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Towards system-level prognostics: modeling, uncertainty propagation and system remaining useful life prediction

Ferhat Tamssaouet

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Ferhat Tamssaouet
07/10/2020

Prediction is very difficult,
especially about the future.

Niels Bohr

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List of publications

The content of this thesis is based on an extension of the contributions presented in the following publications of the author:

Journal papers

- Tamssaouet, F., Nguyen, T. P. K. and Medjaher, K. (2019). System-Level Prognostics Under Mission Profile Effects Using Inoperability Input-Output Model. *IEEE Transactions on Systems, Man, and Cybernetics: Systems*.
- Tamssaouet, F., Nguyen, T. P. K., Medjaher, K. and Orchard, M. (2020). Degradation Modeling and Uncertainty Quantification for System-Level Prognostics. *IEEE Systems Journal*.
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- Tamssaouet, F., Nguyen, T. P. K., Medjaher, K. and Orchard, M. (2019). Uncertainty Quantification in System-level Prognostics: Application to Tennessee Eastman Process. In the 6th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 1243-1248). IEEE.
- Tamssaouet, F., Nguyen, T. P. K. and Medjaher, K. (2019). System Remaining Useful Life Maximization through Mission Profile Optimization. In *Proceeding Asia-Pacific Conference Prognostics Health Management*, (pp. 225-232).
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List of acronyms

ANN	Artificial neural network
ATTF	Actual time-to-failure
CBM	Condition-based maintenance
CDF	Cumulative density function
CLP	Component-level prognostics
DIIM	Dynamic inoperability input-output model
EOL	End of life
ETTF	Estimated time-to-failure
GD	Gradient descent
IIM	Inoperability input-output model
I-O	Input-output model
MP	Mission profile
MSE	Mean squared error
NAG	Nesterov accelerated gradient
PDF	Probability density function
PF	Particle filtering
PHM	Prognostics and Health Management
PM	Predictive maintenance
PMF	Probability mass function
PoF	Physics-of-failure
RUL	Remaining useful life
SGD	Stochastic gradient descent
SLP	System-level prognostics
SRUL	System remaining useful life
TEP	Tennessee Eastman Process
ToF	Time-of-failure

General introduction

According to the second law of thermodynamic, the sum of the entropy of systems has to increase with time. Thus, systems that are subject to energy, heat, and work transfers will most likely degrade. This is the case of all multi-physical systems. Therefore, without loss of generality, one can say that their degradation processes are ineluctable, and consequently lead to their failure.

In this context, several strategies were developed to deal with system degradation. These strategies can be related to fault mitigation or failure prevention. In fault mitigation, the failure is taken into account in the design stage, which tends to increase the fault resilience of systems. Hence, domains such as system reconfiguration, fault tolerance, self-repairing systems, and self-healing can be gathered under the name of fault mitigation.

Despite the outstanding achievements of fault mitigation, failures cannot be eliminated. Therefore, it is necessary to consider them as unavoidable events that have to be prevented. In practice, failure prevention can be performed through *preventive maintenance policies*, which ensure system safety and availability, and through *usage profile adjustment* in order to slow down degradation rates. In a nutshell, failure prevention can be linked-to system behaviors and health state predictions. These predictions are made to ensure that the system usage profile can be optimally planned to maximize the system life and to schedule system-wide maintenance activities.

Regarding maintenance policies, nowadays, they tend to become more and more efficient and proactive. The first maintenance policies included only corrective activities, i.e., they took place after failure occurrence. Due to the increasing complexity and criticality of the modern systems, another type of maintenance has appeared: the systematic one. This latter makes the systems safer but requires higher maintenance costs. To reduce this cost, the condition-based maintenance (CBM) is developed with the logic of maintaining systems only when it is needed according to their real health state. By implementing a CBM strategy, industrial companies significantly reduced the financial resources engaged in maintenance activities. For an illustration, according to (Gray et al., 2012), in 2015, CBM implementation permitted to save more than \$1.4B dollars within only six companies.

In the early studies, to trigger a CBM, practitioners were relying on reliability methods for the estimation and prediction of systems health states. These methods are considered with a probabilistic framework under a "frequentist" standpoint, i.e., examine several components with identical independent distributions (*i.i.d.*). The problem raised here is that the hypothesis of *i.i.d.* may be unrealistic because there are always differences between the considered components. Also, in complex and large-scale systems, it is not systematically possible to have data or historical records. In these cases, traditional reliability approaches are not suitable, and thus a different approach that accounts for the reliability of system health is required. In this context, prognostics and health management (PHM) raised as an alternative to reliability methods to provide practitioners with information that allows triggering CBM,

predictive maintenance (PM), or mission profile (MP) adaptation.

PHM is a modern engineering discipline that aims to supervise and maintain the operational continuity of industrial systems, considering their subtleties and particularities based on real-time sensing or in-field inspections. It is essential to distinguish between two general branches embraced by PHM, which are fault diagnostics and failure prognostics. On the one hand, fault diagnostics is related to system monitoring through the detection and isolation of fault in a given system. Failure prognostics, on the other hand, is concerned with the estimation of the remaining useful life (RUL) or Time-of-Failure (ToF) of a system.

In less than two decades, the topic of prognostics has become a full-blown research framework with a profusion of papers covering numerous scientific problems and various applications.

Notwithstanding this notable progress and convincing results, prognostics has often been approached from a component view. Indeed, usually, prognostics assumes isolated system components without considering the interactions between them and without taking into account the operating conditions. However, even if this assumption can be tolerated in some cases, it cannot be generalized for the following reasons. First, modern systems are a collection of subsystems and components interacting with each other to perform the tasks for which they are designed. For instance, complex engineering systems such as aircraft, power plants, etc. consist of several subsystems interconnected with each other structurally or through closed-loop control systems. Performance degradation in any of these subsystems causes an overall reduction in the system's performance and can lead, in the worst case, to the system failure. Second, the way a system operates significantly determines its degradation rate over time. Indeed, the system components degrade naturally, but also because of the operating context (environmental conditions, behavior, training, and expertise of the user, level of demand in terms of performance, safety, reliability, maintenance intervals, etc.). Thus, two identical systems operating under different operating contexts can have a different lifetime. Finally, from the user's point of view, prognostics at component-level is not of great interest. Indeed, what matters most to the user is the uninterrupted delivery of the service for which the system was designed.

Therefore, for all the reasons mentioned above, it is not sufficient to apprehend a system degradation through the prognostics of its critical components, and it is necessary to scale-up to a higher level. This latter is what we refer to when system-level prognostics is mentioned. In this thesis, system-level prognostics corresponds to the RUL estimation of a system (SRUL), knowing its current health state and future conditions of use. In this definition, a system is defined as an element set (components or subsystems) interacting with each other and with the environment to perform one or more tasks.

In order to propose a prognostics approach at the system-level, several scientific and practical issues need to be addressed. In what follows, the research questions raised during this thesis are detailed, as well as the main contributions made to answer them.

Research issues and main contributions

The primary motivation of this thesis is the prediction of the system remaining useful life for maintenance scheduling or system life maximization through usage profile adjustment purposes. In that perspective, the following research questions need to be addressed.

1. System degradation modeling

One of the main challenges in system-level prognostics is the development of models that allow taking into account the mutual component interactions and the effects of the mission profile on the degradation evolution. However, most systems are composed of heterogeneous elements with different operating mechanisms. Currently, and to the best of our knowledge, no study considers all these aspects in the literature concurrently.

For this purpose, a new modeling approach for scaling up from component to system-level prognostics is proposed to fill this literature gap. This model is a variant of the inoperability input-output model (IIM). Until now, the IIM has been mainly used in the economic field. Hence, its utilization and adaptation to engineering, and more specifically to PHM, constitutes the first contribution of this thesis. Indeed, the proposed IIM-based model combines information on component degradations, component interactions, and mission profile effects to describe the overall dysfunctional behavior of a given system. Each component degradation is expressed in terms of inoperability, i.e., an indication of its performance, which allows considering heterogeneous components (different health indicators, different failure thresholds, and different degradation mechanisms).

2. System degradation parameter estimation

Once the degradation model of a system is formulated, whether for offline or online implementation, its parameters must be determined. This is equivalent to searching for model parameters that minimize the error between its predicted values and the real measurements.

However, as in system-level prognostics, several factors involved in component degradation are considered, there are numerous parameters to be estimated. Among the available parameter estimation methods, the gradient descent (GD) method is proposed for this work. This choice is motivated by the method flexibility, its ability to handle linear or non-linear models, and its computation efficiency. Also, this choice has been validated by various simulations that investigated the GD method convergence towards optimal solutions.

3. System health state degradation estimation and degradation

Notwithstanding the increasing accuracy and precision of prognostics algorithms, their objects of study, i.e., degradation and failure mechanisms, remain stochastic phenomena, and therefore, uncertainty cannot be eliminated. Indeed, various sources contribute to making the estimation and prediction of the state of a system uncertain. These sources become numerous when considering prognostics at the system-level.

To provide a solution to the problem stated above, a new method that allows quantifying the uncertainty in health state estimation and prediction is proposed in this thesis. This method is based on particle filtering. This tool can take into account the non-linearities and

non-Gaussian noise. However, unlike its traditional utilization, in this work, a particle is considered as a vector representing the state of health (inoperability) of the system components. Thus, the weight associated with a particle represents, simultaneously, the approximation of the probabilities corresponding to the inoperability of all the system components. This makes it possible to estimate the state of health of the system by taking into account the interactions between its components and avoids filtering on the state of health of each component separately, which reduces the computation time.

4. System remaining useful life calculation

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 system failure) or when the system reaches a performance that is considered unacceptable. However, the consequence of the degradation of one or more components depends on the considered architecture. Indeed, the system components are often arranged in series or parallel configuration, even if hybrid arrangements may exist. Thus, a system with redundancies (parallel) is more resilient to the failure of one or some of its components.

Consequently, a method dealing with the calculation of the SRUL depending on system configuration and considering the component failure probability distributions is proposed.

5. Effects of mission profile on system remaining useful life

The mission profile is one of the most influential factors in system degradation. However, most of the currently proposed system-level degradation models do not take this factor into account, or only to a limited extent. Thanks to the modeling performance of the proposed IIM-based model, the influence of the mission profile on system RUL is investigated.

6. System remaining useful life maximization

In literature, several studies have already been carried out on the optimization of maintenance activities for prognostics but seldom on the optimization of the operational decisions to delay the system degradation. As the manner in which a system is utilized actively determines the evolution of its health state, we proposed a practical optimization approach based on a genetic algorithm to find the best appropriate mission profiles that satisfy different predefined operating conditions.

7. Online implementation of system-level prognostics

An assumption that makes the approaches proposed in the literature, usually not scalable for prognostics of complex systems, concerns the availability of prior and extended knowledge about the systems under study. In detail, whether they are data-based or model-based approaches, data are needed offline to train models or determine their parameters. These data are generally obtained from run-to-failure experiments or historical records. The obtained models, estimated or trained, are then used to predict the system's future evolution until its failure. Nevertheless, separating the estimation/training step from the prediction step may present some applicability problems. Indeed, in some complex or critical systems, performing run-to-failure experiments can be impossible because of equipment availability, cost, or safety reasons. In these cases, an offline model estimation is not applicable.

In this framework, a methodology for online system-level failure prognostics is presented. This methodology combines system degradation parameter estimation and SRUL prediction. Process and data uncertainty is accounted for, while minimal input information on system degradation is required. Finally, this methodology is designed to be computationally resource-efficient while ensuring an accurate prediction of the SRUL.

Thesis outline

Having highlighted the purpose and scope of the thesis, the content in Chapters 1, 2, 3, 4 and 5 contains the details of the previously mentioned contributions. These chapters begin with an introduction and end with a discussion around the obtained results.

In Chapter 1, a brief overview of state of the art in prognostics and health management domain is reported, and its relationship with the maintenance is emphasized. Then, a comprehensive overview of system-level prognostics and its related issues and challenges are presented. Also, different studies interested in system-level prognostics are reported through a new classification based on the granularity of the system modeling and the approaches used. The analysis of the identified gaps in the literature allowed us to motivate our research work and explain the approach undertaken to contribute to filling them.

Chapter 2 addresses the problem of modeling systems subject to multiple degradation processes by using the inoperability input-output model. First, the background of this model is presented, and its first usages in economics and risk management are detailed. Then, its adaptability to engineering areas is discussed by listing its advantages and drawbacks in comparison to other models used in prognostics. Finally, the adaptation and the utilization of the IIM model in the field of system-level prognostics are exposed exhaustively.

In Chapter 3, the inoperability input-output model is used in order to characterize, estimate, and predict system health state. First, a procedure to estimate the IIM parameters either by using run-to-failure data or online data is proposed. Then, the health state estimation and prediction are detailed, as well as the probabilistic calculation of the IIM. Finally, an online methodology based on the estimation of system degradation model parameters and its online exploitation for SRUL determination is presented.

In chapter 4, we will examine the influence of the mission profile on system RUL through different variations of its parameters, which are the load level and duration. Based on the obtained results, a new methodology aiming at optimizing the mission profile, while handling multiple operational constraints, for SRUL maximization is developed.

In Chapter 5, the proposed modeling framework for system-level prognostics is used to predict the system remaining useful life of a real industrial application, called the Tennessee Eastman Process. In that sense, the system health state is estimated and predicted by particle filtering with an IIM whose parameters are estimated either online or offline. Moreover, a sensitivity study was carried out to verify the variation in the results of the online prediction

methodology in terms of prediction accuracy and calculation time.

Finally, a summary of the results obtained, as well as some perspectives considered for future work, are given to conclude this manuscript.

Literature review and problem statement

The formulation of a problem is often more essential than its solution, which may be merely a matter of mathematical or experimental skill.

Albert Einstein

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1.1 Introduction

Industry 4.0, which is based on the concept of "smart factory", is one of the current trends in the manufacturing domain. Among other organizational services, Industry 4.0 requires quick

and efficient maintenance services to guarantee that companies implement efficient production systems. This need is particularly evident for systems whose failures cannot be tolerated for economic or safety reasons. Hence, it is desirable that their failure mechanisms be anticipated to schedule appropriate maintenance actions. For that, one of the candidate solutions is the utilization of Prognostics and Health Management (PHM).

The purpose of this chapter is to present a comprehensive overview of system-level prognostics (SLP) and its related issues and challenges. As there is almost no literature review on this topic, it would be worthwhile to delineate its contours and specificities in comparison to component-level prognostics (CLP) that is widely covered in the literature. To do this, in Section 1.2, a brief overview of the state of the art of prognostics and health management (PHM) is reported, and its relationship with maintenance is emphasized. Next, the different studies interested in SLP through a classification based on the granularity of system modeling (black-box or white-box) and the approaches used (model-based or data-driven), are discussed in Section 1.3. Then, issues and challenges that arise when dealing with prognostics of complex systems are exhibited. From the analysis of these aspects, the highlighted research questions are introduced at the end of this chapter.

1.2 Maintenance and PHM

The effectiveness of maintenance interventions and the induced costs can be optimized by using the information provided by Prognostics and Health Management (PHM) algorithms (Atamuradov et al., 2017). Indeed, PHM research seeks to link the failure mechanisms evolution with decision making (mainly condition-based maintenance (CBM) and Predictive Maintenance (PM)), through the supply of relevant information on the current and future system health states. As a result, PHM approaches have become a key enabler to achieve efficient maintenance tasks (Pecht, 2009).

In this context, this section presents a brief overview of PHM studies and their connection with maintenance policies. In detail, maintenance is firstly defined, and its types are presented in Subsection 1.2.1. Next, the need for PHM is detailed in Subsection 1.2.2. Finally, the different modules that constitute PHM are exposed with a brief literature review of the main approaches and tools used up to date.

1.2.1 Maintenance

Maintenance is one of the essential functions on which the competitiveness of companies is based. Indeed, the maintenance function is involved in several other functions of a company, from asset management to business continuity assurance (Gouriveau et al., 2016).

1.2.1.1 Definition

The definition and contours of maintenance function have evolved according to the objectives assigned to it. According to British Standards (BS), maintenance can be defined as "all technical, administrative and management actions during the life cycle of an asset, intended to maintain or restore it in a state in which it can perform the required function" (BS 13306, 2010). It thus includes troubleshooting and repair, adjustment, revision, control, and verification of material (machinery, vehicles, manufactured objects, etc.) or immaterial (software) assets. The maintenance department may also participate in studies to improve the industrial process. It must, like other departments of a company, take into account different constraints such as quality, safety, environment, cost, etc. As a result, the maintenance function is closely linked to the "RAMS" services (Reliability, Maintainability, Availability, Security), which, depending on the organization of companies, can be declined in the same department.

The maintenance function has evolved, resulting in several types that can be implemented simultaneously or separately, as explained in the following.

1.2.1.2 Maintenance typologies

There are two complementary ways to perform maintenance actions (Figure 1.1).

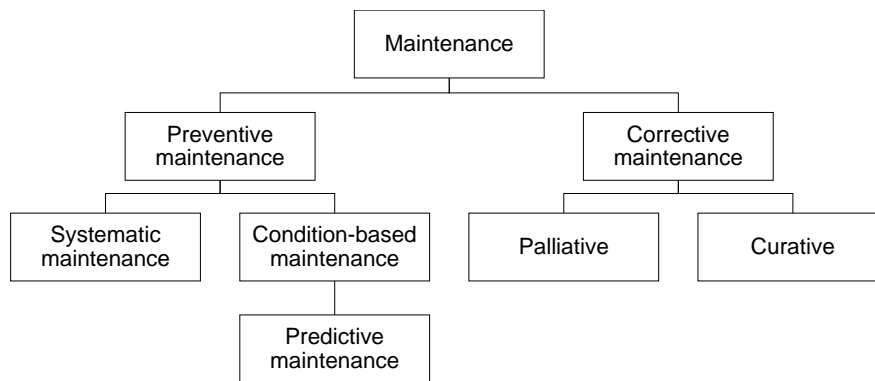


Figure 1.1: Typology of maintenance policies.

Corrective maintenance: It is the most straightforward approach for maintaining an asset. In this strategy, the equipment is allowed to function until its failure, and then the failed components are repaired or replaced. No actions are undertaken to maintain the equipment before, with, in some cases, a temporary operation and the permanent repairs postponed to a later date (Wang et al., 2014). The advantage of this strategy is minimizing the maintenance workforce by keeping the equipment running until its failure and thoroughly using its capabilities. However, the disadvantage of this approach is the unpredictable interruption of production and maintenance costs induced by the repair, often urgent, of the breakdowns. In addition, the repairing cost might increase upon the failure of secondary devices caused by the

primary failure. The labor cost associated with corrective interventions may then be higher than the usual average. Indeed, the failed parts most likely need more extensive repairs than would have been required if the piece of equipment had not been run to failure (Mosallam et al., 2015). Finally, in some cases, a corrective maintenance policy cannot be privileged for systems whose failures can lead to severe safety or environmental issues.

Corrective maintenance can be subdivided into (Gouriveau et al., 2016):

1. **Palliative maintenance:** Troubleshooting the equipment (through temporary actions) in order to enable it to perform all or a part of the required functions. It must, however, be followed by corrective actions as soon as possible.
2. **Curative maintenance:** repair (i.e. lasting) consisting of restoring the equipment to its original state, at least from a functional point of view.

Preventive maintenance: It consists of maintaining equipment before it fails, in an attempt to prevent any failure. Preventive actions are taken either for operational safety (the consequences of a failure being unacceptable), economic (it is cheap) or sometimes for production reasons (the equipment is only available for maintenance at certain time slots). Preventive maintenance can be systematic, condition-based, or predictive (Gouriveau et al., 2016):

1. **Systematic maintenance:** refers to maintenance operations carried out systematically regardless of the machine health condition, either according to a calendar (with a fixed time periodicity, i.e. time-based maintenance) or according to a frequency of use (operating hours, number of units produced, number of movements carried out, etc.). In this case, maintenance activities may include equipment lubrication, parts replacement, adjustment, and inspection for signs of deterioration during the inspection. The main benefits of this type of maintenance are the reduction of equipment breakdown frequency and increase of service life. The disadvantages of this type of maintenance are: 1) the need to interrupt production at regular intervals to carry out the maintenance, 2) the service life of some replaced components is not fully utilized, and 3) the additional costs may be unjustified in relation to the imminence of a breakdown.
2. **Condition-based maintenance (CBM):** refers to maintenance carried out following inspections or measurements (mileage, operating time, etc.), and checks to reveal the state of equipment degradation (infrared thermography, vibration analysis, thickness measurement, oil analysis, etc.). Under CBM, different kinds of sensors are used to measure the real condition of the equipment (Mosallam, 2014). When the equipment degradation status reaches a predefined level, maintenance actions are performed to restore it to its normal condition (Prajapati et al., 2012).
3. **Predictive maintenance.** Quite recently, more challenging requirements have emerged in the maintenance domain, which requires predicting the system's health condition and making decisions accordingly (Jardine et al., 2006). This kind of maintenance is intended to define the maintenance tasks required in the future based on equipment

predicted condition (Jaw and Merrill, 2008). In this way, the equipment is taken out of service only when direct evidence exists that deterioration will occur. Thus, predictive maintenance is carried out following an analysis of the evolution of the equipment deterioration state.

On the downside, CBM/PM requires increased investment in monitoring equipment and training for engineers and operators. The advantages of CBM/PM are the reduction of maintenance costs while increasing efficiency by performing maintenance actions only when there is evidence of abnormal behavior.

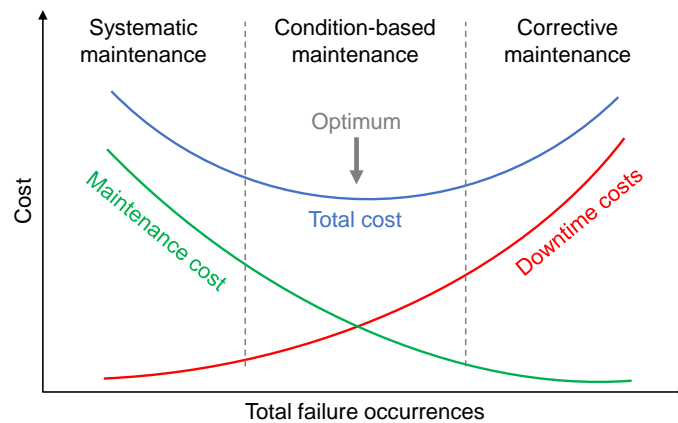


Figure 1.2: Maintenance costs and effectiveness (Peysson et al., 2009).

Identifying an appropriate maintenance strategy for a specific system is not trivial because finding the optimum point to balance between maintenance and the downtime cost is not easy (Figure 1.2). Maintenance experts have to define the best maintenance strategy to adopt for each equipment or system in a given plant, based on two main factors (Mosallam, 2014): 1) measurable factors: such as cost, productivity, availability, system functions, failure modes and identified maintenance requirements and tasks, 2) immeasurable factors: such as safety and comfort. Several approaches are reported in the literature for selecting appropriate maintenance strategy (Velmurugan and Dhingra, 2015; Hemmati et al., 2018). In (De Almeida et al., 2015), a method based on multi-criteria decision-making (MCDM) approach is proposed. The method applies the decision-making theory to maintenance, with particular attention to multi-attribute utility theory. Analytical Hierarchy Process (AHP) is proposed in (De Almeida et al., 2015), where the authors considered only four maintenance criteria: cost, repairability, reliability, and availability. Reliability centered maintenance (RCM) is probably the most widely used approach (Moubay, 2001). It is defined as a process used to determine what must be done to ensure that any physical asset continues to achieve the service for which it is designed within its operation context (Crocker and Kumar, 2000; Ben-Daya et al., 2009). RCM is widely used in many industrial fields, such as steel plants (Deshpande and Modak, 2002), railway networks (Vale and Ribeiro, 2014) and wind turbine industry (Andrawus et al., 2006).

PM is the newest maintenance strategy and required in different industries for many reasons. PM minimizes the costs of maintenance, improves operational safety, and reduces

the quantity and severity of system failures (McMillan and Ault, 2007). Furthermore, it can facilitate the planning of future maintenance tasks by predicting the failures of different equipment. To allow industrial systems to shift from traditional maintenance strategies to PM, Prognostics and health management (PHM) approaches are used (Haddad et al., 2011). PHM approaches have become a key enabler to achieve PM goals (Luna et al., 2009). PHM is a merging research field that links studies of data processing, fault detection, diagnostic, failure mechanisms, and decision-making to PM (Bae et al., 2014). PHM attracts significant interest due to the need for prognostics and decision models, which are important concepts for performing efficient PM strategy (Dragomir et al., 2009).

1.2.2 Prognostics and Health Management

PHM can be defined as a set of methods, tools, and algorithms that provide operators and users with useful information, inter alia, to maintain in operation their system, to better plan the maintenance interventions, to improve future product design in terms of maintainability and monitorability (Sun et al., 2012a), etc. It uses the knowledge available about the system and the data provided by sensors or gathered from exploitation to estimate the current health status of the system, detect abnormalities, diagnose the causes, and predict its time to failure for decision support. PHM is a compilation of seven main tasks depicted in Figure 1.3, from data acquisition to post prognostics and user interface. The most important PHM tasks are detailed in the following.

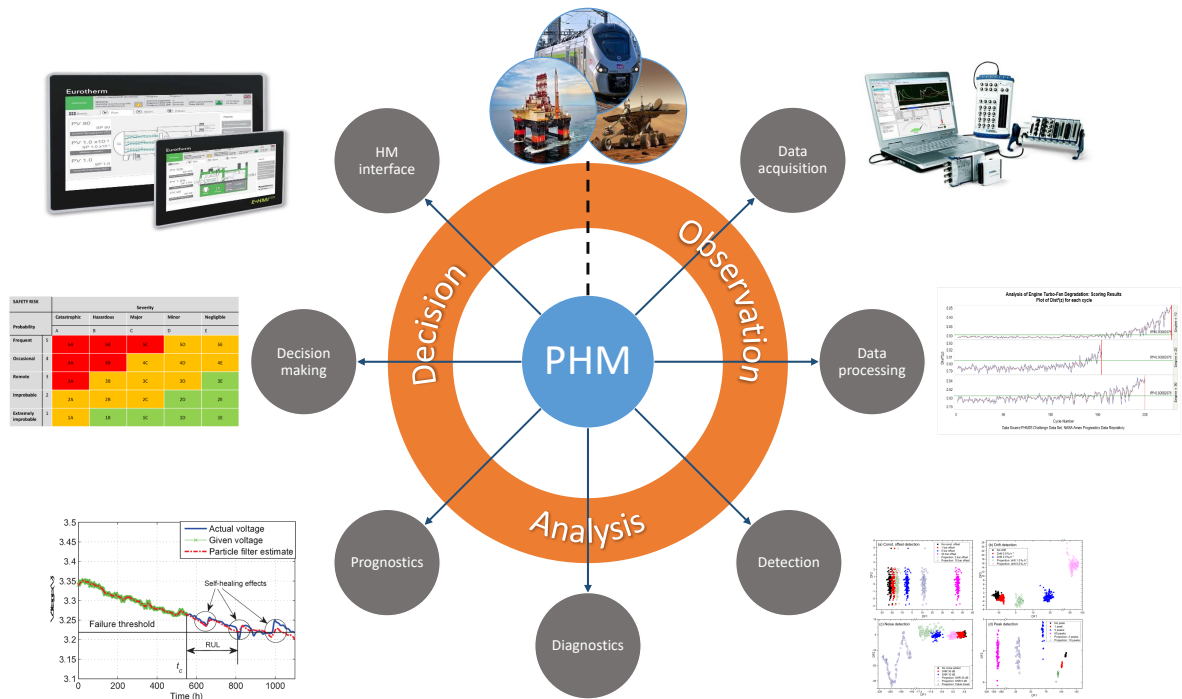


Figure 1.3: PHM modules.

1. **Data processing:** is defined as the collection and manipulations of data to produce meaningful information. Processing sensor data is usually required before the modeling step to provide signals and indicators that are reasonably robust to different variations that might affect the raw data, and which can be used to represent, analyze, and better understand the system behavior and its operating modes (Mosallam, 2014). Data processing methods vary according to the application. Therefore, there is no universal method to process raw data and extract useful information. Instead, one has to choose the appropriate method(s) according to the problem in hand and the chosen target. Consequently, different indicators can be constructed from the same data, but each one will be used for different applications (Atamuradov et al., 2017).
2. **Fault detection:** is defined as the process of determining whether a fault has occurred in the monitored component/subsystem/system. There are two approaches for doing fault detection, namely model-based and data-driven (Rogers et al., 2019).
 - Model-based approach: the methods of this approach are based on a physical model derived from the principle laws of physics. They require performing a large number of experiments on test-benches, prior to production, to estimate the model parameter, tune the models, and derive indicators that can be used to detect faults. The experiments may be time and cost consuming. Model-based methods can be of different types (Mosallam, 2014): models of signals (or signal processing), parity space, parameter estimation, observers, etc.
 - Data-driven approach: another way to perform fault detection is by using data-driven methods. These methods exploit the amount of available data (acquired by using sensors or gathered by operators during operation and exploitation) to learn, in an offline phase, models that allow identifying clearly the normal and the faulty modes of the system. The learned models are then used online to classify new observations in normal or faulty modes, depending on the system's current health state (Mosallam, 2014). The data-driven approach uses methods and tools from machine learning, statistical, data analysis, etc.
3. **Fault diagnostic:** is defined as the process of determining fault characteristics such as kind, size, location, and time of detection. Usually, the diagnostic process follows fault detection, and the main task is to isolate the fault. Many diagnostic methods have been proposed in the literature and can be divided into three main groups, namely, model-based, data-driven, and expert system (Jardine et al., 2006).
 - Model-based methods: they are based on physical laws corresponding to relationships between different system parameters. These methods are used to generate rules that represent the current fault. The generated rules are then passed to a rule-based inference system to deduce the exact diagnostic.
 - Data-driven methods: they learn models from monitoring data using statistical learning or artificial intelligence (AI) algorithms. Then, the rules characterizing the fault states are generated by measuring the distance between the new data and the learned models' outputs.

- Expert system methods: they are not based on physical or data-driven models. They rely on experience feedback provided by operators and/or system engineers. The knowledge can be represented by using different representations: rules, frames, predicate logic, directed graphs, case-based reasoning, etc.
4. **Failure prognostics.** This module is one of the novelties brought by the PHM approach and constitutes the core topic of this thesis. As such, it will be further detailed in the next sub-section.
 5. **Decision-making.** This part of PHM builds upon the advancements already achieved in optimal maintenance decision-making in the field of CBM and PM. The optimality of this decision relies heavily on accurate prognostics and, thus, on the RUL estimations that are provided. The idea here is to perform life-cycle decision-making (Guillén et al., 2016) or lifetime-extension (Tamssaouet et al., 2019c) of the systems at hand, aiming to achieve near-zero downtime and maximizing the reliability and performance of the equipment. For instance, in (Tiddens et al., 2015), the authors conduct a study investigating the adoption of some prognostics approaches. They then provide a framework for implementing prognostics of which the transformation of the actual monitoring data into insightful maintenance decision support. Furthermore, the PHM results, besides maintenance, can be integrated into other phases of the system life-cycle, such as system design & development, production & construction, operations, and phase-out & disposal (Sun et al., 2012a).

1.2.3 Failure prognostics

Failure prognostics is the principal added value provided by the PHM. Indeed, with prognostics, system failures are proactively prevented to limit their consequences and take them into account in future decision-making.

1.2.3.1 Definition

Prognostics is the process of predicting the end of (useful) life (EOL) and/or the remaining useful life (RUL) of components, subsystems, or systems. In the last two decades, the topic of prognostics has become a research framework in its own right with a profusion of papers covering a multitude of scientific problems and various fields of applications (Jardine et al., 2006; Gouriveau et al., 2016; Atamuradov et al., 2017). The interest in this discipline is primarily due to the systems where the failure cannot be tolerated for economic or safety reasons. Hence, the maintenance of these systems must proactively address their failure mechanisms by implementing prognostics algorithms. In that sense, several approaches have been proposed in the literature.

1.2.3.2 Prognostics approaches

Generally, the research conducted in failure prognostics of assets is classified into three main approaches: data-driven, model-based (also called physics of failure), and hybrid prognostics (Figure 1.4).

The first approach exploits the data provided by sensors (monitoring data), which capture the degradation evolution of the system. The data are then pre-processed and processed to extract features, which are used to learn models for health assessment and RUL prediction (Wu et al., 2018; Gu and Chen, 2019). Different tools and models can be used for data-driven approaches, among them we can mention: neural networks (Nguyen and Medjaher, 2019), regressions (Saha et al., 2007), hidden Markov models (Tobon-Mejia et al., 2011) and support vector regression (Benkedjough et al., 2013).

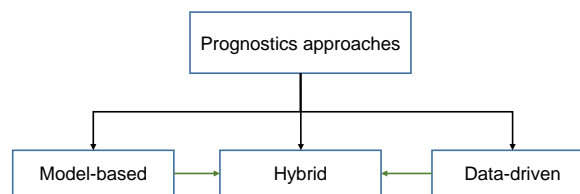


Figure 1.4: Main approaches in failure prognostics.

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 then tuned using the monitoring data to compute the RUL (Chelidze and Cusumano, 2004; Luo et al., 2008). Examples of degradation models are those related to crack by fatigue, corrosion, and wear (Nguyen et al., 2018; He et al., 2012).

Finally, the third approach combines both previous approaches and benefits from their advantages, for example, precision and applicability, but can also inherit from their drawbacks, such as important modeling efforts and need for a lot of representative data.

In the next section, we will focus on the prognostics at the system level as well as the related literature.

1.3 System-level prognostics

Nowadays, industrial systems are increasingly complex (such as aircraft, power plants, etc.). They consist of several interdependent and mutually influencing components. Thus, prognostics at the system-level becomes the most appropriate level for predicting future system behavior and determining its time to failure. However, due to the complexity of large-scale engineering systems, prognostics studies have been limited to the component-level. Yet, the output of these prognostics methods can be practically useful for system managers, operators, or maintenance staff, only if it helps them in making decisions, which are generally based on

system-level parameters. Therefore, there is an emerging need to build health assessment methodologies at the system-level. Some of the reasons that encourage to shift to SLP are presented in the following.

