Tesis Doctoral
Ingeniería en Organización Industrial y Gestión de Empresas

A management framework for enhancing asset management decisions in service-oriented business models

Autor: Asier Erguido Ruiz
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Organización Industrial y Gestión de Empresas I
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El tribunal nombrado para juzgar la Tesis arriba indicada, compuesto por los siguientes doctores:

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Fecha:

A los que me aguantan,
y aún así me siguen queriendo

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Resumen

Dada la cada vez más difícil tarea de competir en términos de calidad y precio en el mercado internacional de equipos industriales, los modelos de negocio centrados en producto están perdiendo su atractivo en detrimento de los modelos de negocio centrados en servicio. En estos últimos, generalmente basados en sistemas de producto y servicio donde ambos conforman una única oferta valor, los clientes compran típicamente el uso o el resultado de los equipos por un determinado tiempo, mientras que la propiedad de los equipos permanece en manos de los proveedores. Esta particularidad conlleva que los proveedores de equipos tengan que asumir la responsabilidad de gestionar los equipos vendidos como si fueran propios, lo cual presenta una importante serie de desafíos y barreras técnicas a la hora de adoptar este tipo de modelos de negocio.

En este sentido, la gestión de activos, a través de su capacidad para tomar decisiones destinadas a mejorar el desempeño técnico y organizacional de los mismos, se presenta como una rama de investigación clave para ayudar a los proveedores a superar dichos desafíos; y por tanto para diseñar e implementar de forma exitosa una oferta conformada por sistemas de producto y servicio. Por este motivo, la tesis que se presenta profundiza, tanto a nivel teórico como práctico en las capacidades que aporta la gestión de activos en el contexto de la servitización, contribuyendo en tres aspectos clave al estado del arte.

En primer lugar, la tesis propone un marco de gestión que formaliza los pasos que los proveedores de equipos deberían dar para optimizar la gestión de activos en función de los servicios que desean ofrecer. Este marco de gestión incluye los principales trabajos de investigación y desarrollo realizados durante la tesis, entre los que se destacan: herramientas de análisis de datos, para tomar decisiones fundamentadas en la fiabilidad de los equipos; mecanismos de optimización basados en simulación, para tomar decisiones óptimas de gestión de activos bajo el paraguas del sistema de producto y servicio seleccionado; y análisis estadísticos, para tomar decisiones con un enfoque basado en el riesgo.

Como segunda aportación a la literatura, se ha complementado este marco de gestión con el desarrollo de soluciones que facilitan la gestión del mantenimiento, ya que es considerado un proceso clave dentro de la gestión de activos y un instrumento crucial para optimizar la explotación de los mismos. En este sentido, la tesis propone un nuevo enfoque para modelar la optimización de las estrategias de mantenimiento de los activos a lo largo de su ciclo de vida, basándose

en variables de decisión dinámicas. Este dinamismo posibilita considerar y aprovechar la información cortoplacista del contexto operacional para lanzar las actividades de mantenimiento en escenarios de negocio más favorables. Así, se consigue mejorar tanto el desempeño técnico como organizacional de los activos y, por tanto, se asegura el alineamiento de las estrategias de mantenimiento con las estrategias globales de la organización.

Por último, debido a que los proveedores de equipos centrados en una estrategia de servitización se ven obligados a absorber un alto grado de riesgo, con el objetivo de mitigarlo y gestionarlo se propone un enfoque estructurado para facilitar la toma de decisiones en base a riesgo. Este enfoque asegura el éxito en la toma de decisiones con un determinado nivel de confianza, para lo cual incluye dos pilares fundamentales. Por un lado, se evalúan las distintas fuentes de incertidumbre que afectan a los servicios a través de la adaptación y particularización del marco propuesto por De Rocquigny et al. [33]. Por otro lado, se cuantifica el impacto de las fuentes de incertidumbre en los objetivos finales, para lo cual se ha desarrolla do un mecanismo de coste-riesgo-beneficio.

Cada uno de los desarrollos mencionados se ha aplicado con éxito tanto al sector eólico como al ferroviario, validando así su idoneidad. En particular, estas aplicaciones analizan algunas de las decisiones más complejas en el contexto de la gestión de activos y la servitización, como son la definición de los contratos, la definición de la estrategia de mantenimiento, la evaluación de la incertidumbre o el análisis de inversiones. En este sentido, y a pesar de la diversidad de las decisiones analizadas, los resultados obtenidos tanto a nivel cuantitativo como a nivel de gestión son satisfactorios. Así, se demuestra la utilidad de las soluciones propuestas a la hora de acompañar a los proveedores de equipos en su estrategia de servitización, ayudándoles a avanzar en la cadena de valor.

Abstract

Shifting from product-oriented to service-oriented business models is critical for manufacturers aiming at moving up the value chain. As a consequence, business models based on the concept of product-service systems, where both product and services are a single offer, have drawn attention of both researchers and practitioners. On these business models, customers effectively purchase the service of products for a defined use period, whilst the ownership of the product remains at manufacturers' side, who have to assume the responsibility of managing such products as their own assets.

This responsibility entails dealing with several technical challenges which are the source of many barriers that hinder the actual adoption of product-service systems. To this respect, asset management research area presents itself as strategic to face such challenges, especially when it is focused on facilitating decisions concerning the assets in order to enhance their technical and business performance. In this context, the present thesis provides theoretical and practical insights regarding the exploitation of asset management capabilities in the context of servitization, making three major contributions.

The main contribution of the thesis is the proposed management framework, which comprehensively considers the different researches and developments performed along it. This management framework formalizes the steps to be adopted by manufacturers in order to optimize their asset management decisions in service-oriented business models, helping manufacturers overcome aforementioned technical challenges and barriers. To this aim, the management framework includes solutions such as data analysis tools, for making decisions based on the reliability of the assets; simulation-based optimisation mechanisms, for making optimal asset management decisions within the boundaries of the product-service system selected; and statistical analyses, for making decisions adopting a cost-risk-benefit approach.

Secondly, being maintenance management a key process to be considered within asset management and a pivotal instrument for optimising assets' exploitation, a novel dynamic opportunistic maintenance optimisation modeling approach is presented. This maintenance strategy ensures that maintenance and organizational strategies are aligned, further enhancing their technical and business performance. In particular, the proposed opportunistic maintenance strategy is based on dynamic reliability thresholds and it allows considering and taking advantage of short-term information in order to trigger maintenance activities at more favourable business contexts.

Finally, seeking to mitigate and manage the significant risks absorbed by manufacturers when they turn to an offer based on product-service systems, the thesis proposes a structured risk-based decision-making approach. To this aim, the framework for assessing the uncertainty in industrial practices proposed by De Rocquigny et al. [33] is adopted and particularised for the after-sales services design. Likewise, a specific cost-risk-benefit mechanism which quantifies the uncertainty propagation until the quantities of interest has been developed. This contribution enhances the capabilities of the management framework when facilitating risk-based decisions, further ensuring the success of made decisions with a certain confidence level.

The contributions proposed in the thesis have been proven useful and valuable in their application to the railway and wind energy industries; therefore confirming their suitability. Within these applications some of the most challenging decisions to be made in the context of servitization and asset management are analyzed and discussed, such as contracts' pricing, maintenance strategy definition, uncertainty assessment or investment analysis. These results, as well as the managerial insights provided, demonstrate the usefulness of the contributions for supporting service-oriented business models decisions, despite the diverse nature that such decisions might have; therefore helping manufacturers move up the value chain.

Appended Papers

Asier Erguido, Adolfo Crespo Márquez, Eduardo Castellano, and Francisco Gómez Fernández. A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms. *Renewable Energy*, 114:843–856, 2017

Asier Erguido, Adolfo Crespo Márquez, Eduardo Castellano, and Francisco Gómez Fernández. A novel dynamic opportunistic maintenance modelling approach. In *European Safety and Reliability Conference (ESREL) 2017, Portorož.*

Asier Erguido, Adolfo Crespo, Eduardo Castellano, and Jose Luis Flores. After-sales services optimisation through dynamic opportunistic maintenance: a wind energy case study. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 232(4):352–367, 2018.

Asier Erguido, Adolfo Crespo Márquez, Eduardo Castellano, José Luis Flores, and Francisco Gómez Fernández Reliability-based advanced maintenance modelling to enhance rolling stock manufacturers' objectives. *Submitted to Reliability Engineering and System Safety*, 2019.

Asier Erguido, Adolfo Crespo Márquez, Eduardo Castellano, Ajith Kumar Parlikad, and Juan Izquierdo. Asset management role for enhancing decisions in product-service systems. framework and application. *Submitted to Computers and Industrial Engineering*, 2019.

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List of Acronyms

OEM	Original Equipment Manufacturer
CAPEX	Capital Expenditure
OPEX	Operational Expenditure
LCC	Life Cycle Cost
RAM	Reliability, Availability and Maintainability
AGAN	As Good As New
ABAO	As Bad As Old
NHPP	Non-homogeneous Poisson Process
GRP	General Renewal Process
LP	Loss of Production
PM	Preventive Maintenance
CM	Corrective Maintenance
TBPM	Time-based Preventive Maintenance
OM	Opportunistic Maintenance
OF	Objective Function
DV	Decision Variable
FM	Failure Mode
SRQ	Set of Research Questions
PSS	Product-Service System
AU	Asset User
TTF	Time To Failure
TBF	Time Between Failures
VA	Virtual Age
R&D	Research & Development
PF	Pareto Front
SBO	Simulation-based Optimization
NSGA	Non-sorted Genetic Algorithm
PDF	Probability Distribution Function
CI	Confidence Interval
ICOM	Input, Control, Ouput, Mechanism
EBA	Energy-based Availability
TBA	Time-based Availability
PBC	Performance-based Contract

Part I.

Memory

1 Introduction

1.1 Background

Original Equipment Manufacturers (OEM) have traditionally focused their efforts on providing highly value-added assets to their customers from a product design and cost perspective. Accordingly, their investments in research and development (R&D) have mainly been oriented towards product and production processes design. Nevertheless, manufacturing industries have been undergoing a severe shift of paradigm over the last years, being increasingly challenged by producers able to offer acceptable quality standards at a low-cost labor base.

Therefore, if the European manufacturing capability is to be retained, competitiveness should be sustained "moving up the value chain" through the delivery of knowledge-intensive products and services [1, 2]. In fact, although products and services have traditionally been considered separately, during recent years they have converged into the concept of product-service systems (PSS), where both product and services are a single offer [3, 4], based on the following two concepts [5]: 1) *servitization*, the product concept evolves towards a position where it is inseparable from the service and 2) *productization*, the service concept evolves towards a position where it is marketed as a product.

In essence, product-service systems decouple the ownership of the product and its use with a competitive purpose that directly refers to customer satisfaction, economic viability and sustainability [1]. As suggested in Tukker [6], the economy based on purchasing products (*"pure products"*) converges in an economy based on the use of those products (*"pure services"*). In this context, the products provide the technical functions for the consumers [7] whereas the services ensure the availability of these functions [8]. Currently, product-service systems are classified into three different types, depending on their product-service content [6]:

1. **Product-oriented:** selling the product in a traditional manner while including within the sale additional after-sales services, such as maintenance, warranty periods, training, etc.

2. **Use-oriented:** selling the use or availability of a product while it is owned by the asset producer.

3. **Result-oriented:** selling the outcome or capability provided by an asset while it is owned by the asset producer.

The product-service system approach provides value in several aspects. On the one hand, products will be more customized to the clients' requirements and needs, leading to new functionalities that will increase the product quality and market share [9]. On the other hand, the product-service system is claimed as a strategic market opportunity, since it enhances the competitive edge through elements -i.e. services- that are not easy copied nor facilitated by competitors [1]. In addition to being a differentiating feature that increases customers' satisfaction and loyalty, product-service systems generate recurrent revenues throughout life cycle of the products, which usually exceed the profit margins of new sold equipment [10, 11].

In spite of the added value that the development of an offer based on product-service systems will bring to manufacturing companies, there are some barriers that should be overcome in order to achieve real success on their application. On the manufacturers' side, these barriers are related to the determination, management, and absorption of risks associated with the service, as well as its pricing; while customers face the barriers related to the cultural change that demands the ownerless consumption of products [1].

Evidence shows that the cultural challenges that have to be given in order to reach an ownerless consumption of the products are coming [12]. In fact, customers are more frequently asking for product-oriented, or even use-oriented and result-oriented product-service systems. This has led some producers to integrate them into their business models, where they have become one of the main business cores [1, 13]. However, most of the OEMs, especially capital goods manufacturers, which as stated have been more focused on new equipment design and sale, have difficulties in offering any kind of services [14].

As aforementioned, these difficulties are related both to the risks absorption that product-service system business models demand at manufacturers' side and to the technical difficulties implied by the services integration within organizations' management [15]. In fact, the ownerless consumption of the assets entails that the product that used to be sold by manufacturers, has now to be managed by them. Therefore, in order to successfully implement an offer based on product-service system business models, manufacturers should be able to properly manage their assets, answering, among others, the following questions:

- What service-level is the organization able to provide for a specific product/asset?
- How might products/asset's failures impact on service-level, and how can the risk of failure be determined and managed?
- How can uncertainty sources that affect service-level and cost, and thus the product-service system success, be managed?
- What decisions should be made in order to maximize the value given by products/assets over their whole life cycle and, especially, during their in-service life?
- What service meets better both the organization and its clients' needs?
- How can a trade-off between service-level and pricing be found?

The increasing concern on these questions rises the interest of asset management research area, which can help manufacturers answer them, at least to some extent. Asset management seeks to increase the organization knowledge regarding their assets in order to obtain as much value as possible from them, ensuring an efficient, effective and sustainable achievement of the organizations' objectives [16]. To this aim, the key topics highlighted in the main asset management standards are [17]:

- **Alignment between the organizational objectives and the asset management objectives.** The assets exploitation should find a balance among cost, service-level and assumed risk in order to satisfy both organizational objectives (e.g. value offer, financial results or clients requirements fulfillment) and asset management objectives (e.g. operational requirements or technical performance).
- **Whole life cycle management.** It allows finding a trade-off between the initial investment and the value added by the asset through its whole life cycle, considering at the same time its contribution to production capacity or service offer and its capital and operational expenditures, i.e. life cycle cost.
- **Risk management.** Decisions should not be made based on just to technical performance, but according to an organizational risk-based approach, evaluating their consequences in terms of profitability, efficiency, quality, regulatory commitments, environment, safety, etc.
- **Integration and sustainability.** Organization should develop enablers related to leadership, communication, information management and skills and competences development in order to maintain the efficiency yet efficacy of the asset management processes.

