digital replicas of an object, process, or system that can be used for a variety of purposes. This concept has the potential to transform the way systems and their components are designed, managed, maintained, and operated. A hierarchical DT model framework could be a feasible solution for tackling challenges related to SLP, particularly addressing challenges of components heterogeneity and large-scale systems. This solution allows investigating the system's behavior in various abnormal situations and thus contributes to solving the problem of missing failure data when training prognostic models.

*Prognostic decision making* As previously mentioned, IoT has changed how we currently approach concepts such as "process monitoring" and "system reliability". As smart devices are now able to continuously acquire operational data and upload files to cloud servers, large databases have begun to accumulate valuable information for decision-making purposes. Literature offers plenty of articles associated with the use of diagnostic procedures for system SoH estimation and failure prognostic algorithms to predict the evolution of SoH in time, conditional on a characterization of future usage profiles. However, only very recently, researchers have started to offer contributions on topics such as Post-Prognostic Decision Making or Prognostic Decision Making (PDM) strategies, which could leverage failure prognostics outcomes to efficiently make decisions about the system operation (e.g., optimization of preemptive and predictive maintenance, mission re-planning, or mission re-design). Condition-based maintenance (CBM) is a straightforward application of PDM strategies. Indeed, CBM aims at scheduling maintenance actions based on information provided by failure diagnostic and prognostic modules, using for this purpose estimates of Remaining Useful Life (RUL) as inputs of the optimization problem where maintenance policies are defined. However, PDM strategies can be used not only to extend the life of components but also to increase the system's throughput. However, as decision-making is

generally made on system-level parameters, prognostics at the system-level, providing information about the system's remaining useful life can improve this decision-making. Hence, integrating the obtained prognostic results into the system control, enhancing its resilience, and keeping it in operation in good conditions and as long as possible should be deepened in further research works.

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