- For system users, what matters is to know if a system, as a whole, is able to provide the service for which it has been designated (Daigle et al., 2012).
- In practice, small amounts of degradation in several components can combine to produce much larger effects on system performance. This consequence is due to the interdependencies between components. Therefore, system EOL computation is more than a simple combination of individual component failures. Direct extrapolation of the component RULs to the system RUL can lead to over- or under-estimation problems (Khorasgani et al., 2016).
- In systems with redundancies, the RUL of the components is not sufficient to determine the impact of degradations or failures on the operability of the system. Thus the system RUL must be used in this case.
- To maintain systems in service or extend their life, information on their future behavior is needed (e.g. schedule system-wide maintenance).
- Applying SLP allows localization of the most vulnerable/critical components of the system to monitor them more.

1.3.1 Definition of system-level prognostics

There is no consensual definition of systems-level prognostics in the literature yet. In (Sikorska et al., 2011), the authors reviewed the definitions given to prognostics, up to 2011, in a general way. It was found that, collectively, these definitions state or imply, between others, that prognostics is, or should be, performed at the component or sub-component level. However, several authors proposed some partial definitions of system-level prognostics related to the issues they addressed. In (Rezvanizani et al., 2014), SLP was defined in contrast with the cellular-level concerning battery health state problem. In this case, the system-level refers to a single component, which is the battery made up of several identical cells. However, this definition cannot be applied in the case of complex systems with several heterogeneous components. In (Khorasgani et al., 2016), 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 takes into account 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 its failures.

In order to give a general definition of SLP, in (Tamssaouet et al., 2018), we proposed to transpose the definition of component-level prognostics (CLP), accepted in the PHM community, at the system level by outlining the meaning of system. This results in the following definition: *the system-level prognostics corresponds to the RUL estimation of a system*

(*SRUL*) knowing its current health state and future conditions of use. A system is defined as a set of elements (components or subsystems) interacting with each other and with the environment to perform one or more tasks (Jamshidi, 2008). In the literature, it is referred to with the terms: system-level prognostics (Medjaher and Zerhouni, 2013; Daigle et al., 2016; Tamssaouet et al., 2018), system approach of prognostics (Bai et al., 2015), multi/multiple components prognostics (Hafsa et al., 2015; Rodrigues, 2018), and prognostics of complex systems (Abbas, 2010; Desforges et al., 2017).

1.3.2 Advantages of SLP on CLP for complex systems

Prognostics at system-level stems from the desire to make assets more resilient based on a holistic overview of the system degradation. Indeed, system-level prognostics is only an approximation of the system's dysfunctional behavior, assuming the independence of its components. However, in most cases, system components mutually influence each other. Therefore, prognostics at system-level will allow us to take 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 predefined thresholds.

As a result, SLP can bring benefits in all stages of the system life-cycle process by increasing system reliability and availability, ensuring security and making systems more resilient (Sun et al., 2012a) while reducing their maintenance costs. It can determine the components to be monitored even if they do not represent a low RUL, but which can influence other components and accelerate their degradation. The system approach can help to locate the root causes of failures and improve the diagnostic function. Indeed, by characterizing the component degradations and their interactions, it is possible to locate the most influential and vulnerable components to the deterioration of the whole system. Finally, system-level prognostics can also improve the organization of the maintenance function (schedule system-wide maintenance, reduce the number of interventions, etc.).

1.3.3 Literature review on system-level prognostics

Several literature-review papers have been published on CLP and which have mentioned system-level prognostics broadly through a few paragraphs. Among those reviews, we can mention for example (Gouriveau et al., 2016; Atamuradov et al., 2017; Kordestani et al., 2019). Their conclusion is that there are not many studies on SLP. However, in the last decade, a growing number of works dealing with SLP issues, in one way or another, have become available, as shown in Table 1.1. Thus, the purpose of this subsection is to introduce exhaustively this literature on SLP.

Table 1.1: Literature review on system-level prognostics studies and related addressed issues.

Paper	Interdependence	Uncertainty	Mission profile	Non-linearity	Approach
(Abbas and Vachtsevanos, 2009)	×	✓	✓	✓	Model-based
(Benaggoune et al., 2018)	✓	✓	×	×	Data-driven
(Daigle et al., 2012)	×	✓	✓	✓	Model-based
(González et al., 2018)	×	✓	×	✓	Data-driven
(Hafsa et al., 2015)	✓	✓	×	✓	Model-based
(Khorasgani et al., 2016)	×	✓	×	✓	Model-based
(Liu and Zio, 2016)	✓	✓	×	✓	Model-based
(Maitre et al., 2016)	×	×	✓	✓	Model-based
(Ribot et al., 2008)	×	✓	×	×	Model-based
(Rodrigues, 2018; Rodrigues and Gomes, 2017)	×	✓	×	✓	Data-driven
(Tamsaouet et al., 2019c)	✓	✓	✓	✓	Model-based

For this purpose, a classification based on the system modeling point of view is proposed (Figure 1.5). This choice was motivated by the fact that one of the most significant issues related to SLP is the system degradation modeling (Maitre et al., 2016; Li et al., 2018). According to the proposed classification, we can distinguish two categories with respect to the granularity of the modeling used: simplified modeling and holistic modeling. Within each category, the classification is detailed according to the methods and tools used.

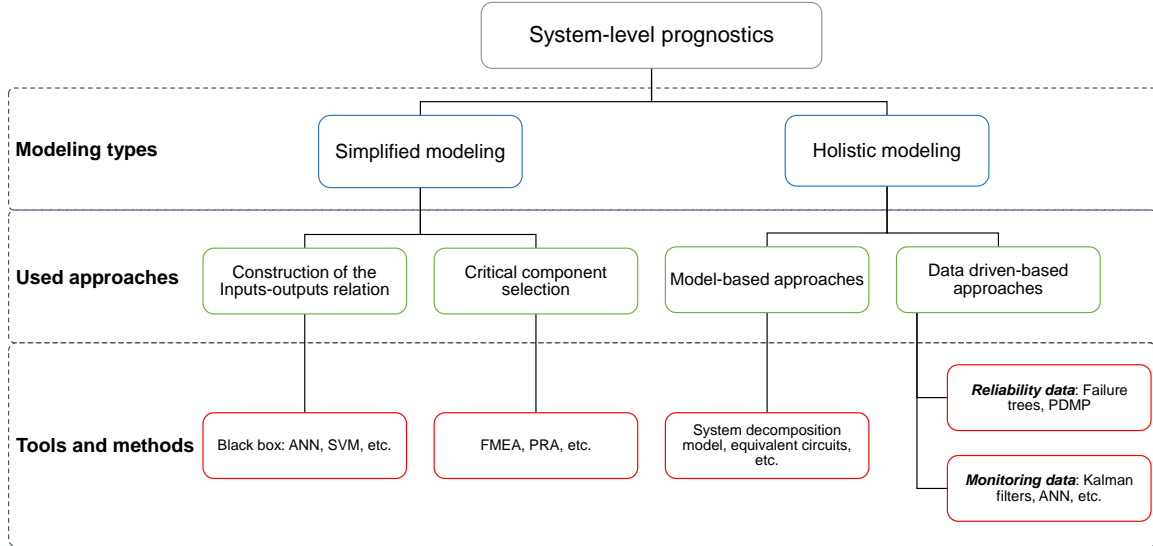


Figure 1.5: Classification of system-level prognostics approaches.

1.3.3.1 Simplified modeling

The studies in this group usually simplify 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 shown in Figure 1.6), and the SRUL is estimated based on the input-output data using machine learning (Li et al., 2018), statistical (Si et al., 2011) or similarity-based (Wang et al., 2008b) methods. The main tools used in this approach are advanced neural networks (Nguyen and Medjaher, 2019) (e.g. Long short-term memory: LSTM), Levy-based process (Nguyen et al., 2018) (e.g. Wiener process), stochastic filtering-based models (e.g. Particle Filtering or Kalman filter), and support vector machine (SVM) based methods.

The advantage of this approach is its ease of application, even without extensive knowledge of the system. On the other hand, this approach requires lots of monitoring data that are not easy to acquire in practice, resulting in a more extended period of model training, which

may not be acceptable for complex systems. Also, because we are not interested in what is actually happening inside the system, we may lose the physical meaning of the modeling, and the health indicators used will be difficult to monitor because of their resulting significant nonlinearities and non-stationarities (Kan et al., 2015). In fact, in complex systems, variations in health indicators result from all the changes that occur within those systems. However, a change in the system's global health indicators may be due to different combinations of the health states of its components, which makes its future behavior prediction difficult.

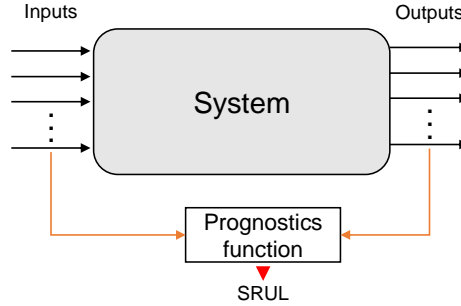


Figure 1.6: Prognostics based on input-output relations.

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

Critical component selection

In that perspective, system prognostics is reduced to prognostics of its critical components identified by using risk analysis and dependability methods (Sarih et al., 2018; Brahimi et al., 2017; Mosallam et al., 2015). The standard (IEC 60300-3-1, 2003) provides a list of methods to support engineers to assess the dependability of a given system. These methods can be divided into two main groups: qualitative and quantitative. The qualitative and semi-qualitative methods rely on experts' judgment of the available data to identify and evaluate potential failures and to make a reasonable judgment of risks. These methods can be decision or experience-based; they provide a qualitative evaluation of the risk such as low, medium, and high. Qualitative methods are usually performed by using checklists, 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. They 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 (IEC 60300-3-1, 2003). 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 (Tixier et al., 2002).

The critical component identification approach was applied in several cases, such as iden-

tifying the contact wire, as the most critical and impacting component of the Overhead Contact System of railway infrastructure (Brahimi et al., 2017), bearings in rotating machines, lithium-ion battery and turbofan engine in commercial airplanes (Mosallam et al., 2015), 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.

1.3.3.2 Holistic modeling

The second group of SLP studies aims to propose 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 evaluating the SRUL by using data-driven or model-based approaches.

Model-based approach

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

According to (Guillén et al., 2013), model-based methods suit better for SLP as it is difficult to use directly the monitoring data 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 (Gu et al., 2007). However, these methods need sufficient physical knowledge about the system under study. Besides, in practice, the complexity of some systems is difficult to model (Pecht, 2009). For example, in PoF models, the material, geometry, and usage profile (i.e. operational and environmental conditions) are required, which are not always available.

Currently, one of the most used models in prognostics is the state-space representation (Sun et al., 2012b), which is given by the following expression:

$$\dot{x} = f(t, x(t), \theta(t), u(t), v(t))$$

$$y(t) = h(t, x(t), \theta(t), u(t), n(t))$$

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 and faulty behaviours, including the fault progression function.

The use of this model in CLP allows taking into account different parameters that influ-

ence the degradation of a component. However, for SLP, the state-space model has several limitations, such as the inability to model heterogeneous components, the no-modeling of component interactions, and the computation time.

Alternatively, a more practical approach is to build up system models by integrating the simpler behavioral equations with experience-based models or utilizing data fusion techniques (Sikorska et al., 2011). In (Daigle et al., 2012), 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 is based on the assumption that the subsystems are independent. Besides, it cannot be widely used in practice because of the complexity of the analytical models. In (Daigle et al., 2016), the authors proposed applying this prognostics approach to Airspace Management in the United States. 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. The aim is then to determine the time before these risks exceed a certain probability. The prediction was conducted using Monte Carlo simulation algorithms. Aircraft are considered as an independent component of a system that is the airspace.

The lack of interdependence modeling in state-based models was addressed in (Xi et al., 2019). In this paper, the authors used a state-space based modeling where dependencies among different degradations can be reflected in a diffusion coefficient matrix. Based on multi-dimensional observations, the hidden degradation states are identified through sequential Kalman filtering. Meanwhile, the unknown parameters in the model are updated iteratively by the expectation-maximization (EM) algorithm. However, this approach was applied to simple systems where homogeneous components are involved. To address the limitation of state-space modeling regarding heterogeneous systems, in (Rodrigues, 2018), the calculation of the SRUL is made on one global performance indicator. This indicator is derived from the aggregation of the individual component performance indicators calculated using independent individual component state-space modeling while accounting for system architecture. However, the authors assume that the relationship between the deterioration of the health indicators and the system performance is known.

Furthermore, when considering uncertainty in the model-based approach of prognostics, SRUL prediction becomes computationally intensive. Khorasgani *et al.* (Khorasgani et al., 2016) presented a prognostics methodology for system-level RUL prediction that considers different sources of uncertainty, such as model uncertainty, measurement uncertainty, and output uncertainty. Two methods were utilized to model the uncertainties: a stochastic simulation approach and an inverse FORM (First-Order Reliability Method). The authors presented an analysis of the computational complexity of the two investigated methods and showed that the inverse FORM was faster than the stochastic simulation approach. To take into account the uncertainty in modeling, the authors of (González et al., 2018) worked on the influence of local prognostics uncertainty on the overall prognostics of a system by using Dempster-Shafer theory. By modeling the system in parallel and serial architectures, the probability of system failure is determined by Bayesian inference. The EOL of the system is defined as the time when the probability of failure reaches a fixed threshold. Here, only the

functional relationships between the components are taken into account.

A more phenomenological system degradation is addressed in (Vasan et al., 2013), where the authors developed an approach of decomposing an electronic system to circuits instead of components. This approach suits this case study because of the difficulty of monitoring miniaturized electronic components. The resulting 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. However, the decomposition into circuits in the case of complex systems can be challenging. Although, in this study, the application was made only on a simple system consisting of three circuits in series: bandpass filter (BPF), mixer circuit, and low pass filter (LPF) circuit.

In contrast to state-space models, in (Wu et al., 2011), component deteriorations were considered as time-dependent stochastic processes. The author assumed that degradation could be modeled as a gamma process where the stochastic load is generated by a Poisson process. The component failure is then defined for when the applied stress exceeds the system strength, which varies according to its degradation rate. However, since real systems are generally non-linear and sometimes non-stationary over time, it is difficult to model their degradation (Song et al., 2014).

Other models are explored in the literature, such as bond graphs or Petri nets. In (Prakash et al., 2018), multiple degradation models are derived by using bond graphs. These models are then adapted with new information about the degradation states of the monitored system. In (Ribot et al., 2008; Blancke et al., 2018), based on Petri nets, a generic online health monitoring architecture was proposed. This architecture is capable of using several prognostics methods for different components, depending on the available models. However, it does not take into account the operating conditions (mission profile) during the system's utilization.

Data-driven approach

Holistic data-driven methods, even if they do not describe system degradation's phenomenology, can account for its evolution through the monitoring of health indicators extracted from sensor data. 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, more or less, to the interdependence of degradation between components. The authors in (Dragomir et al., 2007) presented an architecture where the prognostics process is defined at component-level as well as at the global level. Each local agent uses specific prognostics methods according to the knowledge available on the monitored component. The global agent feeds a neural network with data collected from the local agents. This network is presented as a global prognostics tool to aggregate local prognostics. The weights in the networks are determined by using monitoring data and expertise.

Other methods have been used from the same perspective, such as Bayesian networks. In (Kim et al., 2014), causal Bayesian Networks (BNs) are used to model the dependencies existing between component degradations in order to improve the decision-making on system troubleshooting. The proposed method is detailed for integrating multilevel information such

as prior knowledge and direct experience data to characterize the fault propagation in an electromechanical actuator.

Multivariate distributions were explored through gamma (Rodrigues et al., 2015) and Copula (Li et al., 2016) distributions. The paper (Liu and Zio, 2016) provides a framework for evaluating the reliability and the RUL of a system with two components: a pump with a discrete degradation process and a valve with a continuous degradation process. In (Hafsa et al., 2015), a statistical prognostics approach is proposed to estimate the RUL of a system by considering the degradation rate interactions between its components. In order to establish a common prognostics for each component, a probabilistic Weibull model is used. This model enables representing the failure probability of each component in the system, but each component can only be the "initiator of" or "subject to" degradation of another component (uni-dimensional degradation relationship).

Data aggregation methods have been used through multi-agent methods in (Saha et al., 2009b; Desforges et al., 2017; Benaggoune et al., 2018) and fault trees (Ferri et al., 2013; Rodrigues and Gomes, 2017; Rodrigues, 2018). In (Saha et al., 2009b), 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 prognostics mode when a critical condition is detected and informs the base station. This latter works as a manager of resources and agent control. Recently, (Benaggoune et al., 2018) proposed a new approach for SLP based on Multi-agent systems (MAS) applied to a lorry system. MAS is a paradigm inspired by distributed artificial intelligence, based on an ensemble of individual autonomous and cooperative entities called agents. However, this approach is only applied to time-dependent degradation with the system states' discretization, which reduces its applicability. Also, only linear independent degradations are accounted for in this study. In (Desforges et al., 2017), a prognostics function of complex systems, is presented. This prognostics is carried out by agents, where a new notion called Time Before Out of order (TBO) is introduced. This latter means that a component will likely become out of order because of another dependent component failure. In a series of papers (Rodrigues and Gomes, 2017; Rodrigues, 2018), the authors rely on the functional architecture of a system described by a fault tree to calculate the SRUL from its component RULs. From the system minimum cut sets, the probability of system failure is obtained by using logic gates and the probability density function of each component. In this study, the SRUL is determined as the time remaining for the probability of the system failure to reach a given threshold. Fault trees are compelling tools, but their disadvantage is that the basic events must be independent. In (Ferri et al., 2013), the structural dependencies are considered using the fault tree to improve the scheduling of inspection periods without taking into account the system mission profile.

Recently, the problem of SLP in the cloud was addressed in (Deb et al., 2013). This research considered the transformation of application systems from system-centric architecture to cloud-based systems that leverage shared computational resources to reduce costs and to ensure availability and quality of service, which is essential for critical tasks such as health care monitoring in the cloud.

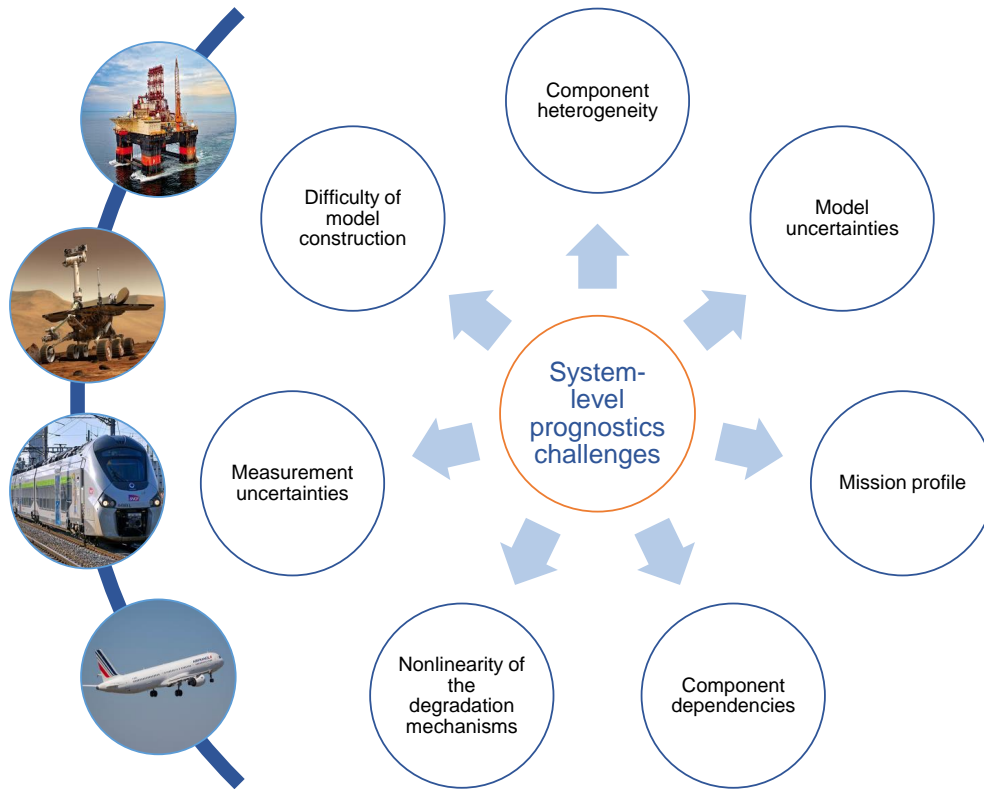


Figure 1.7: System-level prognostics challenges.

1.3.4 Challenges related to system-level prognostics

In light of the literature review in the previous section, it can be concluded that system-level prognostics presents some challenges not faced when dealing with prognostics at component-level. In what follows, we will review the various challenges to be addressed by future SLP studies (Figure 1.7) and give some possible solutions.

1.3.4.1 Interdependencies

Interactions between component degradations have been intuitively felt since the first works on component wear and reliability of systems (McCall, 1965). This has resulted in a large literature in the areas of condition-based maintenance (CBM) and reliability. For instance, maintenance policies of multi-component systems have been widely reviewed in the following papers (McCall, 1965; Cho and Parlar, 1991; Dekker et al., 1997; Nicolai and Dekker, 2008). However, despite the growing interest in prognostics of complex systems, in both theory and practice, no literature review exists on prognostics of multi-component systems subject to different types of dependencies. Hence, an exhaustive classification of component interactions (Table 1.2), inspired by (Keizer et al., 2017), is proposed in this subsection. This classification includes structural, stochastic, resources, and economic interdependencies.

Table 1.2: Component interdependencies classification.

Structural	Technical	<ul style="list-style-type: none"> • Maintenance restrictions (Dekker et al., 1997) • Usage restrictions (Nguyen et al., 2014)
	Architecture	<ul style="list-style-type: none"> • Series configuration (Tamssaouet et al., 2018) • Parallel configuration (hot (Ferri et al., 2013)/ warm (Jiang et al., 2014)/ cold redundancy) • k/N configuration (Huynh et al., 2013) • Arbitrary configuration
Stochastic	Load sharing	<ul style="list-style-type: none"> • Failure load-based sharing (Maitre et al., 2016) • Degradation load-based sharing (Rasmekomen and Parlikad, 2016)
	Common mode degradation	<ul style="list-style-type: none"> • Environment (Lau et al., 2012) • Mission profile (Tamssaouet et al., 2019c)
	Failure induced damages (Nguyen et al., 2014)	
	Degradation interactions (Tamssaouet et al., 2018)	
Resources	Workers (Koochaki et al., 2013), spares (Wang et al., 2008a), tools and transport sharing	
Economic	Negative (Shafiee et al., 2015) or positive (Tian et al., 2011) economic dependencies	

1. **Structural interdependencies** concern the structural and static relationships between different components. First, they can be related to situations where the replacement of a component requires the dismantling or the replacement of other components (Thomas, 1986; Dekker et al., 1997; Nguyen et al., 2014). Second, components can be dependent through the system's physical or functional structure, which can influence the way it fails. For instance, a system whose components are arranged in a series configuration is more sensitive to one component failure than in a parallel configuration or in the case of k/N architecture (Ferri et al., 2013; Tamssaouet et al., 2018). Moreover, even for a parallel architecture, the way of switching between redundancies influences the system failure. As a result, a system with hot redundancy degrades less quickly than a system with warm or cold redundancies (Coit, 2001).
2. **Stochastic interdependencies** mean that the deterioration (or failure processes) of components are (partially) dependent. We can distinguish four types of stochastic interdependencies:
 - Degradation interactions. A degradation of one component influences (generally by accelerating) other component degradations (Liu and Zio, 2016; Tamssaouet et al., 2018; Benaggoune et al., 2018). 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 (Bian and Gebrael, 2014).

- Failure induced damages. The failure of one component leads to an immediate increase in the degradation level or even immediate failure of other components (Nguyen et al., 2014). For example, in a computer, a fan failure will induce a processor degradation or failure.
 - Load sharing, which can be induced by a component failure or degradation. Indeed, a failure of one or more components increases the load on the remaining functioning ones, which will hence deteriorate faster. This fact can be observed in a set of pumps used to distribute the same amount of gas/liquid (Maitre et al., 2016). A component deterioration can also increase the load on the other ones, as outlined in (Rasmekomen and Parlikad, 2016) for the tube fouling in a distribution network.
 - Common mode deterioration. Several components can fail or deteriorate simultaneously, due to similar mission profile (Tamssaouet et al., 2019c) (e.g. components sharing a common power supply) or environmental conditions (Lau et al., 2012) (e.g. wind turbines in an offshore field under weather conditions).
3. **Resources interdependencies**, which arise when several components are connected through shared limited set of spares (Wang et al., 2008a), workers (Koochaki et al., 2013), tools or budget. As a consequence, a maintenance optimization is required on the system-level rather than on the component-level.
 4. **Economic interdependencies** mean that combining maintenance on multiple components is either more expensive (negative economic dependence) (Shafiee et al., 2015) or less expensive (positive economic dependence) (Nicolai and Dekker, 2008; Tian et al., 2011) than maintaining each component separately.

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

1.3.4.2 Uncertainty

Uncertainty is intrinsically related to any prediction (Das et al., 2019) and, therefore, to failure prognostics. The main types of uncertainty (Figure 1.8) that affect both the current and future degradation state are process uncertainty, model uncertainty, measurement uncertainty, and future uncertainty.

Firstly, process uncertainty refers to the variability of a process behavior due to operating and environmental conditions. In detail, this uncertainty translates into the variation of the system's physical parameters (resistance, inductance, stiffness, capacitance, etc.) (Atamurov et al., 2017). To mitigate this uncertainty in new systems, a robust design should be considered with minimal sensitivity to material, manufacturing, or operating variations (Lee et al., 2014). For systems already in operation, the uncertainty related to system parameters

can be tackled by using adequate methods to quantify them, such as interval (Jaulin et al., 2001) or probabilistic (Tamssaouet et al., 2019a) ones.

Secondly, the model uncertainty is one of the uncertainties that most affect the prediction accuracy in prognostics (Doucet et al., 2000). Indeed, either for the nominal model or the degradation model of a system, they represent only an approximation of the real behavior, which does not consider all the involved parameters. For the nominal model of a system, the uncertainties can be the result of a set of assumptions used during the modeling process and which lead to models that do not fit precisely the real behavior (Atamuradov et al., 2017). For the degradation model, it is generally obtained from accelerated life tests, which are conducted on different samples of components (Pecht, 2009). In practice, the data obtained by accelerated life tests, performed under the same operating conditions, may have different degradation trends. To take this uncertainty into account, the problem of modeling and estimating the state of a system has been approached in a probabilistic form, and by using tools derived from possibility theory (fuzzy logic) (Zio and Di Maio, 2010; Ramasso and Gouriveau, 2014) or Dempster-Shafer theory (evidential theory) (González et al., 2018). The probabilistic representation of uncertainty is often used in filtering methods (particle filters (Orchard et al., 2008), Kalman filter (Celaya et al., 2012), etc.) to estimate the system state by combining imprecise models and noisy measurements.

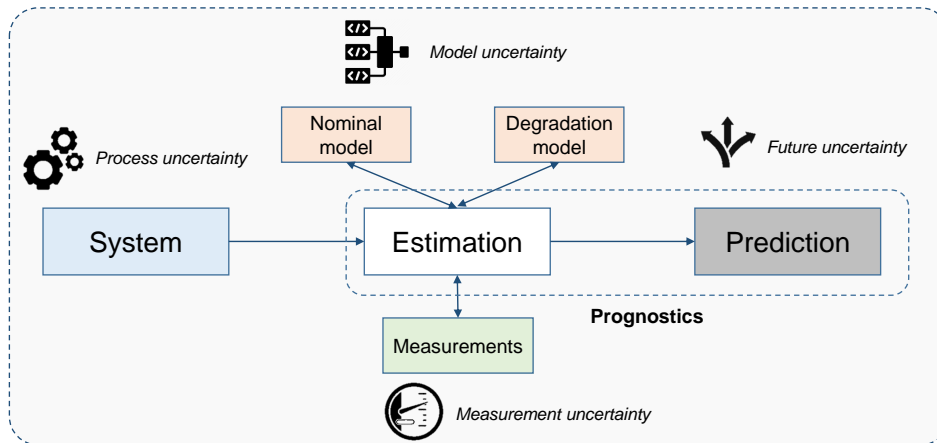


Figure 1.8: Uncertainty sources in prognostics.

Thirdly, whatever the approach used for prognostics, measurement uncertainty is at the core of the prediction process. Indeed, sensor data are used to train algorithms, in the case of data-driven methods, and to estimate model parameters, in the case of model-based methods. 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 non-linearity in the response (Saha and Goebel, 2008). Therefore, it is necessary to consider this noise when estimating the system's health state.

Finally, once the state of the system is known and its uncertainty quantified, the purpose of prognostics is to predict the future evolution of the system, which is inherently uncertain. Indeed, the system's future usage and operating conditions are unknown, making its future

state and the RUL predictions very uncertain. In this framework, Markov chains have been proposed to emulate usage profiles for batteries in (Pola et al., 2015). Similarly, the authors in (Pecht, 2009), 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 CLP to SLP leads to an increase in the number of uncertainty sources, which causes more issues when predicting the SRUL. Another problem that makes scaling up from CLP to SLP difficult is the heterogeneity of components within a system, which is the subject of the next subsection.

1.3.4.3 Components heterogeneity

Nowadays, systems are composed of several components with different characteristics. These components can be electronic, mechanical, hydraulic, pneumatic, etc. Each component uses different energies, and the energy transformations within systems make them able to perform complex tasks (Cameron and Larsen-Freeman, 2007). This heterogeneity of components poses a big challenge for SLP. Indeed, as shown in Table 1.3, 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 (Ye and Xie, 2015). In (Cheng et al., 2010), a review was made of the different parameters that can be used to monitor the state of health of systems and, thus, the different degradation mechanisms affecting them.

In literature, several studies have been carried out for diagnostics of heterogeneous systems, but only a few ones addressed the prognostics of these systems. Specifically, the problem here is how to design a single model for the degradation of an entire system. In (Rodrigues, 2018), 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 component on the system performance is known, which is a strong assumption. In (Tamssaouet et al., 2018), it was proposed to normalize all the health indicators of a component to one parameter, which is called inoperability. A distributed approach for prognostics on system-level is also proposed in (Ribot et al., 2008; Daigle et al., 2012; Benagoune et al., 2018). This approach addressed the problem of component heterogeneity in a way that each component can be monitored by different parameters and different models. However, the approach assumes that the component degradations are independent.

Table 1.3: General degradation parameters which can be monitored in components (Cheng et al., 2010).

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, position, flow

1.4 Literature discussion and positioning

In this section, we point out the downsides of existing approaches to system-level prognostics (SLP) and show the motivations of our contribution. Then, we position and explain the plan of the approach undertaken and which contributes to answering some of the issues already highlighted.

1.4.1 Downsides of existing approaches

The review of existing approaches for SLP presented in previous sections provides us a critical overview of the literature gaps. In fact, there is no study in any of the previously mentioned approaches that addressed the degradation of a system comprehensively. Indeed, each work proposed for SLP, so far, suffers from one or more of these following limitations:

- The assumption that the components are independent of each other. This assumption can lead to a significant deviation of the predicted SRUL from its true value.
- The need for large amounts of data (especially for data-based approaches) and large computational capacity (whether for data-driven or model-based approaches). This constitutes an obstacle to an online implementation of these approaches.
- The lack of generality. Indeed, most of the degradation models proposed in the literature are intended for particular types of homogeneous systems. In reality, most complex systems include components of different natures (i.e. heterogeneous components).

- Deterministic prediction of SRUL. This limitation is especially concerned with data-driven approaches. However, a system failure is intrinsically a stochastic phenomenon that cannot be predicted by a scalar value.
- The lack of studies on the effect of mission profile on multi-component system degradation. Indeed, the way in which a system is used greatly influences the evolution of its degradation. Also, the mission profile can be a major enabler to increase the availability of systems because, in some cases, several profiles, inducing different degradation rates, can be applied while ensuring the system functions. This possibility has been considered in the literature in only very few studies.

1.4.2 Positioning, contributions and proposed approach

Naturally, our objective in this thesis is to contribute to the release of the limitations outlined above. Therefore, the proposed step-by-step approach is shown in the synoptic diagram of Figure 1.9. As we can see in this scheme, the approach can be divided into four parts:

- The first part concerns the modeling of system degradation.
- The second part concerns the online implementation of prognostics at the system level.
- The third part is devoted to mission profile control in order to maximize the SRUL.
- The final part concerns the validation of the approach on a real industrial system, which is the Tennessee Eastman Process.

In the first part (corresponding to Chapter 2), the framework of degradation modeling at the system-level, which is the inoperability input-output model (IIM), is presented. This model has been widely used in other research fields and, in this thesis, is introduced and adapted for prognostics purposes. The developed IIM allows considering the interdependencies between components, component-specific degradations, and the effect of the mission profile. By using the concept of inoperability, this model can be applied to heterogeneous systems with different operating conditions, degradation mechanisms, and failure thresholds. The prognostics approach based on the IIM can be defined as a hybrid one because it considers 1) the characteristics of component degradation phenomena captured by model-based studies, 2) the interactions between components and the impact of mission profile that are identified based on monitoring data.