Specifically focusing on OEMs interested in product-service system business models implementation, physical asset management plays a key role within the comprehensive asset management structure. In fact, physical asset management focuses on coordinating the activities of organizations in order to obtain as much value as possible from the physical assets, balancing costs, risks, opportunities, and benefits during the life cycle of the assets [18], which is central for starting designing profitable product-service systems.

In this context, and particularly due to the several life-cycle processes to be considered in the physical asset management, such as operation, maintenance or decommissioning among others, maintenance management emerges as a pivotal instrument for OEMs that want to shift to product-service systems. Figure 1.1 shows the relationship between maintenance and physical asset management, which is not only related to the main life cycle stages, but also to physical asset management support and strategic plan definition. These relations are summarized as follows:

- **Acquisition process:** information regarding operational reliability, maintainability, expected life cycle cost, risk analysis, etc. of the assets will help the investment decision-making process.
- **Operation process:** information regarding times to restoration, preventive maintenance schedules, safety procedures, etc. will at the same time condition and fit the operational constraints of the assets.

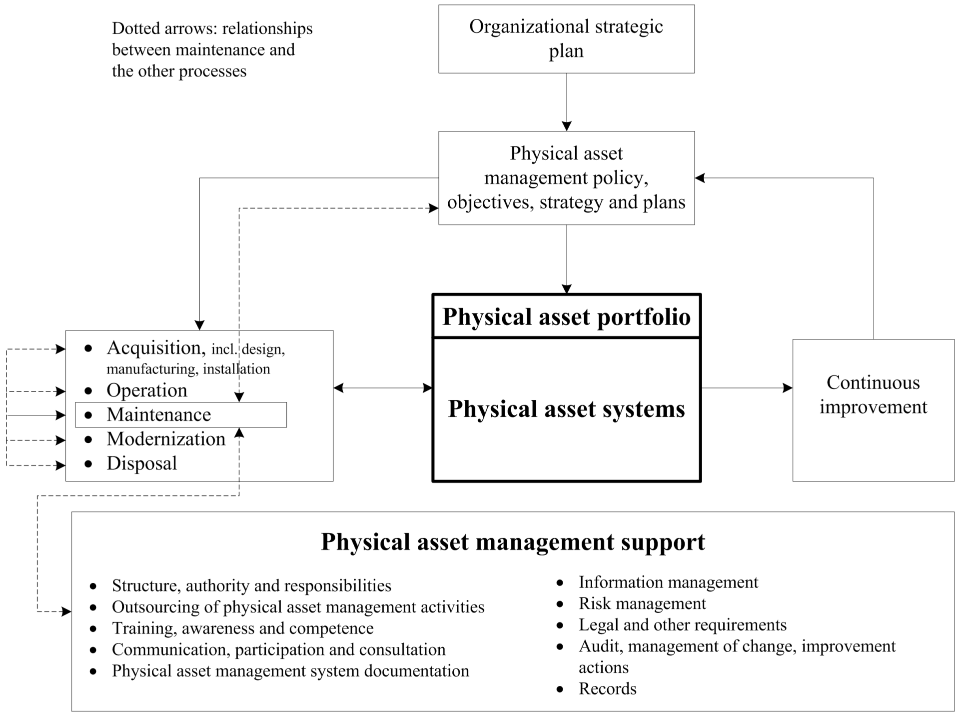


Figure 1.1 Relation between maintenance and physical asset management processes [18].

- **Modernization process:** information regarding preventive and corrective maintenance cost, unavailability and/or remaining useful life of components will help making decisions regarding assets' modernization in order to satisfy the new requirements demanded by customers and/or organization.

- **Disposal process:** information regarding disposal cost, reuse of components and/or remaining useful life will help make the decision of which assets to dispose of and when.

- **Physical asset management support:** according to available resources (qualified staff, list of subcontractors, maintenance procedures or facilities, etc.) maintenance management will contribute to decisions regarding needed profiles of personnel, skills to be acquired, specifications of maintenance to be outsourced, requirements for the information system, etc.

- **Asset management:** impact of maintenance strategies on asset management policies, strategies and plans will be studied through dependability and life cycle cost analysis, ensuring the fulfillment of established organizational objectives according to the organizational structure.

It is noteworthy that beyond the impact and importance that maintenance management might have on the physical asset management, it is its relevant contribution to the organization's added value which concerns [19]. To this respect, it is especially important the interaction between the organizational strategy and maintenance function, which leads to a bidirectional influence and alignment of their objectives [18].

On the one hand, organizational strategies and plans impact on maintenance decisions, e.g. through the establishment of the physical assets' requirements or the facilitation of resources to achieve those objectives. On the other hand, maintenance management makes decisions on the assets to meet organizational objectives and provide further information regarding the assets and their requirements. This information will directly impact on the organizational strategic plans and will definitely add value to the organizations' decision-making processes such as investment decisions or new services identification.

Therefore, if organizations, and especially OEMs, should "move up the value chain" it is necessary to develop advanced physical asset management tools that help their decision-making process. Tools that align the organizational objectives with the physical asset objectives. Tools that help the organizations make decisions according to assets' life cycle cost and service-level. Tools that help organizations deal with uncertainty and make decisions according to an organizational risk-based approach. Tools that help organizations identify, select and deploy new services. On the whole, tools that facilitate OEMs moving towards excellence levels in asset management and towards a profitable product-service system offer.

1.2 Problem description

If OEMs are to move up the value chain through the development of product-service systems, they will have to tackle several issues dealing with asset management, specially with physical asset management. As stated, asset management and physical asset management standards might help at this point. They establish, in a generic approach, which are the elements and requirements to be considered in order to define, implement, maintain and improve each asset management strategy. However, even if these standards define *"what"* shall be done from the organizational strategic perspective, they do not focus on defining *"how"* should it be done from a technical perspective.

Technical solutions answering to *"how"* question should bear the four central issues of the asset management:

- **Whole life cycle management.** Analytical and simulation models able to estimate the long-term performance of the assets regarding different key performance indicators (i.e. service time, production or cost) should be developed, such as life cycle cost models.
- **Alignment between organizational objectives and asset management objectives.** Asset management decisions should be a mean to achieve organizational objectives, such as improving market perception (clients' satisfaction) or increasing market share (new product-service system design and deployment). Thus asset management decisions should be directly conditioned by the organizational strategy.
- **Risk management.** Decision-making process should be optimized according to an organizational risk-based approach. To this aim, decisions' impact on the long-term performance of the assets, as well as on the organizational objectives' achievement under uncertain scenarios, should be analyzed.
- **Integration and sustainability.** Efficacy and efficiency of the asset management processes should be ensured through generating information that will both facilitate decision-making at different organizational levels and enable communication among such levels.

According to the state-of-the-art analysis (see Chapter 2), there are mainly two challenges to be faced when designing such technical solutions, regarding both academic knowledge generation and its practitioner application: 1) developing advanced physical asset management methodologies, algorithms and tools that enable, at least to some extent, to respond to the stated asset management central issues, and 2) framing the use of these methodologies, algorithms and tools in order to allow their effective yet efficient utilization in real industrial applications, ensuring their sustainability.

According to the former challenge, there is a lack of technical solutions that allow consistently aligning the assets' maintenance strategies with the organizational strategies, especially in the current dynamic business context [20]. Likewise, these technical solutions should be designed regarding the life cycle perspective of assets, which will allow identifying a trade-off between performance and cost, and accordingly making decisions regarding maintenance, new investments, disposal or/and renewals in a risk-based approach [21].

Furthermore, in order to fully align the technical solutions with the main asset management objectives, they should not only be focused on optimizing assets performance, but on generating value to the organizations [16]. To this respect the whole knowledge generated should converge on new business opportunities, such as product-service systems, which will generate recurrent incomes for OEMs and will be a differentiating feature that will increase customers' loyalty and market share.

The second challenge deals with the utilization of the advanced technical solutions in the industry, where there is still a gap to be bridged [22]. Therefore, in order to boost their utilization, such tools should be framed and connected in a way that they are easily applied. Furthermore, they should provide information that facilitates the decision-making process of different stakes at the organization, such as asset managers, organization managers, maintenance operators, accountants, etc. As stated, this information will improve communication between the different levels of the organization, making the asset management process more effective and efficient, and thus, more sustainable.

Returning to the question posed at the beginning, there is a need to develop technical solutions that allow answering *"how"* asset management shall be tackled: from the modeling of life cycle cost of the assets and the definition of advanced maintenance strategies, to the final value generation through new product-service systems identification.

1.3 Research area and questions

1.3.1 Scope and limitations

The scope of this thesis is the design of profitable product-service system scenarios through the optimization of manufacturers asset management processes. On the one hand, the optimization of organizations' asset management processes is based on three main points: 1) the optimization of maintenance strategies, 2) the calculation of new investments' suitability and 3) the identification and quantification of the risk associated to the asset-regarded decision-making process. On the other hand, the design of profitable product-service system scenarios focuses on 1) the evaluation of different after-sales services' profitability under the uncertain scenarios to be faced and 2) the identification of the actions that could be taken by the decision-makers to make their product-service systems more competitive, both from the perspectives of the asset-providers and asset-users.

Although herein presented research demonstrates that the thesis scope has been successfully addressed, it has certain limitations that need to be acknowledged:

- Algorithms and tools developed have mainly been conceived for manufacturers that manage fleets of assets.
- Modeling of the case studies has required assumptions that simplified the problem, mainly regarding the modeling of maintenance processes.
- It is not considered the effect that supply chain management issues might have both on asset management and product-service system implementation.
- Financial issues entailed by asset management or the product-service system design are not considered.
- Reliability is calculated in a historical failure data-driven approach.
- Only economic dependence of assets is considered.

1.3.2 Purpose and objectives

The purpose of this research is to propose a management framework, provided with advanced physical asset management algorithms and tools, which allows manufacturers both achieving excellence levels in asset management and designing successful product-service systems.

The specific objectives are the followings:

1. To define a novel maintenance policy that consistently aligns the maintenance strategy with the overall business strategy.
2. To develop simulation tools able to evaluate the physical asset management strategy in the long term, according to the life cycle cost, availability or other key performance indicators.
3. To develop a tool able to automatically calculate the reliability and maintainability of the organizations' assets considering the proper indenture level.

4. To design a proper product-service system considering both the asset-user and the asset-provider interests; specifically implementing multi-objective heuristics in order to find optimal physical asset management strategies from both perspectives.

5. To measure, quantify and manage the uncertainty sources that might condition maintenance and after-sales services decision-making process, and thus the product-service systems success, enabling making decisions on a risk-based approach.

6. To validate the suitability of the technical solutions developed through their application to the railway and wind energy sectors.

7. To provide a management framework, understood as a set of technical solutions, which allows manufacturers aligning their asset management strategy with the specific product-service system business model pursued, further facilitating their servitization process.

1.3.3 Research questions

The first set of research questions (SRQs) concerns the strategic approach to be followed by an organization in order to achieve excellence levels in asset management and after-sales services. These research questions deal with the physical asset management processes to be defined, the information flows required and the design of the product-service systems.

SRQ1: Do organizations know how to tackle the asset management? Which steps shall be followed by an organization to achieve excellence levels in asset management? How can the different data sources of an organization be handled in order to improve the decision-making process regarding the asset management? How can the know-how regarding the assets be used to design product-service systems?

The second set of research questions concerns the alignment between the maintenance and organizations' business strategies. These questions require the development of new maintenance strategies that simultaneously consider assets' internal factors (e.g. failures or dependencies among assets) and external operational factors (e.g. environmental conditions, production schedules or other organizations' interests) within the maintenance decision-making process.

SRQ2: How can the maintenance strategy be optimized in order to consistently align it with the organizations' business strategy? How can assets' internal dependencies and external operational factors be considered in the decision-making process? To which extent should external operational factors vary the maintenance decision-making process?

The third set of research questions concerns the management of uncertainty, which directly conditions the maintenance and the product-service system success. These questions are not only focused on the identification and quantification of uncertainty sources' impact, but also in how the organizations should deal with them in the decision-making process.

SRQ3: How do the different uncertainty sources condition the maintenance strategy and the after-sales services? Which is the risk associated to these uncertainty sources and how can it be managed by the organization? How should the product-service system be designed on an uncertain scenario in order to ensure its success? How could the profitability of reducing the uncertainty of any of the sources be quantified?

The relationship between the appended papers and the addressed set of research questions is shown in Table 1.1.

	SRQ1	SRQ2	SRQ3
Paper I[23]	✓	✓	
Paper II [24]		✓	
Paper III [25]	✓		✓
Paper IV [26]	✓	✓	
Paper V [27]	✓		✓

Table 1.1 Relationship between sets of research questions (SRQ) and appended papers.

1.4 Summary of the thesis building blocks

The study of the already mentioned problems, as well as the efforts to answer the research questions, have guided the thesis research through the development of a management framework conceived for helping companies to reach excellence levels in both asset management and after-sales services. As shown in Figure 1.2, the management framework consists of three main building blocks, which at the same time are the building blocks of the thesis. These building blocks are, according to the state-of-the-art analysis (see Chapter 2), central topics to enhance manufacturers' asset management and servitization processes. Consequently, each of these blocks has been studied in detail, understanding their current state-of-the-art and proposing innovative solutions and applications in order to enhance their use in the context of the problem under consideration.

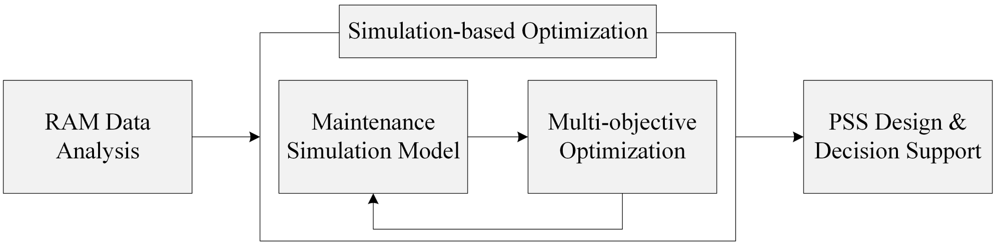


Figure 1.2 Thesis building blocks.

As the reader may notice, the building blocks cover from data analysis, to advance simulation and optimization mechanisms that facilitate the final decision-making process of product-service systems. It should be highlighted that a considerable amount of effort has been directed towards the whole process information flow, being the outputs of the mechanisms developed at each building block the inputs of the following one.

This characteristic is expected to enhance the use of the management framework in industrial environments, which is indeed one of the main objectives of the present thesis, along with contributing to the body of literature in the domains of asset management and servitization. To this respect, the reader may address in Table 1.2 the relation among the main contributions of the thesis to the existing literature and each of the stated building blocks. Finally, for a better understanding of the thesis dissertation and its structure, a brief summary of each of the building blocks is herein introduced.