In Chapter 3, a methodology for online failure prognostics is presented. This methodology requires minimal input information on system degradation since the parameters of the IIM model are estimated online using our developed algorithm based on gradient descent. The resulting IIM model is then exploited by a particle filter to estimate the health state of the system, by taking into account the process uncertainty and the monitoring data received from the sensors. Once a fault is detected, and based on the functional architecture of the system, its estimated health state is propagated into the future to determine its SRUL. The results

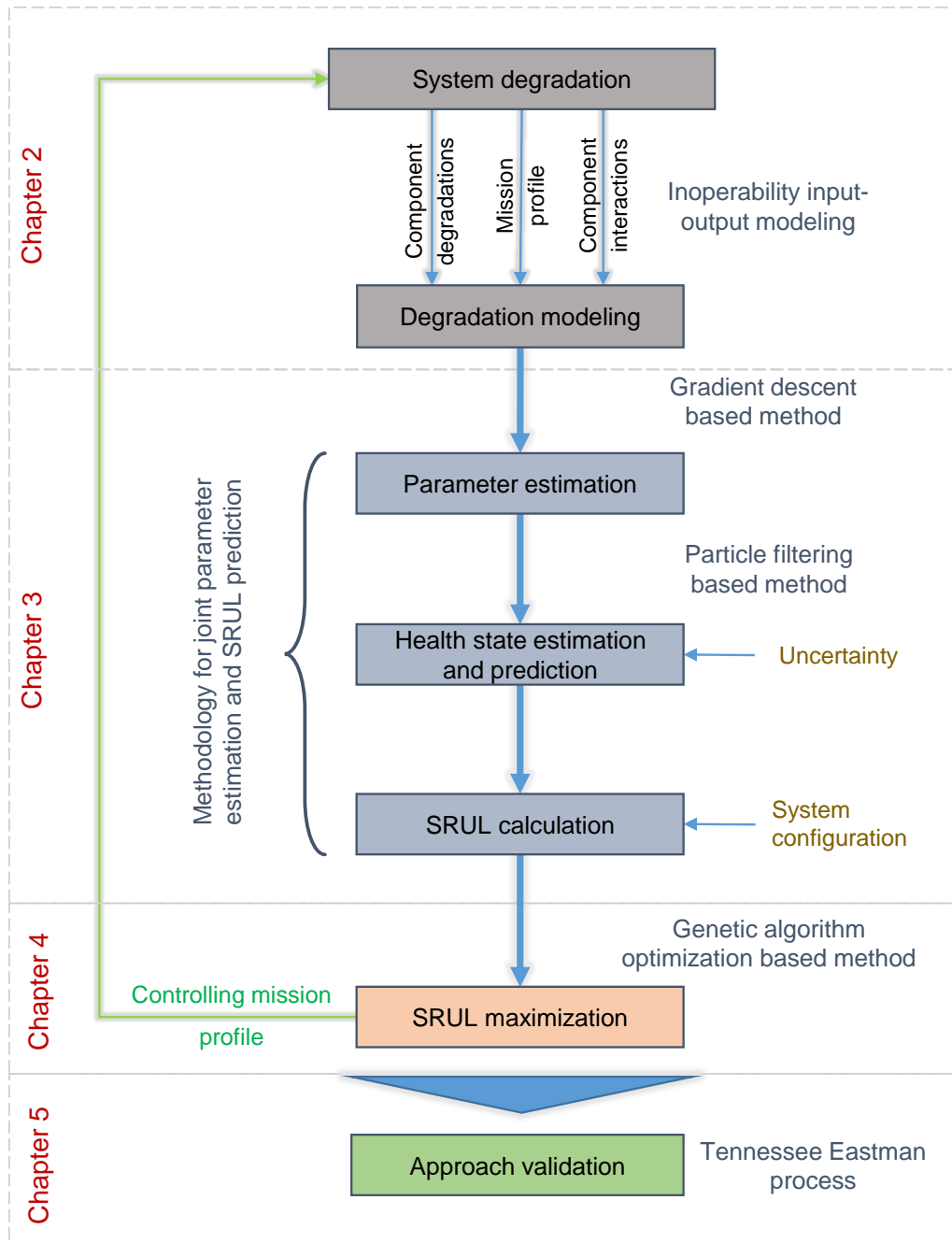


Figure 1.9: Synoptic scheme of the thesis.

of this methodology are evaluated, at each execution of the dedicated algorithm, to find a balance between prediction accuracy and computation time.

In Chapter 4, the impact of the mission profile on system degradation and on its SRUL are analyzed through the variation of its parameters, which are the load level and its duration. Then, the mission profile parameters are optimized, using an adaptive method based on a genetic algorithm, to maximize the SRUL while handling multiple operational constraints.

Once the modeling framework is set up, and the SRUL prediction methodology is developed, we are interested, in Chapter 5, in validating this approach on a real system, which is the Tennessee Eastman Process. To do so, the system health state is estimated and predicted by using a particle filter with an IIM whose parameters are estimated either online or offline. Besides, a sensitivity study is carried out to verify the variation in the results of the online prediction methodology in terms of prediction accuracy and calculation time.

1.5 Conclusion

In this chapter, a brief overview of the state of the art of prognostics and health management (PHM) is reported, and its relationship with maintenance is emphasized. This overview highlighted the limitations of component-level prognostics when dealing with complex systems. Those limitations mainly concern the assumptions of component independence and the availability of sufficient and representative data and knowledge about the system. Then, a comprehensive overview of system-level prognostics is presented through a new proposed definition and related issues and challenges. Also, different studies interested in system-level prognostics are reported through a new classification based on the granularity of the system modeling used: simplified modeling and holistic modeling. In each category, the classification is defined with respect to the methods and tools used. Finally, from the analysis of the identified gaps in the literature, we motivated our research work and explained the approach undertaken to contribute to filling them.

In the next chapter, we will present the first contribution of this thesis, which is the development of a modeling framework for scaling up from component- to system-level prognostics. This model, based on the inoperability input-output model (IIM), allows tackling the issues related to system-level prognostics such as modeling the interactions between the system components and the mission profile effect.

System degradation modeling: Inoperability Input-output Model

All models are wrong, but some
are useful.

George Box

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2.1 Introduction

The discussion of the related works in the previous chapter highlighted the literature gaps compared to practice requirements. One of the significant gaps is that none of the system-level prognostics (SLP) studies takes into account the mutual interactions among heterogeneous components, which further skews the estimation and prediction of system health state.

Therefore, in this chapter, the problem of modeling a multi-component system, where each component is subject to its degradation phenomenon, is addressed by using the inoperability

input-output model (IIM). First, the background of this model is presented, and its first utilization in economics and risk management are detailed in Section 2.2. Then, the adaptation and the usage of the IIM model in the field of SLP are exposed exhaustively in Section 2.3. Finally, its transposition to engineering areas is discussed by listing its advantages and drawbacks in Section 2.4.

2.2 IIM background

The inoperability input-output model is inspired by the input-output model (I-O) developed by Leontief Wassily in 1936 (Leontief, 1936). In this Section, we will trace the history of the IIM model (Figure 2.1), from the Input-output model to its adapted model used in this manuscript for prognostics.

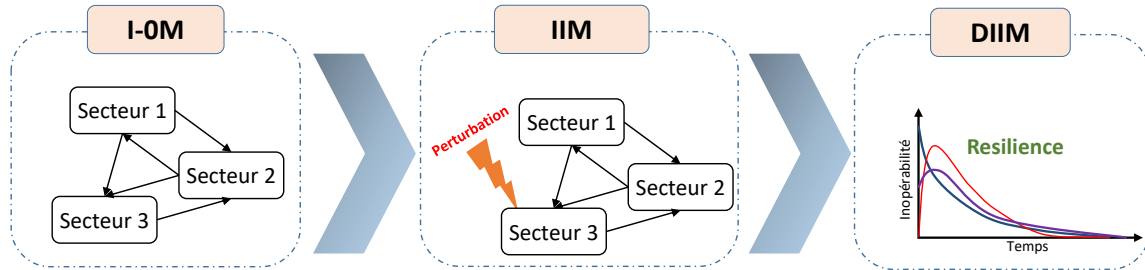


Figure 2.1: Historical evolution of the inoperability input-output model.

2.2.1 Input-output model

In economics, an input-output model is a quantitative model that represents the interdependencies between different sectors of a national economy or different regional economies (Leontief, 1936). Wassily Leontief (1906–1999) is credited with developing this type of analysis and earned the Nobel Prize in Economics for his formulation of this model.

The I-O model focuses on inter-industry analysis to determine the economic flows expressed as the number of goods exchanged between different sectors of activity. The model depicts inter-industry relationships within an economy, showing how the output from one industrial sector may become an input to another industrial sector (Miller and Blair, 1985) and describes the equilibrium behavior of both regional and national economies (Isard, 1966; Liew, 2000; Lahr and Stevens, 2002). For this purpose, a matrix called inter-industry matrix is introduced, where the values in the columns represent the inputs of an industry sector, while the values in the rows represent the outputs of a given sector.

To illustrate the use of the I-O model, let us consider an economy with n sectors, in which each sector i produces x_i units of a single homogeneous good. Assume that the j -th sector, in order to produce 1 unit, must use a_{ij} units from sector i . Furthermore, assume that each sector sells some of its output to other sectors (intermediate output) and some of its output to consumers (final output, or final demand). Let the final demand in the i -th sector be d_i .

Then, the relation between the production units of sector i with the ones of the other sectors are represented by the following equation:

$$x_i = a_{i1} \cdot x_1 + a_{i2} \cdot x_2 + \dots + a_{in} \cdot x_n + d_i$$

In other words, the total output equals the intermediate output plus the final output. If we let A be the matrix of coefficients a_{ij} (also called the matrix of technical coefficients), x be the vector of total output, and d be the vector of final demand, then our expression for the economy becomes:

$$x = A \cdot x + d \iff (I - A) \cdot x = d$$

If the matrix $I - A$ is invertible, we can rapidly derive the solution of this linear system, which is equal to $x = (I - A)^{-1} \cdot d$, given some final demand vector d . Furthermore, if the principal minors of the matrix $I - A$ are all positive (known as the Hawkins-Simon condition), the required output vector x is non-negative.

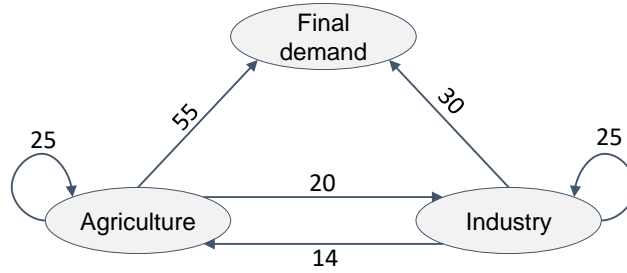


Figure 2.2: Example of simplified economic configuration.

For an illustration, a simplified macro-economic scheme is represented in Figure 2.2 through two sectors of activity: agriculture and industry. These two sectors produce goods for households (final demand) but also consume goods. The global productions x and the matrix of technical indices A are presented in Table 2.1.

Table 2.1: Example of technical factors in a simplified I-O model

		Outputs			Total production
		Agriculture	Industry	Final demand	
Inputs	Agriculture	$\frac{25}{100}$	$\frac{20}{100}$	$\frac{55}{100}$	100
	Industry	$\frac{14}{50}$	$\frac{6}{50}$	$\frac{30}{50}$	50

One of the challenges faced when applying the I-O model, in reality, is measuring or estimating the input-output tables (i.e. the matrix A). In fact, the mathematics of input-output economics is straightforward. Still, the data requirements are enormous because the expenditures and revenues of each branch of economic activity have to be represented. As a result, not all countries can collect the required data. However, many developed countries

estimate their input-output accounts annually and with much higher recency.

Other extensions were later created based on the original Leontief model, including the non-linear Leontief model (Krause, 1992), energy I-O analysis (Griffin and Gregory, 1976; Proops, 1984), and environmental I-O analysis (Converse et al., 1971; Lee, 1982). The authors in (Haines and Nainis, 1974) developed an I-O model of supply and demand in a regional water resources system. Olsen et al (Olsen et al., 1997) developed an I-O model for risk analysis of distributed flood protection. Extensions of I-O analysis are described in (Lahr and Dietzenbacher, 2001). I-O model has been widely used in planned economies (Moon, 1982) and is still used in the national accounts of several countries in the form of input-output tables (Yamano and Ahmad, 2006).

2.2.2 Inoperability input-output model

Grounded on Leontief's work, a first-generation inoperability input-output model (IIM) of interconnected systems was developed in (Haines and Jiang, 2001; Santos and Haines, 2004; Lian and Haines, 2006). This model, which can be considered as a physical-based one, was derived to express the global effects of negative events on highly interdependent infrastructures or multi-sector economies. The IIM considers multiple intra- and inter-connected systems. The output is the inoperability that can be triggered by one or multiple failures due to their inherent complexity or to external perturbations such as natural hazards, accidents, or acts of terrorism. It allows analyzing how these external perturbations, in an infrastructure, may affect other infrastructures, emphasizing the cascading effects and the intrinsic vulnerabilities. This dysfunctional model added the consideration of physical flows between infrastructures in addition to the economic flows taken into account in the I-O model.

In detail, the IIM aims to determine the inoperability of a system after an adverse event (Figure 2.1). The inoperability is defined as the inability of the system to perform its intended natural or engineered functions. In this model, the term inoperability can denote the level of the system's dysfunction, expressed as a percentage of the system's "as-planned" level of operation. Alternatively, inoperability can be interpreted as a degradation of a system's capacity to deliver its intended output or supply due to internal failures or external perturbations. Although inoperability in its current scope applies to physical and economic losses, it can be extended to assess the impacts of failures. Besides, other factors for assessing failures (e.g. loss of lives, environmental quality, etc.) can supplement the economic factors used in the context of inoperability. Therefore, the inoperability can take different forms, depending on the nature of the problem and the system under study. For instance, in circumstances where the level of production is a significant concern, it may be defined as the fraction between the unrealized production (i.e. the expected level of production minus the actual production) and the expected production level. For example, if the system under consideration is a power plant, its inoperability can be defined as the ratio between the unrealized energy (the difference between the desired and the produced energies) and the desired energy. The concept of inoperability also attempts to capture the quality of a system's function. Assuming that the quality can be quantified, then a defective system whose performance is of degenerate

quality (by opposition to a perfect system) will be considered partially operable and thus has a nonzero inoperability.

Without loss of generality, the inoperability of a component (sector or infrastructure) $q_i(t)$ is expressed as:

$$q_i(t) = \frac{|performance_i(t_0) - performance_i(t)|}{performance_i(t_0)} \quad (2.1)$$

where $performance_i(t_0)$ represents the flawless state (the non-degraded performance) and $performance_i(t)$ represents the current performance of the component in question.

In its static form, the IIM is presented under the following formula:

$$q = A \cdot q + c \quad (2.2)$$

where q is the inoperability of sectors, c is the inoperability brought by an external event (for example, a drop in demand, an industrial accident, etc.), and A is the matrix of interdependencies.

In the case of inoperability calculated according to Leontief's theory of economic equilibrium (Leontief, 1986), a static demand-reduction model (Haines et al., 2005) for n sectors or infrastructures is given by:

$$\delta x = A^* \cdot \delta x + \delta c^* \quad (2.3)$$

where δx is the difference between the planned production (x_0) and the degraded production (x_d), δc^* is the difference between the planned final demand (c_0) and the degraded final demand (c_d), and A^* is a square $n \times n$ matrix whose elements (a_{ij}^*) (Leontief technical coefficient) represent the ratio of the input from infrastructure i to infrastructure j with respect to the overall production requirements of infrastructure j .

The inoperability is computed by applying the following transformation to the reduction of production:

$$q = P \cdot \delta x$$

where P is $n \times n$ matrix (Haines et al., 2005) which is equal to:

$$P = [diag\{x_0\}]^{-1}$$

Following this transformation, the IIM has the form:

$$q = \tilde{A} \cdot q + \tilde{c} \quad (2.4)$$

where $\tilde{A} = P \cdot A^* \cdot P^{-1}$ and $\tilde{c} = P \cdot c^*$. Note that \tilde{c} assumes the role of an external induced inoperability. Although it is mathematically possible to have $a_{ij} > 1$, the \tilde{a}_{ij} coefficients are strictly less than one (Kujawski, 2006).

The inoperability q brought by the perturbation \tilde{c} is given by:

$$q = (I - \tilde{A})^{-1} \cdot \tilde{c} \quad (2.5)$$

As a result of equation 2.5, the elements in vectors q and \tilde{c} are equal to zero, unless an exogenous perturbation(s) occurred. In such a case, the shock on the demand side (i.e. one or more elements in \tilde{c} become positive) propagates to the economy output through the inverse $(I - \tilde{A})^{-1}$ (Percoco, 2006).

2.2.3 Dynamic inoperability input-output model

The static model of IIM does not take into account the evolution of the system after a perturbation. To address this issue, a dynamic IIM (DIIM) is introduced. This new formulation considers the return to equilibrium of a system after a perturbation (Lian and Haines, 2006):

$$q(t+1) = q(t) + K \cdot [A \cdot q(t) + c(t) - q(t)] \quad (2.6)$$

where K refers to the industry resilience coefficient matrix. Each element k_i in this matrix measures the resilience of sector i , given an imbalance between the supply and the demand. For instance, in the case of a terrorist attack or any other catastrophic event, k_i measures the recovery rate of the activity (or industry) sectors. For a demand reduction, k_i measures the production adjustment rate of the sector. In the case of physical infrastructure, this resilience capacity may refer to redundancies and the possibility of investing quickly in new equipment. For instance, Figure 2.3 represents the dynamic post-disruption recovery of four infrastructures (electricity production, rail transportation, water supply, and gas supply) after a reduction of 10% in electricity production (inoperability = 0.1).

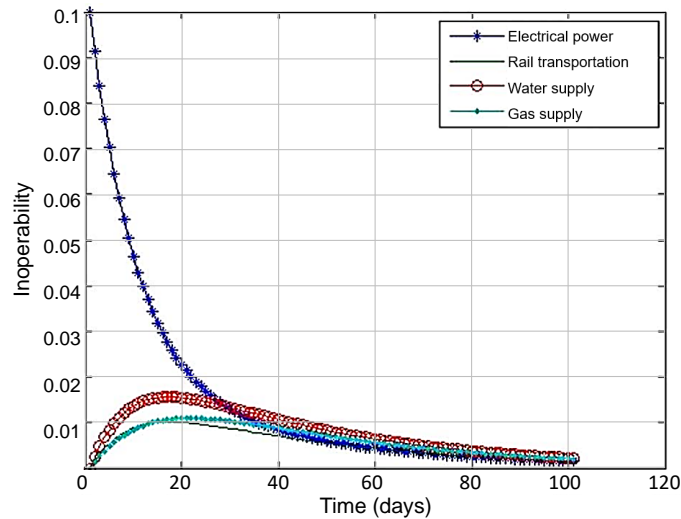


Figure 2.3: Recovery illustration in dynamic inoperability input-output of sectors after snow disasters reducing electricity production by 10 % (Xu et al., 2011).

Various extensions of the DIIM are proposed in the literature. One can cite the dynamic IIM (DIIM) with varying time perturbation (Orsi and Santos, 2010a), considering different perturbations that do not occur once but vary over time (for example, absenteeism problem in the case of an epidemic). One can also mention the work published in (Santos, 2008), where a probabilistic version of the IIM is proposed and applied in a transportation network. Finally, the authors in (Oliva et al., 2011) propose to use fuzzy logic to address the lack of statistical data within an uncertain context.

In recent years, the IIM and its extensions have been widely used in different domains other than economics, such as critical infrastructures (Reed et al., 2009; Setola et al., 2009; MacKenzie et al., 2012), supply-chain (Wei et al., 2010; Barker and Santos, 2010), information systems (Ali, 2018) and risk management (Tchangani, 2017). However, to the best of our knowledge, the IIM was not yet applied to engineering systems and even less to failure prognostics.

2.2.4 Beyond the state of the art

The IIM is originally interested in modeling interconnected infrastructures or economic sectors. However, in system-level prognostics, we consider engineering systems constituted of several components with their own degradation processes and their mutual interactions. Therefore, to apply the IIM (or the DIIM) in prognostics, we can assimilate each component to an infrastructure, and its influences on the degradation of other components can be assimilated to the interactions between the infrastructures. Despite this similarity, the IIM must be adjusted to apply in the field of SLP for the following three reasons:

1. For the IIM, which is applied to infrastructures or economics, the initial and external disruptions are considered and translated into an initial inoperability $q(t_0)$. The effect of a decrease in demand is expressed by the parameter $c(t)$. However, in prognostics, the degradations are internal to the system components and can be eventually accelerated by the influences of other components and by the environment.
2. The DIIM currently assumes monotonically decreasing functions to represent the recovery of directly affected sectors (Orsi and Santos, 2010b), while the uncertain behavior characterizing a system degradation is not fully accounted for in the existing DIIM formulations.
3. In the case of risk analysis and economics, the IIM aims to find the equilibrium point, i.e., the state preceding the disruption. Indeed, by assuming that the final demand is stationary, $c(t) = c$, the inoperability will reach an equilibrium when $q(t) = (I - A)^{-1}c$. However, for prognostics, one can assume easily that, without maintenance interventions, all systems will fail when t tends towards infinity (even if they have regeneration phenomena as in batteries (Li et al., 2014), for instance). Then, for engineering systems, the most important objective is to calculate the system failure times, because this is the information that interests the practitioners.

The next section will discuss the adaptation of IIM for modeling engineering complex systems and show its utilization for failure prognostics.

2.3 System-level modeling based on the IIM: application to prognostics

Before presenting the model that will be used to represent the degradation of multi-component systems, we will first detail the object of our study as well as the underlying assumptions. Thus, in this contribution, we are interested in systems constituted of M components that interact between them (differently depending on the system architecture) and influenced by the system mission profile (Figure 2.4). To this end, the following general assumptions related to component degradations are considered.

- The degradation process can be considered as a time-dependent or state-dependent process.
- The degradation of each component i is monitored by one or more appropriate sensors that provide noisy measurements. The sensors are selected based on the identified failure mechanisms to be tracked in time.
- The failure thresholds of the component degradation processes are supposed to be known. This represents a less restrictive assumption because the failure thresholds can be defined following run-to-failure experiments or chosen by the system's designers, experts, or operators for safety or operational reasons. The component failure thresholds can also be found in some standards.

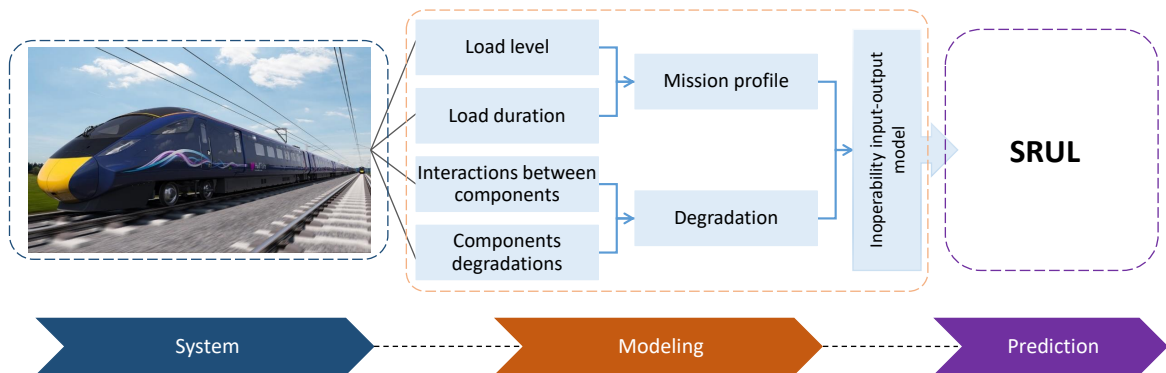


Figure 2.4: Summary of the IIM-based modeling approach.

With these assumptions in mind, the system degradation can be characterized by its inoperability, which is expressed at each time t by a vector $q(t)$ containing the inoperability of each component. Following that, the proposed IIM-based model for assessing the inoperability of complex systems and their components has been developed first in (Tamssaouet et al.,

2018). Assuming a first-order Markov process, the proposed model (Figure 2.4) follows this recursive formula:

$$q(t) = K(t).[A.q(t - 1) + c(t)] \tag{2.7}$$

where:

- $q(t)$ is a vector representing the overall inoperabilities of the system components at time t ;
- A is a matrix representing the multi-dimensional interdependencies between the system components;
- $c(t)$ represents the internal inoperabilities of the system components at time t ;
- $A.q(t)$ represents the inoperabilities of the components due to their interdependencies;
- $K(t)$ is a diagonal matrix representing the environment or mission profile effects on the component inoperabilities at time t .

As it can be seen in (2.7), the degradation of a component i , characterized by an inoperability $q_i(t)$, depends on its inherent natural degradation mechanisms expressed by $c_i(t)$ and on the degradation induced by the interactions with other components through the matrix A . Concerning the influence factor $K(t)$, it represents the dynamics of the degradation evolution, accelerating or reducing it, with respect to the environmental and the operating conditions.

In the following subsection, the different parameters of the proposed model will be discussed in detail.

Discussion of the IIM parameters

2.3.0.1 Inoperability

It corresponds to a column vector of inoperabilities of the n components of the system at time t :

$$q(t) = [q_i(t)]_{n \times 1} \quad ; \quad \forall i = 1, 2, \dots, n \tag{2.8}$$

Definition: The inoperability of a component $q_i(t)$ represents the decrease of its performance compared to its flawless state (non-degraded performance). In practice, the component performance can be related to its precision, its stability, etc. It is expressed as:

$$q_i(t) = \frac{|performance_i(t_0) - performance_i(t)|}{performance_i(t_0)} \tag{2.9}$$

For prognostics, and as shown in Figure 2.5, the inoperability can be interpreted as the ratio between G (distance between the system current state from its initial state) and H (distance between the initial state and the failure threshold). Furthermore, the inoperability holds the properties presented below.

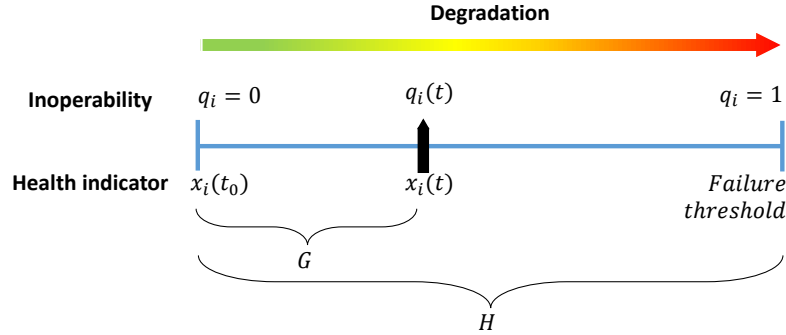


Figure 2.5: Schematic representation of the inoperability concept.

Inoperability properties:

- The inoperability of each component is a unique value between 0 and 1.
 - $q_i(t) = 0$: the component i is healthy (with an ideal performance);
 - $q_i(t) = 1$: the component i is considered faulty, i.e., the component has reached its failure threshold.
- In general, at the initial state, we have $t_0 = 0$ and $q_i(t_0) = 0$.

The inoperability of each component can be obtained by monitoring a health indicator (extracted from sensor signals) or a function combining several health indicators (using data fusion techniques). The calculation of a component inoperability from its monitored health indicator is explained hereafter.

Transforming a health indicator to an inoperability value

The health indicators of components are used to monitor the evolution of their degradations. They are derived from sensor signals or condition monitoring data related to the evolution of corresponding physical parameters (i.e. health indicator) such as presented in Figure 2.6. However, the values of these physical parameters vary over different intervals. To facilitate further analysis and assessment, they should be normalized in a range of $[0, 1]$. Therefore, the inoperability can be obtained from each component health indicator as follows:

$$c(t) = \frac{x(t) - x(t_0)}{L - x(t_0)} \quad (2.10)$$

where:

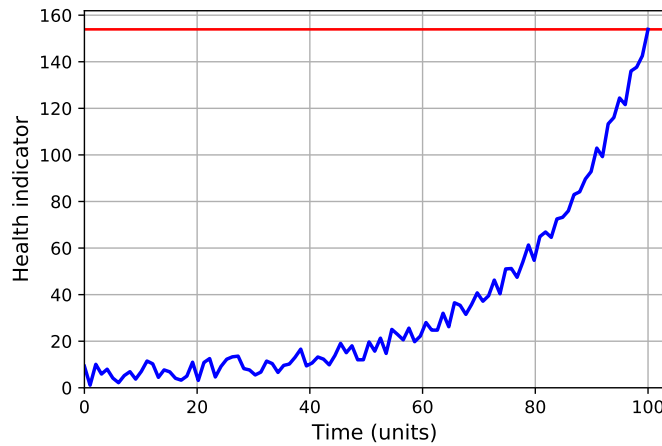


Figure 2.6: Simulated data of a health indicator degradation over time.

- $x(t)$ is the value of the health indicator at the current time t ;
- $x(t_0)$ is the value of the health indicator at the initial time t_0 ;
- L is the failure threshold corresponding to the health indicator.

This method is well suited to normalization because 1) it does not introduce distortion into data, as shown in Figure 2.7; and 2) presents a direct relationship between data before and after transformation. However, it assumes that all the input values of sensors belong to a known interval. If new data go outside the interval already set, the model will be distorted. This problem can be addressed by applying out-of-range methods, which discard the values that fall outside the determined intervals, or consider them equal to 1 (if $x(t) > L$) or 0 (if $x(t) < x(t_0)$).

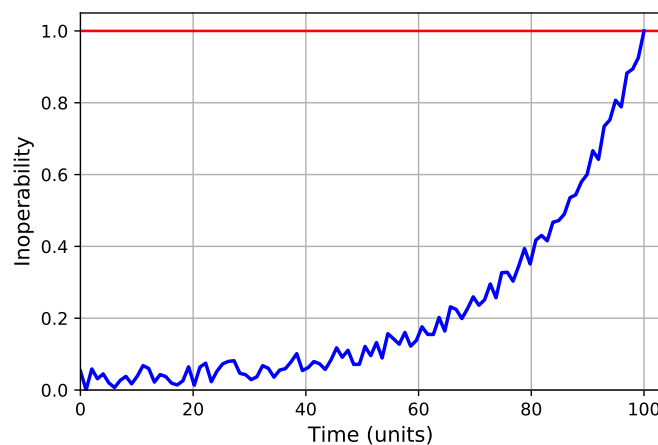


Figure 2.7: Transformation of health indicator to inoperability using direct standardization.

The normalization method based on the logistic function (sigmoid function) can also be used (Figure 2.8). This function transforms all the \mathbb{R} values of each health indicator into

values going from 0 to 1. However, in this case, it is necessary to transform the raw data x in x' :

$$x'(t) = \frac{x(t) - \tilde{x}}{\lambda \cdot \frac{\sigma}{2\pi}} \quad (2.11)$$

where \tilde{x} is the mean value, λ is the size of the response, and σ is the standard deviation. Thus, the normalized value can be obtained by using the logistic function:

$$c(t) = \frac{1}{1 + e^{-x'(t)}} \quad (2.12)$$

This method ensures that the inoperability interval $[0, 1]$ is not exceeded. Nevertheless, it involves a distortion in the inputs and therefore leads to loss of information about the nature of the degradation process.

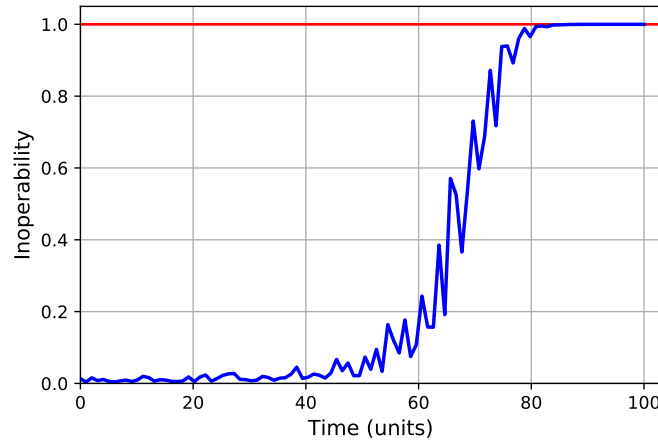


Figure 2.8: Transformation of health indicator to inoperability using logistic function.

In a nutshell, both of the above normalization methods allow addressing two problems of SLP: 1) different health indicators with heterogeneous intervals, and 2) different failure thresholds for homogeneous components. Indeed, a real system is a large assembling of components of different natures (mechanical, hydraulic, electrical, software, etc.). This, in turn, makes the normalization stage of utmost importance for system-level prognostics. The last advantage, but not the least, of transforming the health indicators into inoperability measures is the communication improvement with system managers. Indeed, for someone who is not familiar with the ranges of a health indicator, it is not easy to visualize the state of degradation of a component just by referring to the values of his related health indicator. However, by using inoperability, it is enough to multiply it by 100 to obtain a percentage of the degradation of a component, which is easily understandable. This enables, for example, to raise the awareness of decision-makers to the urgency of maintenance actions.

2.3.0.2 Matrix of interdependencies

This matrix formalizes the different interdependencies between the system components.

$$A = [a_{ij}]_{n \times n} \quad ; \quad \forall i, j = 1, 2, \dots, n \tag{2.13}$$

Each component a_{ij} of the matrix corresponds to the influence of the inoperability of a component j on the inoperability of a component i .

Table 2.2: Degradation influence between multiple components.

case	Description
$a_{ij} = 0$ and $a_{ji} = 0$	Component j and i are independently subject to gradual degradation.
$a_{ij} > 0$ and $a_{ji} = 0$	Component j influences unilaterally the degradation behavior of component i .
$a_{ij} > 0$ and $a_{ji} > 0$	Components j and i influence each other.

Properties of matrix A :

- A is a square matrix $n \times n$ where n is the number of components;
- The IIM can handle negative values of a_{ij} for the cases where the degradation of one component slows down the degradation of other system components. However, we focus on the more common and realistic cases where $a_{ij} \geq 0$ (McCall, 1965), i.e., when a component j is degraded, it does not affect ($a_{ij} = 0$) or accelerate ($a_{ij} > 0$) the degradation of a component i ;
- $a_{ij} = a_{ji} = 0$ means that there is no interaction between the components i and j ; and $a_{ij} = 0.5$ means that the inoperability of a component i is increased by half of the inoperability of a component j ;
- When $i = j$, $a_{ij} = 0$ because it is considered that the inoperability of a component does not affect the component itself;
- The bigger a_{ij} is, the greater is the influence of j on i .