1.4.1 RAM data analysis

One of the key issues for companies that seek to improve their asset management is to properly handle the data gathering and analysis processes. In particular, data gathering and analysis regarding reliability, maintainability and availability of the assets is critical for a successful definition of physical asset management strategies [18]. Whereas these are widely studied topics in the literature, most of the companies still strive to get good data quality and to consequently translate these data into useful information that facilitates the decision-making process.

Thesis contributions	Year	CT	Thesis building blocks: RAM Analysis	Simulation-based Optimization	PSS Design & Decision Support
Paper I [23]	2017	JP		✓	
Paper II [24]	2017	CP		✓	
Paper III [25]	2018	JP		✓	✓
Reliability App [28]	2019	RS	✓		
Paper IV [26]	unpubl.	JP		✓	
Paper V [27]	unpubl.	JP	✓	✓	✓

CT: Contribution Type; JP : Journal Paper; CP : Conference Paper; RS : Registered Software

Table 1.2 Thesis contributions' focus in relation to the building blocks of Figure 1.2.

Especially in the case of reliability analysis, it is common to rely on false premises which might lead to erroneous conclusions and therefore, to a biased decision-making process [29]. To avoid this false premises, special emphasis, on the basis of a systematic approach, should be placed on identifying and testing statistical models suitable for the real data [29].

From a practitioner's perspective, the process to treat and analyze failure data and convert it into reliability information should bear [29]: 1) identification of proper indenture level; 2) collection of proper data by dealing with scarce, noisy or/and censored registries; 3) identification of failure trends that respond to the effect of repair actions; 4) statistical distributions fits; and 5) evaluation of goodness of the mentioned fits.

In order to support organizations at this step, a tool for converting failure data into useful reliability information has been developed. By means of a kit of failure data-driven reliability algorithms adopted from the existing literature, the developed tool is designed to automatically identify the survival functions that characterize the asset at the chosen indenture level, considering among others censored data or confidence intervals. Likewise, it also implements an automated statistical analysis for fitting maintainability distributions for the chosen indenture level. This tool [28], has been developed in R programming language and provided with a user-friendly interface that brings together the algorithms supporting the tool and the practicality desired in the industrial scenarios.

1.4.2 Simulation-based optimization

Maintenance simulation model

Asset management reference standards, such as ISO 55000 [16], make special emphasize on the need of effectively and efficiently obtain value from the assets. To this aim, it is important a risk-based management of the assets during their whole life cycle in order to ensure their sustainability. In particular, maintenance management plays a key role on the attainment of such objectives since it allows, at least for physical assets, managing the risk of failures through different maintenance activities (e.g. inspections, repairs, replacements, etc.).

Accordingly, organizations should be able to evaluate the impact of different maintenance strategies on their physical assets in order to make decisions, considering their main maintenance processes, resources' constraints, failure impacts, etc. Taking into account the stochastic nature of the maintenance process (i.e. failure occurrence, repair processes, etc.), and with the objective of facilitating the decision-making process at this step, an agent-based simulation has been developed in order to model these processes and evaluate the maintenance strategies, according to the long term key performance indicators established by the organization, such as life cycle cost or availability among others.

Likewise, according to ISO 55000 [16], asset management should directly bear organizations' main strategies and objectives. Therefore, maintenance and organizations' strategies should remain aligned, directly considering within the maintenance strategies the main goals of the organization. Nevertheless, the fact that organizations are opened to global markets and competitors make organizations' business objectives and strategies changeable [30].

In order to be able to respond to these organizations' changes, maintenance strategies should also have a dynamic nature. Accordingly, a new dynamic opportunistic maintenance policy has been developed. The dynamic opportunistic maintenance continuously considers assets' internal (i.e. reliability of the assets (step 1 outcome) and economic dependencies) and external factors (i.e. specific business objectives fulfillment) in order to optimize maintenance decisions and consistently align them with the organizations' strategies and objectives.

Multi-objective optimization

As aforementioned, according to the main asset management standards, a trade-off between service quality and costs should be found. This implies that different objectives in conflict with each other should be optimized at the same time during the definition of the maintenance management strategies. Multi-objective meta-heuristics are specially suitable for finding optimal solutions in such cases, and have already been successfully implemented in several maintenance optimization problems [31].

Multi-objective meta-heuristics are able to provide high quality non-dominated solutions and a diverse Pareto-Front [31]. The optimal Pareto-Front determines the optimal solutions regarding the objectives considered, i.e. there exists no feasible solution that would decrease some objective without causing a simultaneous increase in at least one other objective [32]. Thus, these optimal solutions will provide the decision-makers with very valuable information for finding good compromises (or trade-offs) among the different variables to be optimized [32].

As a consequence, the thesis research has also been focused on developing a Simulation-based Optimization (SBO) mechanism that automates the integration of both the iterative evaluation of different maintenance strategies and the implementation of multi-objective meta-heuristics.

1.4.3 Product-service system design & decision support

The asset management strategy should not only be focused on making decisions to reduce costs and improve availability, but on ensuring that decisions made bring additional value to the organization as well. This is guaranteed by a value-oriented approach that enables to fulfill the customers' requests and needs, whilst offering profitable solutions according to the organization resources and capabilities.

In this context, as aforementioned, offering the asset users a set of product-service systems, instead of solely the assets themselves, appears as an interesting way of adding value to the assets, and consequently, to the organization [13, 1]. Accordingly, and based on the multi-objective simulation-based optimization mechanism developed on step 3, which enables to find optimal maintenance strategies both from asset users and asset providers' interests, there have been considered two research topics at this step:

1. **Product-service system design under uncertain scenarios.** The risk-based decision-making approach to be considered in order to achieve excellence levels in asset management requires the assessment of uncertainty sources' impact in after-sales services. To this aim, the framework for assessing the uncertainty in industrial practices proposed by De Rocquigny et al. [33] has been adopted and particularized for the after-sales services design.

2. **Cost-risk-benefit analysis.** Due both to the long-term nature of product-service systems and the cited uncertainty sources, either asset users or asset providers' interests might be jeopardized. In order to minimize the risk that entails the design of an unsatisfactory product-service system, a cost-risk-benefit analysis that ensures the success of the service provided with a certain confidence level has been developed.

1.5 Outline of the thesis

The overall structure of the study takes the form of 5 chapters, including this introductory chapter. Chapter 2 begins by laying out the theoretical dimensions of the research, and identifies both literature and practitioner gaps. Chapter 3 describes the research methodology adopted for developing the thesis research. Likewise, it provides a brief summary of each of the appended papers, which the reader may address in Part II. Chapter 4, presents the results obtained during the thesis and their corresponding discussion ordered by research question. Finally Chapter 5 presents the concluding remarks and the future research lines.

2 State of the art

This chapter describes the state of the art of the main research fields of the present thesis, with the objective of both deepening on the knowledge regarding such fields and identifying either the academic or the practitioner gap to be bridged. This thesis can be associated with several literature topics, yet it will be emphasized on the key topics considered in each of the phases shown in the process of Figure 1.2. Accordingly, the most directly related literature topics are on asset management, maintenance management and modeling, reliability data analysis, simulation-based multi-objective optimization algorithms, uncertainty assessment and product-service systems.

2.1 Asset management

As introduced in Chapter 1, manufacturers undergoing the servitization process are facing a change of context originated from the ownerless consumption of their sold products. In this new paradigm, the products are owned by manufacturers, while customers (a more suitable term for the users of these products) are typically buying the availability and the capability of these products [1]. Therefore, in product-service system scenarios, rather unknown for most manufacturers, sold products become assets to be managed by manufacturers, which entails significantly higher risks absorption than in "pure products" business models [34, 7, 9].

Most of such risks arise from the technical advances and complexities of currently manufactured products, which indeed difficult their management, and thus the product-service system implementation [35]. Accordingly, if manufacturers increased their knowledge regarding their products, specifically identifying how their decisions would affect their performance in the long term, manufacturers could potentially reduced their absorbed risks and successfully face the servitization process [15]. To this respect, asset management, understood as a business process that systematically optimizes the assets' exploitation during their whole life-cycle to pursue the organizational objectives [36], becomes a central process for manufacturers adopting product-service system business models.

Asset management has been recognized central when sitting the meeting point between technical and business performance of assets [36], achieving the balance between assets' costs (i.e. financial, environmental and social) and their operational performance while meeting customers' needs and stakeholders' interests [37, 38]; a balance indeed required in the servitization context [39]. Hitherto, there have been several attempts to standardize the specifications and guidelines of asset management (see [16, 40, 41, 42, 43, 44]), and regardless their background, these standards meet at highlighting the aforementioned asset management fundamental pillars [45]:

1. life-cycle management, finding a trade-off between initial investment and the value added by the product;

2. risk-based management, evaluating the decisions from different perspectives, such as technical, economic, safety, etc.;

3. alignment between asset management and organizational objectives, exploiting the assets balancing cost, service-level and assumed risk;

4. value creation, delivering the assets' functionality at the required level of performance satisfying organization's and stakeholders' objectives;

5. and integration and sustainability, ensuring the efficiency yet efficacy of the asset management processes through leadership, communication, information management and skills and competences development.

In fact, this last pillar, value creation and, in particular, value-based decision-making, are two of the main focus of the last ISO 55000 standard series regarding asset management [16]. Organizations should assess how they create value through their assets, understanding value as the aptitude of the assets for satisfying the organizational interests, aligned with organizational strategic criteria and vision [46]. Then, decision-makers will be able to make the right choices over the assets [46].

According to Tao et al. [47], in order to effectively and efficiently create and deliver value to customers, and especially when managing both products -as assets- and services, four basic perspectives should be assessed in asset management: historical or past view, future view, and views of the outside (outward) and the inside (inward) of the business. Whereas outward and inward views are mainly focused on efficiently managing the assets in order to create value; past and future views focus on what value is provided by the asset and how it is perceived by the customer. Figure 2.1 complements and adapts the perspectives in Tao et al. [47] for manufacturers adopting product-service system business models, which may be described as follows:

- **Historical view - Past performance and value.** Performance history of products and services are measured in order to analyze whether stakeholders' expectations are being met in terms of effectiveness, efficiency or/and created value. It should be noticed that both organizations' inward and outward views have to be regarded in the past view, for which lagging indicators should be defined [17]. Assessing past performance and value will guide present decisions, ensuring and effective and efficient management.

- **Inward view - Investments in asset portfolio and LCC.** Products' and services' needs are assessed in order to make decisions either about investments, such as new technology acquisition or development, or about management, such as supply chain or maintenance. Whereas investments should be analyzed considering both internally and externally created value, as well as considering sector's market trends or competitors product and service offer (benchmarking), investments are encompassed within the inward view of the organization.

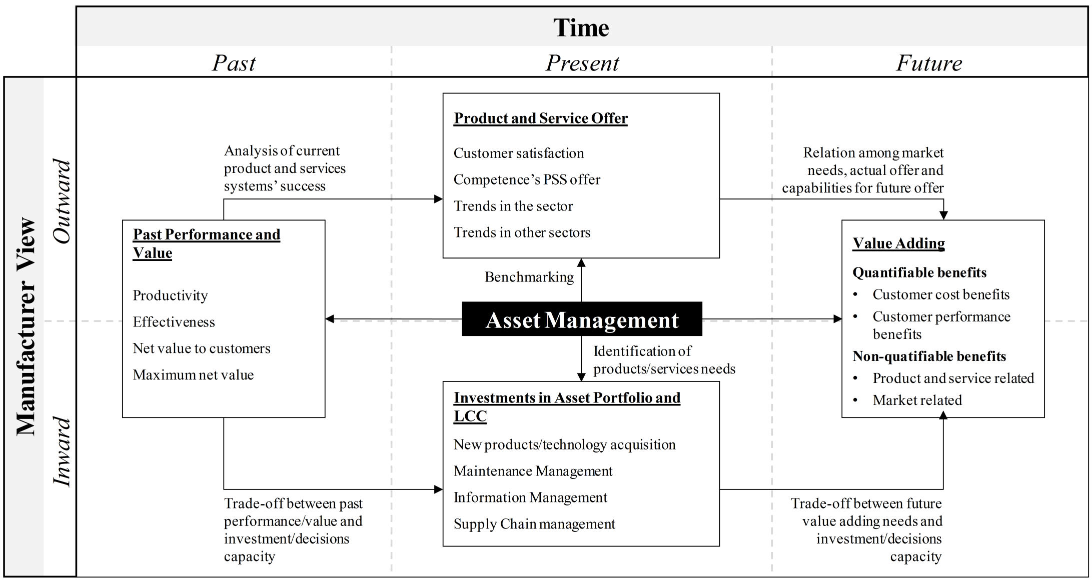


Figure 2.1 Asset management perspectives for Original Equipment Manufacturers.

Such investments should ensure that organizations' capabilities are enhanced in order to meet stakeholders' present and future demands.

- **Outward view - Product and service offer.** Customers' satisfaction and competitors' product-service systems offer are identified in order to guide the decision-making process of manufacturers. To this respect, it is important not only to consider product-service system stakeholders' interests, but also trends within or outside the sector, establishing leading indicators that will enable to evaluate the suitability of decisions made [17].

- **Future view - Value adding.** New products and/or services developments are sought in order to add value to the organization's offer, both in quantifiable (e.g. cost or service-level) and non-quantifiable terms (e.g. market leading image). Future value adding seeks a compromise between internal capabilities and external trends and demands.

In order to optimize organizations' asset management decision-making process, it is critical not to consider the stated views independently, but as an interconnected system (see the interactions in Figure 2.1). For instance, when making investments or management decisions either about products or services, both product performance and customers' expectations or needs should be evaluated; or when making decisions related to future value adding, actual product and service portfolio performance, investment capabilities and customers' interests should be considered.

Accordingly, asset management has to be considered a holistic process, which is not restricted neither to a certain level of the company nor to just one of its areas [48, 36]. On the contrary, it involves several organizational levels due to its multidisciplinary nature, such as maintenance operators, controllers, accountants, human resources and senior management; which will further enrich the value creation process of organizations.

2.2 Maintenance in the context of asset management

Many of the decisions to be made regarding asset management, not only in the context of product-service systems but in its whole organizational scope, directly concern physical assets, e.g. assets' maintenance, disposal or modernization (see Figure 1.1); for which maintenance management becomes a cornerstone [18]. Accordingly, maintenance management has regained attention during last years, evolving from a *necessary evil* for industrial companies to a really value adding activity to be considered; indeed, to a business issue [20].

Maintenance is defined in EN 13306 [49] standard as the "combination of all technical, administrative and managerial actions during the life cycle of an item intended to retain it in, or restore it to, a state in which it can perform the required function". Different maintenance strategies can be followed by the organizations when seeking such aim, classified as shown in Figure 2.2.

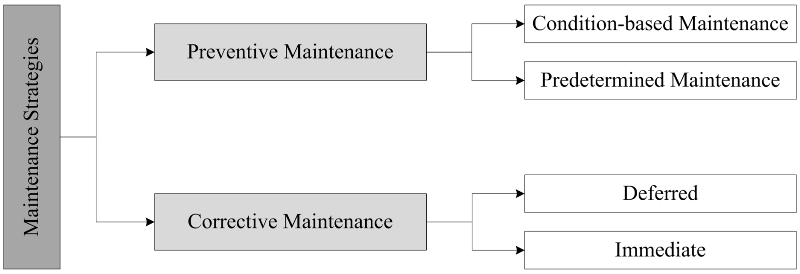


Figure 2.2 Classification of maintenance strategies according to EN 13306 [49].

Accordingly, there are two main maintenance types, depending on whether the maintenance activity is performed after or before the failure occurrence, corrective and preventive maintenance respectively. The main advantage of the former maintenance strategy, also known as *run to failure*, is the whole amortization of the asset investment, since the asset is not replaced before its end of life cycle. However, it has several drawbacks, both in terms of failure consequences, e.g. regarding safety, environment or damage to other assets, and in terms of maintenance planning. Therefore, corrective maintenance should only be applied in non-critical assets in order not to risk the organizational success [19].

In the case of preventive maintenance strategies, they are categorized into predetermined and condition-based maintenance. Predetermined maintenance seeks to establish different periods for performing preventive interventions on the assets, according for example to operation time or number of failures. Its main strengths are its simplicity to be planned and comprehended by the organization, as well as the reduction of failure rate and unexpected failures, hence improving results in terms of cost and availability. However, since predetermined maintenance is based on the hypothesis that life of the maintained item is independent of its condition at any time [50], it might lead to sub-optimal scenarios. On the one hand, a too conservative estimation of asset's failure rate might lead to over-maintain it. On the other hand, a too optimistic estimation, might lead to undesirable failures, having to bear their consequences [51].

Such errors of overestimating or underestimating the failure rates of the components might be avoided by the use of condition-based maintenance. This strategy is based on detecting the failures of the assets according to their performance and/or monitored parameters with a consistent lead-time to being able to prevent them [49]. To this aim, a generic approach is to observe a performance parameter and trigger preventive maintenance when it exceeds the normal value. Whereas this maintenance strategy provides the best solution in terms of failure prevention, the drawbacks that it presents in terms of expertise required and investment cost make it yet difficult to apply them on large scales [51].

Either preventive or corrective maintenance strategies, or a combination of them, pursue different objectives, as distinguished by Márquez [19]:

- Technical objectives. They are linked to operational imperatives as equipment availability or people safety.
- Legal objectives. They are linked to the mandatory regulations to be fulfilled in the different sectors, generally considered a maintenance competence and goal.
- Financial objectives. They are linked to the satisfaction of the technical objectives at the minimum cost, considering the life cycle performance of the equipment.

Although it is not considered as a traditional maintenance objective, as well as the asset management directly considers the organizational strategy, the maintenance management should also directly consider organizational objectives if business results are to be increased [52]. In fact, it should be one of the main concerns of the maintenance manager to align the maintenance strategies with the business needs; ensuring that the business drivers recognized by the management and stakeholders are regarded in the defined maintenance strategies [53, 54, 55].

Maintenance models become a powerful tool in order to optimize the combination and implementation of the different maintenance strategies, so that the cited objectives are achieved [20]. Accordingly, they have been an object of research during the last decades [56, 57, 20], being their main concerns to enhance assets systems reliability, preventing the occurrence of failures and reducing the overall maintenance cost [57].

Maintenance modeling

In his review, Wang [57] provides in-depth analysis of the maintenance policies that are principally researched in the maintenance optimization models, classifying them into two main categories: single-unit systems and multiple-unit systems. In general terms, the maintenance policies for single-unit systems base the maintenance decision-making process on [57]: the age of the assets (age-based); the time between maintenance activities (time-based); the number of failures (failure-based); the cost of the maintenance activity (cost-based); or the maintainability of the assets.

In spite of the differences among the cited maintenance policies, the maintenance optimization models are generally focused on the establishment of certain thresholds. These thresholds act then as the decision variables and they drive to optimal maintenance strategies. Therefore, in order to follow any of the cited maintenance policies, these thresholds are defined with regard to either the age of the assets, the number of failures or the respective indicator (such as reliability, in Figure 2.3).

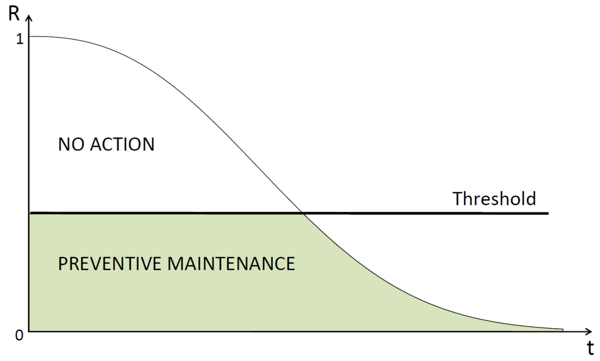


Figure 2.3 Maintenance decision-making based on reliability thresholds.

It should be pointed out that the maintenance policies of single-unit systems are the basis for the ones proposed for multiple-unit systems [57]. Nevertheless, the single-unit maintenance policies tend to overlook the fact that the systems are complex, consisting of several subsystems that might have different types of dependencies among them (see Figure 2.4). Therefore, when the maintenance decision process is focused on single-units systems, it could lead to sub-optimal solutions [57]. By contrast, the multiple-unit maintenance policies do consider complex systems and their dependencies, potentially leading to find better solutions. In Nicolai and Dekker [58] these dependencies are divided into three main classes:

- Economic dependencies. Performing maintenance activities in several systems simultaneously lead to potential cost savings compared to performing them separately [59].
- Structural dependencies. Performing a maintenance activity in a system implies further maintenance activities in other systems [60].
- Stochastic dependencies. The risk of failure of two different systems is not independent [61].

There are two basic approaches currently being adopted in research regarding multiple-unit maintenance [62]: group maintenance and opportunistic maintenance. On the one hand, group maintenance strategies set different groups of systems that will be maintained simultaneously, attending to any of the previously explained maintenance strategy, such as, their number of failures, their age or their operation time [63, 64]. Group maintenance is specially suitable when disassembly and reassembly costs are high [57].

On the other hand, opportunistic maintenance (OM) paradigm seeks to take advantage of the events caused either by internal or external factors that are potentially favorable for triggering maintenance activities [57, 65] (see Figure 2.4), leading to a dynamic decision-making process. Internal and external factors can be described as follows:

- Internal factors. They are directly influenced by maintenance activities, as well as by the assets' complex structure and the cited dependencies among their systems. Advantage is taken from other maintenance activities that are being carried out in order to perform further maintenance actions in other systems, reducing the overall cost or assets' risk of failure [57].

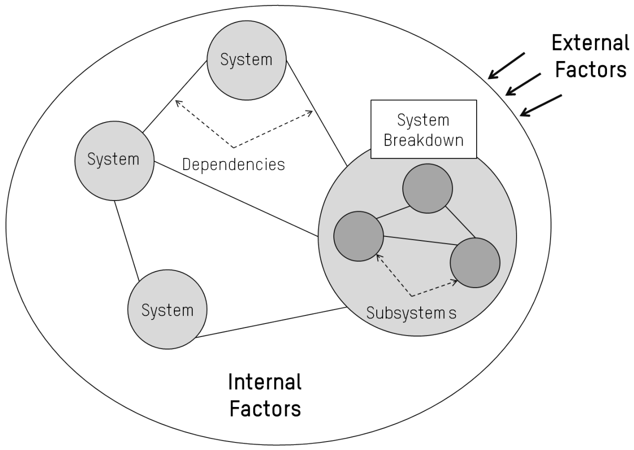


Figure 2.4 Complex assets' structure.

- External factors. They are related to the environmental or context situations that foster the arrival of maintenance opportunities. These opportunities do not have to be directly influenced by maintenance, being possibly influenced by other situations, such as customer requirements or production schedule [65].

Due to its ability for considering short term information regarding internal and external factors and thus, take advantage of favorable maintenance windows, opportunistic maintenance provides valid solutions to the current industrial needs [66]. Accordingly, literature devoted to opportunistic maintenance optimization models has grown exponentially [22], demonstrating its suitability in several sectors, such as in oil refineries [67], wind farms [68], power plants [22] or railway [21].

According to the opportunistic maintenance models reviewed, when either internal or external opportunities arise, the decision of maintenance is usually made according to the traditional maintenance variables [57]: time intervals, age, reliability, condition state (e.g. degradation) or number of repairs. Likewise, as shown in Table 2.1, most of the OM models optimize the main maintenance criteria -assets' cost or/and availability-, considering further interesting maintenance research fields, such as multi-level maintenance, imperfect maintenance or redundancies.

The following classification helps distinguish the latest opportunistic maintenance models according to their maintenance policy:

- **Age-based OM.** They assume that the risk of failure is proportional to the age of the components. Thus, if the opportunity of maintenance arises and the age of any component is over its established age-threshold, it will undergo maintenance. Age-based OM studies have explored the impact of different factors on this policy, namely: uncertainty caused by the lack of failure data [69], imperfect maintenance influence [70], imperfect prediction of failures [71] or multi-criteria optimization [22].

- **Reliability-based OM.** Reliability of the systems is estimated according to varied methods, such as failure data analysis or degradation models. This reliability is then compared to a reliability threshold and it is decided whether the maintenance task should be triggered or not. Reviewed reliability-based opportunistic maintenance models deal with several topics: economic and structural dependencies [72], multi-level maintenance [73], multi-objective optimization considering imperfect maintenance and capacity constraints [74], redundancies [75], etc.

- **Condition-based OM.** Maintenance decision is directly made according to the health state or the remaining useful life (RUL) of the systems, which can be identified through either condition monitoring systems (CMS) or inspections. Condition-based OM reviewed, address several research fields, such as: multi-state series–parallel systems [76], simultaneous consideration of structural, stochastic and economic dependencies [77], degradating multi-unit systems [78], redundancies [79, 80], impact of uncertain suppliers behavior [81] or integration of OM and failure prediction based on neural networks [82].
- **Others.** Although most of the reviewed researches implement the above mentioned OM policies, other OM policies might be considered as well. In Zhou et al. [83] maintenance is determined by the changes in job shop schedule, whilst in other studies, maintenance decision is made according to the number of times that the system has been minimally repaired [84] or to the maintenance activity duration [65].

Source	Research Field	OM Policy					Repairability		Resources		Optimization	
		Threshold		DV	Dependence							
		S	D		In	Ex	Non-Rep	Rep	Inf	Lim	OF	Algorithm
Zhou et al. [85]	Economies of Scale	■	□	R(t)	■	□	■	■	■	□	C	DP
Laggoune et al. [67]	Economies of Scale	■	□	Age	■	□	■	□	■	□	C	MC
Laggoune et al. [69]	Data Uncertainty	■	□	Age	■	□	■	□	■	□	C	MC
Tian et al. [82]	Predictive Maintenance	■	□	Health	■	□	■	□	■	□	C	Exact
Ding and Tian [68]	Economies of Scale	■	□	Age	■	□	□	■	□	■	C	MC
Zhou et al. [83]	Changes in Job Schedule	■	□	Job schedule	□	■	■	□	■	□	C	DP
Zhou et al. [76]	Series-Parallel systems	■	□	State	■	□	■	□	■	□	R	SO
Horenbeek and Pintelon [77]	Degradation monitoring	■	□	Health	■	□	□	■	■	□	C	Sim
Cavalcante and Lopes [22]	Multi-criteria decision	■	□	Age	■	□	■	□	■	□	C	Sim
Nguyen et al. [73]	Multi-level PM	■	□	R(t)	■	□	■	□	■	□	C	MC
Huynh et al. [72]	Redundancies and CBM	■	□	R(t)	■	□	■	□	■	□	C	GPS
Zhang and Zeng [78]	Structural dependencies	■	□	Health	■	□	■	□	■	□	Det	Exact
Caetano and Teixeira [21]	Degradation monitoring	■	□	Health	■	□	■	□	■	□	LCC	MILP
Sarker and Faiz [70]	Multi-level PM	■	□	Age	■	□	□	■	■	□	C	ES
Abdollahzadeh et al. [74]	Multi-level PM	■	□	R(t)	■	□	□	■	□	■	C & LOLP	MOPSO
Shi and Zeng [86]	Predictive Maintenance	■	□	Health	■	□	■	□	□	■	C	PSO
Babishin and Taghipour [84]	Redundancies	■	□	Repair Num	■	□	■	□	■	□	C	Sim
Keizer et al. [79]	Redundancies and CBM	■	□	Health	■	□	■	□	■	□	C	DP
Zhu et al. [71]	Uncertainty in PhM	■	□	Age	■	□	■	□	■	□	C	MC
Atashgar and Abdollahzadeh[75]	Redundancies	■	□	R(t)	■	□	□	■	□	■	C & LOLP	MOPSO
Abdollahzadeh and Atashgar[81]	Redundancies	■	□	Health	■	□	□	■	□	■	C & LOLP	MOACO
Ba et al. [65]	External Opp.	■	□	M(t)	□	■	■	□	■	□	C	GA
Attar et al. [80]	Redundancies	■	□	Health	■	□	■	□	■	□	C & A	NSGA II
Zhang et al. [87]	Multi-level PM	■	□	R(t)	■	□	□	■	■	□	C	FFO

S: Static; D: Dynamic; In: internal; Ex: External; Rep: repairable; Inf: Infinite; Lim: Limited ; OF: Objective Function; C: cost; LOLP: Loss of Load Probability; R: Revenue; A: Availability; Det: Deterioration; DP: Dynamic Programming; MC: Monte Carlo; SO: Stochastic Ordering;GPS: Generalized Pattern Search; MILP: Mixed Integer Linear Problem; ES: Exhaustive Search; PSO: particle swarm optimization; MOPSO: multi-objective particle swarm optimization algorithm; MOACO: multi-objective and colony optimization; NSGA II: Non-dominated sorting genetic algorithm;

Table 2.1 A review of the recent works in Opportunistic Maintenance Optimization (sorted by publication date).