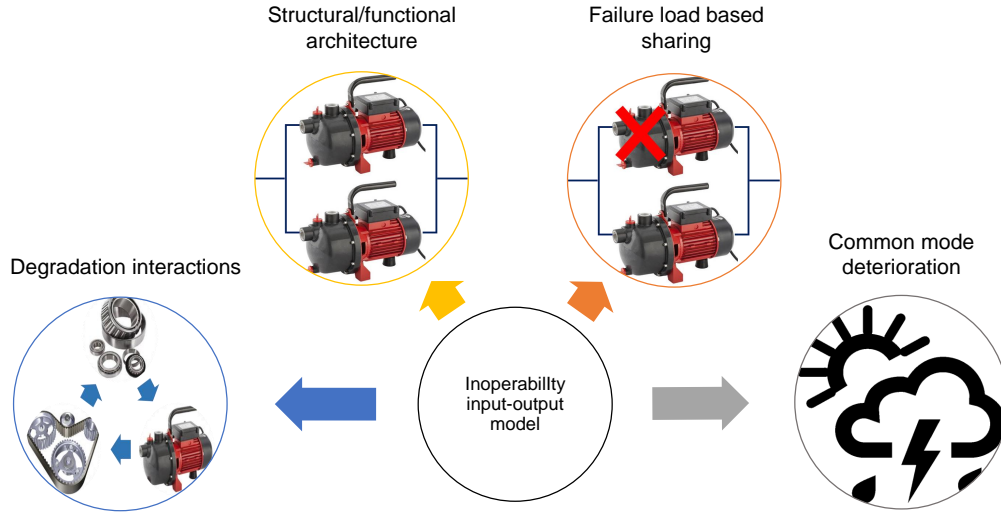


Figure 2.9: Interdependence types considered in modeling with the IIM.

2.3.0.3 Matrix of influence factors

As all systems interact with their environment, it is necessary to take into account the environmental conditions when considering the evolution of the system's health state. These conditions consist of environmental parameters (ambient temperature, humidity, etc.) or operating conditions, also called mission profile (setpoints, load durations, production loads, etc.), and affect the system during the major phases of its life cycle. In our model, these influence factors are represented by the matrix K :

$$K(t) = \text{diag}[k_i(t)]_{n \times n} \quad (2.14)$$

where k_i is specific to each component. Without loss of generality, k_i is assumed to be positive.

The added value provided by this factor is its variation over time, depending on the changes in the operating or environmental conditions. The meaning of the different values of k_i is explained in Table 2.3.

In table 2.3, when $k_i = 1$, it is considered that the environment has no influence on the component i at time t . Indeed, this means exactly that the inoperability of a component i is only due to its internal degradation and the degradation induced by other components.

It should be noted that here the interpretation of factor K differs from the one initially proposed in (Haimes and Jiang, 2001), where it expresses the restoration of the operability of a system. In our work, the factor K is used to take into account the effects of a mission profile on the evolution of system degradations. As shown in Figure 2.10, the variation of k_i will accelerate or decelerate the original degradation of a component i .

Table 2.3: Signification of the influence factor k .

	Inoperability	Meaning
$k_i = 0$	q_i is stationary	The component does not degrade.
$k_i > 0$	q_i varies over time	$k_i = 1$: Normal case when a system operates in a normal condition with a normal work load.
		$0 < k_i < 1$: When a system operates in a favorable environment or with a low work load, its degradation processes are slower than in the normal case.
		$k_i > 1$: Accelerated degradation due to a hostile environment or a high work load.

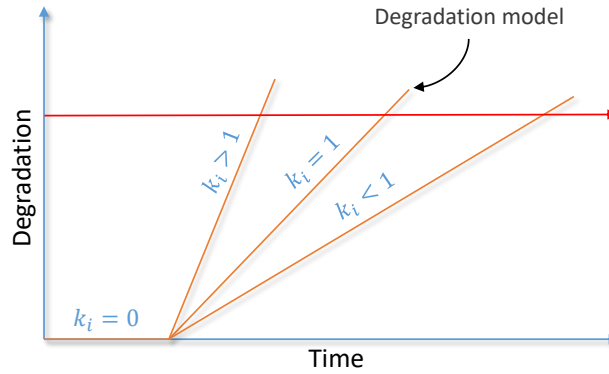


Figure 2.10: Degradation model variation in function of influence factor values.

2.4 Advantages of the use of the IIM in system-level prognostics.

2.4.1 Discussion of the advantage of the proposed IIM compared to the state-space model.

Currently, in the category of model-based prognostics approach, one of the most used models is the state-space representation (Sun et al., 2012b). The state-space representation model and the IIM seem to have the same structure. Nevertheless, the IIM focuses on system degradation modeling, which is the purpose of the prognostics, and this gives it several advantages (Table 2.4).

Firstly, the IIM allows modeling separately the degradation specific to each component and the degradation due to the interactions with other components. The obtained model

is, therefore, generic as it can be reused for modeling other systems by only changing the interdependency matrix A .

Secondly, the factor K , which represents the influence of the operating conditions (or mission profiles), is not directly a part of the degradation model, but it is a parameter that allows modifying the evolution of the degradation. This will make it possible to determine a direct relationship between system degradation and its mission profile to minimize the degradation and maximize the SRUL (Tamssaouet et al., 2019c).

Thirdly, by normalizing the health indicators in the IIM, heterogeneous systems can be considered. Indeed, in a complex system, several components are functioning in different ways to perform sub-tasks and achieve its primary function. Therefore, the components may have different degradation mechanisms and will be assessed with different health indicators and failure thresholds. The IIM is particularly adapted for this type of system since it proposes a single indicator of degradation, which is the inoperability, and a unified failure threshold (i.e. $q(t) = 1$).

The last advantage of using the IIM concerns improved communication with the managers of the systems. Indeed, it is not apparent for a layperson to visualize the state of degradation of a component by referring to the values of its health indicator (i.e., $x(t)$). To overcome this situation, it is enough to multiply the inoperability by 100 to obtain a percentage of the degradation of a component, which is easily understandable.

Table 2.4: Summary of the IIM's advantages over the state-space modeling.

IIM	State-space modeling
Heterogeneous components and thresholds	Homogeneous components
Reuse of components degradation model	Need to build degradation models for each system
Simple relationship between degradation and mission profile effect	Complex relationship between degradation and mission profile effect

2.4.2 Degradation interactions modeling using IIM

The proposed IIM can address a wide range of multi-dimensional interdependencies between the system components (Figure 2.9). These possibilities are described hereafter.

1. Stochastic interdependencies :

- The degradation interactions are characterized by the matrix A . In fact, this matrix represents the influence of the degradation of one component on the other components.

- The common-mode deterioration is represented by the matrix K . This matrix represents the acceleration or deceleration of component degradations due to the environment or mission profile effects.
 - The failure load based-sharing: this can be modeled by increasing the value of the matrix K when one component's inoperability reaches the value of 1.
2. For structural interdependencies, especially those related to performance, they are taken into account when calculating the SRUL as a function of the individual RULs of the components determined by propagating the IIM.

2.5 Conclusion

In this chapter, we were interested in modeling the degradation of multi-component systems by using the inoperability input-output model. This model has already demonstrated its effectiveness in the fields of economics and critical infrastructure management. In order to do so, we first explained the genesis of the IIM by beginning with Leontief's well-known input-output model. However, modeling in economics differs from that of engineering and, more specifically, that of prognostics. Based on this difference and prognostics specificities, the adaptation of the model was detailed with the new parameter meanings. As a result, the adapted IIM combines now information from the component degradations, the component interactions, and the mission profile effects to describe the overall degradation behavior of a given system. Moreover, the adapted model can be utilized for systems with heterogeneous components, different thresholds, and non-linear dynamic behaviors. Besides, through the concept of inoperability, the IIM eases communication with system managers and decision-makers.

Having a modeling framework able to represent the system degradation comprehensively, we propose in the next chapter a methodology for estimating the different parameters of the IIM and its utilization for failure prognostics.

System health state estimation and SRUL prediction

Critical thinking is an active and ongoing process. It requires that we all think like Bayesians, updating our knowledge as new information comes in.

Daniel J. Levintin

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3.1 Introduction

In the last chapter, a modeling framework for system-level prognostics (SLP) is presented. However, one of the principal barriers when deploying a mathematical model in practice is the identification of its parameters. Then, the model can be used to estimate and predict the system's health state. Nevertheless, because of the inherent stochasticity of the degradation phenomena, the model's results and parameters should be continuously adjusted to be consistent with reality. Hence, this chapter aims to provide a methodology for online joint

degradation model parameter estimation, system health state estimation, and SRUL prediction. For this purpose, the inoperability input-output model, introduced in the previous chapter, will be used.

This chapter is organized as follows. Section 3.2 presents a procedure to identify the IIM parameters either by using run-to-failure data or from online data. Section 3.3 details the health state estimation and prediction, and describes the probabilistic calculation of the IIM. Finally, section 3.4 deals with the proposed online methodology for estimating the IIM parameters and the determination of the SRUL.

3.2 Construction of system degradation model

In order to properly model system degradation processes, it is necessary to analyze its functioning and monitor its health state. In this perspective, in the following subsections, the analysis prior to prognostics implementation is developed. Then, a method for estimating the parameters of the IIM is presented. The obtained model will be used to continuously estimate and predict the system health state.

3.2.1 Functional and dysfunctional system analysis

To build a representative system degradation model, it is necessary to study the system's behavior, and perform functional and dysfunctional analyses before deploying an effective monitoring process. These studies allow providing the following essential information:

1. **Critical components to be monitored.** In general, systems have numerous elements interacting with each other, but not all of them may cause the interruption of their primary tasks. With the resource optimization performed in manufacturing, most of the system components contribute, in one way or another, to realize or maintain its main function. However, not all of these components are critical, i.e., significantly contribute to the evolution of the system degradation process, and thus do not warrant increased monitoring of their health state. Thus, a selection of critical components to be monitored must be made before implementing any monitoring process. This can be achieved by using risk analysis and/or dependability methods (Brahimi et al., 2017; Sarih et al., 2018).
2. **Selection of physical parameters to monitor.** After locating the critical components, the system expert should identify the appropriate physical parameters to monitor. These parameters are chosen on the basis of experience feedback gathered during the exploitation of the system. Therefore, it is necessary to know the failure modes that may affect the system components, and thus, depending on these modes, choose one or more parameters to be monitored (Mosallam et al., 2015).

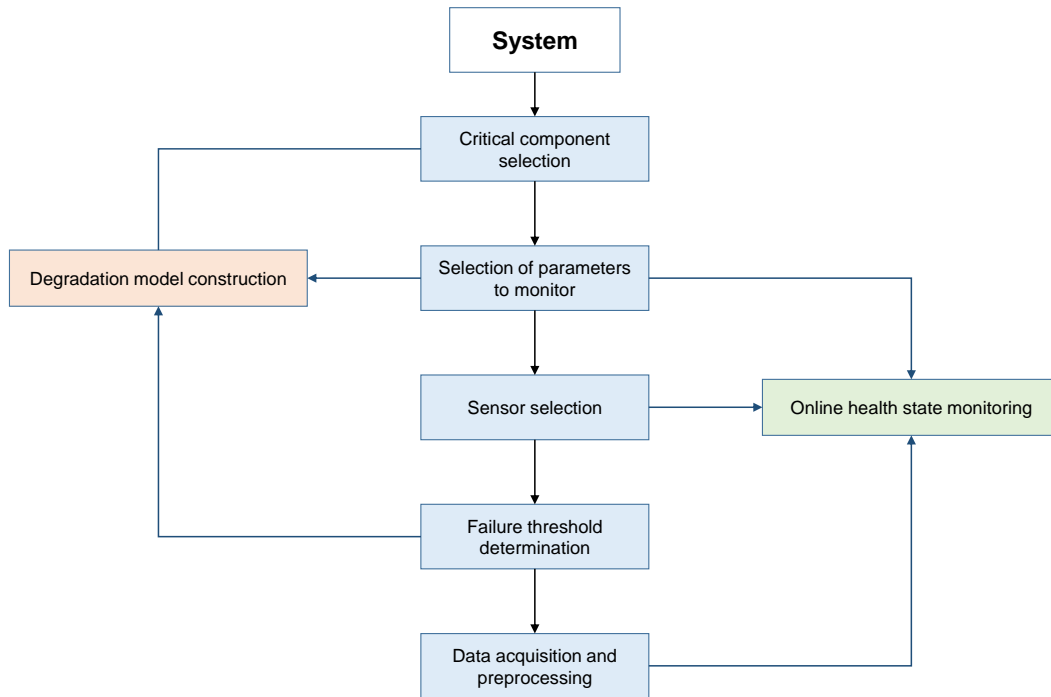


Figure 3.1: System analysis prior to system degradation modeling.

3. **Sensor selection.** After selecting the parameters representing the degradation process, it is necessary to choose the appropriate sensors to record representative data. A sensor is a device that receives a stimulus and responds with an electrical signal. Various sensors, such as vibration, temperature, current, acoustic emissions, etc., can be used to collect different types of measurements. Wireless technologies, such as Bluetooth, provide an alternative solution to cost-effective data communication. The criteria for selecting sensors for monitoring a system should consider six aspects: parameters to be monitored, reliability, accuracy, span, resolution, characterizes properties, and cost (Cheng et al., 2008).
4. **Failure threshold determination.** The problem of determining failure thresholds remains a crucial hurdle for the deployment of a model-based prognostics approach. In practice, several ways, such as statistical or expert knowledge-based, can be utilized to set the failure threshold. First, statistical methods are either experimental (run-to-failure experiments) or simulation-based (if the degradation phenomenology is known and modeled). The obtained failure threshold can be a single value (if only one simulation/experiment is conducted) or distribution if several experiments/simulations are done (which corresponds to the notion of hazard zone (Saxena et al., 2010; Tang et al., 2011)). Second, failure thresholds can be chosen by the system's designers, experts, or operators for safety or operational reasons. Finally, they can be found in standards.
5. **Data acquisition and pre-processing.** Once the sensors are chosen and installed on the components to be monitored, the corresponding signals are first pre-processed before using them for prognostics purpose. Data pre-processing involves data cleaning,

for errors/noise cancellation, and data analysis, for in-depth interpretation (Gouriveau et al., 2016).

The acquired representative and reliable data are used to build degradation models for failure prognostics. Hence, the next subsection presents the proposed model parameter estimation method. The estimation can be done offline (with run-to-failure experiments) or online (with the actual monitoring data).

3.2.2 Model parameter estimation

In a model-based prognostics approach, data are mainly used to identify and update the parameters of a pre-determined degradation model. Indeed, the model structure is usually constructed based on physical laws (phenomenological models) or accelerated aging experiments (empirical models). However, its parameter values are generally unknown and must be determined or adjusted to fit the case study. Thus, determining a model is equivalent to searching for its parameters to minimize the error between the values predicted by the model and those given by the real measurements. In the literature, there exist numerous methods that can be applied for parameter estimation. Among them, the gradient descent (GD) method (Snyman and Wilke, 2018) is proposed for this work. The following subsection motivates the choice of this method and presents its utilization for the IIM parameter estimation.

3.2.2.1 Gradient descent method for the IIM parameter estimation

Among the reasons which justify the choice of the gradient descent method for estimating the IIM parameters, we can cite the following ones.

- It can be applied for linear/non-linear models. Indeed, the only requirement for a function to be minimized with the GD is to be differentiable.
- It can effectively handle a great number of parameters at the same time. This suits the case of SLP, where it is necessary to simultaneously estimate multiple parameters related to the system components.
- It is an easy method to implement and is also flexible: the stopping criterion can be determined regarding the trade-off between the needed accuracy and the available computing resources.
- Compared to other methods, such as Newton's method or inversion of the Hessian using conjugate gradient techniques, GD may have a rather slow convergence. However, it is not computationally intensive, making it suitable for an online application.

Furthermore, thanks to its extensions, GD can be adapted to various case studies. Indeed, depending on the amount of available data used, we can classify the algorithms of the gradient descent into 3 groups (Snyman and Wilke, 2018).

1. **Batch gradient descent (BGD):** also known as Vanilla GD, utilizes the entire training data in order to estimate the unknown parameters.
2. **Stochastic gradient descent (SGD):** performs a parameter update with respect to randomly selected samples.
3. **Mini-batch gradient descent (MGD):** this approach uses random samples but in batches. This means that we do not calculate the gradients for each observation but for a group of observations.

In contrast with batch gradient descent, stochastic gradient descent and mini-batch gradient descent may have a faster convergence. Still, in the case of very noisy data, they can suffer from oscillation and volatile estimation. This is due to the fact that the randomly selected data used to calculate the gradients cannot be representative of the modeled behavior. Since the only difference between the three methods is the size of the data samples used to calculate the gradient, we opted, in the first instance, for a BGD-based algorithm, which is presented hereafter.

In this framework, by using GD algorithm, the IIM parameters are identified to minimize the mean squared error (MSE) between the inoperability estimated by the model, \hat{q}_i , and the in-field measured inoperability, q_i :

$$\mathcal{L}(\hat{q}_i, q_i) = \frac{1}{N}(\hat{q}_i - q_i)^2 \quad (3.1)$$

The algorithm 1 describes how to determine all the IIM parameters, including the internal inoperability evolution of every component $c_i(t, \theta_i)$, the interdependencies matrix A and the matrix of the external influencing factors K . Without loss of generality, let us consider that $c_i(t, \theta_i)$ is a differentiable multi-variable function of time ¹ and other parameters θ_i that need to be estimated. In Algorithm 1, the stopping criterion Sc can be set as a fixed number of iterations, a given value of MSE (less is the MSE more is the accuracy of the model) or when an optimum is reached (a null gradient).

The gradient descent can be combined with a line search for finding the locally optimal step size γ on every iteration. Performing the line search can be time-consuming while using a fixed small γ can yield poor convergence. In this document, we propose to use Nesterov accelerated gradient (NAG) because it is not computationally consequent and speeds the GD convergence drastically (Ruder, 2016). NAG first makes a big jump in the direction of the previously accumulated gradient, measures the gradient, and then makes a correction, which results in a complete gradient update. This anticipatory update prevents from going too fast

¹The same procedure can be applied for a state-based model (recursive model).

Algorithm 1 General algorithm for estimating the IIM parameters related to a component i

1. Set initial values of the IIM parameters $(a_{ij}^0, k_i^0, \theta_i^0)$
2. Set a stopping criterion Sc
3. At the $(h + 1)$ -th iteration step $(h \in N^+)$, **while** Sc not satisfied

- Evaluate $\hat{q}_i(t) = k_i^h \left[\sum_{j=1, j \neq i}^M a_{ij}^h q_j(t-1) + c_i(t, \theta_i^h) \right]$
- Calculate the gradients regarding each parameter: $\frac{\partial \mathcal{L}}{\partial k_i^h}, \frac{\partial \mathcal{L}}{\partial a_{ij}^h}, \frac{\partial \mathcal{L}}{\partial \theta_i^h}$
- Update the IIM parameters:

$$k_i^{h+1} = k_i^h - \gamma \frac{\partial \mathcal{L}}{\partial k_i^h} = k_i^h - \gamma \frac{2}{N} \left[\sum_{j=1, j \neq i}^M a_{ij}^h q_j(t-1) + c_i(t, \theta_i^h) \right] (\hat{q}_i - q_i)$$

$$a_{ij}^{h+1} = a_{ij}^h - \gamma \frac{\partial \mathcal{L}}{\partial a_{ij}^h} = a_{ij}^h - \gamma \frac{2}{N} q_j(t-1) (\hat{q}_i - q_i)$$

$$\theta_i^{h+1} = \theta_i^h - \gamma \frac{\partial \mathcal{L}}{\partial \theta_i^h} = \theta_i^h - \gamma k_i^h \frac{2}{N} \frac{\partial c(t, \theta_i)}{\partial \theta_i^h} (\hat{q}_i - q_i)$$

4. end **while**
-

and results in increased responsiveness, which significantly increases the performance of the GD.

Depending on the prior knowledge available about the system, Algorithm 1 can be adapted to estimate only the unknown parameters. In the next subsection, different cases with various levels of the prior system knowledge will be explored to illustrate the performance of the proposed algorithm for the estimation of the IIM parameters.

3.2.2.2 Investigation on the proposed algorithm performance for the IIM parameter estimation

In order to investigate the performances of the proposed algorithm for the IIM parameter estimation, let us consider a system with three components: component #1, #2, and #3, which are subject to specific degradations due to erosion and fatigue. The inner component degradation models are chosen to be linear and non-linear as follows:

$$c(t) = \begin{bmatrix} c_1(t) \\ c_2(t) \\ c_3(t) \end{bmatrix} = \begin{bmatrix} 2 \cdot 10^{-5} \cdot t + 10^3 \\ 6 \cdot 10^{-9} \cdot t^2 \\ 3 \cdot 10^{-3} \cdot e^{1.1 \cdot 10^{-4} \cdot t} \end{bmatrix}$$

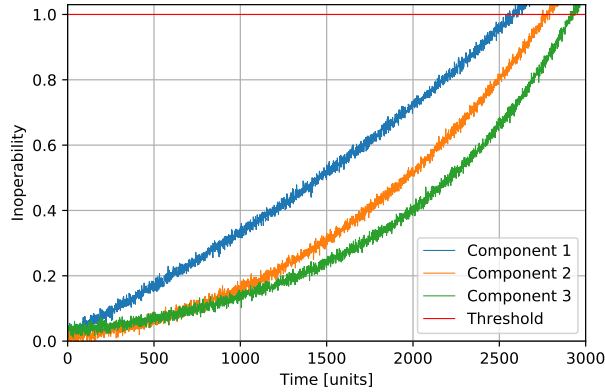


Figure 3.2: Inoperability evolution of a system with three components.

The components also interact between them, which increases their inoperabilities. In addition, they are influenced by the system’s mission profile, which changes the rate of their degradation. This mission profile accelerates the degradations of the two components #1, #2, and decelerates the degradation of the component #3. The matrices A and K are given as follows:

$$A = \begin{bmatrix} 0 & 0.2 & 0.1 \\ 0.1 & 0 & 0.3 \\ 0.06 & 0.26 & 0 \end{bmatrix}; K = \begin{bmatrix} 1.3 & 0 & 0 \\ 0 & 1.2 & 0 \\ 0 & 0 & 0.9 \end{bmatrix}$$

By using these parameters, the data representing the inoperability evolution of the components are generated, as shown in Figure 3.2. In this simulation, a Gaussian noise with the distribution $\mathcal{N}(\mu, 0.01)$ is added to represent the stochastic aspect of degradation. The objective now is to investigate if the proposed algorithm can retrieve the correct IIM parameters with these data.

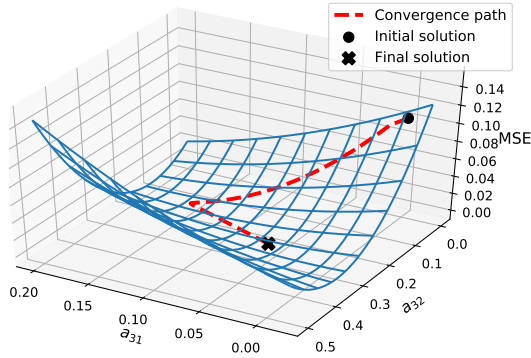
Case with the assumption that the component degradation models and the mission profile effects are known

Some works on SLP have already considered the case where the component degradation models and the mission profile effects are known (Daigle et al., 2012; Benagoune et al., 2018). However, these studies ignored the interactions between the components, which may affect the accurate prediction of the SRUL. Therefore, it is necessary to take into account the mutual interactions between the components to avoid the bias in the SRUL prediction.

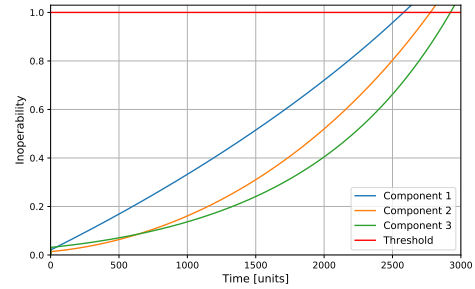
To determine the interdependencies matrix while assuming that the component degradation models and the mission profile effects are known, the GD-based algorithm is tuned as follows: the stopping criterion Sc is a null gradient, the learning rate γ is equal to 0.01, and the initial values of the matrix A_{init} are set to zero, i.e., $A_{init} = 0_{(3,3)}$. By using an Intel core iZ 7700 and 16 Gb RAM under a Python environment, the algorithm converges within 7 seconds. As shown in Figure 3.3a, the parameters concerning component #3 (i.e. a_{31} and a_{32}) converge from the initial solution to the final solution while the MSE is decreasing. The

complete estimated matrix A is given as follows:

$$A = \begin{bmatrix} 0 & 0.2001 & 0.995 \\ 0.0999 & 0 & 0.3005 \\ 0.0598 & 0.2613 & 0 \end{bmatrix}$$



(a) Convergence path of the matrix A (component #3).



(b) Evolution of the component inoperabilities using the estimated model.

Figure 3.3: Case with component degradation models and environment effects known.

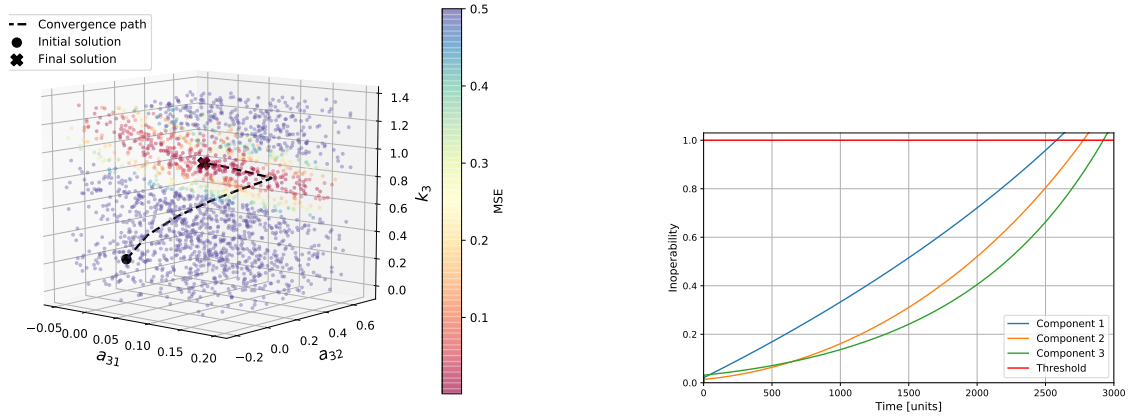
As one can notice, the estimated matrix A is very close to the one used to generate the simulated data. This small difference is due to the added noise. By using this estimated matrix and the prior knowledge on the system, the inoperability evolution of the components shown in Figure 3.3b are similar to the ones in Figure 3.2.

Case with the assumption that the component degradation models are known

Another factor that makes bias to prognostics predictions and increases the uncertainty related to its results is the impact of mission profile (MP). Indeed, the degradation model can be obtained from run-to-failure experiments that are conducted under predefined conditions. However, in practice, the components undergo other conditions related to the MP of the system. Indeed, if the system MP is more stressful than the conditions under which the degradation models were determined, the SRUL prediction will be more optimistic, and this can expose the system and its users to serious danger because the maintenance interventions will be planned after the failure. Otherwise, the maintenance actions can be planned well before the system fails, and this will reduce the system productivity and profitability. Therefore, the operating conditions under which the system evolves should be taken into account to increase the prediction accuracy.

For this case study, in order to determine the interdependencies and the influence factors matrices while assuming that the component degradation models are known, the proposed algorithm is tuned as follows:

- The stopping criterion is a null gradient;



(a) Convergence path of the parameters A & K (component #3).

(b) Component inoperabilities evolution using the built model.

Figure 3.4: Case with only component degradations models known.

- The learning rate is equal to 0.01;
- The initial solutions are set as follows: $A_{init} = 0_{(3,3)}$ and $K_{init} = 0_{(3,3)}$.

Considering a total of 8 unknown parameters, the algorithm converges within 47 seconds. As shown in Figure 3.4a the parameters of component #3 (i.e. a_{31} , a_{32} and k_3) are moving from the initial solution to the final solution while MSE is decreasing through iterations. The estimated matrices A and K are given as follows:

$$A = \begin{bmatrix} 0 & 0.1964 & 0.1013 \\ 0.09765 & 0 & 0.2987 \\ 0.065 & 0.2515 & 0 \end{bmatrix}; K = \begin{bmatrix} 1.304 & 0 & 0 \\ 0 & 1.205 & 0 \\ 0 & 0 & 0.9034 \end{bmatrix}$$

As one can notice, the values of A and K are very close to those used to generate the simulated data. We can also notice that the accuracy of the estimation diminishes slightly compared to the case when only the matrix A is estimated. This is because it is difficult to distinguish between the degradations, which are due to the interdependencies and those related to the MP effects. By using this estimated matrices A and K , the inoperability evolution of the components shown in Figure 3.4b are similar to the ones in Figure 3.2.

Case with unknown values of all the IIM parameters

In this case, the only information available on the system is the trend of its component degradations. Therefore, the IIM parameters to be estimated are A , K and $c(t)$. Because of this wide range of unknown parameters, we propose to apply a stochastic gradient descent. This extension of the GD algorithm consists of the estimation of the model parameters by using only a randomly selected subset of the data rather than the entire data set. This allows reducing the computational burden and achieving faster convergence (Snyman and Wilke,

2018).

The initial solutions supplied to the algorithm are as follows: $A_{init} = 0_{3,3}$, $K_{init} = I_3$ and

$$c_{init}(t) = \begin{bmatrix} 0.001 \cdot t + 0.001 \\ 0.0001 \cdot t^2 \\ 0.0001 \cdot e^{0.0001 \cdot t} \end{bmatrix}$$

The application of the SGD algorithm leads to the following results:

$$c(t) = \begin{bmatrix} 2.4 \cdot 10^{-5} \cdot t + 0.005 \\ 7.3 \cdot 10^{-9} \cdot t^2 \\ 3 \cdot 10^{-3} \cdot e^{0.5 \cdot 10^{-4} \cdot t} \end{bmatrix}; A = \begin{bmatrix} 0 & 0.23 & 0.08 \\ 0.099 & 0 & 0.29 \\ 0.09 & 0.22 & 0 \end{bmatrix}; K = \begin{bmatrix} 1.29 & 0 & 0 \\ 0 & 1.19 & 0 \\ 0 & 0 & 0.87 \end{bmatrix}$$

As one can notice, in this case, the accuracy of the estimation is lower than if there is prior information on the system degradation. However, by using these obtained parameters, the inoperability evolution of the components shown in Figure 3.5 is also close to the true ones presented in Figure 3.2. Indeed, the SRUL obtained using the estimated parameters, while considering a series configuration, is equal to 2678 time units against 2582 for the true one. This is still a good result, that is only drifted by 3.7% from the correct value, in regards to the little prior information available about the system.

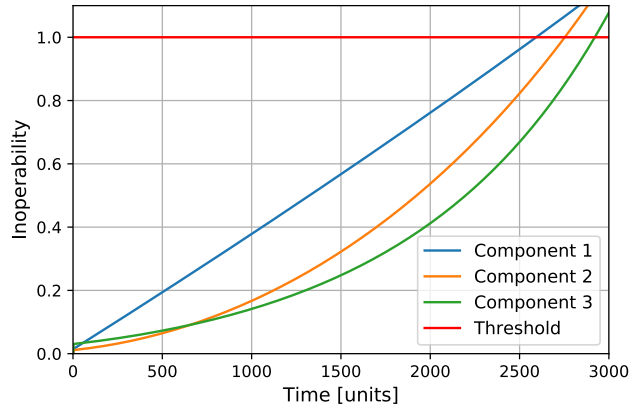


Figure 3.5: Component inoperabilities evolution using an estimated IIM with a minimum of prior information.

Once the IIM model is determined, it will be used to assess the system's health state and its future evolution to predict its system remaining useful life, which is the subject of the next section.

3.3 System health state estimation and prediction

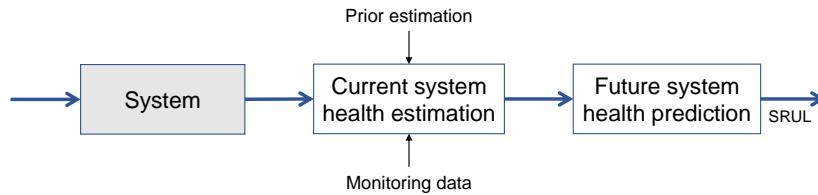


Figure 3.6: Health monitoring steps.

Failure prognostics, strictly speaking, is divided into two main phases: estimating the actual health state and predicting its future evolution (Figure 3.6). However, these two phases must be done online and adapted to the system's current situation. This constitutes the main difference between prognostics and reliability (Acuña and Orchard, 2018). Indeed, in reliability, one has a functioning scheme allowing to know the statistical health state evolution of the system by using distributions such as exponential or Weibull ones (Elsayed, 2012). This approach (also known as survival method) assumes that several statistically identical items (equipment, components, or systems) initiate the operation at the same time. The probability of successfully accomplishing their purpose along a stated time interval (i.e. the reliability function) can be estimated as the ratio among the number of items that succeeded the mission over the total amount of items. However, this reliability function corresponds only to prior knowledge about the evolution of failure risk without taking into account the unit-to-unit difference in items and the actual state of each item. In summary, the survival method makes it possible to adapt the bathtub reliability curve (Figure 3.7) to each component but without providing information on the specific and the actual behavior of each item.

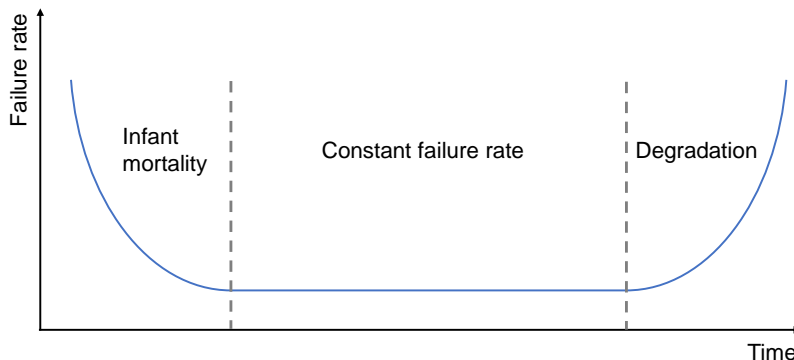


Figure 3.7: Bathtub reliability curve.

To rectify this limitation of the survival method, one of the first methods proposed for model-based prognostics is the similarity-based method. The main idea of this method is to construct many offline possible sub-models for degradation indicator and then choose online the best sub-model given the monitoring information (Eker et al., 2014). This method may be relevant for a linear, stationary, white-noised system. However, in the case of a non-linear, non-stationary system, it is impossible, and at best very expensive, to predict all the possible behaviors of a system in advance.