2.3 Reliability data analysis

Currently manufactured assets, especially in the context of the Industry 4.0, are provided with the needed technology and sensors in order to enable the operational data gathering [51]. These data, however, should be translated into useful information if any decision-making process is to be supported, including as well asset management and maintenance decision-making processes such as, inspections, maintenance, retrofitting, new assets acquisition or new technology inclusion [18]. In fact, as suggested by Horenbeek et al. [20], if maintenance decisions are based on wrong or incomplete data, they might lead to sub-optimal or even wrong results.

In the context of asset management, especial emphasize should be made on the performance of the assets, where the analysis of reliability, availability and maintainability (RAM) can certainly facilitate the decisions to be made [19]. In particular, much of the current literature on RAM analysis has been focused on the modeling and accurate estimation of reliability [88], which has not only been motivated by its importance in terms of improving the operational safety and economic efficiency of the assets, but also by the high uncertainty related to it, which indeed difficults and makes it a challenge to accurately estimate it.

As a wide research area, reliability models that regard either to the operational or strategic decision-making processes have been presented [88]. For instance, prognostics techniques monitor different sources of data in order to estimate assets' degradation and try to predict their failure occurrence out of this information [89], enabling to make operational decisions that anticipate such failures and avoid service disruptions and other related costs [90]. On the contrary, other reliability studies focus on fitting time-to-failure models aiming at identifying the failure hazard of the assets, thus facilitating the estimation of the number of failures that might be given during a certain period of time [91, 29].

In fact, whereas prognostics techniques offer very precise information compared to the reliability studies based on time-to-failure models [50], there are some complexities that hinder their utilization when the number of systems under study increase. Such complexities mainly regard to the technology to be deployed, the algorithms to be developed or the particularities of each system [51]. However, time-to-failure models do not lay on any particularity of the systems nor in the technology to be deployed, thus being useful in industrial environments where the amount and complexity of the assets is immense and there are not resources for the extensive implementation of prognostics techniques. In fact, once the time-to-failure modeling process is properly defined, the main requisite for the reliability analysis success is the data set size; since the bigger the failure sample, the more reliable any statistical methodology is, which is indeed often a problem due to failure occurrence scarcity [92, 93].

Due to this simplicity of the time-to-failure modeling, many of the literature maintenance optimization problems assume these models' output as their input [29], i.e. previously described reliability-based maintenance models. Nonetheless, O'Connor (cited in [94]), acknowledges that the reliability analysis based on time-to-failure models performed by practitioners often present a lack of strictness, and they assume false premises such as independence of components, identically distributed variables, constant failure rates, etc. Thus, these analysis lead to the adoption of not appropriate reliability models, which therefore might lead to the previously commented sub-optimal maintenance strategies [20], and later on, to sub-optimal decisions on asset management and product-service systems.

In order to avoid these misconceptions, Louit et al. [29] presented a practical procedure for the selection of time-to-failure models based on field reliability data (see Figure 2.5). Special attention is paid on this research to the "renewal assumption" made by practitioners when assessing the reliability of the assets. The renewal assumption considers that the time between failures one and two, should follow the same statistical pattern as the time between failures two and three, three and four, and so on. In other words, it considers the system under study as "non-repairable", where the system goes to a state "as good as new" whenever it undergoes a repair activity [29]. Thus, failures are considered to be independent and identically distributed (iid), which might not be always true in real industrial contexts [95].

Actually, it is a common industrial situation that systems change their behavior after undergoing a repair activity, either for the better, when the following failure time is expected to be extended compared to the previous one, or for the worse, when the following failure is expected to happen sooner. In such cases, "repairable systems approach" should be considered, where failures are not assumed to be independent and identically distributed [96]. Accordingly, repairable systems might be restored to their fully operational capabilities (as good as new, AGAN) by any method other than restore, or they could also be minimally restored, where they are considered to be at same operational capabilities than before the failure happened (as bad as old, ABAO) [96]. Likewise, as it occurs in the most realistic scenario, systems could be restored to an operational condition worse than if they were new, but better than if they were old, which leads to the concept of imperfect maintenance [97].

As a consequence, before any statistical method is applied, the renewal assumption should be tested through the analysis of trends in failure occurrence [94]. In such analysis, the failure occurrence in time is analyzed, and if no trend is present in the observed failure data, then the iid assumption can be made, and traditionally used statistical distributions such as Weibull or Exponential distributions could be used [29]. On the contrary, if an increase or decrease in failure appearance is evident on the failure data sample, then a trend can be observed and the iid assumption is not valid, as neither are traditionally used statistical distributions. This trend analysis could be performed using either graphical methods, plotting the failure occurrence against the age of the systems, or analytical methods, testing different statistics such as Mann, Laplace or Lewis-Robinson [96, 98].

On the occasions where a trend is present in the failure occurrence pattern, non-stationary statistical approaches should be used to model time between failures, which do consider the restoration factor of maintenance activities or, in other words, the imperfect maintenance [29, 97]. In order to exemplify the suitability of non-stationary models to describe the existence of trends in data, the practical procedure proposed by Louit et al. [29] suggests the use of Non-homogeneous Poisson Process (NHPP) due to its capacity for describing minimal repair activities in a simple manner (see Figure 2.5). Nonetheless, the authors point out that other non-stationary models that more comprehensively describe imperfect maintenance could be implemented as well.

So far, there have been several methods proposed for treating the restoration factor of repair activities, such as $[p,q]$ rule, $[p(t),q(t)]$ rule, improvement factor, virtual age or shock model (see [97]). In particular, the imperfect maintenance model "General Renewal Process" (GRP)

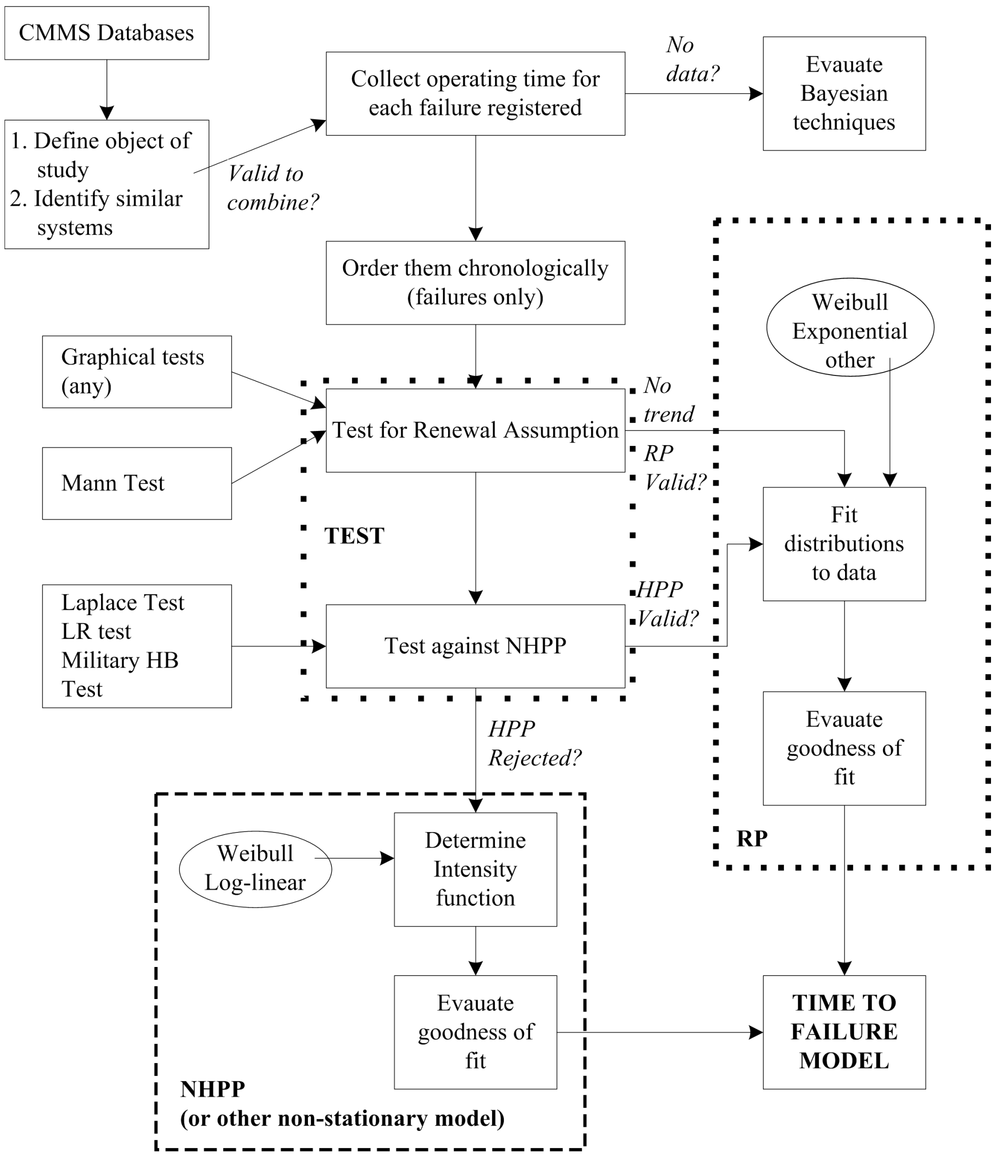


Figure 2.5 Framework for time-to-failure model selection - a practitioners'approach (adopted from [29]).

proposed by Kijima et al. [99], based on the idea of the virtual age, has attracted a lot of interest [100]. This interest is due to its flexibility for modeling both the behavior of the systems before failure and the quality of the repair activities during the different life stages of the systems [101]. Furthermore, the GRP has been demonstrated to be useful for industrial applications as well, where the maximum likelihood (ML) estimation approach presented in Yañez et al. [101] enables to find solutions even for extremely limited failure datasets. The GRP modeling is based on two main concepts:

1. Virtual Age (VA). The calculated age of the system immediately after repair process, where $VA = 0$ is as good as new.

2. Rejuvenation parameter (q). The effect of the repair process in the virtual age of the systems.

In the GRP, whenever a maintenance activity is performed, the virtual age of the asset is updated, where a value of $q = 1$ leads to a perfect maintenance ($VA = 0$, AGAN), $0 < q < 1$ leads to an imperfect maintenance and $q = 0$ leads to minimal repair (see Equation 2.1). Thereby, after the system repair, its failure probability distribution conditioned to the survival of the new virtual age can be estimated according to Equation 2.2.

$$VA^{new} = VA^{old} \cdot (1 - q) \tag{2.1}$$

$$F\left(t|VA^{new}\right) \quad = \quad P\left[T \leq t|T > VA^{new}\right] = \frac{F\left(t\right) - F\left(VA^{new}\right)}{1 - F\left(VA^{new}\right)} \tag{2.2}$$

Finally, when such statistical time-to-failure models are developed, it is a key point for decision-makers to identify at which indenture level should it be applied. In other words, it should be decided at which hierarchical level of the asset are maintenance decisions made [49], so that the reliability analysis is also performed at that level. Only in the cases that the indenture level is properly defined will the reliability analysis and the previously reviewed maintenance optimization problems be valuable for facilitating both maintenance and asset management decision processes [19].

2.4 Simulation-based optimization mechanisms

Decision-making processes related to both asset management and product-service systems require to simultaneously deal with several conflicting objectives, i.e. decisions that foster one of the objectives might be detrimental for another objective. For instance, in the asset management-related decisions, the maximization of the operational performance of the assets might entail an increase of the life cycle cost (i.e. financial, environmental and social) [38, 37]; or in the service-related decisions, customers' satisfaction might be opposed to the product-service system economic viability [1].

On such occasions, multi-objective problems should be modeled in order to facilitate decisions that find a compromise among the conflicting objectives [32]. Nonetheless, when multi-objective functions are established, the search for optimal solutions becomes hard [35]. Thus, decision-makers need to be provided with mechanisms that elicitate preferential information to facilitate their decision-making processes [102]. To this respect, multi-objective optimization search techniques, such as Newtonian methods, genetic algorithms or particle swarm optimization, provide valuable insights for finding a compromise between conflicting objectives [35].

These algorithms allow finding the optimal Pareto-Front, also termed non-dominated solutions, that is, the feasible solutions for which there is not any other feasible solution that improves one criterion without causing a simultaneous worsening of at least one other criterion [32]. Therefore, the Pareto-Front usually consists of a possibly uncountable set of solutions that find optimal compromises, rather than a single solution as in global optimization [32].

By the study of the Pareto-Front plot, which is represented in Figure 2.6 for a bi-objective optimization problem, the decision-maker will not only be able to identify what solutions should be adopted in order to achieve the compromise they seek, but how their preferences on a certain objective might penalize another objective [32]. In fact, due to the value added by the Pareto-Front in the decision-making process, the two aspects according to which multi-objective algorithms are valued are as follows: the high quality of the non-dominated solutions, i.e. the accurate estimation of the Pareto-Front, and a proper diversity on the Pareto-Front [103, 104].

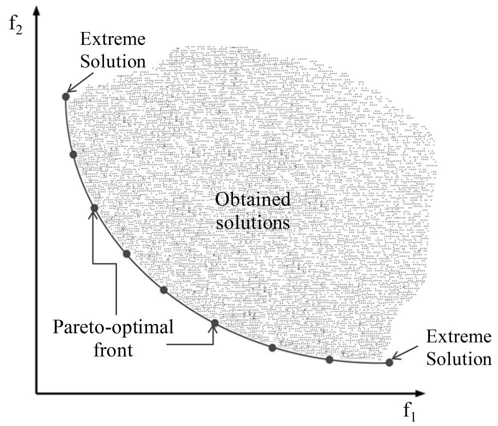


Figure 2.6 Pareto-Front representation for a bi-objective optimization [104].

In particular, maintenance optimization problems are generally NP-hard [80], which entails a considerable computational effort to evaluate the whole combinations. To this respect, classical analytical or semi-analytical optimization approaches usually suffer severe limitations, and can only be applied to simple systems which do not represent real problems [105]. On the contrary, global search and optimization approaches, especially through heuristics and meta-heuristics, have been demonstrated to provide high-quality Pareto-Fronts in maintenance optimization problems, avoiding local optima [80, 31, 105].

In fact, when the problem is NP-hard, such as in the case of maintenance optimization problems, meta-heuristics tend to offer better results than heuristics [32]. Heuristic algorithms select the most appropriate local solution according to comparative rules, where the search method is based on the intuition of the particular problem, thus being problem-specific. On the contrary, meta-heuristic algorithms are based on the intuition of the search itself, rather than on the problem. To this aim, meta-heuristics define top-level general search strategies which will guide lower-level heuristics [106], enabling to evaluate a wider range of solutions and avoiding the local optima in difficult domains. Although several meta-heuristics have been used for solving maintenance optimization problems, evolutionary algorithms have been widely demonstrated useful in the area [80, 105, 107].