The approach that has since gained consensus for the implementation of a model-based prognostics is the Bayesian approach (Jouin et al., 2016). The latter is based on a model that gives prior estimates of the system health state and, by using actual measurements of the system, allows prior estimates to be corrected to obtain posterior estimates based on the Bayes rule. This procedure is also known as state filtering, which is the subject of the next subsection.

3.3.1 System health state filtering

In the following, considering a multi-component system, the degradation state and the state noise of its components at time step t_k are respectively noted by vectors x_k and w_k while y_k and v_k represent the measurement and the measurement noise captured by the sensors at the current time. The system degradation evolution, x_k , is described by the state-space model:

$$\begin{aligned}x_k &= f_k(x_{k-1}, w_{k-1}) \\ y_k &= h_k(x_k, v_k)\end{aligned}\tag{3.2}$$

where

- $f_k : \mathbb{R}^{n_x} \times \mathbb{R}^{n_w} \rightarrow \mathbb{R}^{n_x}$ is the state transition function that is possibly non-linear;
- $\{w_k, k \in \mathbb{N}\}$ is an independent identically distributed (*i.i.d.*) state noise vector sequence of known distribution;
- $h_k : \mathbb{R}^{n_x} \times \mathbb{R}^{n_v} \rightarrow \mathbb{R}^{n_z}$ is the measurement function that is possibly non-linear;
- $\{v_k, k \in \mathbb{N}\}$ is an *i.i.d.* measurement noise vector sequence of known distribution.

The measurements $\{y_k, k \in \mathbb{N}\}$ are, thus, assumed to be conditionally independent given the state process $\{x_k, k \in \mathbb{N}\}$ described by a first-order Markov model.

The Bayesian solution to the problem of estimating the dynamic state x_k , given the measurements y_k up to time k is sought in terms of the probability density function (PDF) $p(x_k|y_{0:k})$. This PDF contains all the information about the state x_k , which is inferred from the measurements $y_{0:k} = \{y_m, m = 0, \dots, k\}$ and the initial distribution of the system state $p(x_0)$ which is assumed known.

In the so-called prediction step, the Chapman-Kolmororov equation is used to obtain the prior probability distribution of the system state x_k at time k , starting from the probability distribution $p(x_{k-1}|y_{0:k-1})$ at time $k-1$ (Arulampalam et al., 2002; Li and Kadiramanathan, 2001):

$$\begin{aligned}p(x_k|y_{0:k-1}) &= \int p(x_k|x_{k-1}, y_{0:k-1})p(x_{k-1}|y_{0:k-1})dx_{k-1} \\ &= \int p(x_k|x_{k-1})p(x_{k-1}|y_{0:k-1})dx_{k-1}\end{aligned}\tag{3.3}$$

in which the transition probability distribution $p(x_k|x_{k-1})$ is defined by the system equation 3.2, with a known distribution of the noise vector w_k , and where the Markovian assumption underpinning the system model presented by equation 3.2 is used.

At the time k , a new measurement y_k is collected and used to update the prior distribution, via Bayes rule, and then obtain the required posterior distribution of the current state x_k (Arulampalam et al., 2002):

$$p(x_k|y_{0:k}) = \frac{p(x_k|y_{0:k-1})p(y_k|x_k)}{p(y_k|y_{0:k-1})} \quad (3.4)$$

where the normalizing constant is

$$p(y_k|y_{0:k}) = \int p(x_k|y_{0:k-1})p(y_k|x_k)dx_k \quad (3.5)$$

The recurrence relations 3.3 and 3.4 give the exact Bayesian solution (Doucet et al., 2000; Doucet et al., 2001; Arulampalam et al., 2002). Unfortunately, except for few cases, e.g., linear Gaussian state-space models (Kalman filter (Kalman, 1960)) or Gaussian state-space models with slight non-linearity (Extended Kalman filter (Smith et al., 1962)), it is not possible to calculate analytically these distributions (Table 3.1), since they require the calculation of complex high-dimensional integrals.

Table 3.1: Bayesian methods for model-based prognostics.

Kalman filter	Extended Kalman filter	Unscent Kalman filter	Particle filter
Exact solution only for: <ul style="list-style-type: none"> • linear systems • additive Gaussian noises 	Analytical approximation. It is accurate only for systems with: <ul style="list-style-type: none"> • slight non-linearity • Gaussian noises 	Analytical approximation. It can be applied for: <ul style="list-style-type: none"> • non-linear systems • Gaussian noises 	Numerical approximations which, within limits, tend to be accurate. It can be applied for: <ul style="list-style-type: none"> • non-linear systems • non-Gaussian noises

One way to overcome this problem is to resort to Particle filtering (PF) method (also called Monte Carlo sampling) (Arulampalam et al., 2002), which is a popular technique explored by several works in prognostics domain (Orchard, 2006; Acuña and Orchard, 2017; Wang et al., 2019). This tool can be applied to systems with non-linear dynamics and non-Gaussian noises.

The traditional utilization of PF is concerned with estimating only one distribution. However, in this work, for SLP, we are interested in estimating the posterior density of the M system components at each time instant k given the observations y_k . Particularly, when using the IIM, we are concerned with the estimation of the inoperability PDF of M components. Thus, in our work, a particle is considered as a vector representing the state of health (inop-

erability) of the system components. Then, the weight associated with a particle represents the approximation of the probabilities relative to the inoperability of all the M components at the same time, as shown in Figure 3.8. The process of estimating the inoperability state of a system at time k is shown in Figure 3.9 and detailed in the following.

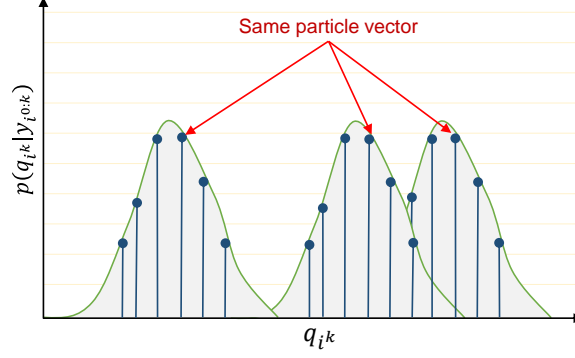


Figure 3.8: Inoperability PDF of a system with 3 components.

Each distribution $p(q_i^k | y_{0:k})$ represents the inoperability PDF of one component i . The distributions have the same shapes since they are constituted by the same particles with the same weights $w_k^{(l)}$, but different inoperability values $q_i^{(l)}$ for each component i .

Firstly, using the IIM, the prior probability density distributions PDF of the system component inoperabilities $p(q_k | q_{k-1})$ at time k are predicted based on the ones at the previous time $k - 1$:

$$p(q_k | q_{k-1}) \sim IIM(q_{k-1}) \quad (3.6)$$

Next, given new observations y_k at time k for a component i , $i \in \{0, 1, \dots, M\}$, the system posterior PDF inoperabilities are updated by PF. In detail, considering a set of N particles $\{q^{(l)}\}_{l=1, \dots, N}$, their associated normalized weights $\{w^{(l)}\}_{l=1, \dots, N}$ are evaluated by the likelihood functions $p(y_i^k | q_i^k)$ using importance distribution functions $\pi(q_i^k | q_{i,k-1}, y_{1:k})$:

$$w_k^{(l)} \propto w_{k-1}^{(l)} \prod_i \frac{p(y_i^k | q_i^{(l)}) p(q_i^{(l)} | q_{i,k-1}^{(l)})}{\pi(q_i^k | q_{i,k-1}, y_{1:k})} \quad (3.7)$$

Finally, to overcome the degeneracy problem with traditional PF schemes, a resampling process is applied at each time step to replace the particles with low importance weights with particles that have higher importance weights. Resampling is a mapping from $\{q_k^{(l)}, w_k^{(l)}\}_{l=1}^N$ to $\{q_k^{(l)*}, \frac{1}{N}\}_{l=1}^N$ where the new particles $q_k^{(l)*}$ are chosen randomly from a set of previous ones. The probability of a particle to be chosen is equal to its importance weight. By considering the resampling procedure at each time step, the same weight $w_k = \frac{1}{N}$ is assigned for all the particles.

The posterior PDF of the system inoperability at time k (Figure 3.9) can be approximated

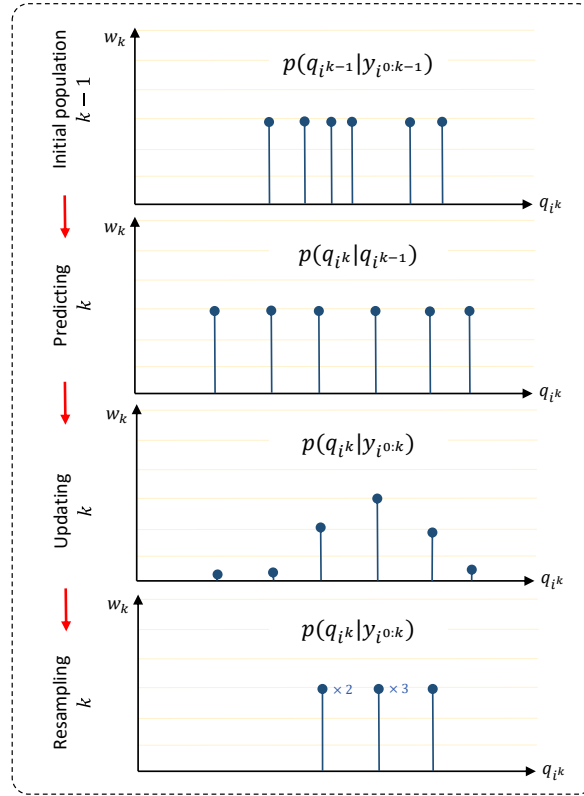


Figure 3.9: Illustration of the inoperability estimation using PF-based algorithm at the instant k .

This scheme shows the distribution of inoperability for a single component i . The other components of the system will have the same evolution of particle weights with different inoperability values.

before the resampling step by:

$$p(q_k | y_{0:k}) \approx \sum_{l=1}^N w_k^{(l)} \delta_{q_k}^{(l)}(q_k) \quad (3.8)$$

where $\delta(\cdot)$ denotes the Dirac delta function.

The estimation procedure is repeated at every instant k , $k \in \{1, 2, \dots, k_p\}$, where k_p is the starting time of the prediction step presented in the next subsection.

3.3.2 Inoperability uncertainty prediction

Prognostics, and thus the generation of long-term predictions, is a problem that goes beyond the scope of filtering problem since it involves future time horizons in which no measurements are available for the Bayesian updating given by equation 3.7. Let us assume that a fault is detected and diagnosed at a time instant k_p , then the sequence of predicted inoperability

probability density $p(q_k|y_{1:k_p})$ for $k \geq k_p$ can be expressed by:

$$p(q_k|y_{1:k_p}) = \int \cdots \int \prod_{h=k_p+1}^k p(q_h|q_{h-1})p(q_{k_p}|y_{1:k_p}) \prod_{h=k_p}^{k-1} dq_h \quad (3.9)$$

where $p(q_k|y_{1:k_p})$ is the predicted *PDF* of the inoperability at time k given the measurements acquired from the initial time until the instant k_p . Unfortunately, the calculation of this integral is computationally high and even impossible in some cases. One way of solving this integral when considering non-linear systems is using Monte Carlo simulations (Acuña and Orchard, 2017). However, due to the computational cost of these simulations, other methods based on Bayesian inference are proposed in the literature, among which particle filtering (Saha et al., 2009a). Nevertheless, this latter tool is more suitable for estimation problems and needs to be adapted to use it for predictions.

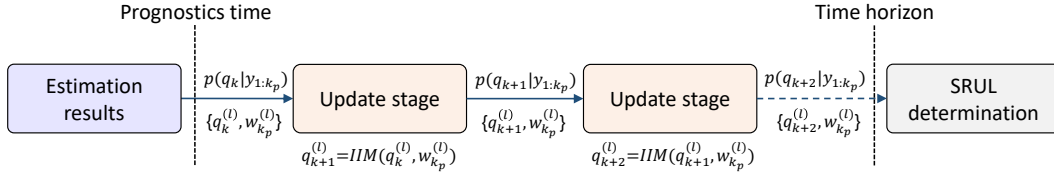


Figure 3.10: Procedure for long-term inoperability prediction.

In this work, to reduce the computation requirement, we suggest to follow the procedure proposed in (Doucet et al., 2000) and which is based on the assumption that the particle weights are constant from time k_p to time k . The error induced by this assumption can be neglected for other sources of error, such as those caused by the model inaccuracy or by the process and measurement uncertainties (Orchard, 2006). According to this procedure, the predicted inoperability PDF of the system's components at time k (i.e. $p(q_k|y_{1:k_p})$) is given by:

$$p(q_k|y_{1:k_p}) \approx \sum_{l=1}^N w_k^{(l)} \delta_{q_k}^{(l)}(q_k) \quad (3.10)$$

where the particle inoperability $q_k^{(l)}$ is obtained by applying recursively equation 3.6 to $q_{k_p}^{(l)}$, as shown in Figure 3.10.

Once the prediction of the future system inoperability is made, it will be used to determine the system remaining useful life (SRUL), as explained in the next subsection.

3.3.3 SRUL determination

Before detailing the method of calculation of the SRUL, we first present in subsection 3.3.3.1, the different approaches for evaluating a component RUL, which constitute the majority of the studies in prognostics. Then, subsection 3.3.3.2 deals with the calculation of the SRUL from the system configuration based on the component failure probability distributions.

3.3.3.1 Remaining useful life calculation approaches

Assuming a one-component system (or a whole multi-component system considered as one unity) is in a functional state, and no maintenance is necessary. It starts to operate with a specific initial health level that is mostly stable during the early periods of operations. This stability continues until a critical stage where an early incipient fault occurs, and then the risk of failure grows with time. When a prognostics algorithm is developed, the main goal is to estimate this time of failure (ToF), at which the system cannot operate under desired conditions (Pecht, 2009). This estimation is a statement about an uncertain event in the future. Still, it is based on the fundamental notions of systems' deterioration, monotonic damage accumulation, pre-detectable aging symptoms, and their correlation with a model of system degradation (Pecht, 2009). With regard to these notions, a prognostics framework detects and assesses the system deterioration with the goal of estimating the remaining useful life (RUL) before the failure. The accuracy of the RUL estimations is a key notion in condition-based and predictive maintenance strategies. It also has a critical value to improving safety, reliability, mission scheduling, and lowering costs and downtime (Peng et al., 2010). The deviation between the actual RUL (also called actual time-to-failure ATTF) and the estimated RUL (known as estimated time-to-failure ETTF) is of critical importance to this accuracy.

The true remaining useful life is an unknown future variable that can only be known after the occurrence of a failure (Jones et al., 2001). The estimated remaining useful life, on the other hand, is the amount of time from the current time to the failure time (Medjaher et al., 2013). As defined by the industry-standard in (ISO 13381-1: 2004(E), 2004), the estimated RUL, along with the risk of failure modes, is the basic definition of prognostics. Therefore, it is generally the principal focus of prognostic studies and the estimation of RUL (Efthymiou et al., 2012). Accordingly, it is defined as (Jardine et al., 2006):

$$RUL = t_f - t_c \quad (3.11)$$

where t_c is the current time, and t_f is the time of failure (ToF).

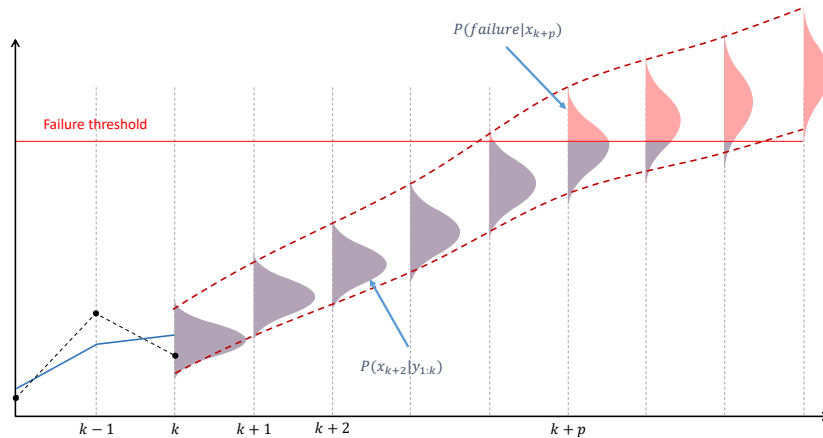


Figure 3.11: Conventional state-based calculation of the RUL.

In equation 3.11, t_c is already known, we are then interested in finding t_f . For this purpose, different approaches have been explored to tackle the problem of estimating ToF, i.e., t_f . Depending on the method used to predict the future health state evolution, two main approaches can be distinguished: deterministic and probabilistic. In the case where only one trajectory is predicted, ToF will be a scalar value (deterministic) (Pham et al., 2012). However, the prognostics objects of study, i.e., degradation and failure mechanisms, are essentially stochastic phenomena. Therefore, the uncertainty cannot be eliminated, and a probabilistic approach is needed to handle this uncertainty. In this probabilistic approach (most used in model-based prognostics (Saxena et al., 2010)), a population of samples is obtained from the posterior state PDF at the time when prognostics is initiated. Then, each of the samples is used as an initial condition for simulating new state trajectories in "random walk" fashion by iterating the state transition equation with random realizations of the process noise. At each iteration, the hazard zone function is evaluated in order to identify if the system states reached the hazard zone. This latter information is used to compute the failure distribution as a cumulative distribution function (as shown in Figure 3.11). While the state transition equation assumes the system is healthy, simulated state trajectories may migrate from a healthy region to a failure region and vice-versa. Due to the nature of the random process, the trajectories do not exhibit strictly monotonic behavior. This behavior is illustrated in Figure 3.12 for the prediction of 20-steps of 8 system state trajectories.

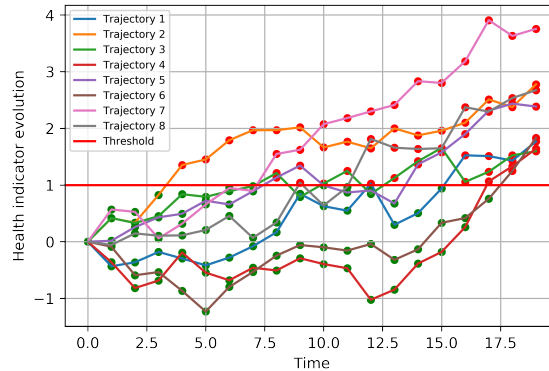


Figure 3.12: 20-steps trajectory prediction

To overcome this limitation, two methods have been proposed in the literature:

1. **Trajectory-based calculation method:** this method applies when using sample-based prediction methods (such as Monte Carlo or particle filtering PF). In this approach, at each instant, we examine the number of trajectories that have exceeded the failure threshold (or entered the hazard zone). The CDF of ToF is calculated by using this formula (Paez et al., 2019):

$$p(\text{ToF} \leq k) = I(x) = \frac{1}{N} \sum_{i=0}^N I(x^i) = \frac{N_f}{N} \quad (3.12)$$

where N is the total number of state trajectories, N_f number of trajectories beyond the

threshold (or hazard zone) and

$$I(x^i) = \begin{cases} 1 & h(x^i) \geq \text{threshold} \\ 0 & \text{otherwise} \end{cases} \quad (3.13)$$

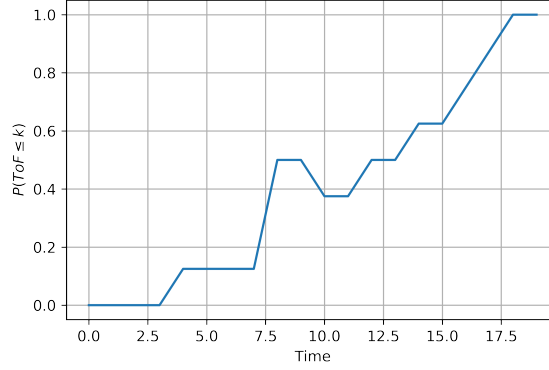


Figure 3.13: CDF of ToF following a trajectory-based approach.

The result can be represented as a CDF in the case of monotonic degradation. But in the case of non-monotonic degradation, the properties of a CDF are not held, as shown in Figure 3.13 for the state trajectories of Figure 3.12. However, when the determination of the ToF PDF is not necessary, a trajectory-based method can be adopted as it requires no complex calculation.

2. **State-based calculation method:** This method is based on the conventional method of probabilistic calculation of the RUL (the one shown in Figure 3.11) with modifications to hold the properties of a CDF in the case of a non-monotonic or regenerative degradation process (Acuña and Orchard, 2018). As shown in Figure 3.14, this new state-based calculation of RUL allows to obtain the ToF PDF (i.e. $P(F_k)$) in the most pessimistic case according to (Paez et al., 2019).

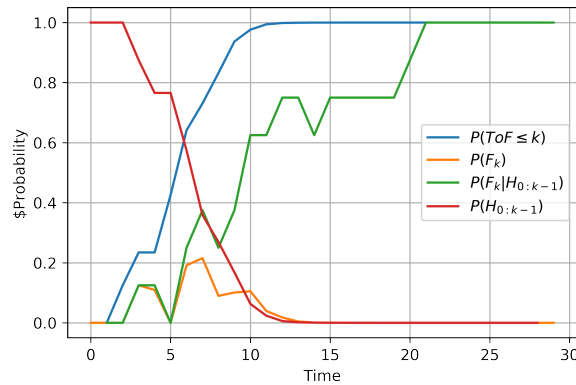


Figure 3.14: New state-based calculation of the RUL

In the following, a generalization of the RUL calculation method to a multi-component

system by considering its functional configuration will be proposed. This generalization can be applied to a state-based or trajectory-based RUL computation. However, only the details of the state-based calculation method are presented because 1) it can be applied regardless of the prediction method used (sample-based or not), 2) it is more mathematically rigorous in terms of the obtained results (Acuña and Orchard, 2018), and 3) it provides the ToF PDF.

3.3.3.2 SRUL calculation

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) (Rodrigues, 2018) or when the system reaches a performance that is considered unacceptable (Tamssaouet et al., 2020a). It allows giving a unique measure on 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. Indeed, the system components are often arranged in a mechanical or logical series or parallel configuration. For example, a system with redundancies (parallel) will be more resilient to the failure of one or some components. Therefore, the SRUL must be calculated according to the system configuration.

Assuming that the system is healthy at the time k_p , where the prediction algorithm is launched, the SRUL can be computed as follows:

$$SRUL = \tau_F - k_p \quad (3.14)$$

with τ_F is the system time-of-failure (ToF) or the system end-of-life (EOL).

$$\tau_F = \inf(k \in N : \text{system failure at } k) \quad (3.15)$$

Note that the time-of-failure (ToF) is chosen here instead of the end-of-life (EOL) time because it is more general and can be used in multiple applications. In addition, it can be applied in cases where there is no system degradation but only the interruption of the operational continuity, such as the discharge of a battery. Furthermore, this corresponds better to the concept of inoperability, which is both concerned with the system performance and its health state.

In practice, and given the complexity of industrial systems, it is essential to consider the uncertainty associated with the ToF. To do this, the notations and the new paradigms proposed in (Acuña and Orchard, 2017; Acuña and Orchard, 2018) are used in the following of this chapter. Indeed, in these works, the authors demonstrated the misinterpretation of the cumulative probability of ToF given by:

$$p(ToF = k) = \int_x p(\text{failure} | x_k) p(x_k | y_{1:k_p}) d_{x_k} \quad (3.16)$$

where x_k , $x_k \in R^{n_x}$ is the vector of n_x elements that characterize the component states. In this equation, the probability distribution of the state given the measurements $y_{1:k_p}$ is

approximated by $p(x_k|y_{1:k_p}) = \sum_{l=1}^N w_k^{(l)} \delta_{x_k}^{(l)}(x_k)$ and $p(failure|x_k)$ corresponds to the probability of failure, conditional to the components states x_k . In literature, the probability measure shown in equation 3.16 has been misinterpreted as a Cumulative Mass Function (CMF) of the ToF. This interpretation is correct for strictly degenerative systems, i.e., systems for which the health indicators increase monotonically. In this case, the probability measurement will increase monotonically from 0 to 1. However, it cannot be applied for systems having regenerative phenomena. Also, this probability measure is defined at a discrete time. Thus it should be interpreted as a Probability Mass Function (PMF). So, the corrected expression provided in (Acuña and Orchard, 2018) and which is used to compute the ToF PMF will be generalized in the following to the case of multi-component systems.

Let us denote the healthy and the faulty system at time k by H_k and F_k , respectively; and also consider $H_{k_p:k} = (H_{k_p}, H_{k_p} + 1, \dots, H_k)$ as the sample space that determines all possible sequences where the system has not catastrophically failed until the time k . Then, according to the definition of the conditional probability, the true failure probability at time k is given by:

$$P(F_k) = \frac{P(F_k, H_{k_p:k-1})}{P(H_{k_p:k-1}|F_k)} \quad (3.17)$$

where $P(F_k, H_{k_p:k-1}) = P(F_k \cup H_{k_p:k-1})$. Furthermore, as the system can only fail once (without maintenance intervention), we can write $P(H_{k_p:k-1}|F_k) = 1$, since $P(H_{k_p:k-1}|F_k)$ corresponds to the probability of staying healthy until time $k-1$, given that the failure has occurred at time k . By applying the definition of joint probability, equation 3.17 can be rewritten as:

$$P(F_k) = P(F_k|H_{k_p:k-1})p(H_{k_p:k-1}), \quad \forall k > k_p \quad (3.18)$$

The first term of equation 3.18, i.e., $P(F_k|H_{k_p:k-1})$, corresponds to the failure probability measure that has been used in the literature so far. Equation 3.18 is equivalent to equation 3.19:

$$P(F_k|H_{k_p:k-1}) = \int_{R^{n_x}} p(failure|x_k)p(x_k|y_{1:k_p})d_{x_k} \quad (3.19)$$

In the previous equations, the corresponding probability of ToF is expressed with regard to the system state. However, in the case of inoperability, its formulation becomes:

$$P(F_k|H_{k_p:k-1}) = \int_{R^{n_q}} p(failure|q_k)p(q_k|y_{1:k_p})d_{q_k} \quad (3.20)$$

The advantage of using the inoperability is that the probability of failure can be determined by taking into account either the failure threshold (i.e. $p(failure|q_k = 1)$) or a given performance threshold (i.e. $q_k < 1$). This can be useful when reasoning in terms of performance and not in terms of failure. It can also be useful for systems where the failures can be catastrophic. Therefore, one prefers to determine the SRUL when the system approaches the failures rather than when reaching them.

The second term of equation 3.18, $p(H_{k_p:k-1})$, stands for the probability that one com-

ponent is healthy until time $(k - 1) - th$, which corresponds to a finite union of events. By using the properties of conditional probabilities, one can write:

$$\begin{aligned}
p(H_{k_p:k-1}) &= p(H_{k-1}|H_{k_p:k-2})p(H_{k_p:k-2}) \\
&= p(H_{k-1}|H_{k_p:k-2})p(H_{k-2}|H_{k_p:k-3})p(H_{k_p:k-3}) \\
&= \dots \\
&= \prod_{h=k_p+1}^{k-1} p(H_h|H_{k_p:h-1})
\end{aligned} \tag{3.21}$$

As F_h and H_h are exclusive events, the failure event can be modeled through a Bernoulli stochastic process: $p(H_h|H_{k_p:h-1}) = 1 - p(F_h|H_{k_p:h-1})$. It follows that:

$$p(H_{k_p:k-1}) = \prod_{h=k_p+1}^{k-1} (1 - p(F_h|H_{k_p:h-1})) \tag{3.22}$$

$$p(H_{k_p:k-1}) = \prod_{h=k_p+1}^{k-1} (1 - \int_{R^{n_q}} p(failure|q_h)p(q_k|y_{1:k_p}))d_{q_k} \tag{3.23}$$

The failure probability described in equation 3.20 is defined as the product of $P(F_k|H_{k_p:k-1})$ and $p(H_{k_p:k-1})$, where the first term corresponds to the likelihood of failure at time k (assuming that the system was healthy for all previous time instants). The second term indicates the probability that the system was healthy until time $(k - 1)$. In (Acuña and Orchard, 2017), it has been proved that $P(F_k)$ effectively holds all properties for a probability measure as a function of time.

The expressions presented in equations 3.18 and 3.22 are valid when performing prognostics of a single component or a multi-component system. However, in the case of multi-components, the way of characterizing $p(F_k|H_{k_p:k-1})$ will be evaluated according to the system configuration, as explained in what follows.

Series configuration

According to this structure, the failure of one of the M components will cause the failure of the complete system. This is because the operation of each element depends on the operation of the remaining ones (Figure 3.15). Therefore, the probability that the system will fail at time k , conditional that the system is healthy at $k - 1$, is a finite union of the failure events of the components:

$$p(F_k|H_{k_p:k-1}) = p(F_{1k}, F_{2k}, \dots, F_{Mk}|H_{k_p:k-1}) \tag{3.24}$$

If we consider that the probability of simultaneous failures in different components is null, the component failure events can be considered as incompatible. Thus equation 3.24 can be

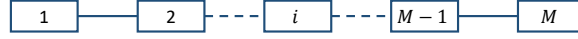


Figure 3.15: Schematic illustration of a series configuration.

written as:

$$p(F_k | H_{k_p:k-1}) = \sum_{i=1}^M p(F_{i^k} | H_{k_p:k-1}) \quad (3.25)$$

where $p(F_{i^k} | H_{k_p:k-1})$ is the probability that the component i will fail at time k , conditional that the system is healthy at $k - 1$ and M is the number of components in series. Then:

$$p(F_k | H_{k_p:k-1}) = \sum_{i=1}^M \int_{q_k \in R^{n_q}} p(failure_i | q_{i^k}) p(q_{i^k} | y_{i^k:k_p}) d_{q_k} \quad (3.26)$$

Note that for evaluating the $p(F_{i^k} | H_{k_p:k-1})$ of each component, it is necessary to calculate $p(q_{i^k} | y_{i^k:k_p})$ from $p(q_{i^{k-1}} | y_{i^k:k_p})$. Therefore, this calculation step takes into account the interactions between the components by using the IIM.

Parallel configuration

This configuration is characterized by a parallel association of M components that are considered functioning in hot redundancy. In this structure, the failure of one or more elements does not cause the failure of the system, but only when all the elements fail (Figure 3.16). Therefore, the probability that the system will fail at time k , conditional that it was healthy at $k - 1$, is a finite intersection of the failure events of the components which should be independent. This means that the failure of one or more components does not affect the remaining functioning components.

To provide the probability of failure of a system with a parallel configuration, we assume that the sampling time is very small. Then at most, only one component fails during the interval $[k - 1, k]$.

$$\begin{aligned} p(F_k | H_{k_p:k-1}) &= \prod_{i=1}^M p(F_{i^k} | H_{k_p:k-1}) \\ &= \prod_{i=1}^M \int_{q_k \in R^{n_q}} p(failure_i | q_{i^k}) p(q_{i^k} | y_{i^k:k_p}) d_{q_k} \end{aligned} \quad (3.27)$$

Remark: In this chapter, the term "healthy" refers to the state where the system has not yet experienced a catastrophic failure, but degradation is initiated so that the prognostics can be triggered. The term "faulty" refers to the occurrence of a catastrophic failure.

Until now, the SRUL was determined under the assumption that the degradation model

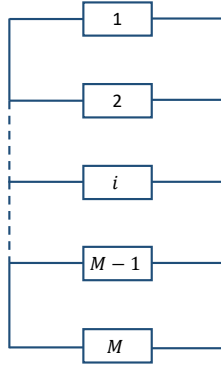


Figure 3.16: Schematic illustration of a parallel configuration.

(i.e. the IIM) is available and that its parameters do not change during the system health estimation stage. In the following section, a methodology for joint parameter estimation and SRUL prediction is proposed in order to relax this assumption.

3.4 Methodology for joint parameter estimation and SRUL prediction

Two principal reasons, for which it is essential to develop a new methodology for online joint parameter estimation and SRUL prediction, are:

- The problem of online prediction of RUL/SRUL has been widely studied through filtering or machine learning methods (Orchard and Vachtsevanos, 2009). However, these methods suggest that the system degradation models are already estimated (for model-based methods) or trained (for data-driven methods) and can be used by merely updating them. Nevertheless, in practice, this information is not available. In this case, the parametric estimation of the degradation model must be done online at the same time as the system health state estimation and prediction.
- In a Bayesian approach of prognostics, the estimates given by the model are corrected by actual measures about the system health state without changing the parameters of the model. However, in the case of SLP, uncertainties associated with modeling can be very high. Therefore, the degradation model needs to be adaptive with regard to the monitored system.