Evolutionary algorithms are particularly suitable to solve multi-objective optimization problems due to their capacity to deal simultaneously with a set of possible solutions [108], termed as population. It allows them to only need a single run in order to find several members of the Pareto-optimal, in contrast to traditional mathematical programming techniques, which have to run a series of separate runs [106]. Likewise, evolutionary algorithms can lead with discontinuous or concave Pareto-Fronts, whereas these are real a concern for mathematical programming techniques [32]. Furthermore, whilst many multi-objective optimization algorithms focus on either searching optimal solutions or on multi-criteria decision-making, evolutionary algorithms simultaneously address both issues [32].

The main concept underpinned in the evolutionary algorithms is the biological evolution theory, where the heritable characteristics of biological populations are changed over successive generations, depending on how genes are transferred from parents to offsprings. Consequently, in the context of evolutionary algorithms for optimization problems, individuals are the encoded solution to some problem, which would represent a a biological *genotype*. This genotype consists of a set of chromosomes, which are at the same time defined by separate genes which take on certain values (alleles) from some genetic alphabet. Then, several individuals defined by their set of chromosomes will generate a *population*, to be evolved on the successive generations [32].

Accordingly, the evolutionary algorithm systematically generates individuals that are decoded into a set of parameters that will define the solution to be evaluated in the objective functions. These solutions, as in nature, will be modified through Evolutionary Operators until suitable solutions are found, avoiding local optima. The three major evolutionary algorithms are as follows [106]:

- *Mutation*: a particular modification is made on the individual chromosome string.

- *Recombination*: each parent individual (member of current generation) is cut and recombined with a piece of the other to generate offsprings individuals (member of next generation).
- *Selection*: individuals providing above-average results are more often selected (reproduced) to become members of the next generation compared to below-average individuals.

The list of available multi-objective evolutionary optimization algorithms keeps being improved with more innovative and efficient techniques, with a predominance of genetic algorithms variations. However, the logic underpinned in those algorithms has the same basics (See Table 2.2) [106]:

1. *N individuals* are initialized in a *population* P and evaluated according to their fitness.
2. Dominated solutions are removed from P $\left(P \rightarrow P^{i}\right)$, according to the dominance ranking use (rank [109, 110], depth [104, 111] or count [112, 113]).
3. Use a density estimator, such as niching [111, 110] or crowding [104], ensuring a diverse Pareto-Front but limiting the number of individuals in P^{i}, thus keeping the population at reasonable computational number.
4. Generate a second population P^{ii} (children) performing the previously cited evolutionary operations: selection, recombination and mutation.
5. Select individuals for creating the next generation P^{iii}, based on either a combination of P^{i} and P^{ii}, or just P^{ii}.
6. If the termination criteria is not met, then P^{iii} is set to P as $P_{current}$. Infeasible individuals are repaired or removed, and dominated individuals are removed from $P_{current}$.
7. An archive of non-dominated and feasible individuals is retained by merging P^{iii} with the archive P^{iv}, to which the non-domination operators are applied. The P^{iv} archive contains the known Pareto-Front (PF_{known}).

As it can be seen, as well as developing an algorithm for finding optimal solutions, it is required to evaluate the objective functions, which can be either a simple function, or a complex simulation model [80]. In the specific context of asset management and product-service systems, where several stochastic and uncertain processes or changing environments might condition the outcome of the decisions to be made, it is difficult to handle them analytically [71, 114]. Such stochastic processes might regard either to failure occurrences, specific condition monitoring alarms, weather or environmental conditions, spare parts supply, etc. [35, 65]. Furthermore, decisions on both asset management and product-service systems comprehend several and diverse areas, where their long-term impact should be analyzed [39, 36].

These factors make simulation modeling techniques a powerful tool to analyze the long-term impact of decisions affecting asset management and product-service systems [69, 80, 9]. Simulation techniques have already been successfully utilized to solve diverse engineering problems [81, 115], where it has been leveraged their capacity to model *as is* scenarios and out of these

Initialize population P and P^{iv}
Evaluate Objective $F(x)$ values over population P
Assign Rank Based on Pareto Dominance
Compute Niche Count
Assign Shared Fitness or Crowding
While not terminal condition (number of generations or other)
Selection of "good" individuals from $P \rightarrow P^i$
Recombination, mutation of individuals in $P^i \rightarrow P^{ii}$
Evaluate Objective Values of Children P^{ii}
Rank (P^i union P^{ii}) $\rightarrow P^{iii}$ based on Pareto Dominance
Compute Niche Count
Assign Shared Fitness or Crowding
Reduce $P^{iii} \rightarrow P$
Copy $P^{iii} \rightarrow P^{iv}$ based on Pareto Dominance
End While

Table 2.2 Generic multi-objective evolutionary algorithm Pseudo Code [106].

scenarios evaluate how different decisions would affect the initial situation (*what if* scenarios). In fact, this success has fostered the development of a battery of software tools that allow the simulation modeling, such as Anylogic [114], Vensim [116] or Arena [117].

The starting point of any simulation model is the study and definition of a real-world problem in order to derive the conceptual model. Then, this conceptual model is coded into a computer model and through experimentation process solutions, i.e. decisions, are found [118]. However, on this process, some assumptions and simplifications are usually introduced, which often are imposed by the choice of the simulation paradigm [119, 120, 121]. In fact, the choice of the simulation paradigm plays a critical role on the conceptualization process of the simulation [120]. The main three simulation paradigms available are briefly summarized as follows:

- **System Dynamics.** Introduced by MIT Professor Jay Forrester in the 1950, it captures the complexity of a system and helps analyze its behavior. It allows modeling the interaction of the basic building blocks of a complex system through feedback loops, which drive at the same time the complex dynamic behavior of the system itself [122]. These feedback loops exist when information resulting from one action travels through the system and eventually returns to its origin, either positively (or self-reinforcing) and negatively (or self-correcting) [123, 120].
  Likewise, System Dynamics allows to quantify the behavior of the system determined by a stock-flow diagram. Stocks are the accumulations of rates of flows, which are mathematically expressed by integrating the net difference between the inflow and the outflow over time [120, 124]. Accordingly, the state of the system is described by the level of the variables at any specific time, modeling the problem in an aggregated level [120].
  Therefore, System Dynamics operates at high abstraction levels, with minimum details, and it is positioned as a strategic decision modeling paradigm where high level influences

are to be analyzed (e.g. the impact of advertising and word of mouth in the diffusion of a new product [114]). The reader is addressed to Sterman [123] for further information.

- **Discrete-event simulation.** Introduced by IBM engineer Geoffrey Gordon, it considers the real-world systems to be modeled as processes, i.e. a sequential operations being performed to entities [114]. In this simulation paradigm, also termed “process-centric” [125], the changes in the state of the systems’ processes are triggered by discrete events. The model is governed by a clock and an ordered event list, and it starts with the first item on the list and finishes either when the model stops or the list is empty [120].
  Discrete-event simulation model is expressed as a flowchart -similar to a process diagram- that usually begins with a “source” block or operation. This operation generates entities (e.g. products) and inserts them into the process. When the entities have gone through the process, they end in the “sink” block, which removes the entities from the model [114]. At each block, entities will undergo certain operation, which might include stochastic service times, delays, need of resources, etc.
  In this simulation paradigm, both resources and entities keep their individuality. They might have attributes and differ from each other, being differently treated by the process as well. Therefore, the level of abstraction offered by discrete-event modeling is notably lower than in system dynamics; being rather suitable when operational and tactical decisions have to be made.

- **Agent-based simulation.** Relatively new compared to the other two paradigms, it has gained much attention during the last decades. This paradigm is focused on representing the individuals of the real system, i.e. agents, and modeling their interactions both with other agents and their environment [126].
  There is not a standard language for agent-based modeling, which depending on the software is created using graphical editors or scripts. However, the behavior of the agents in terms of their actions and reactions that will determine their interactions with other agents or the environment, is generally modeled according to different internal states or/and to some behavioral rules executed after specific events [120, 114].
  Likewise, there is not consensus among academics regarding the specific properties that an object should have to be called an “agent”, since their potential properties might vary a lot for the different applications [114, 127]. Yet, usually mentioned characteristics are as follows [120, 128, 126]:

  - Autonomy: agents might have rules that determine their behavior, without needing a central controller to determine it.
  - Reactivity: agents are able to identify changes both in other agents and the environment, and consequently respond to those changes.
  - Pro-activeness: agents might act according to their own goals, without waiting to an external change.
  - Adaptability: agents might have memory and learn and adapt their behavior based on the past experience.

> In contrast to the other two simulation paradigms, the agent-based simulation does not assume any particular abstraction level, since agents can be as much detailed or aggregated as needed, representing either specific customers or generic ideas [114]. Furthermore, it can be combined with the other paradigms if needed [114].

Even if agent-based simulation is more resource-consuming both in terms of CPU power and memory compared to System Dynamics and Discrete Event models, it offers some features that have increased its popularity among academics and practitioners [120, 114]. On the one hand the modeler does not need to know how the whole system behaves nor what are its key variables and dependencies, but they can start identifying and adding agents and defining their behaviors, thus modeling the system bottom-up in an iterative process [129, 114]. On the other hand, the heterogeneity of the agents can be determined either by the behavioral rules and their attributes [130], which ensures the flexibility to model complex real systems. In fact, this feature is further strengthen by the adaptive behavior of the agents, which allows modeling learning mechanisms useful for representing human decision-making processes [120].

These features, along with the wide range of abstraction level that can be handled by the agent-based simulation modeling, make it highly valuable for modeling real complex systems [114]. Likewise, it is also highly valuable for modeling asset management problems and product-service systems, where the dependencies among the complex hierarchical assets and their environment can be modeled; the aging of the assets and their different states (preventive-corrective maintenance, running, standby, etc.) can be represented; the scalability of the problems is ensured by easily adding more agents; and the consequences of the decisions made at high abstractions levels can be evaluated at very low levels and vice-versa, facilitating operational, tactic and strategic decisions [114].

Consequently, in order to optimize the decisions related both to asset management and product-service systems within organizations, both simulation models and multi-objective optimization algorithms should be integrated. Whilst the formers will ensure to successfully handle the real complex systems and the long-term impact of made decisions, the latters will enable to guide the search, through the systematic analysis of selected *what if* scenarios in order to find the optimal solutions according to the established objectives. Simulation-based optimization mechanisms allow this integration, where the implementation of above described multi-objective algorithms will guide the search of optimal solutions, i.e. asset management strategies, and the simulation models will enable to evaluate such strategies; finally conforming a high-quality Pareto-Front. Figure 2.7 illustrates a simulation-based optimization mechanism, where the NSGA II evolutionary algorithm proposed by Deb et al. [104] is implemented[1]:

1. An initial population, representing the asset management strategies, is randomly generated $\left(P^i\right)$.

2. The objective function values are calculated for each individual according to the simulation model developed.

[1] In fact, the Non-Sorted Genetic Algorithm II proposed by Deb et al. [104] has been implemented to solve the railway and wind energy maintenance problems derived during the thesis, very successful in previous maintenance optimization problems [31, 107].

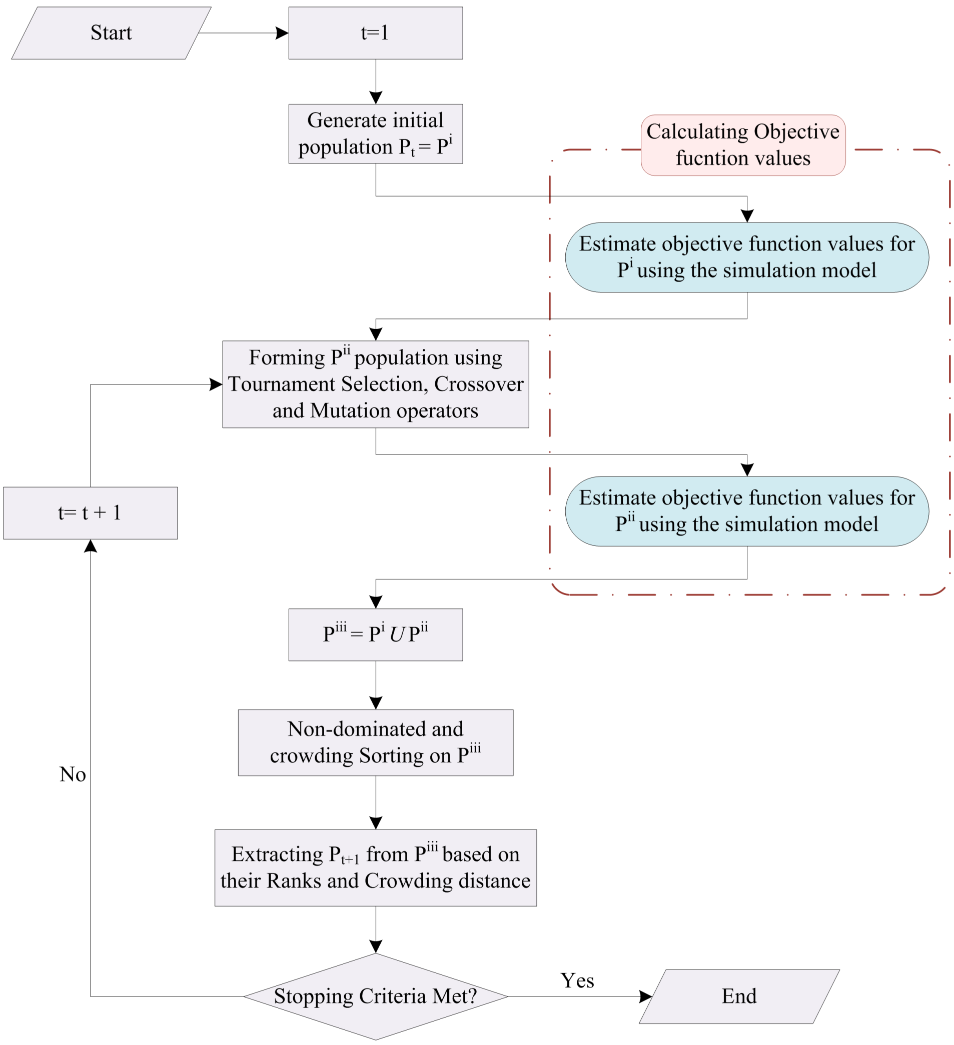


Figure 2.7 Simulation-based Optimization Mechanism for NSGA II (adapted from Attar et al. [80]).

3. Offspring set of individuals is generated by applying crossover and mutation operators, and then selecting the best ones $\left(P^{ii}\right)$.
4. The objective function values are calculated for the selected offspring individuals according to the simulation model developed.
5. Parents and offsprings populations are combined in order to create the new population by selecting the best individuals based on non-dominated sorting and crowding distance concepts $((P^i$ union $P^{ii}) \rightarrow P^{iii})$.
6. Such steps are repeated until the stopping criteria are met.

2.5 Uncertainty assessment

Aforementioned simulation and optimization techniques help determine the life-cycle cost and service-level that certain asset management strategies entail in the long-term, thus providing manufacturers with useful insights for the after-sales services design and management. However, due to the several stochastic processes to be dealt with in both asset management and after-sales services during the long life-cycle of the assets [35, 65], usually ranging between 20-30 years, the performance of the assets during their in-service life might be significantly uncertain [69].

In fact, some of the main problems that manufacturers face when they have to design their product-service system portfolio is to assess such uncertainties [34, 131], which significantly increase assumed risks by manufacturers, understanding risk as defined in ISO 31000 [132]: the effect of uncertainty on objectives. Particularly, manufacturers usually strive at identifying how the different uncertainty sources might affect to the service-level and the price of the service they are willing to offer [133, 134].

In this context, being able to identify and to understand which are the uncertainty sources that might jeopardize both asset management and product-service systems' success is central; it will enable manufacturers to mitigate absorbed risks through the exploitation of arising opportunities to reduce such uncertainties [135]. Without loss of generality, uncertainty sources might be classified as follows [135]:

- Endogenous. The uncertainty source is within the influence boundary of the system, i.e. the uncertainty source might be managed and even reduced by decision-makers. They are mainly related to product and organization factors, such as data quality, lack of specific knowledge or system model accuracy.

- Exogenous. The uncertainty source is outside the influence boundary of the system, and therefore, decisions to manage or reduce them are often out of the direct control of decision-makers. They are usually provoked by forces outside from the control of the organizations, such as, changes in environmental conditions, market evolution (new competitors/products arrival, innovations, financial changes, etc.) or political and cultural context (products regulations, protocols, etc.).

It is a usual approach to develop separate models for dealing with endogenous and exogenous uncertainties, and then combine them into an integrated uncertainty model, i.e. uncertainty management [136]. This approach does facilitate decision-making processes focused both on anticipating downside risks and on benefiting from potential upside opportunities. Nonetheless, in order to make successful decisions, and regardless the endogenous or exogenous nature of the uncertainty sources to be dealt with in the decision processes, uncertainty management requires the modeling of such uncertainty sources by expressing their happening likelihood estimation [137]. In fact, mathematical modeling and grappling with uncertainty in a formal way have been major areas of interest for many researchers [135].

To date, there have been both numeric and non-numeric efforts for expressing the uncertain events likelihood. However, numerical expressions have been demonstrated more valuable than non-numeric expressions, especially in terms of providing insights for designers and engineers seeking to incorporate future uncertainty studies into their work [135]. Most part of the numeric expressions have their foundation on the study of probability [137], where its quantification through statistical analyses and the identification of confidence or tolerance intervals for managing the uncertainty have become key topics [138, 139].

Specifically, the quantification of the uncertainty allows organizations to address four central target categories for enhancing their decision-making processes [33]: *understand*, *accredit*, *select* and *comply*. *Understanding* the influence of uncertainty on the whole decision-making process, as well as ranking such uncertainties according to their importance, will guide to identify further requirements in terms of additional measurements, modeling or research and development (R&D) efforts. Likewise, uncertainty assessment enables to *accredit*, i.e. give credit to, a model or a method of measurement; ensuring that they reach acceptable quality levels, and therefore, that they are suitable for making decisions. Also, uncertainty assessment facilitates the comparison of different decisions to be made in terms of relative performance level, thus enabling organizations to *select* optimal choices, for instance regarding maintenance policy or systems design. Finally, uncertainty assessment might as well *comply* or demonstrate that a certain criterion or regulatory threshold is met, especially important on certification processes.

In particular, when uncertainty sources' impact is assessed and quantified in order to enhance any of the previously cited targets, and especially in practitioner domains such as asset management and product-service systems in the manufacturing context, the uncertainty impact should be considered at different levels. To this respect, De Rocquigny et al. [33] emphasize on the need of quantifying uncertainty at three levels (see Figure 2.8):

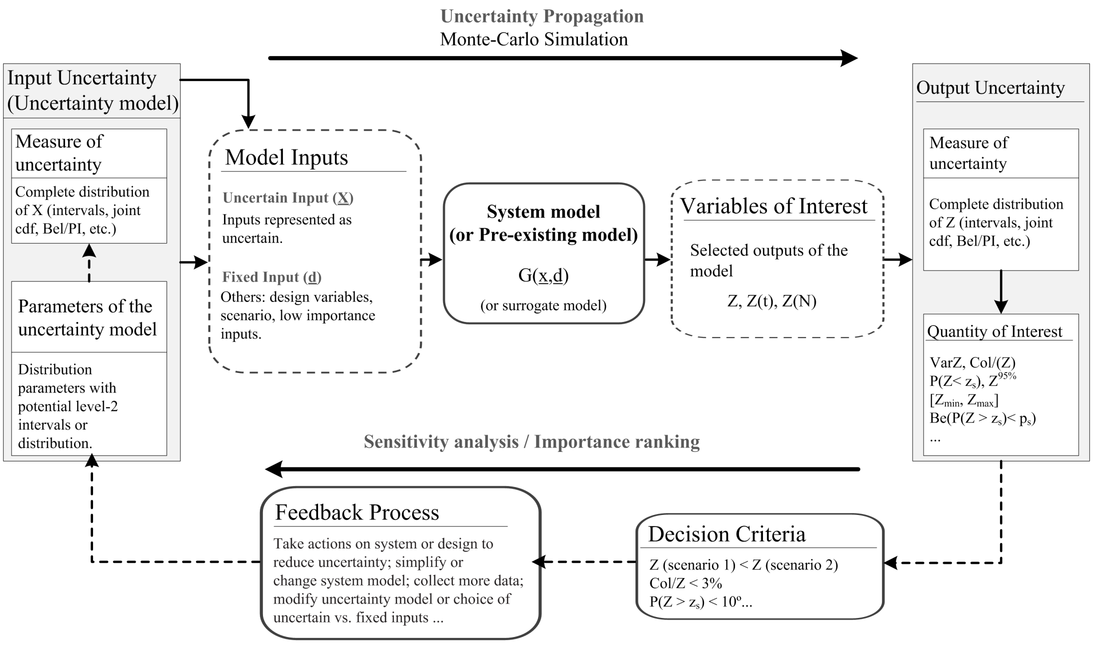


Figure 2.8 Conceptual framework for uncertainty consideration [33].

1. **System model or Pre-existing model** $[G(\underline{x}, \underline{d})]$**.** It may be viewed as a deterministic or stochastic model, or chain of models, representing the industrial problem to be studied. It links inputs (uncertain or fixed variables) to outputs (upon which decision criteria are established) and it can comprehend a great variety of situations, such as mechanical structures, maintenance processes, or even natural risks. The complexity of the model is not limited anyway, it can vary from straightforward analytical formulae to complex engineering simulation models.

2. **Model inputs** $(\underline{x}, \underline{d})$**.** A number of continuous or discrete inputs that directly determine the output of the system model. Model inputs are classified into uncertain inputs $(\underline{x})$, conditioned by the previously described sources of uncertainties; and fixed inputs $(\underline{d})$, which are variables considered to be known or variables under full control, i.e. without uncertainty or with little impact on model uncertainty. The definition of model inputs as uncertain or fixed is usually a matter of choice rather than theory; sensitivity analysis and model calibration are essential for making such distinction.

3. **Variables of interests** $(\underline{z})$**.** The output of the system model and the basis for making decisions according to specific quantities of interest and established decision criteria. They are often represented as scalar variables or small-size vectors in order to easily establish the stated decisions criteria, although they might be of large dimension or even a function as well. It should be noted that depending on pursued uncertainty assessment target, the quantities of interest that determine the decision criteria should be differently defined, such as accepting a maximum variability on the output $\left(\sigma^2(z) < VariabilityThreshold\right)$ or ensuring a minimum value of the output with a probability $(P[Z > z_s] \geq ProbabilityThreshold)$.

Therefore, uncertainty at each of these three levels should be measured according to previously cited numeric and non-numeric expressions [137], which is usually performed in a practitioner approach by statistical analysis or probability distribution functions (pdf). It should be noted that, on some occasions, there is a lack of knowledge regarding the uncertainty description of inputs, for example, when estimating the reliability of a component based on scarce data [69]. In such cases, there is a need of analyzing "uncertainty about the uncertainty", which might as well be viewed as generating a level-2 uncertainty. For instance, it might be needed to analyze the pdf for the parameters of the pdf of an uncertain model input [33].

As illustrated in Figure 2.8, it is central to assess how uncertainty propagates from the inputs of the model to the outputs or the variables of interests, increasing the accumulated uncertainty at each of the three levels. This *propagation process*, also known as uncertainty analysis, implies estimating the pdf of $\underline{z} = G(\underline{x}, \underline{d})$ once the pdf of the input variables and the intrinsic uncertainty of the model have been assessed. This estimation might be performed through diverse methods, such as Monte Carlo Sampling or accelerated sampling techniques [33].

Based on the information provided by the uncertainty propagation, the final step to close the loop defined in the *Conceptual framework for uncertainty consideration* in Figure 2.8 is related to the *sensitivity analysis*. Also termed as *importance ranking*, it allows identifying the relation between the input variables $\underline{x}$ with respect to a given quantity of interest in the output $\underline{z}$, ranking them according to their importance indices [140]. Based on such ranking, a feedback process should be motivated in order to make decisions regarding the assessment of the different uncertainty sources, especially with regards to endogenous uncertainties, over which decision-makers have a greater influence [135]. Whilst there might be more or less explicit feedback actions to be taken, which depend as well on the specific targets pursued with the uncertainty assessment process, feedback actions can be summarized as follows [33]:

- **Understand/ Accredit.** Firstly, the feedback process is focused on reconsidering uncertainties according to their importance in the whole system model. Then, the system model is refined/enhanced in order to reduce such uncertainties. This is mainly performed through research and development efforts in both model inputs, e.g. better data gathering, and system model, e.g. more accurate or efficient model definition. Likewise, such feedback actions will further enable to accredit the model.

- **Select.** Shifts to other business scenarios where the uncertainty sources do not have such a significant impact on the organizational variables of interest are sought. Likewise, this feedback process enhances the decision-making process regarding resources allocation aiming at minimizing uncertainty, e.g. focusing research and development efforts on reducing uncertainty in critical outputs that will reduce cost while maintaining safety standards.

- **Comply.** The feedback process seeks to improve the measurements or adjustments of the design or the control variables/scenarios in order to meet either established criteria or regulatory thresholds.

In spite of the suggested classification, the feedback process often involves more than just one action and it pursues more than one target. In fact, uncertainty assessment is usually one step in a larger organizational process, as it would be in the case of the servitization, which will determine the real scope of the uncertainty assessment [33].

The feedback process represents the final step in the uncertainty assessment framework of Figure 2.8, fully aligning it with the risk assessment process defined in ISO 31000:2009 standard series [132], which requires to identify, analyze and evaluate risks, in order to finally focus the efforts on mitigating them. Therefore, assessing manufacturers' uncertainties by adapting the framework in Figure 2.8 will enable them to mitigate their risks when undergoing the servitization process, further satisfying their stakeholders' interests [132].

2.6 Product-service System: definition, business model and tactics

As introduced in Chapter 1, if Original Equipment Manufacturers want to remain competitive, they should "move up the value chain". Instead of focusing their business development on enhancing their products and production processes and competing only in product and quality offer, they are recommended to enhance their value offer through knowledge-intensive products and services [1, 2].

This fact has led to the emergence of Product-Service Systems, where both product and services conform a single offer [3, 4], and the business model is no longer selling "only product" but selling an "integration of product and services" [141, 142]. This integration aims at decoupling the ownership of the product and its use, evolving to an economic paradigm based on the use of the products (*"pure services"*) rather than on the purchase of those products (*"pure products"*) [6, 12]. In this context, products provide the technical functions to consumers [7], while services ensure that customers' demands are met [8]; further increasing expected results in terms of customer satisfaction, economic viability and sustainability [1].

Original Equipment Manufacturers that want to increase their competitiveness by offering product-service systems, are expected to undergo the *servitization* process [5]. In order to progressively undergo this process, there are three main product-service system business models that could be adopted by manufacturers (see Figure 2.9), which will directly determine how value is created, delivered and captured:

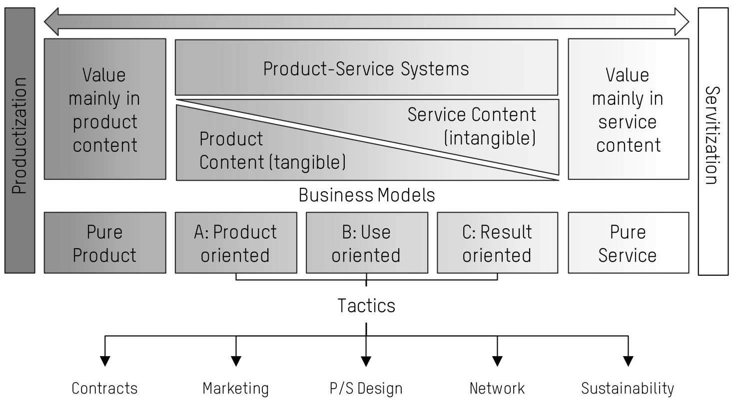


Figure 2.9 Product-service system categories, adopted from Tukker [6].

1. **Product-oriented.** This business model is still geared by the product, bought and owned by the client as in the traditional sale. Nonetheless, some additional services are sold and provided by the manufacturer along with the product, such as consultancy, warranties, maintenance, recycling, financing scheme, etc. [7]. Product-oriented business model is probably one of the most widespread product-service system business models, being warranty service part of many products for instance. Let them serve as more uncommon product-oriented product-service system examples the healthcare equipment supply and take-back [143] or the food delivery services with online ordering and waste management [144].

2. **Use-oriented.** This business model suggests to sell the use of the product rather than the product itself. The product ownership shifts to the manufacturer, therefore increasing the risks and responsibilities of the provider compared to product-oriented business models [39]. Quite common use-oriented product-service systems are product lease, renting or pooling, where as well as owning the product, the manufacturer is responsible for repairing, maintaining and controlling it. Daily examples can be observed in the car sharing systems or rental services [145, 7], yet use-oriented business models have also been studied in other industries, e.g. office furniture [146] or telecentre/office space [5].