Figure 3.17 presents an overview of the proposed methodology for an online combined estimation of the IIM parameters and SRUL probabilistic prediction. Requiring only the trends of the component-level degradation (i.e. $c(t)$), it allows performing three principal tasks: 1) online estimation of the system health state, 2) online update of the IIM parameters and 3) online probabilistic SRUL prediction. In detail, the IIM, whose initial parameters were estimated offline by performing run-to-failure experiments or were randomly-generated,

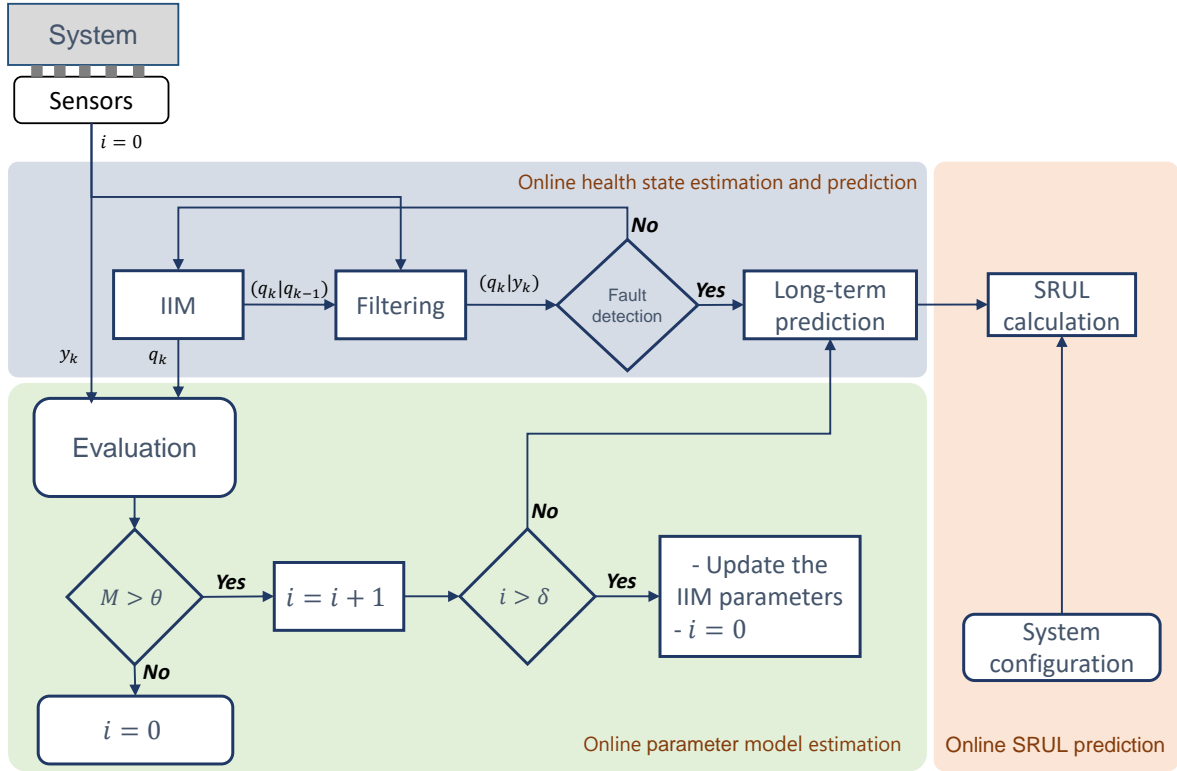


Figure 3.17: Methodology for online joint parameter estimation and SRUL prediction

is used at time k to predict (short-term prediction) the health state at time $k + 1$ (prior estimation). At the time $k + 1$, when new pre-processed degradation data acquired by sensors are available, the prior estimation is filtered to obtain the posterior one using particle filtering. If an anomaly has been detected or a threshold value for the inoperability of a component has been exceeded, the posterior PDF is propagated (long-term prediction) to calculate the SRUL; otherwise, we continue filtering. After every short-term prediction, the prior health state estimation is evaluated with respect to the actual data. If there is a discrepancy, the long-term prediction is updated along with the estimated SRUL (if an anomaly is already detected). In this case, the parameter i , which represents the number of consecutive discrepancies observed, is incremented; otherwise, it is reinitialized. If several discrepancies appear consecutively (i exceeding a number δ set by the user), the gradient descent is used to update the IIM parameters.

As mentioned above, the proposed methodology requires an effective way to assess whether the difference between the measurement acquired by sensors and the predicted health state obtained by IIM is significant. For this purpose, we propose the 2 following methods (Figure 3.18):

- **Evaluation of prediction expectation.** This method can be used when one is interested in knowing if the expectation given by the model is close to the value given by

the sensor. In the case of particle filtering, we can obtain this difference M as follows:

$$M = \sum_{l=1}^N w_k^{(l)} \delta_k^{(l)}(q_k) - y_k \quad (3.28)$$

with this difference should be less than a fixed value ($M \leq \theta$).

- **Evaluation of the uncertainty characterization.** This evaluation can be utilized when a better characterization is considered more important than the expectation of the SRUL. In this case, the number of particles that fall within the accuracy range of the sensor values is determined, i.e.:

$$M = \sum_{i \in \{n=1 \dots N | q_k \notin [y_k - \alpha \delta_{data}, y_k + \alpha \delta_{data}]\}} w_k^{(l)} \quad (3.29)$$

with the number of particles that should be included in the confidence interval is fixed by the user, and α is a parameter to delimit this confidence interval. Since most modern sensors are calibrated to have a Gaussian uncertainty, it is possible to use the 68–95–99.7 rule without performing distribution tests (such as normality test of studentization). This rule represents the percentage of values that lie within a band around the mean in a normal distribution with a width of two, four, and six standard deviations, respectively, i.e., including 68.27%, 95.45% and 99.73% of the possible values, respectively. Thus, depending on the confidence that we have on the sensor measures, one percentage value can be chosen.

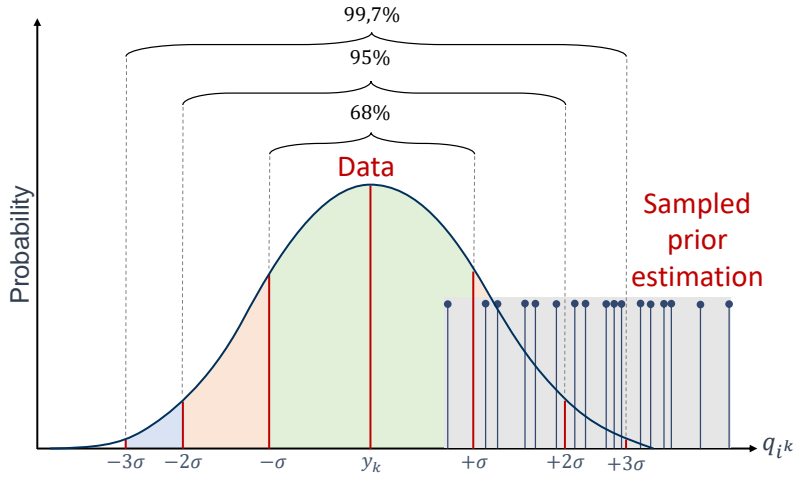


Figure 3.18: Evaluation of the filtering performance.

In summary, the proposed methodology allows online system state estimation and SRUL prediction, with accurate and reliable results. Indeed, the update of the IIM parameters and the long-term prediction of the component inoperability evolution is not done systematically, but only when a discrepancy is observed. This procedure prevents unnecessary computational time. Also, the parameter estimation process can be stopped when its execution time is equal

to the sampling time of measurements, or the loss function is close to zero. Note that the obtained values of the IIM parameters will be used as the initial values in the next iteration when a new measurement is acquired. Then, even if the optimum is not reached at a certain iteration of the algorithm, it is approached in the direction of that optimum. This guarantees a precision of the final results in terms of parameter estimation and thus improves the accuracy of health state estimation and prediction. For the computing time devoted to the prediction of the SRUL, two options are available: 1) the stopping criterion must be less than the sampling time in order to propagate the built IIM and predict the SRUL, 2) the calculations related to prediction and estimation are parallelized (Tamssaouet et al., 2020b). In the following, the stopping criterion corresponds exactly to the sampling time.

3.5 Conclusion

In this chapter, the inoperability input-output model has been utilized to predict the system remaining useful life. In order to do so, two scientific locks have been solved. The first one concerns the estimation of IIM parameters. Indeed, in model-based prognostics, actual data are used to determine the parameters that minimize the error between the values predicted by the model and the actual measurements. In this perspective, the gradient descent algorithm was used because of its flexibility. The performance of this algorithm was evaluated according to several case studies to ensure the accuracy of its estimation. The second lock concerns the use of the estimated IIM in order to monitor the state of health of the system and predict its future evolution. In this case, the particle filtering method was used as it can be applied to non-linear systems and Gaussian noise. Besides, the proposed method has been modified to estimate distributions representing the health states of several components at the same time. Finally, an online methodology was proposed to combine the parametric estimation of the IIM with the estimation and prediction of the health state of the system. This methodology allows facilitating the computations with a minimum of prior knowledge on the system degradation mechanisms while minimizing the calculation efforts.

In summary, a practical approach for system-level prognostics is presented through the construction of a new modeling framework and a methodology for joint system degradation parameter estimation and SRUL prediction. The results of this approach are used in the next chapter in a decision-making process to maximize the SRUL by controlling the mission profile.

Post-prognostics decision: From mission profile effects analysis to SRUL maximization

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Chaque problème que j'ai résolu est devenu une règle qui a ensuite servi à résoudre d'autres problèmes.

René Descartes

4.1 Introduction

Monitoring and predicting a system's health state aim, among others, at scheduling its maintenance activities and the supply chain resources deployed therein. This has been widely discussed in the literature under the terms of condition-based and predictive maintenances (Jardine et al., 2006; Dragomir et al., 2009; Prajapati et al., 2012). However, in an effort to be proactive, several studies are beginning to focus on incorporating prognostics information into system control and future operation planning (Tang et al., 2008). Furthermore, as decision making is generally made on the whole system, prognostics must then be carried out at the system-level as well. Therefore, in this chapter, we will investigate the influence of the mission profile on the system RUL through different variations of its parameters. Then,

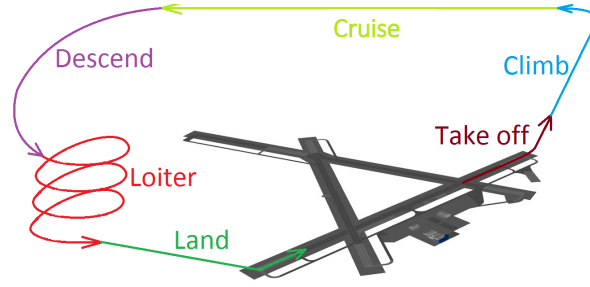


Figure 4.1: Illustration of a standard aircraft mission profile.

based on these results, a new methodology to optimize the mission profile, while handling multiple operational constraints, for the SRUL extension will be developed.

The remaining of this chapter is organized as follows. Section 4.2 analyzes the effect of the mission profile on the SRUL using a mechatronics case study and representing a subway. Section 4.3 presents an algorithm for optimizing the subway mission profile parameters and the maximization of its RUL.

4.2 Effect of mission profile on system degradation

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 the system remaining useful life (Tamssaouet et al., 2019c; Tang et al., 2008). This MP can be a steady-state operating (such as in thermo-fluid systems) or having a particular cyclic pattern. This kind of pattern can be found, for instance, in an aircraft MP (Figure 4.1). Each step of this MP impacts differently the aircraft components. In prognostics, future mission profiles and their impact on the system should be adequately characterized in order to perform efficient and accurate RUL/SRUL predictions. Some works have focused on the characterization of future mission profiles based on their past evolution through machine learning (Rozas et al., 2020) or statistical methods (Pola et al., 2015). However, the effect of the MP on system-level degradation and SRUL has not been investigated yet.

To fill this gap, the performance of the IIM to handle the effect of the mission profile will be investigated in this chapter through a case study. Firstly, subsection 4.2.1 describes the case study (a subway), which is represented by a mechatronic system, and its modeling using the IIM. Then, the effect of the mission profile on the subway RUL will be examined in subsection 4.2.2 by considering various operating conditions: 1) constant usage profile, 2) a usage profile with a variable level (magnitude) of load, and 3) a usage profile with a variable duration of load.

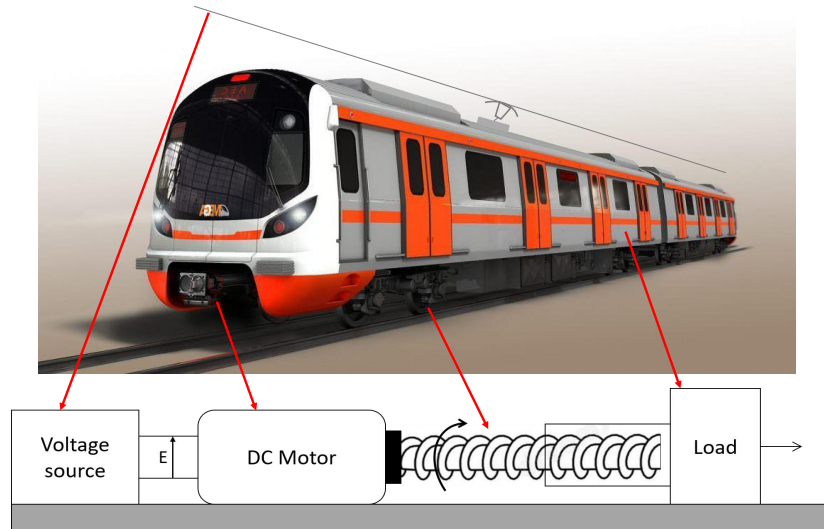


Figure 4.2: Scheme of the studied system.

4.2.1 System description and its degradation modeling

A subway, also known as the underground, tube, or metro, is a type of high capacity public transport generally found in urban areas. Unlike buses or trams, subway systems are electric railways that operate on an exclusive right-of-way. The motion power is provided by a separate locomotive where the electric motor is situated.

In what follows, because of the complexity of subways and lack of data, it was modeled as a mechatronic system to show the effectiveness of the proposed modeling approach. The mechatronic system was proposed by (Medjaher and Zerhouni, 2013), and its primary purpose is to position horizontally a load which is situated at the right side of Figure 4.2. The system is composed of a voltage source, which can be a battery, a DC motor providing a rotational movement, and a screw transforming this latter movement to a translational one. The mechatronic system illustrated in Figure 4.2 can be likened to a subway as follows. The battery delivering a constant amount of energy can be assimilated, in the case of a subway, to an overhead line or a third rail. The DC motor represents the electrical traction motor of modern trains. The screw is considered as the transmission chain. Finally, the load can be compared to subway payload.

In this case study, three components are considered: the stator, the rotor, and the screw (respectively, components 1, 2, and 3). These components are subject to the following degradation phenomena: 1) drift in the DC motor's winding (stator), 2) deterioration of the DC motor's permanent magnet (rotor), and 3) bending of the rotating shaft. The causes and the models of these degradations are explained below (Tamssaouet et al., 2019b).

- For the electrical resistance (related to the stator), the degradations can be caused by the variation of the resistivity of the winding due to temperature changes inside the DC

motor. The performance, in this case, can be monitored by measuring (or estimating) the electrical flux $\Phi(t)$ of the inductance, which is linked to the resistivity of the winding, as expressed by the following equation:

$$\Phi(t) = \frac{R(t) \cdot U}{L} \quad (4.1)$$

where $R(t)$ stands for the winding resistance of the DC motor, L is the inductance and U is the voltage delivered by the battery.

Note that as the inductance of the winding is constant, as well as the voltage delivered by the battery, the electrical flux of the winding varies due to the variation of the resistivity. Therefore, the internal stator resistance is assumed to vary according to the following model:

$$R(t) = R_0 \cdot (1 + \alpha \cdot t) \quad (4.2)$$

where R_0 is the initial electrical resistance of the DC motor, and α is a shape parameter representing the degradation growth rate.

- The magnetic degradation in the mechanical part (rotor) concerns the diminution of the magnetic field generated by the permanent magnet of the DC motor. The performance of this mechanical part can be determined by the variation of the electromagnetic torque T_{em} . By considering a series excitation of the motor and by neglecting the electromagnetic losses, this torque can be expressed by the following equation:

$$T_{em}(t) = K_c(t) \cdot \Phi(t) \cdot I(t) = K_c(t) \cdot \frac{U^2}{L} \quad (4.3)$$

where $K_c(t)$ is a parameter which depends on the structure of the motor and $I(t)$ is the electrical current crossing the winding, which is equal to $\frac{U}{R(t)}$. Since the input voltage U and the inductance L are constant, the variation of the electromagnetic torque is due to the degradation of the internal structure of the motor expressed by the variation of $K_c(t)$ over time. An exponential degradation model can represent this latter parameter:

$$K_c(t) = K_{c_0} \cdot e^{\beta \cdot t} \quad (4.4)$$

where K_{c_0} stands for the initial torque coefficient of the DC motor and β for the degradation growth rate.

- Finally, the bending of the shaft can be induced by overloading the DC motor and by external perturbations, which decrease the stiffness of the linking part between the screw and the mass. The inoperability of this linking part is determined by its stiffness K_s as follows:

$$K_s(t) = K_{s_0} \cdot e^{\gamma \cdot t} \quad (4.5)$$

where K_{s_0} represents the initial stiffness of the linking part between the screw and the mass, and γ is a shape parameter characterizing the degradation growth rate.

The above degradation models are represented by the vector $c(t)$ in the inoperability

input-output model. This vector is obtained by normalizing the health indicator $x_i(t)$ of each component:

$$c_i(t) = \frac{x_i(t) - x_i(t_0)}{thres_i - x_i(t_0)} \quad (4.6)$$

Regarding the matrix of interdependencies A , and as the study of this particular system is not the main target of this chapter, we propose to use the following values:

$$A = \begin{bmatrix} 0 & 0.02 & 0.09 \\ 0.01 & 0 & 0.05 \\ 0.02 & 0.03 & 0 \end{bmatrix} \quad (4.7)$$

Note that the above mentioned values can be obtained when using the parameter estimation method presented in chapter 3.

Next, we suppose that the subway operates in the normal condition, hence the matrix of influence factors K is equal to:

$$K = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \quad (4.8)$$

Considering the numerical input values of the parameters given in Table 4.1, and the equations 4.7, 4.8, the evolution of the inoperability of the studied system is shown in Figure 4.3. In this case, the estimated SRUL is equal to 3371 time units. In the next subsection, numerous variations of the influence factors k of the mission profile on the subway will be investigated to analyze how the SRUL will be affected under different operating conditions.

Table 4.1: Values of the input parameters.

Symbol	Description	Numerical value
U	Voltage source	10 V
K_{c_0}	Initial torque coefficient of the DC motor	0.47 N.m/A
K_{s_0}	Initial stiffness of the linking part between the screw and the mass	3.33×10^{-6} N/m
R_0	Initial electrical resistance of the DC motor	0.61 Ω
α	Predefined parameters related to degradations	5×10^{-5}
β		10^{-3}
γ		10^{-5}
$thres_1$	Failure thresholds of the three parts of the system three parts of the system	4×10^3 V.m
$thres_2$		25 N.m
$thres_3$		10^{-4} N.m

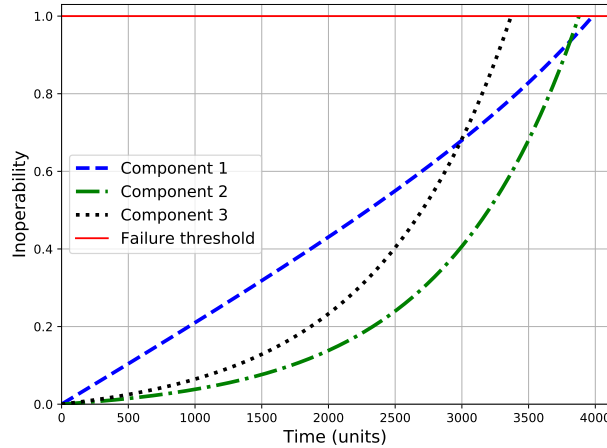


Figure 4.3: System inoperability component evolution without considering the mission profile effect.

4.2.2 Mission profile effect on the SRUL

In practice, the components of subways, and generally of all systems, degrade naturally, but also because of the operating context (environmental conditions, behaviors, training, and expertise of the user, levels of demand in terms of performance, safety, reliability, maintenance intervals, etc.). Indeed, two identical systems working under different operating contexts can have different SRUL. So, it is interesting in this context to consider various operating conditions of the system when performing prognostics. Using these investigation results, the optimal mission profile can be determined in order to increase the system durability and ensure its reliable operation.

To analyze the impact of the mission profile on the subway RUL, various simulation scenarios (see Figure 4.4 for their summary) are investigated. First, it is assumed that the effect of the load is constant over time, then the impact of its magnitude on the SRUL is investigated in subsection 4.2.2.1. Next, the effect of a constant profile mission on the system (an action that the system performs in the same period and load throughout its operational life) is examined in subsection 4.2.2.2. Finally, in subsection 4.2.2.3, several mission profiles with different durations and variable intensity are simulated to show the variation of the SRUL.

4.2.2.1 Impact of the magnitude of mission profile on the SRUL

In practice, the system health evolution differs according to its operation modes. For example, in a production line, these variations can be translated by the efficiency rate and, for a rotating machine (as in the case of a subway), by the maximum speed reached. To determine the effect of the system load on the SRUL through the increase of the influence factor k_i , a sensitivity study was carried out. In this case, it is assumed that the influence of the mission profile is

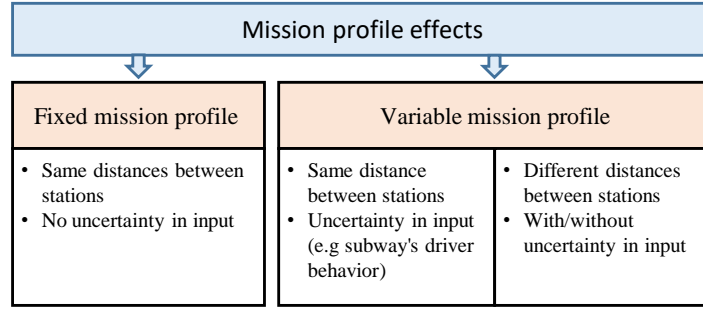


Figure 4.4: Summary of simulation scenarios to investigate the mission profile impact on the subway SRUL.

the same on all components, i.e., $k_1 = k_2 = k_3 = k$.

$$K = \begin{bmatrix} k & 0 & 0 \\ 0 & k & 0 \\ 0 & 0 & k \end{bmatrix}$$

By considering different values k of matrix K , the ratio of the resulting SRUL to the one obtained without considering the effects of usage profile, i.e., $\frac{SRUL_k}{SRUL_{k=1}}$, is shown in Figure 4.5. One can notice that the higher the load (K greater) of the system, the more is its SRUL decrease. Besides, when $k \in [1, 1.5]$, the SRUL decreases linearly, and for $k > 1.5$, the SRUL decreases according to a convex function. This means that when the load on the system is high, the influence of this load on the SRUL is no longer linearly proportional to the load. In other words, the SRUL decreases less rapidly as a function of Δk when k exceeds a certain value.

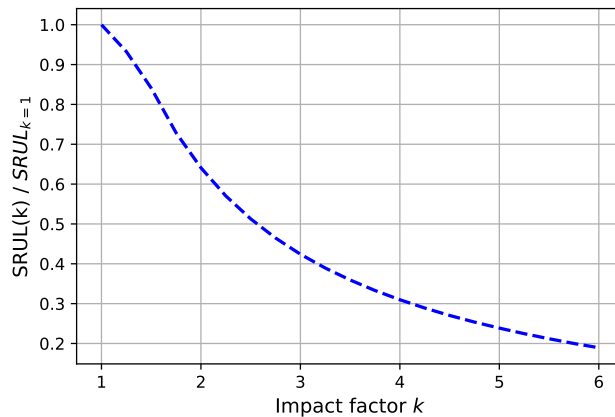


Figure 4.5: Percentage decrease in the SRUL as a function of increase in influence factor K .

4.2.2.2 Impact of a constant mission profile on the SRUL

In the case of subways, we assume that the component degradations are proportionally affected by the velocity. This is rather realistic because one can imagine that, depending on the quality of the rails, an increase in the subway's speed will generate more vibrations and thus increase the component degradations.

Generally, the cruise (maximum) speed of the subways is around 30 km/h . So, by considering a linear relationship between this speed and the influence factor, the values of k as a function of speed are given in Figure 4.6. The profile of the subway's speed (Figure 4.7) is described as follows:

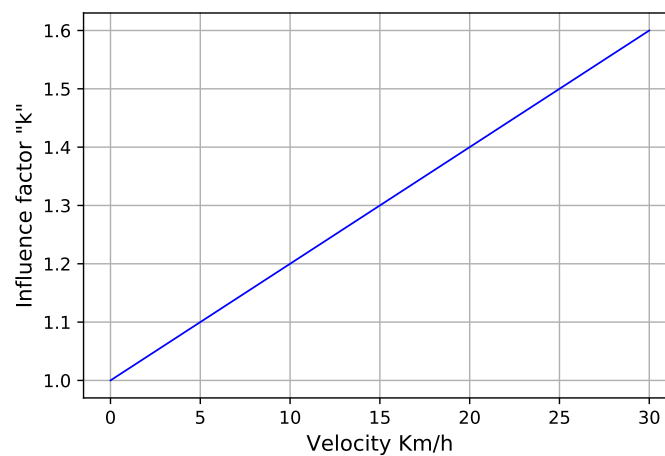


Figure 4.6: Relationship between K and the subway speed.

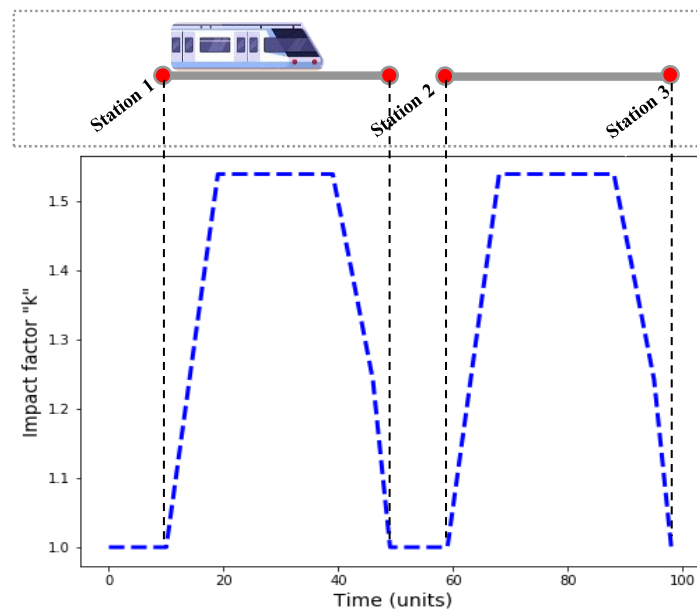


Figure 4.7: Variation of the influence factor K within two missions

- From 0 to 10 time units, the subway is at a standstill, and therefore the degradation is not influenced by external parameters. However, as the engine continues to run in the station, the system will continue to degrade naturally and, therefore, $k_i = 1$.
- From 10 (t_{start}) to 20 time units, the subway's speed increases and therefore also the degradation proportionally to the speed.
- From 20 (t_{cruise}) to 40 ($t_{decelerate}$) time units, the subway reaches its maximum speed during a mission period. The system decelerates as it approaches a station at $t = 40$ and brakes suddenly between 47 (t_{stop}) and 49 time units.

By considering that the effect of velocity is the same on the subway's components and by assuming that the distance between the stations is constant, this speed profile is repeated over the simulation time to monitor the system degradation. In Figure 4.8, which represents the component inoperability evolution over the eight first mission periods, one can figure out that the inoperability strictly depends on the mission profile. More clearly, within a mission period, the inoperability is either increasing, stable, or decreasing according to the variation of the mission profile characterized by the factor k_i . For $k_i = 1$, i.e., when the mission profile impact is absent, the component inoperability evolution will linearly increase. At the end of this simulation, the obtained SRUL is equal to 2767 time units. From these results, one can notice that the SRUL has decreased by 18% compared to the SRUL obtained without taking into account the mission profile. Therefore, when the operating conditions under which the system evolves are not taken into account, the SRUL predictions become more optimistic than they should be. This can expose the system and its users to danger because the maintenance interventions will be planned after the real failure.

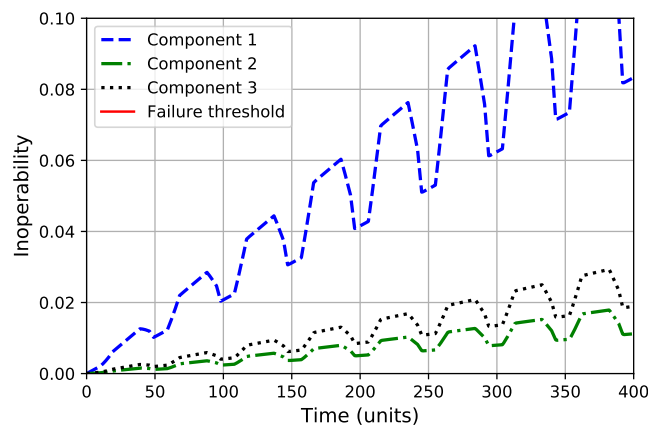


Figure 4.8: Component inoperabilities evolution within eight first mission periods considering a constant mission profile.

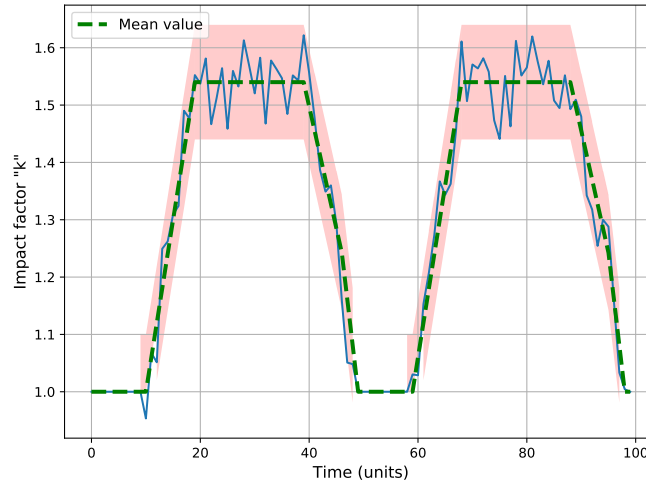


Figure 4.9: Illustration of variation of the influence factor K within two missions with a Gaussian noise.

4.2.2.3 Impact of variable mission profile on the SRUL

In practice, the usage profile of a system is not deterministic. Indeed, it varies over time, or from one cycle to another, because of delays in the input signals, the user behavior, etc. In the case of a subway, these variations can be caused by:

- **Behavior of the subway's driver:** to express these variations, a Gaussian noise, that is assumed to follow the distribution $N(\mu, 0.05)$, is added into the mission profile, as shown in Figure 4.9. Note that μ represents the exact value of the impact factor.
- **Different distances between the subway stations:** to capture this variation, the key time instants of the profile (t_{start} , t_{cruise} , $t_{decelerate}$ and t_{stop}) were randomly noised through a uniform distribution $[0, 50]$, as shown in Figure 4.10. Note that, in this study, $t_{start} > t_{cruise} > t_{decelerate} > t_{stop}$. The variation of t_{start} refers to the delay in starting up of the subway (e.g. the doors not closing in time, signaling problems, etc.). In this case, the variation in the mission profile also implies that the acceleration and deceleration of the subway will be different from one mission to another.

Figure 4.11 shows the Probability Density Function (PDF), obtained by Monte Carlo simulations, of the SRUL under the variation in usage profile due to the behavior of the subway's driver. The mean value of this distribution is equal to 2654 time units, and the standard deviation is equal to 33 time units. The resulting SRUL values are less than the one obtained in the case of a constant usage profile (i.e. 2767 time units). This result highlights the importance of investigating the mission profile variation in order to avoid significant damages caused by wrong SRUL estimations.

Figure 4.12 presents the PDF, obtained by Monte Carlo simulations, of the SRUL under

the variation of the usage profile due to different distances between the subway stations. The mean value of the SRUL is equal to 2739 time units, and the standard deviation is equal to 40 time units. This result shows that there are 73.5% cases in which the SRUL is less than the SRUL (2767 time units) obtained in the case of a constant mission profile. Once again, this highlights the importance of investigating the mission profile variation when evaluating the SRUL.

Finally, we considered the case in which the subway's speed value is uncertain and where the duration of the maximum speed is varied. This case allows taking into account both of the two variation types of the mission profile for the SRUL evaluation. From the results shown in Figure 4.13, one can figure out that the longer the duration of the maximum speed is, the smaller the SRUL is. In fact, the longer duration in which the system works with the maximum load is, the shorter the lifetime will be. However, one can notice that the variation is not very significant. This is due to the fact that when a system accomplishes its journey several times, and even if the duration of one cycle of use is short, it degrades as much as when it is used for an extended period.

4.3 SRUL maximization through mission profile optimization

As shown in the previous section, the mission profile affects significantly the SRUL. In fact, it can accelerate the degradation of some components more than others and differently from one profile mission to another. Therefore, it is necessary to identify the most appropriate mission profile for maximizing the SRUL while respecting the operational constraints. In what follows, we will focus on post-prognostics decisions regarding the mission profile.

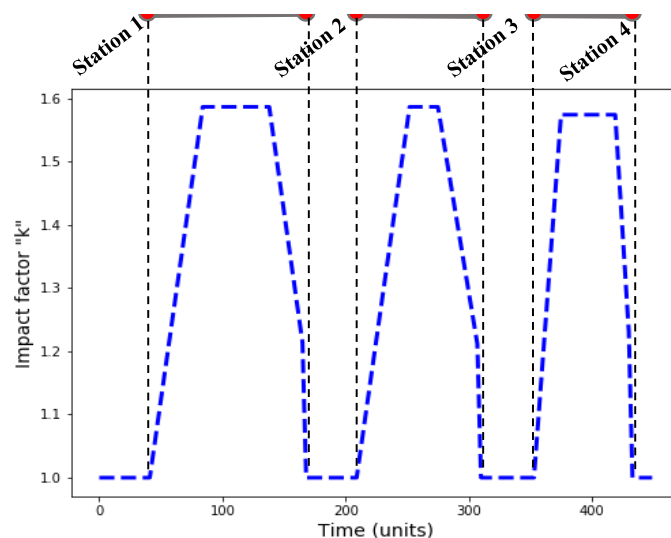


Figure 4.10: Illustration of variation of the influence factor K within three variable missions with different durations.

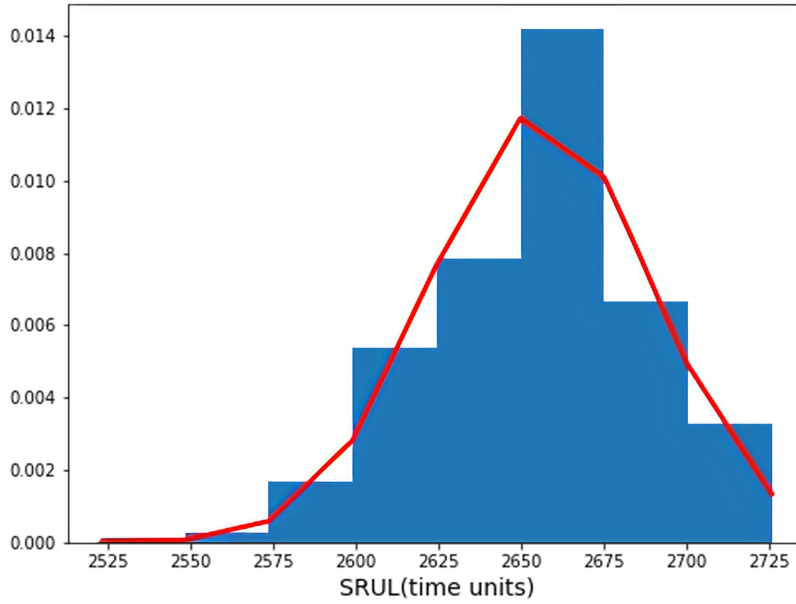


Figure 4.11: PDF of the SRUL with uncertainty in the usage profile.

As a mission profile (MP) is characterized by numerous parameters (such as load levels and durations) and also specified by different operational constraints, the identification of the best MP can be expressed as optimization of multiple variables while handling with various constraints. This optimization issue can be solved by using different techniques like exact methods (linear programming, branch and bound procedure, for example) or heuristic approaches (such as evolutionary algorithms). Among heuristic approaches, the genetic algorithm (GA), one of the evolutionary algorithms, is a mature method utilizing heuristic rules to produce improved approximations of the objective function over a number of iterations. Even though GA does not guarantee a global optimum solution, it is a commonly used method giving one of the best results (Pandey et al., 2014). The possible solutions are evaluated with a fitness function, and the best solutions are utilized to produce other possible ones, while the bad solutions are eliminated through natural selection. The process of producing new solutions based on the best ones on hand is called crossover and mutation.

Thanks to the evolutionary mechanism, the GA allows handling numerous optimization variables, investigating a wide range of solutions, and supporting heterogeneous constraints (equality and non-equality). Therefore, it offers an adequate solution for the MP optimization problem investigated here. In detail, we propose in Algorithm 2 a variant of the GA to solve the MP optimization problem.

Note that corresponding to every MP, the SRUL is evaluated based on the IIM with its estimated parameters. This SRUL value is used as the evaluation criterion for possible solutions.

Besides, for MP optimization, the proposed GA must well handle different constraints. As the basic GA is not explicitly dedicated to solving constrained optimization problems,

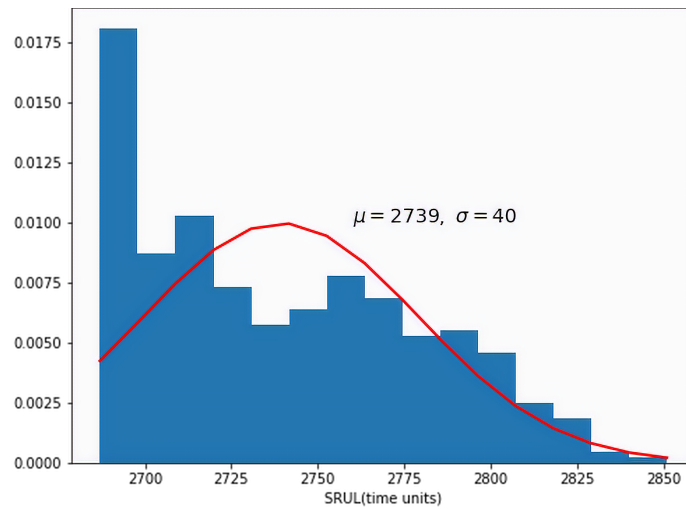


Figure 4.12: PDF of the SRUL according to the variability of the use cycle.

Algorithm 2 Profile mission optimization based on a variant of Genetic Algorithm

1. *INITIALIZATION*: randomly generate an initial population of N profile missions. Verify if an individual profile mission satisfies the constraints. If not, regenerate it.
 2. **while** generation number $< N_G$ **do**
 - *EVALUATION* : evaluate the population.
Calculating SRUL corresponding to every profile mission by the IIM.
Handling constraints: penalize individuals which do not satisfy the constraints by adding a cost.
 - *MATING SELECTION*: select parents to reproduce offsprings.
 - *CROSSOVER*: apply crossover operator to the mating pool to generate offsprings. Offsprings are added to parents to recreate the population.
 - *MUTATION*: mutate the offsprings at different positions by genetic mutation operator.
Some of the parents are not affected by mutation.
Generate some new individuals which satisfy constraints and add them to the population.
 3. **end while**
 4. *SOLUTION SELECTION*: select the profile mission having highest SRUL in the last generation.
-

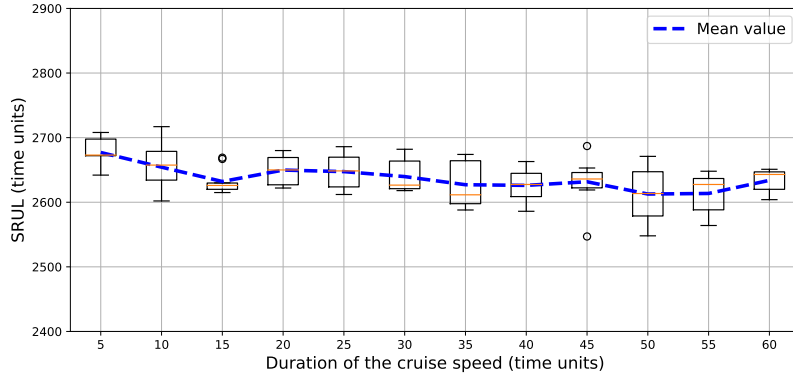


Figure 4.13: Variation of the SRUL in function of noisy mission profiles with different durations.

researchers have developed several methods to fill this gap. Among these methods, one can cite the penalty function method, the Lagrange multiplier method, and the complex search method (Deb, 2000). In this thesis, a death penalty method is used because of its simple implementation. Indeed, this method consists of assigning a very high cost when one of the solutions does not satisfy the constraints. Thus, in the next generation, bad solutions are effectively eliminated through a natural selection. However, in the case of a strict constraint, the natural selection makes the feasible space very small compared to the entire search space. To address this problem, the GA operations should be modified in order to create and mutate chromosomes with some local search optimization that fulfills the equality constraints. Finally, to maintain a diversity inside a population and avoid premature convergence, a part of the population is created and added to the population resulting from mutation and crossover (Pandey et al., 2014).

The procedure described above for mission profile optimization will be used in the following sub-section to extend the SRUL of the subway case study presented in the previous section.

Subway SRUL maximization

In what follows, we refer to the subway system presented earlier. The subway runs through stations whose distances between them are assumed to be constant. Given that the effect of velocity is the same on the subway's components, the optimization objective in this case study consists in finding the set of the mission profile parameters (t_{start} , t_{cruise} , $t_{decelerate}$, t_{stop} and v_{cruise}) that maximizes the SRUL while respecting the following operating constraints:

- Distance between the stations is constant (1200 m).
- Cruise speed is less than 50 km/h .
- The subway's journey time between two stations is limited to 120 time units.

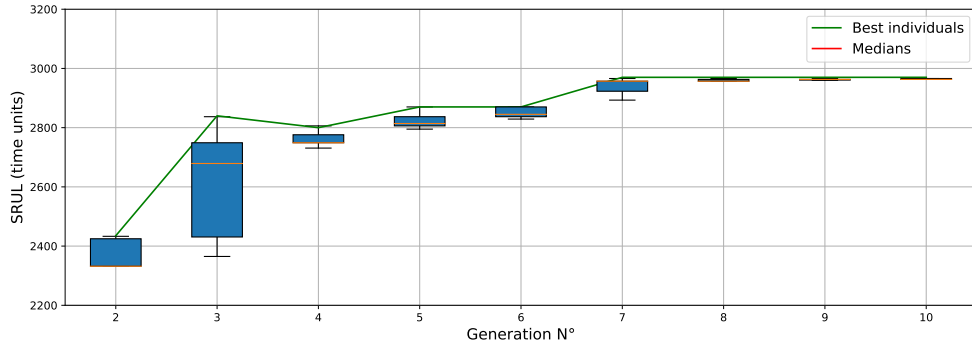


Figure 4.14: Population evolution through generations.

Using the GA-based method proposed previously, the MP parameters, that are presented in the form of chromosomes of five genes (v_{cruise} , t_{start} , t_{cruise} , $t_{decelerate}$ and t_{stop}), are optimized. The GA configuration is summarized in Table 4.2.

Table 4.2: Genetic algorithm parameters and rules.

Number of individuals	200
Number of parents	50
Selection type	Best fitness
Crossing type	One point
Mutation type	Uniform random selection with multiple mutations
Termination criteria	Generation: 10

Figure 4.14 shows the extension of the SRUL of the profile mission population through different generations. One can easily notice that the proposed algorithm converges after 7 generations. In fact, from this generation, the SRUL values corresponding to different profile missions in the population are almost the same, i.e., different solutions have the same objective function value. Some of the best solutions obtained by the GA after 10 generations are shown in Table 4.3. They provide the best objective function value (i.e. the largest SRUL) that is equal to 2970 *ut*. All those solutions satisfy the operational constraints, i.e., the subway will make its journeys within the time limits and without exceeding its maximum speed, while reducing the degradations affecting its components. The existence of multiple solutions that maximize the system lifetime offers the ability to flexibly change the profile mission for adapting to real situations. Indeed, the planned mission profile may be modified along the way, depending on the problems the end-users might face. For example, blocking the subway doors when they are closing induces a delay in the subway start. In this case, rather than choosing solution 1 in Table 4.3 (with start time at 10 *ut*), the driver can opt for solution 2 (with start time at 16 *ut*), and thus adapt the mission profile to the operational conditions while maximizing its lifespan.

In Figure 4.15, the mission profiles obtained in the first and last generation of the genetic algorithm are presented. One can notice that with the optimized mission profile (after 10 evolutionary generations), the subway SRUL is extended by more than 22% compared to

Table 4.3: Solutions for the mission profile parameter optimization.

Solution number	v_{cruise}	t_{start}	t_{cruise}	$t_{decelerate}$	t_{stop}
1	12.7	10.9	22.6	104.9	118.2
2	12.7	16.4	26.4	114	118.9
3	15.6	13.5	25.7	72.7	108.9

that one of the best solution obtained in the first generation. Indeed, for the non-optimized mission profile, the subway undergoes more set-point changes, and therefore, degrades more quickly and requires more frequent inspection and maintenance. This is true for a vast range of systems subject to highly varying operating conditions such as wind turbines (Zaher et al., 2009) and pneumatic actuators.

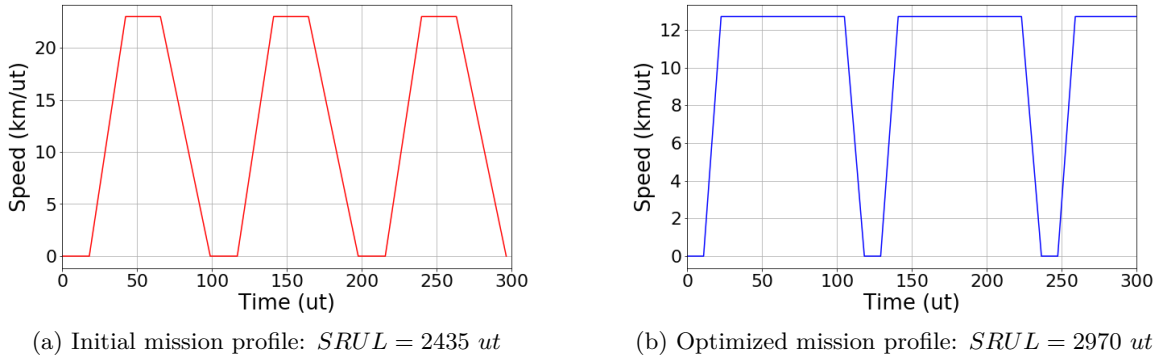


Figure 4.15: Illustration of the subway's mission profile before and after optimization.

4.4 Conclusion

In this chapter, we focused on analyzing the mission profile effect on system-level degradation and the SRUL. The performance of the inoperability input-output model, which allows taking into account time-varying profiles and system stress, has been one more time highlighted. Furthermore, the importance of considering the mission profile in the determination of SRUL was proven. Various mission profile scenarios were simulated in the subway case study to evaluate its SRUL. These simulations showed that in the case of a constant mission profile, without taking into account the MP information for SRUL prediction, the result may deviate by 18% compared to the one obtained when considering the MP impact. Also, in the case of variable mission profile, the SRUL can decrease by up to 8% due to driver-induced variability, and 73.5% of the SRULs obtained when the distance between stations is varied are less than the SRUL obtained in the case of a constant mission profile.

In light of the obtained results when investigating the mission profile impact on SRUL, a

practical optimization approach based on a genetic algorithm was developed. This approach is proven as effective in finding the best appropriate mission profiles that maximize the SRUL while satisfying different operational constraints. In detail, several optimized profile missions are found, which allow the subway SRUL to be extended to more than 22%. The multiplicity of optimal solutions is another advantage of our approach. Indeed, the planned mission profile may be modified along the way, depending on operational problems. Hence, the existence of these multiple solutions offers the ability to flexibly change the profile mission for adapting to real situations while ensuring the system remaining useful life maximization.

Application of the proposed methodology on real industrial case study: Tennessee Eastman Process

It doesn't matter how beautiful your theory is, it doesn't matter how smart you are. If it doesn't agree with experiment, it's wrong.

Richard Phillips Feynman

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5.1 Introduction

In the previous chapters, we have proposed a system degradation modeling framework and a methodology for joint parameter estimation and SRUL prediction. These solutions allow removing the most important locks identified in the area of system-level prognostics (SLP). However, a legitimate question that can be raised here is: how well do these contributions perform in a practical case? Thus, to highlight the applicability of the proposed developments, a simulation of a real industrial plant, called the Tennessee Eastman Process (TEP), is considered. As this system was not intended, initially, for prognostics purposes, its fundamental paradigms are changed to liken system degradation.

The remainder of this chapter is organized as follows. Section 5.2 contains a description of the process and its variables. In section 5.3, the adaptation of the TEP simulation for SLP is detailed. Following this adaptation, the IIM of the TEP is formulated in section 5.4, and its parameters are estimated off-line. Then, by using this model and online monitoring data, the TEP health state is estimated and predicted by PF in section 5.5. Finally, the proposed methodology for online joint SRUL prediction and parameter estimation is investigated in section 5.6. In this latter section, a sensitivity study is also carried out to verify variations in the results in terms of prediction accuracy and calculation time.

5.2 System description

The Tennessee Eastman Process built by the Eastman Chemical Company has been widely used as a realistic benchmark for process control optimization, fault diagnostics, and, to a lesser extent, for component-level prognostics (Datong et al., 2011). Downs and Vogel (Downs and Vogel, 1993) described it in detail and provided its simulation where the components, kinetics, and operating conditions have been modified for proprietary reasons. The TEP involves five major units (working in open-loop), including a two-phase reactor, a partial condenser, a separator, a stripper, and a compressor. It also contains eight reactants: A , B , C , D , E , F , G and H .

5.2.1 Process flowsheet

The schematic piping and instrumentation diagram (P&ID) of the TEP is shown in Figure 5.1. In the TEP, the gaseous reactants $\{A, C, D, E\}$ are fed to the reactor where the liquid products G and H are formed. The reactions in the reactor are given by equations 5.1:

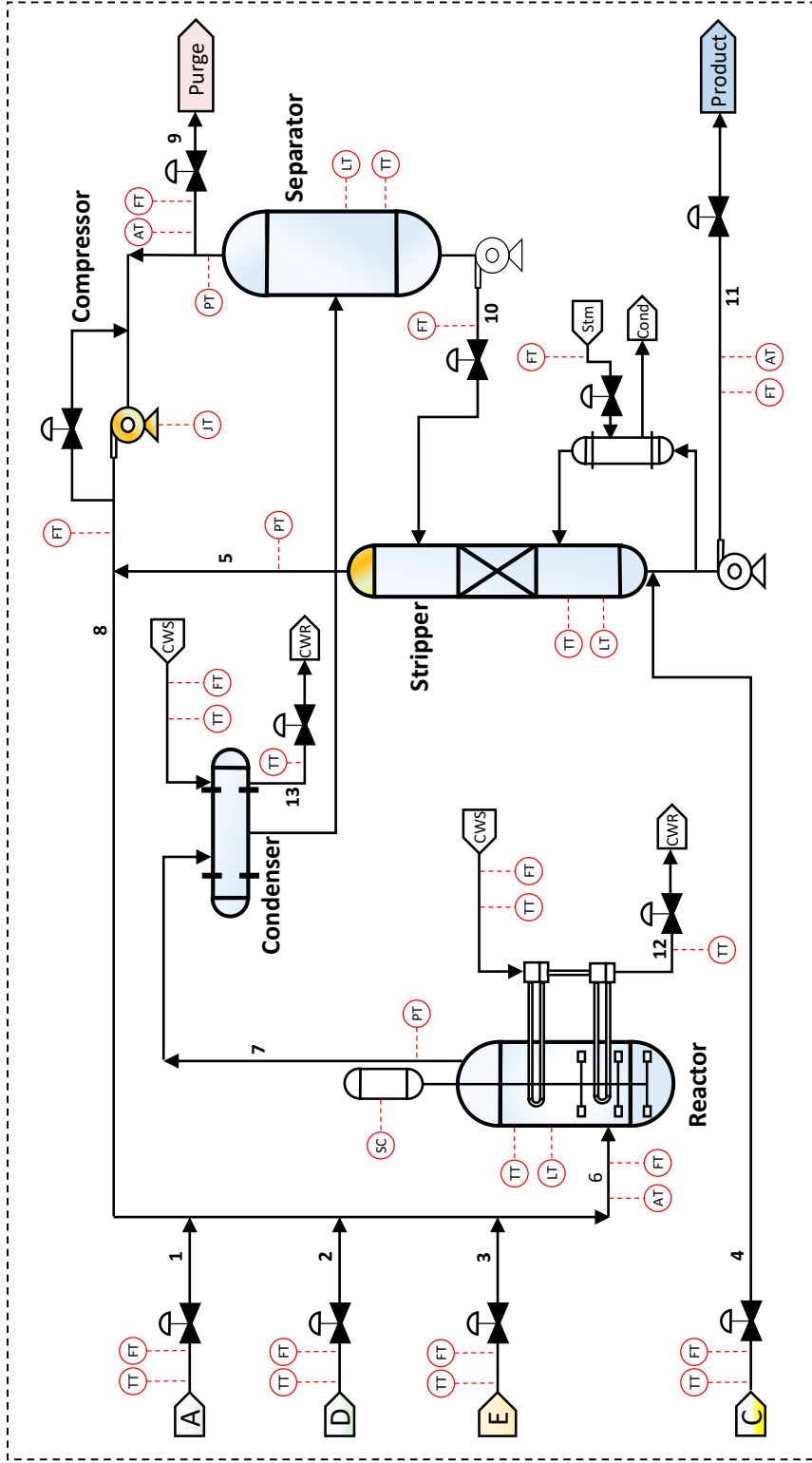
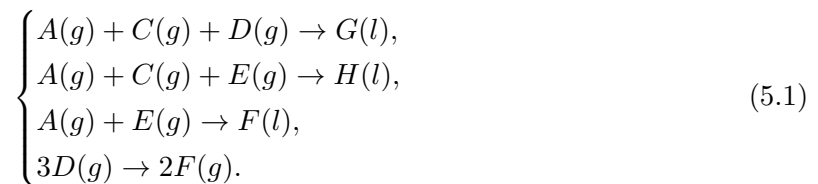


Figure 5.1: PI&D of the Tennessee Eastman Process.

Variable	Description
XMV(1)	D feed flow (Stream 2)
XMV(2)	E feed flow (Stream 3)
XMV(3)	A feed flow (Stream 1)
XMV(4)	Total feed flow (Stream 4)
XMV(5)	Compressor recycle valve
XMV(6)	Purge valve (Stream 9)
XMV(7)	Separator pot liquid flow (Stream 10)
XMV(8)	Stripper liquid product flow (Stream 11)
XMV(9)	Stripper stream valve
XMV(10)	Reactor cooling water flow
XMV(11)	Condenser cooling water flow
XMV(12)	Agitator speed

Table 5.1: Manipulated variables in the TEP (Downs and Vogel, 1993).



where F is a byproduct of the reactions.

The reactions are irreversible, exothermic, and approximately first-order with respect to the reactant concentrations. The reaction rates are Arrhenius functions of temperature where the reaction for G has higher activation energy than the reaction for H , resulting in a higher sensitivity to temperature.

The reactor product stream is cooled through a condenser and then fed to a vapor-liquid separator. The vapor exiting the separator is recycled to the reactor through a compressor. A portion of the recycle stream is purged to keep the inert and byproduct from accumulating in the process. The condensed component from the separator (Stream 10) is pumped to a stripper. Stream 4 is used to strip the remaining reactants from Stream 10, which are combined with the recycle stream via Stream 5. The products G and H exiting the base of the stripper are sent to a downstream process, which is not included in the diagram.

5.2.2 Process variables

The process contains 53 measured and 12 manipulated variables. The manipulated variables (XMV(1) to XMV(12)) are listed in Table 5.1. These variables are used to control the process. Among the measured variables, 22 ones (from XMEAS(1) to XMEAS(22)) are sampled every 5.88 seconds approximately (Table 5.2). These variables represent continuous process measurements, such as temperatures, pressures, flow rates, levels, etc. The remaining

variables, i.e., 31 variables, correspond to reactant composition measurements. All the process measurements include a Gaussian noise following distribution of $N(u, 0.01^2)$.

Variable	Description	Units
XMEAS(1)	A feed (Stream 1)	kscmh
XMEAS(2)	D feed (Stream 2)	kg/hr
XMEAS(3)	E feed (Stream 3)	kg/hr
XMEAS(4)	Total feed (Stream 4)	kscmh
XMEAS(5)	Recycle flow (Stream 8)	kscmh
XMEAS(6)	Reactor feed rate (Stream 8)	kscmh
XMEAS(7)	Reactor pressure	kPa gauge
XMEAS(8)	Reactor level	%
XMEAS(9)	Reactor temperature	Deg C
XMEAS(10)	Purge rate (Stream 9)	kscmh
XMEAS(11)	Product separator temperature	Deg C
XMEAS(12)	Product separator level	%
XMEAS(13)	Product separator pressure	kPa gauge
XMEAS(14)	Product separator underflow (Stream 10)	m^3/hr
XMEAS(15)	Stripper level	%
XMEAS(16)	Stripper pressure	kPa gauge
XMEAS(17)	Stripper underflow (Stream 11)	m^3/hr
XMEAS(18)	Stripper temperature	Deg C
XMEAS(19)	Stripper steam flow	kg/hr
XMEAS(20)	Compressor work	kW
XMEAS(21)	Reactor cooling water outlet temperature	Deg C
XMEAS(22)	Separator cooling water outlet temperature	Deg C

Table 5.2: Process measurements in the TEP (Downs and Vogel, 1993).

5.2.3 Process faults

The Tennessee Eastman Process simulation contains originally 21 pre-programmed faults (Downs and Vogel, 1993). In (Bathelt et al., 2015), 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

Fault number	Description
IDV (3)	Step in D feed temperature (Stream 2)
IDV (11)	Random variation of the reactor cooling water inlet temperature
IDV (13)	Deviation in reaction kinetics
IDV (16)	Deviation in the heat transfer of the heat exchanger of the stripper
IDV (17)	Deviation in heat transfer in reactor
IDV (25)	Step in E feed flow (Stream 3)

Table 5.3: Examples of process disturbances (Downs and Vogel, 1993; Bathelt et al., 2015).

Table 5.3). The simulation program allows the faults to be implemented either individually or in combination with another one.

5.2.4 Simulation program

The simulation code for the process is available in FORTRAN, and a detailed description of the process and simulation is presented in (Downs and Vogel, 1993; Bathelt et al., 2015). There are six modes of the process operation corresponding to various G/H mass ratios and hourly production rates of Stream 11 (Table 5.4). The mode A is the default mode. The product mix is normally dictated by product demands. The production rate is set the by market demand or by the capacity limitations.

Mode	G/H mass ratio	Production rate
1 (default mode)	50/50	7036 kg h^{-1} G and 7038 kg h^{-1} H
2	10/90	1408 kg h^{-1} G and 12.669 kg h^{-1} H
3	90/10	10 kg h^{-1} G and 1111 kg h^{-1} H
4	50/50	Maximum production rate
5	10/90	Maximum production rate
6	90/10	Maximum production rate

Table 5.4: The 6 production modes of the TEP.

Hereinafter, the open-loop functioning of the TEP is simulated using the code developed by (Ricker, 2015).

5.3 Prognostics in the case of the TEP

In early studies, the TEP was intended for testing control strategies in order to regulate it after the introduction of one or more disturbances, by controlling the manipulated variables (Table 5.1). Its initial objectives were to maintain the process variables at desired values (normal operating limits), to minimize the variability of the product rate and the product quality during disturbances (Stream 11) and to prevent the variables from reaching shutdown thresholds. Thus, the adopted control strategies attempt the process to recover quickly and smoothly from the disturbances, the production rate changes, or the product mix changes (Jaffel et al., 2016; Ge and Song, 2008). Besides, The TEP has been used to optimize the production by determining the operating conditions for its 6 production modes (Jockenhövel et al., 2003). Finally, it was also used for fault diagnostics by injecting the faults and trying to detect them and locate the root causes (Eslamloueyan, 2011; Hao et al., 2014).

To use this system for prognostics purposes, the system's initial paradigms are changed as follows (Tamssaouet et al., 2019a):

- An interruption of the operational continuity resulting from the violation of the variables

shutdown limits is considered as a system failure. Therefore, only components with shutdown constraints are considered, i.e., the reactor, the stripper, and the separator. Each of these components is monitored by a single parameter: pressure for the reactor, and liquid level for the stripper and the separator. Table 5.5 lists the specific operational constraints related to the system parameters that the control unit should respect.

Table 5.5: TEP operating constraints (Downs and Vogel, 1993).

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

- The system is in open-loop, i.e., no control strategy is implemented to bring the system back to its normal mode after a fault injection. Indeed, one can assume easily that, without maintenance actions, any system has to fail for $t < \infty$ (even if it has regeneration phenomena).

Therefore, for this case study, the goal is to predict when the system's monitored parameters (considered as health indicators) will exceed the shutdown thresholds. If these health indicators are within the range of normal operating limits (Table 5.5), the system is considered healthy. Once these indicators are outside this range, the system is considered in a degraded state. At this time, the prediction of its future state and the determination of its SRUL are launched.

5.4 TEP modeling and parameter estimation - offline phase

To predict the SRUL of the TEP, it is essential to build its degradation model and estimate the parameters of this model.

5.4.1 Model formulation

In Matlab simulations of the TEP (Ricker, 2015), two disturbances predefined in (Bathelt et al., 2015) were injected. These disturbances, occurring in the reactor and the stripper respectively, are represented as a deviation in the reactor cooling water flow (IDV (13) in Table 5.3) and a deviation in the heat transfer of the heat exchanger of the stripper (IDV (11) in Table 5.3). Then, the own degradation process of the components (i.e. $c_1(t)$ and $c_2(t)$), are assumed to follow equations 5.2 and 5.3, respectively.

$$c_1(t) = \alpha \cdot c_1(t - 1) + \beta \quad (5.2)$$

$$c_2(t) = \epsilon \cdot c_2(t - 1) \quad (5.3)$$

with α , β , and ϵ are the parameters of the two models to be estimated from the monitoring data.

For the interdependence matrix A , and as it is not possible to perform run-to-failure experiments on each component or to know the corresponding interaction phenomenology, the matrix A will be estimated and adjusted to make the proposed model better fit the monitoring process data.

Finally, regarding the matrix of influencing factors K , its diagonal elements k_i are equal to 1 because the data are acquired in the default production mode.

The formulation of the resulting model, whose parameters will be estimated in the next subsections, is as follows:

$$\begin{pmatrix} q_1(t) \\ q_2(t) \\ q_3(t) \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{pmatrix} \times \left\{ \begin{pmatrix} 0 & a_{12} & a_{13} \\ a_{21} & 0 & a_{23} \\ a_{31} & a_{32} & 0 \end{pmatrix} \times \begin{pmatrix} q_1(t-1) \\ q_2(t-1) \\ q_3(t-1) \end{pmatrix} + \begin{pmatrix} \alpha \cdot c_1(t-1) + \beta \\ \epsilon \cdot c_2(t-1) \\ 0 \end{pmatrix} \right\}$$

5.4.2 Data pre-processing and inoperability calculation

Before using the TEP data to estimate the parameters of its IIM model, it is necessary to process these data, i.e., transform them into inoperability measures. To do so, after the injection of the two faults mentioned above, the raw data ($x_i(t)$) acquired from the TEP simulation (Figure 5.2) are normalized to the initial state ($x_i(t_0)$) and the failure threshold (L_i) by using the following formula:

$$q_i(t) = \frac{x_i(t) - x_i(t_0)}{L_i - x_i(t_0)} \quad (5.4)$$

Their initial states correspond to the parameter base values (Downs and Vogel, 1993) given as follows:

- Reactor pressure ($x_1(t_0)$): 2700 *kPa*
- Stripper level ($x_2(t_0)$): 3.47 *m*
- Separator level ($x_3(t_0)$): 4.7 *m*

and the failure thresholds correspond to the shutdown limit values given in Table 5.5.

The results of this normalization is given in Figure 5.3, where the data represent the inoperability of the following components: the reactor $q_1(t)$, the separator $q_2(t)$ and the separator $q_3(t)$.

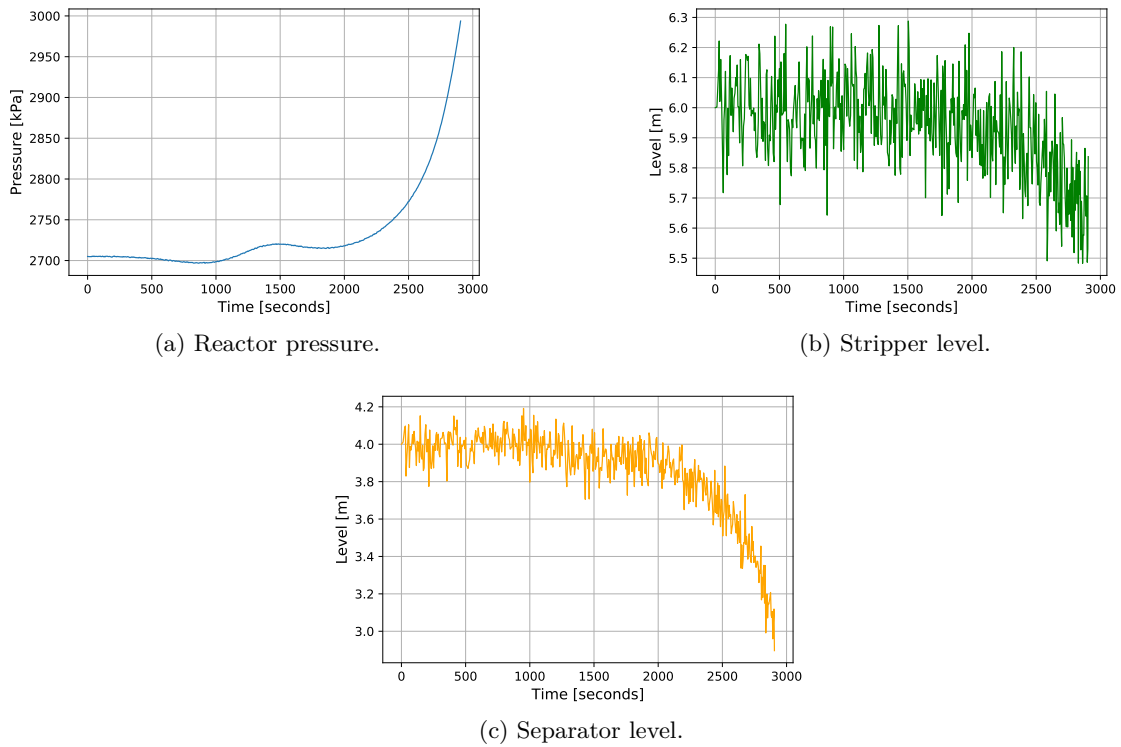


Figure 5.2: Raw data of the TEP before normalization.

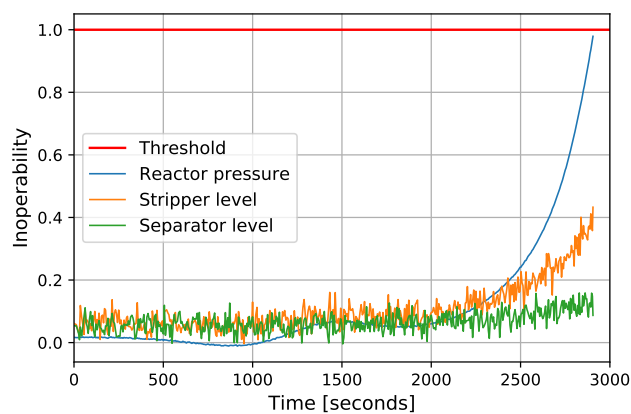


Figure 5.3: Raw data of the TEP after normalization (Inoperability).

5.4.3 IIM parameter estimation

The historical monitoring inoperability evolution of the TEP components (Figure 5.3) is used as the input data of our proposed estimation algorithm based on the gradient descent method (presented in Section 3.2) to estimate the IIM parameters. To achieve this, we consider as a stopping criterion the difference of the MSE in two successive iterations less than 10^{-10} , and the learning rate is set to 0.005 (i.e. $\gamma = 0.005$). This latter value is determined empirically to reach the minimal convergence time of the algorithm, as shown in Figure 5.4.

The initial values of the component internal degradation parameters, i.e. α , β and ϵ in equations 5.2 and 5.3, are set randomly (in order to show the robustness of the estimation method). After performing the proposed estimation algorithm, we obtain: $\alpha = 1.018$, $\beta = 0.001$ and $\epsilon = 0.9$. This leads to the following internal degradation models of the components:

$$c(t) = \begin{cases} c_1(t) \\ c_2(t) \\ c_3(t) \end{cases} = \begin{cases} 1.018 \cdot c_1(t-1) + 0.001 \\ 0.9 \cdot c_2(t-1) \\ 0 \end{cases}$$

Also, the estimated interdependencies matrix A is:

$$A = \begin{bmatrix} 0 & 8 \cdot 10^{-3} & 2 \cdot 10^{-8} \\ 3 \cdot 10^{-4} & 0 & 3 \cdot 10^{-8} \\ 2 \cdot 10^{-4} & 10^{-4} & 0 \end{bmatrix}$$

One can notice that the last column elements of the estimated matrix A are smaller compared to the other matrix elements. This is due to the fact that in this simulation, the separator is not degrading by itself and thus does not significantly influence the degradation of the other components. However, its influence on the other component degradations is not null, i.e., $a_{i3} \neq 0$. In fact, the separator degrades because of the influence of the other components, and as a result, it, in turn, influences them.

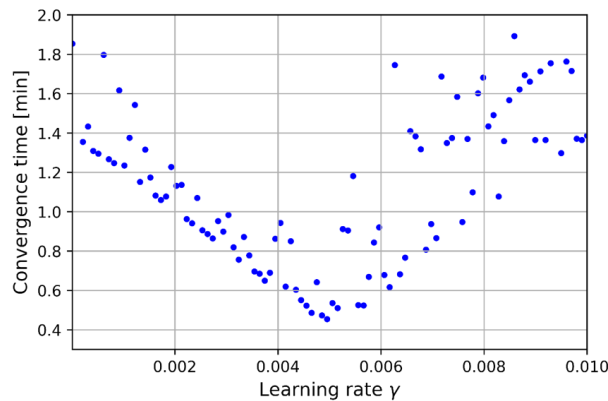


Figure 5.4: Convergence time as a function of the learning rate values.

By using the above results, and considering that at $t = 0$ the system is in a healthy state, the data obtained by the built IIM are given in Figure 5.5. When comparing Figs. 5.3 and 5.5, one can notice that the estimated IIM model captures well the evolution of the system degradation processes.

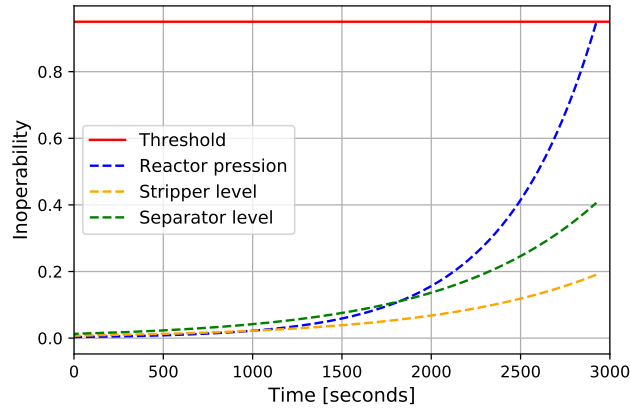


Figure 5.5: TEP inoperabilities evolution using the estimated IIM.

As now, the degradation model of the system is determined, it will be used, in the next section, to estimate its health state and predict its SRUL.

5.5 TEP health state estimation and SRUL prediction - online phase

The purpose, here, is to predict the SRUL when taking into account the process uncertainty, which is due to the natural variation of the process and a new injected fault which is a random variation of the reactor cooling water inlet temperature (IDV (11) in Table 5.3). To do this, the actual monitoring data and the IIM model estimated offline, in the previous section, are used to estimate and predict the inoperability of the process units. Based on the prediction of the system's future health, the SRUL will be calculated.

5.5.1 Inoperability estimation and prediction

The offline estimated IIM (in section 5.4) is used by a particle filtering (PF) to estimate the component inoperabilities. To evaluate the inoperability densities, 200 particles were used with the initial distributions of the components inoperabilities considered as Gaussian. The selection of the particles to be retained after each filtering step was done by using the residual resampling method (Arulampalam et al., 2002). When the inoperability of any component exceeds its normal operating limit, which is equal to an inoperability of 0.2 (as indicated in Table 5.5), the prediction step will be launched (at time k_p).

The results of the estimation and prediction of the inoperabilities uncertainty of the system

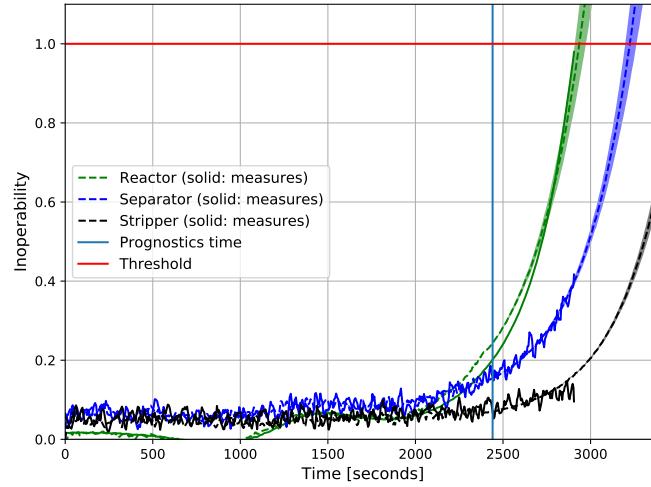


Figure 5.6: TEP unit health state estimation and prediction.

components are shown in Figure 5.6. The reactor is the first component to go out of its normal operating limit after 2440 seconds (i.e. $t_p = 2440s$). This time corresponds to the time where the long-term inoperability prediction is launched. Also, it is the reactor pressure, that triggers the system shutdown (system failure) at 2905 seconds. One can notice that the uncertainty related to the predicted inoperability increases for $t > t_p$. This is due to the fact that no measurements were received and, therefore, there is neither updating of the particle weights nor resampling.

5.5.2 SRUL determination

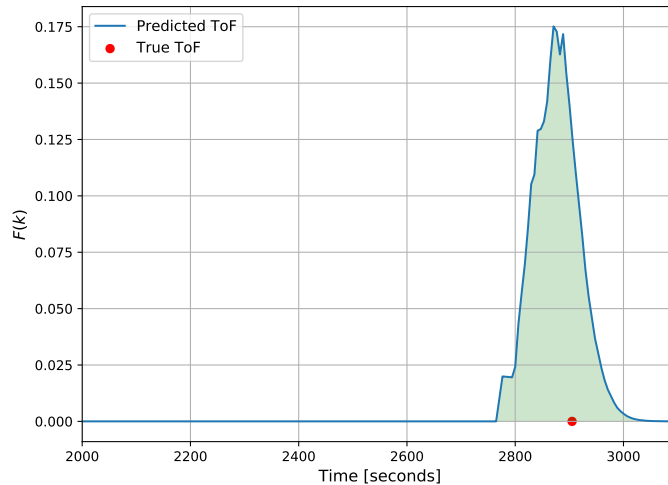


Figure 5.7: Time-of-Failure probability distributions of the TEP components at $t_p = 2440s$.

For this case study, the operability of the studied system depends on the operability of its components since they all contribute to the realization of the system function (G and

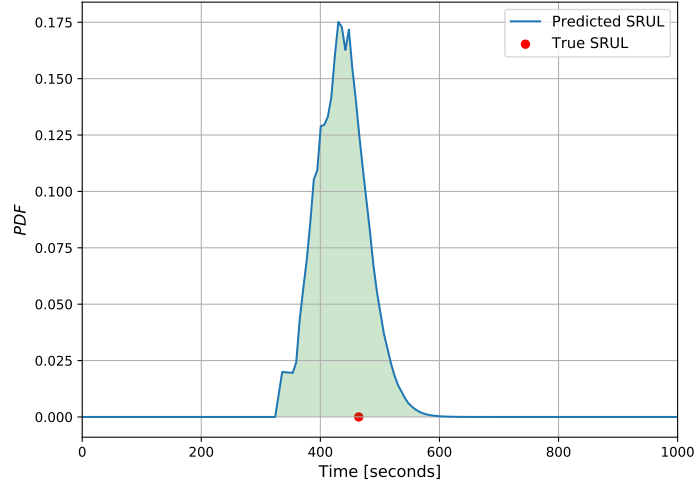


Figure 5.8: SRUL probability distributions of the TEP components at $t_p = 2440s$.

H production). Therefore, one can conclude that the system has a series architecture. By applying the calculation method described in subsection 3.3.3, the ToF PMF of the system determined at $t_p = 2440$ seconds is shown in Figure 5.7 and the SRUL PMF is given in Figure 5.8. The mean value of the SRUL is equal to 445 seconds. The true SRUL, which is equal to 465 seconds, is within the 95% confidence interval of the predicted SRUL distribution. One can conclude that the predicted SRUL is close to reality and is slightly pessimistic. This result allows early scheduling of maintenance actions and, therefore, puts the system, its operators, and its environment in a safer situation.

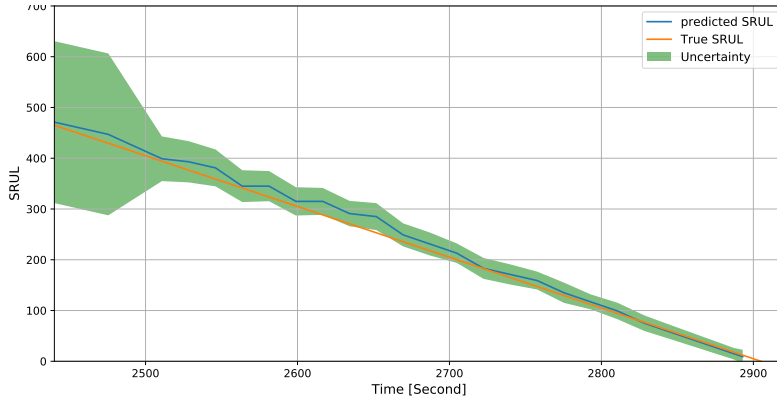


Figure 5.9: SRUL prediction performance with $\alpha=0.1$.

In order to discuss the performance of the proposed methodology, a study of the prognostics horizon impact on the result intervals is performed by considering the α -accuracy metric. This metric, proposed in (Saxena et al., 2010), determines whether a prediction falls within an $\alpha\%$ interval. In fact, α -accuracy is a useful metric to judge if a prognostics algorithm converges to the true value as more information is accumulated over time. Indeed, a faster convergence is desired to estimate the SRUL earlier and more accurately. To that end, in this

study, several prognostics times are considered within the interval [2440, 2890], as shown in Figure 5.9 and the accuracy is defined with $\alpha = 10\%$. The figure shows the mean values and the uncertainties of the predicted SRUL distributions compared with the true SRUL. As it can be seen, the prediction of the SRUL becomes more accurate each time the measurements are obtained, and all the predictions over time fall in the confidence interval.

5.6 Online joint SRUL prediction and parameter estimation

In section 5.4, the system degradation model was determined offline. This required performing run-to-failure tests in order to observe how its health state evolves. However, the Tennessee Eastman Process is a continuous production process, and it is not desirable to let its parameters drift until the shutdown, as this can lead to financial losses and safety risks. It is then not possible to early estimate the parameters of the degradation model and to use it to predict online the evolution of the system health state. Indeed, according to Vapnik's theory of sample complexity (Vapnik, 2013), only part of the training samples are needed by an estimation algorithm to keep its error within an acceptable interval. Following this theory, and in the absence of run-to-failure data, the IIM parameters can be estimated when enough monitoring data are available. The model will then be updated according to the new observations. To enhance the accuracy of the estimation, a digital filter is applied to the raw data in order to reduce their noises. In this case, a Savitzky-Golay filter (Savitzky and Golay, 1964) is chosen because it allows increasing the precision of the data without distorting the signal trend.

5.6.1 Discussion of the online TEP estimation and prediction results

To predict the TEP SRUL online, the methodology described in section 3.4 is utilized. The input of this methodology is only the structure of the IIM, i.e., the number of critical components to monitor, the health indicators corresponding to the healthy state and to the failure threshold, and the trends of the component degradations. Broadly, these inputs correspond to the IIM structure given in equation 5.4.1. Then, each time new measurements characterizing the system inoperabilities are available, the entire acquired signal is filtered and then used to estimate or update the estimated parameters of the IIM model, and predict the system remaining useful life.

In order to reduce the computation time related to the application of the methodology described in section 3.4, one must evaluate the outputs of the estimated IIM with respect to the monitoring data to investigate whether it is necessary to update the IIM. The procedure of the IIM update and the SRUL prediction is set as follows:

- When a discrepancy between the predicted value by the IIM and the monitoring data is greater than 1σ on both sides of the mean value (i.e. $\theta = 0.01$), which represents

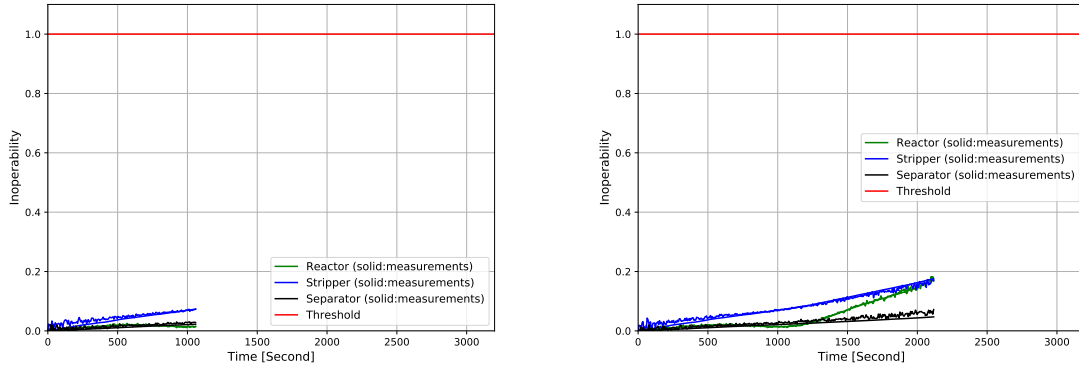


Figure 5.10: Estimated component inoperabilities at $t = 1100 ut$ and $t = 2100 ut$.

the process measurement standard deviation, the parameter δ is incremented by 1, and a long-term prediction of the system health state is performed.

- When three successive discrepancies are detected (i.e. $\delta = 3$), the IIM parameters will be updated using the GD method.

Figure 5.10 shows the estimated and measured inoperability of the TEP units at $t = 1100 ut$ and $t = 2100 ut$. One can notice that the estimation given by using the IIM (determined by GD) and the PF corresponds to the actual measurements of the component inoperabilities despite the non-linearity properties of the system. Also, in Figure 5.11, we can notice that the predicted ToF PMF is close to the true ToF, and the uncertainty is decreasing over time when more data are available and used to update the IIM parameters.

By applying the proposed methodology, the IIM parameters were updated only 89 times out of a total of 494 data samples. The long-term prediction of component inoperabilities was made only 23 times, versus 82 cycles of the system after the anomaly was detected. The total computation time was 140 seconds by using an Intel core iZ 7700 and 16 Gb RAM, which means that the average duration of a single iteration of the proposed methodology is 1.25 seconds. Knowing that the system fails after 2905 ut of operation, it is reasonable to consider low computational resources while ensuring a good prediction of the SRUL, even though the TEP is a highly critical facility and the resources allocated in our work are reasonable to deploy in reality.

5.6.2 Sensitivity analysis

To evaluate the sensitivity of the methodology applied here to predict the SRUL online, with respect to its parameters, i.e., θ and δ , several simulations were conducted. We firstly perform the sensitivity analysis regarding θ , i.e., the parameter used to evaluate the discrepancy between the estimate made by the IIM and the actual measurements of the system. Then,

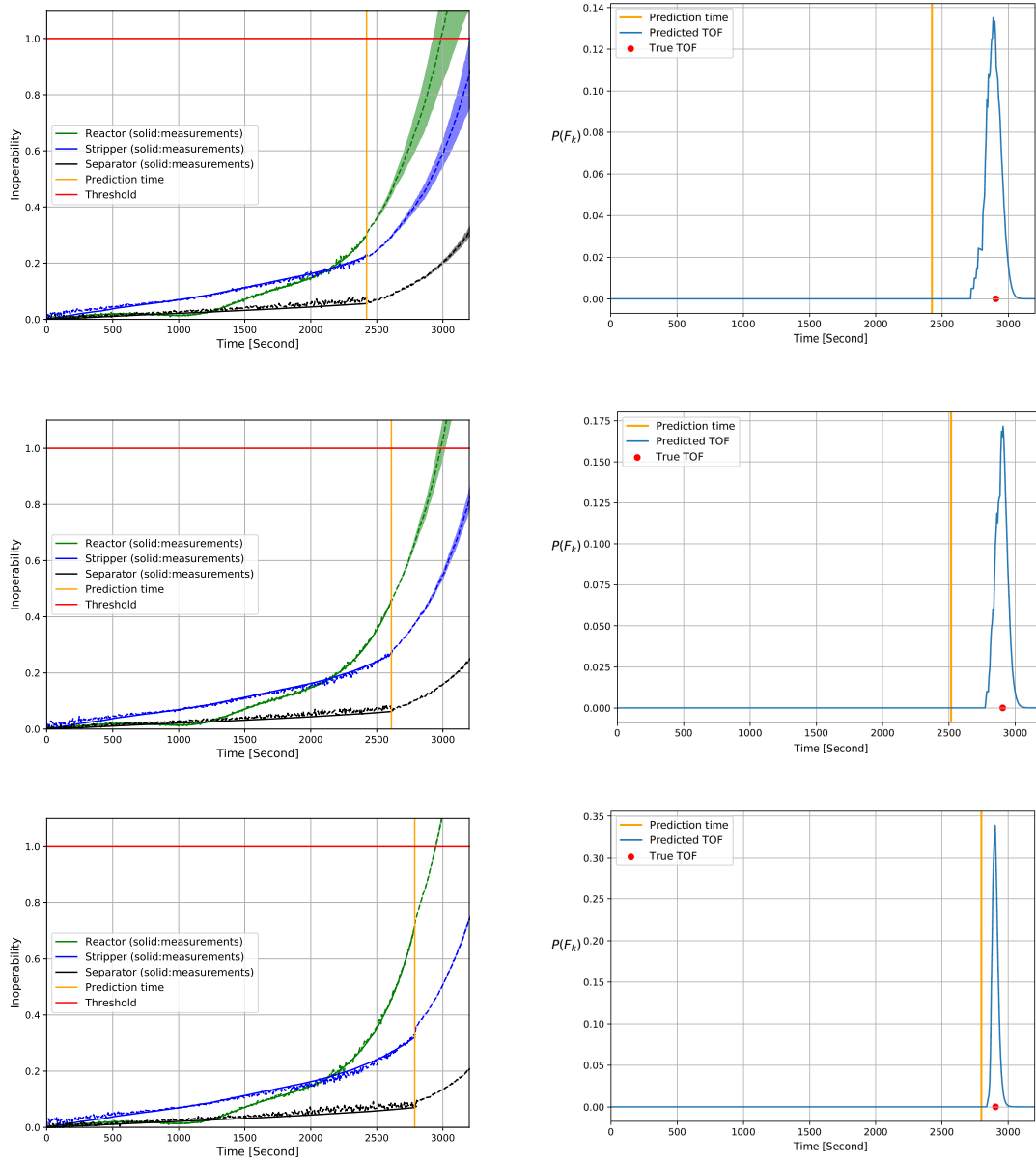


Figure 5.11: Predicted component inoperabilities and ToF PDF at different instants.

we investigate the parameter δ characterized the number of successive discrepancies needed to recompute the IIM parameters and derive the optimal value that ensures an accurate prediction of the SRUL while minimizing the computation time.

5.6.2.1 Sensitivity analysis in regard to θ

The evaluation thresholds (confidence interval) considered for determining if there is a discrepancy between the estimate made by the IIM and the monitoring data are 1σ , 2σ , and 3σ (i.e. 1, 2 and 3 standard deviation, respectively, on both sides of the mean value), with $\delta = 3$. The result in terms of computation time, long-term prediction updates, and IIM parameter updates are shown in Table 5.6. One can notice that tighter the width of the confidence interval is, more are the calculation time and prognostics updates. However, concerning the number of IIM parameter update times, they still almost the same regardless of the value of θ considered. This can be explained by the fact that the model can be well estimated from the first iterations of the methodology. However, because of the system's non-linearities and noise, the SRUL needs to be predicted several times.

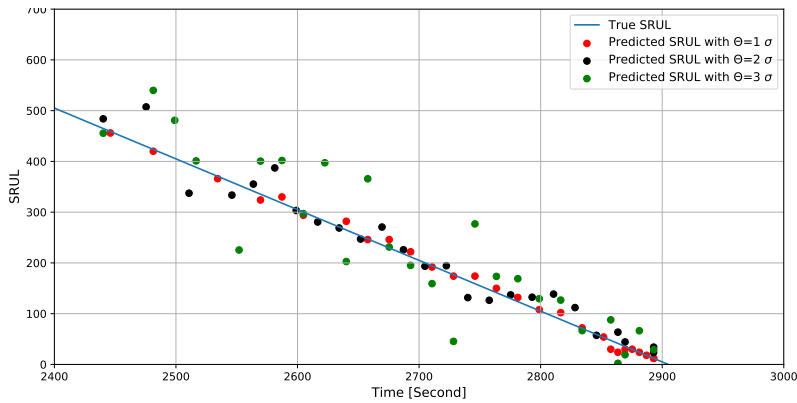


Figure 5.12: Predicted SRUL in function of the parameter θ .

Precision	1σ	2σ	3σ
Parameter corrections	81	81	80
Prognostics updates	91	28	27
Calculation time	140	103	88

Table 5.6: Calculation performances in function of the parameter θ .

Figure 5.12 shows the evolution of the predicted SRUL according to the confidence interval width. One can notice that the wider the confidence interval, the less is the accuracy of the prediction.

5.6.2.2 Sensitivity analysis in regard to δ

Figure 5.13 shows the variation of the computation time (represented by the green line) and the MSE (represented by the blue line) of the IIM outputs in function of the number of successive discrepancies (i.e. δ) needed to recompute the IIM parameters. To estimate the accuracy of the GD descent results, a MSE is calculated at the first prognostics time, i.e., $t_p = 2440$.

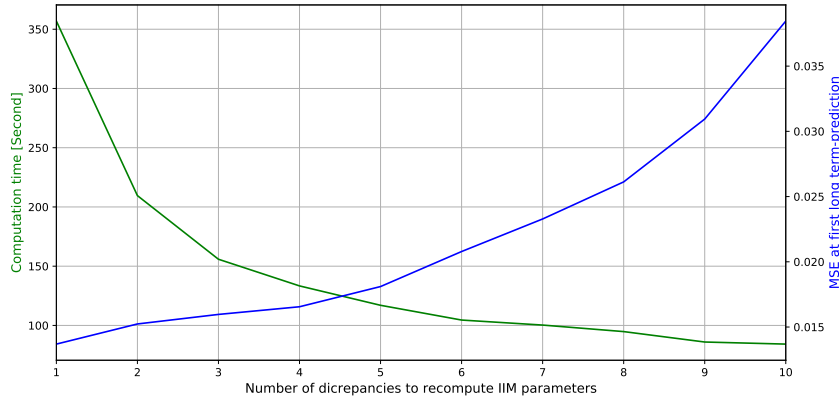


Figure 5.13: Computation time and accuracy of the IIM parameter estimation in function of the number of discrepancies to recompute the IIM parameters.

One can notice that the computation time is decreasing when the number of discrepancies to recompute the IIM parameters is high (the inverse for the accuracy of the IIM parameters estimation). Indeed, the more the GD is performed, the closer the estimated IIM parameters to the optimal solution. Hence, by considering the reduction of the computation time, and the increase of the prediction accuracy, the optimal δ value can be 4 or 5.

5.7 Conclusion

In this chapter, the theoretical contributions of this thesis were applied to a realistic system, which is the Tennessee Eastman Process. As this system was not intended for prognostics purposes, an adaptation was proposed for its use in assessing system-level prognostics approaches. Its choice was motivated by the absence of real in-field data acquired on real plants operating under real conditions. 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. To overcome this situation, the TEP was a relevant alternative for testing our scientific developments.

First, some faults were injected into the process units to generate degradation data. Then, the system degradation modeling based on the IIM was implemented, from the formulation of the model to the estimation of its parameters, by using the proposed GD-based method. The derived model was exploited by particle filtering to estimate and predict the system's health state evolution while quantifying the uncertainty. Finally, the online SRUL prediction

methodology, presented in the previous chapter, was applied to this case study, and a sensitivity analysis was conducted to find the best parameters to utilize to get accurate results with low computation resources.

This chapter concludes the contributions presented in this thesis. The general conclusions and future work will be presented in the next chapter.

General conclusion and future work

Conclusion

In this research work, we addressed the topic of system-level prognostics (SLP) from degradation modeling to decision-making issues.

In the first chapter, we surveyed the existing literature related to this topic. Based on a comprehensive review, each study's advantages and disadvantages were discussed, and critical conclusions were derived. In detail, the majority of studies do not investigate various factors influencing system degradation, for instance, interdependencies between components, mission profile, and related uncertainties. These limitations are mainly due to the lack of a modeling framework that allows simultaneously taking into account all these aspects. Besides, several assumptions that reduce the applicability of existing approaches of SLP have been outlined, such as the need for a large amount of data or extensive prior knowledge about system degradation mechanisms and the need for oversized computational capacity. Also, several challenges that remain to be solved to provide an implementable SLP approach have been identified. These challenges include handling uncertainty for health state estimation, developing a new method for SRUL calculation, and mission profile parameter optimization. Finally, the positioning and the main contributions of the thesis have been exposed in order to release the identified assumptions and to tackle the highlighted challenges.

The second chapter aimed to fill the literature gap about SLP modeling. This was achieved by using a model, namely the inoperability input-output model (IIM), that came from the field of economics and adapted to engineering science specificities, more particularly to failure prognostics. The proposed IIM-based model allows considering multi-dimensional interdependencies between components, mission profile, and inner component degradations. This model can be utilized for systems having heterogeneous components and thresholds and non-linear dynamic behaviors. Besides, through the concept of inoperability, the IIM eases communication with system managers and decision-makers.

Chapter 3 focused on developing a comprehensive methodology for online prognostics. This methodology makes it possible to update the model parameters (if they have already been estimated offline by using run-to-failure experiments) or to estimate them online. In that sense, a flexible method based on a gradient descent algorithm and adaptable to the available information on the system was proposed. Then, by using the new proposed version of the particle filter method, the prior health state estimate given by the IIM model was combined with the real data of the system to evaluate a posterior estimate and predict its degradation evolution. Next, the results of this prediction were used to calculate the remaining useful life of the system while considering its configuration. This calculation was conducted based on the recent developments and achievements proposed at component-level prognostics and generalized in this thesis to SLP. Finally, a new method that strikes a balance between

computation time, which is very important in online implementations, and SRUL prediction accuracy was developed.

Chapter 4 was dedicated to a critical post-prognostics issue that is to propose solutions for an extension of the system remaining useful life. The analysis of the mission profile effects on the SRUL has shown the importance of this factor in the system degradation evolution. Hence, a method based on a genetic algorithm was proposed to maximize the SRUL by optimizing the mission profile parameters to maintain the system in good health state as long as possible while handling multiple operational constraints. This method has been tested on a realistic case study, which is a subway, and allowed increasing the subway lifespan by 22%.

In chapter 5, the applicability of the proposed methodology on a real industrial system was proven through the Tennessee Eastman Process. In order to use this system for prognostics purposes, a paradigm shift was proposed. Given the scarcity of data and benchmarks that would permit the SLP approach evaluation, the TEP has turned to be an appropriate system that can be used by other works in that aim. Next, the degradation modeling of the TEP system was constructed using the IIM. Then, the utilization of the joint methodology allowed us to predict the SRUL in reasonable computation time.

Several publications have been generated as part of the research work hereby discussed. On the one hand, the modeling framework proposed in this thesis and the analysis of the mission profile effects have been disclosed in the following publications:

- Tamssaouet, F., Nguyen, T. P. K. and Medjaher, K. (2018). System-level prognostics based on inoperability input-output model. In Annual Conference of the Prognostics and Health Management Society.
- Tamssaouet, F., Nguyen, T. P. K. and Medjaher, K. (2019). System-Level Prognostics Under Mission Profile Effects Using Inoperability Input-Output Model. IEEE Transactions on Systems, Man, and Cybernetics: Systems.

On the other hand, the proposed method for uncertainty quantification and SRUL calculation, and the related results obtained in the case of the Tennessee Eastman Process are summarized in the following publications:

- Tamssaouet, F., Nguyen, T. P. K., Medjaher, K. and Orchard, M. (2020). Degradation Modeling and Uncertainty Quantification for System-Level Prognostics. IEEE Systems Journal.
- Tamssaouet, F., Nguyen, T. P. K., Medjaher, K. and Orchard, M. (2019). Uncertainty Quantification in System-level Prognostics: Application to Tennessee Eastman Process. In the 6th International Conference on Control, Decision and Information Technologies (CoDIT) (pp. 1243-1248). IEEE.

In addition, the presented online methodology for joint parameter estimation and SRUL prediction is fully described in the papers below:

- Tamssaouet, F., Nguyen, T. P. K., Medjaher, K. and Orchard, M. (2020). Online joint estimation and prediction for system-level prognostics under component interactions and mission profile effects. *ISA Transactions*.
- Tamssaouet, F., Nguyen, T. P. K., Medjaher, K. and Orchard, M. (2020). A contribution to online system-level prognostics based on adaptive models. In the Fifth European Conference of the Prognostics and Health Management Society.

Finally, the method for SRUL maximization through mission profile optimization is detailed in the following article:

- Tamssaouet, F., Nguyen, T. P. K. and Medjaher, K. (2019). System Remaining Useful Life Maximization through Mission Profile Optimization. In *Proceeding Asia-Pacific Conference Prognostics Health Management*, (pp. 225-232).

Limitations

Although the work presented in this thesis contributes to enrich the knowledge in PHM, it is a first attempt to resolve some of the locks at system-level prognostics. Hence, it presents some limitations, detailed in the following:

- In this manuscript, we only limit the scope of our work to two modules of Prognostics and Health Management. We have assumed that the tasks of monitoring, detection, and diagnostic have been carried out upstream.
- Concerning the SRUL calculation, and for clarity of presentation and regarding the architectures of the considered systems, only parallel and series configurations were investigated. This choice can be justified by the fact that 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, in practice, it exists other 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. Assessing the SRUL of those complex systems is a critical-challenge that was not yet addressed in our work.
- Also, in the calculation of SRUL in a parallel configuration, the degradation dependencies and load-sharing are taken into account but not the failure dependencies. However, in some systems, the failure of one component leads to an immediate increase in the degradation level or even the immediate failure of other components.

Future work

The limits, we have identified, allow us to give middle-term and long-term perspectives concerning the development of a practical approach for system-level prognostics.

- In some cases, a system's ability to deliver its service is not solely correlated to the health of its components. Other global system performance criteria need to be considered. In this perspective, we plan to construct an indicator describing the system's operability that merges the health state of the system components with other global system performance indicators.
- To increase the applicability of our approach, other system architectures should be studied. This can be achieved by the use of methods that allow the analysis and modeling of its functional operation by using, for instance, network reliability, structured analysis, design techniques (SADT), graph theory, reliability block diagram, etc.
- In order to consolidate the applicability and investigate the robustness of the contributions presented in this thesis, other TEP modes and faults need to be studied. Also, as it can be noticed, in this work, the proposed SRUL optimization method was not applied to the Tennessee Eastman Process. This is because one of the main objectives of the TEP control is to minimize the variability of the product rate and quality in the presence of disturbances. This criterion should be incorporated into the proposed optimization method.
- The current trend in the industry is the integration of results from different operational functions, such as control, health monitoring, and operational safety. As decision-making is generally made on system-level parameters, prognostics at system-level, providing information about the system remaining useful life, can improve decision-making. Hence, the integration of the obtained prognostics results into the system control, to improve its resilience and keep it in operation in good conditions and as long as possible, should be deepened in further works.
- Finally, to enable widespread implementation of system-level prognostics approaches, future works are necessary to develop new algorithms to enhance computational capabilities and reduce execution time.

If we teach only the findings and products of science – no matter how useful and even inspiring they may be – without communicating its critical method, how can the average person possibly distinguish science from pseudoscience?

Carl Sagan

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Résumé — Le pronostic est le processus de prédiction de la durée de vie résiduelle utile (RUL) des composants, sous-systèmes ou systèmes. Cependant, jusqu'à présent, le pronostic a souvent été abordé au niveau composant sans tenir compte des interactions entre les composants et l'impact de l'environnement, ce qui peut conduire à une mauvaise prédiction du temps de défaillance dans des systèmes complexes.

Dans ce travail, une approche de pronostic au niveau du système est proposée. Cette approche est basée sur un nouveau cadre de modélisation : le modèle d'inopérabilité entrée-sortie (IIM), qui permet de prendre en compte les interactions entre les composants et les effets du profil de mission et peut être appliqué pour des systèmes hétérogènes. Ensuite, une nouvelle méthodologie en ligne pour l'estimation des paramètres (basée sur l'algorithme de la descente du gradient) et la prédiction du RUL au niveau système (SRUL) en utilisant les filtres particulaires (PF), a été proposée. En détail, l'état de santé des composants du système est estimé et prédit d'une manière probabiliste en utilisant les PF. En cas de divergence consécutive entre les estimations a priori et a posteriori de l'état de santé du système, la méthode d'estimation proposée est utilisée pour corriger et adapter les paramètres de l'IIM. Finalement, la méthodologie développée, a été appliquée sur un système industriel réaliste : le Tennessee Eastman Process, et a permis une prédiction du SRUL dans un temps de calcul raisonnable.

Mots clés : Pronostic orienté système, modèle d'inopérabilité entrée-sortie, quantification de l'incertitude, estimation paramétrique, Tennessee Eastman Process.

Abstract — Prognostics is the process of predicting the remaining useful life (RUL) of components, subsystems, or systems. However, until now, the prognostics has often been approached from a component view without considering interactions between components and effects of the environment, leading to a misprediction of the complex systems failure time.

In this work, a prognostics approach to system-level is proposed. This approach is based on a new modeling framework: the inoperability input-output model (IIM), which allows tackling the issue related to the interactions between components and the mission profile effects and can be applied for heterogeneous systems. Then, a new methodology for online joint system RUL (SRUL) prediction and model parameter estimation is developed based on particle filtering (PF) and gradient descent (GD). In detail, the state of health of system components is estimated and predicted in a probabilistic manner using PF. In the case of consecutive discrepancy between the prior and posterior estimates of the system health state, the proposed estimation method is used to correct and to adapt the IIM parameters. Finally, the developed methodology is verified on a realistic industrial system: The Tennessee Eastman Process. The obtained results highlighted its effectiveness in predicting the SRUL in reasonable computing time.

Keywords: System-level prognostics, inoperability input-output model, uncertainty quantification, parameter estimation, Tennessee Eastman Process.