3. **Result-oriented.** This business model does not necessarily involve the product, but the outcome or capability provided by it. Thus, product ownership lays on the manufacturer and the customer pays according to the agreed-upon result [1]. Some typical result-oriented product-service systems are pay-per-print (pay per service unit), companies that offer "climatization comfort" rather than gas or cooling equipment [6] or companies selling washed clothes instead of washing machines [147]. The Total-Care Package offered by Rolls-Royce to airlines companies is also a paradigmatic example, where rather than selling the gas turbine engine, Rolls-Royce delivers "power-by-the-hour" to the airlines [1].

Even if product-service system business models represent a major opportunity for manufacturers to move-up the value chain and gain competitiveness [34], it is usually difficult for them to undergo the servitization process. Product-service system business models require the integration of the services within their strategic and operative management, which is a significant challenge for industries [15, 148]. As a consequence, this integration has not been successfully accomplished by most manufacturers, neither has it been supported by adequate models, methods and tools [15, 7].

As described, in use-oriented and result-oriented product-service systems business models the ownership of the product does not longer belong to customers, but to manufacturers. This fact requires manufacturers to be able to manage their sold products in a way that their customers' interests are satisfied [34]. In other words, sold products evolve from *just products* to *assets to be managed* by manufacturers, which increases the risks and responsibilities to be assumed by manufacturers throughout the whole asset life cycle [9]. This fact indeed requires a mindset change, from the concept of "product thinking" to the concept of "system thinking", where some barriers that should be overcome in order to guarantee a successful adoption of product-service systems arise:

- **Ownerless consumption of the products.** Whereas customers' willingness towards the ownerless consumption of the products is raising, with an increase of clients demanding for such business models [39], some customers are still reluctant to it. The foundation of this reluctance is mainly related to the dependence on the manufacturer that the ownerless consumption of the assets generates on customers [1].

- **Price and contracts definition.** Due to the general long-term nature of product-service systems and the more complex networks that they require, contracts are usually more difficult to define than the outright selling of an asset [39]. Thus, it is crucial to handle and fulfill the interests of each involved stakeholder over time, adapting the terms of agreement to the product-service system context [149].

- **Risk and responsibilities definition.** The described long-term nature of product-service systems entails to properly define the risks and responsibilities related to them, not only regarding the product performance along its life cycle but also regarding each stakeholder responsibilities so that this performance is guaranteed, e.g. spare-parts providers responsibilities [1].

- **Stakeholders' requirements fulfillment.** It is difficult to translate customers' requisites into product-service system requisites, which increases the complexity of aligning physical products characteristics to the service [148], which indeed central for creating value through the product-service system [150].

- **Flexibility and adaptability.** Customers might have diverse requirements and operational processes that have to be considered within the product-service system offer portfolio. Thus, manufacturers need to be able to adapt either service or/and product specifications to satisfy such a wide range of needs [151, 152]. Furthermore, such needs might change through the life cycle of the product, where manufacturers' flexibility becomes essential [150].

- **Management decisions complexity.** Product-service systems demand non-traditional business networks and changes in relationships with current stakeholders, which increase the complexity of the management decisions [153]. Furthermore, the new ways found to serve the users' needs might demand the identification and development of non-traditional business networks involving diverse actors which would not have worked together otherwise [144].

- **Sustainability.** Even if sustainability has traditionally been considered one of the main advantages of product-service system business models [1], it is not intrinsic to any product-service system offer. In fact, product-service system solutions often lead to negative effects in the environment [39], being difficult to find a compromise between economic and environmental benefits [154].

In order to overcome these barriers and enhance the success of the product-service system adopted, manufacturers have to make decisions at different *tactics*, defined as *"the company's residual choices at an operational level"* [39, 155]. Such decisions will directly determine how much value is delivered by the previously chosen business model, conditioning how services are combined and implemented by companies within their operations [39, 155]. Reim et al. [39] identified that the most distinguished tactics are related to contracts, marketing, network, product and service design, and sustainability (see Figure 2.9).

As described, business models closer to *"pure service"* require more complex contracts, having to deal with responsibilities and terms of agreement. Such responsibilities and terms, to be addressed by *contracts* tactic, are mainly related to how tasks are divided between contract parties and to how rights and liabilities are assigned from a legal perspective [39]. In particular, responsibilities of the stakeholders are related to service-level, price, control of the asset use, responsibility for downtimes, maintenance times, etc. [152]

Therefore, accurately defining such factors in contracts appears as a good opportunity to lower the risk-level that use-oriented and result-oriented business models involve [156], which otherwise might lead to tense situations such as needing more effort than expected from the different parties. Likewise, having a formalized contract model that enables to adapt contract tactics to the product-service system context and stakeholders' interests is central [149].

Marketing tactic addresses decisions related to 1) the communication of value to the stakeholders, 2) the extension of interaction with customers and 3) the identification of customer and market insights to implement the chosen product-service system business model [39]. Within marketing tactic a value-driven communication, defined as *"the path through which the product-service system provider chooses to differentiate its offerings from its competitors"* [39], becomes fundamental. Especially the case of business models requiring an ownerless consumption of the products, since customers will be typically buying a quite different solution compared to their earlier experiences. Some examples of communicating the value delivered by advanced product-service systems could emphasize on how manufacturers assume some responsibilities that used to be assumed by customers or how these business models can lead to more environmentally friendly solutions [142].

Product-service systems require a closer relationship between manufacturers and customers, where trustworthiness between both actors is needed to achieve the established goals [153]. This interaction will enable to gather valuable insights regarding both product-service system operation performance and consumers and market needs, guiding and enhancing innovations regarding future product-service system offer [152, 157, 151]. Likewise, well defined marketing tactics are essential for increasing product-service systems transparency, and thus avoid the consumers reticence for an ownerless consumption [1].

Network tactic describes the relationships and interactions with the stakeholders of the product-service system, such as suppliers, dealers, customers or service partners [152]. In order to ensure a successful implementation of product-service system business models, it is not only due a proper election of partners, but also to establish a close collaboration between the partners with efficient information sharing [143, 39]. To this respect, the type of partners, the type of relationships and sharing and coordination of activities have a great impact on the success of the product-service system [39].

Likewise, it should be considered that deploying services, or moving towards different business models, adds several new tasks in terms of operations, requiring to develop new networks and partnership infrastructures [158, 154]. For instance, a major difference between traditional sale and use-oriented or result-oriented business models is that revenues are not generated at the sale point but on the established contract periods. Therefore, a network that allows manufacturers to bear the financial pressure that this can cause is necessary, e.g. considering partners able to handle reverse logistics or financial service institutions [159]. Nevertheless, it should be considered that developing such new networks will suppose an additional management effort due to task coordination [153, 142].

The forth tactic drawn from literature, *product and service design* tactic, identifies how manufacturers should design both their products and services to successfully meet stakeholders' interests and implement specific product-service system. To this aim, especial emphasize is placed on aligning the physical product characteristics, such as maintainability or re-usability [150], with the service offer specifications. For instance, in product-oriented product-service system business model, in which maintenance is offer as a service, highly reliable and maintainable designs should be sought [160], whereas in use-oriented product-service system, where assets are expected to be more frequently used, a longer durability should be sought [144].

The long term characteristics of the product-service systems is usually a rather challenging issue when aligning physical products characteristics to the service. In fact, it is not only necessary to know the real requisites for the product through their life cycle, but it also requires a high flexibility in order to adapt the product to customers' needs [150, 151]. Yet, it is considered as a great opportunity for both successfully meeting agreed-upon requirements and customizing and adapting product-service system offer to individual customers' needs [39].

Last but not least, *sustainability* tactic aims at fostering the third of the cited key strategic objectives of the product-service system -along with economic profitability and value offer to customers [1]. Sustainability has been considered as one of the main advantages of product-service systems with regards to traditional sale, even taken for granted in many cases [39]. It is usually argued that product-service system business models respectively enhance and increase product efficiency and lifetime, minimizing resources utilization. For instance, product-oriented business models are expected to better organize maintenance and to enhance products or services reliability while the product-service system is used [39]; or in use-oriented business models manufacturers might own the products once the product-service system has finished, which could lead to a reuse process [144]. In fact, some authors argue that the change from "pure product" business model to use-oriented and result-oriented business models might trigger both incremental and radical innovations [6, 161].

Nonetheless, as previously described, sustainability is not an intrinsic condition of product-service systems, and they sometimes might lead to negative effects in the environment [154]. Accordingly, manufacturers should actively deploy sustainability tactics in order to develop new technologies and solutions that will achieve both to meet legal and market conditions and to add greater value to customers [162, 161]. In this context, manufacturers should actively try to enhance assets' life cycle efficiency and lifetime, for which maintenance, recycling or second life researches acquire high relevance.

The studies reviewed thus far provide evidence about the complexity entailed by undergoing the servitization process. It does comprehend diverse areas within organizations, thus requiring to build capabilities on relationship building, as well as in technical and management domains [163]. In fact, the development of such capabilities constitutes a transverse and holistic process involving every stakeholder (suppliers, manufacturers, customers, etc.) and whose extent determines the value delivered by the product-service system [163, 164].

2.7 Bridging practitioner and literature gaps through research

Aiming at helping manufacturers undergo their servitization process by means of asset management optimization, which is the main purpose of the present thesis, there have been identified some specific literature and practitioner gaps that should be bridged. These gaps are related to the building-blocks of the thesis, as well as to the particular purposes and research questions to be addressed: from the alignment between maintenance strategies and organizational strategies, to the risk management on the after-sales services and product-service system design supported by asset management tools.

2.7.1 Dynamic maintenance modeling

Wide research can be found in the literature devoted to the alignment of the maintenance strategies with the organizational strategies from a managerial perspective [165, 19, 52]. In fact, this alignment is highly recommended in the latest asset management standard series ISO 55000 [16] in order to achieve excellence levels in the field. However, maintenance optimization modeling research field has not specifically addressed such alignment yet; even if suitable maintenance optimization models could foster the alignment further enhancing the interest of industrial organizations in their application [56, 59, 20].

As previously reviewed, maintenance optimization models are mainly focused on triggering maintenance activities according to the main maintenance criteria, such as assets' failure risk, reliability or age; without considering the specific business context of the organizations. Even if optimizing maintenance according to these criteria might probably have a positive impact in the organizational objectives, they do not assure neither the consistent alignment between maintenance and organizational strategies nor a comprehensive fulfillment of such organizational objectives. In fact, they might lead to sub-optimal solutions due to disregarding some important business issues [20]: personnel management, overall equipment effectiveness, logistics, environmental impact, etc.

The dynamic nature of the business environments, opened to global markets and competition [30], arises as a especially challenging factor to be considered when maintenance strategies and optimization models that align maintenance and organizational objectives are to be developed [19, 52, 20]. Thus, the maintenance optimization models should provide some flexibility for adaptation to changes in both the organizational environment and objectives, being able to trigger the maintenance activities based on short-term information regarding those factors.

Gap 2.7.1. The reader can address in the appended paper II the main concepts of the novel dynamic opportunistic maintenance modeling approach developed for aligning maintenance and organizational strategies, as well as the methodological process to apply it. Papers I and IV further validate and demonstrate the suitability of applying this new maintenance modeling approach in two sectors, such as wind energy and railway. This fragment of the thesis research is encompassed within the scope of the first and second sets of research questions (SRQ1 and SRQ2).

2.7.2 Data analysis in practitioner contexts

Maintenance optimization problems usually rely on very specific assumptions for their proper application, which are not usually considered by practitioners when they apply them [29]. It is also the case of herein developed reliability-based optimization models, even though they do not require sophisticated statistical inputs nor specific technology to be deployed per failure mode analyzed [162, 29]. This fact, often results in the misapplication of maintenance optimization models, which might not only lead to sub-optimal solutions, but also to completely wrong solutions that might jeopardize organizations' success [20].

Reliability-based models do require specific statistical theoretical knowledge, as well as enough data gathered and analyzed at proper indenture levels; factors over which industrial companies' knowledge is limited [29]. In fact, statistical reliability analysis are rarely performed when defining the maintenance strategies. On the contrary, such maintenance strategies are usually based on criticality analysis based on failure consequences and frequency (through failure rates or mean time between failures).

In order to bridge such practitioner gap and to enable industrial companies to implement maintenance optimization problems, the author has worked on systematically analyzing reliability at proper indenture levels in industrial contexts. The approach adopted is based on the comprehensive practical procedure for the selection of time-to-failure statistical models proposed by Louit et al. [29], which includes the main concepts to be born in mind when analyzing failure data, such as: censored data or failure trends identification among others.

Gap 2.7.2. The reader can address the description of the tool developed in R programming language for systematically converting censored failure data into useful reliability information in [28]. It allows selecting the indenture level at which the reliability analysis is to be performed, and then, statistical distributions are systematically fit by means of a kit of failure data-driven reliability algorithms adopted from the existing literature.
This fragment of the thesis research is encompassed within the scope of the first set of research questions (SRQ1).

2.7.3 Simulation-based optimization mechanisms in practitioner contexts

As aforementioned, in particular in maintenance optimization problems, and in general in asset management and product-service systems scenarios, multi-objective simulation-based optimization mechanisms are required to find optimal solutions that balance conflicting objectives [80, 71]. Such mechanisms represent a research domain by their own, either in terms of efficient simulation modeling, new optimization algorithms, or a combination of both [32, 120, 114]. However, the novelty of the thesis with regards to simulation-based optimization mechanisms relies on their practitioner exploitation for enhancing asset management and servitization related decisions, rather than on their definition.

In fact, regardless their potential for facilitating several decision-making processes, they have been rarely adopted in the industrial context, being even more unusual than already mentioned reliability statistical analysis. Therefore, this research studies how simulation-based optimization mechanism enables decision-makers to truly represent their preferences on their decisions, further analyzing the impact of such decisions, for example in terms of: feasibility of the product-service system to be adopted, impact of the maintenance strategy, needed resources definition, needed investments in the asset portfolio and their return on investment, etc.

The proposed simulation-based optimization mechanism seeks a neither sector nor problem specific solution in order to ensure its further industrial use. To this aim, general structures have been adopted for defining the decision variables of the problem, such as those related to the novel dynamic maintenance strategy proposed or to the deployed resources, as well as for the implementation of the simulation-based mechanism itself. Nonetheless, it should be highlighted that different industrial companies have different processes, and thus the simulation model has to be specifically adapted for each case study.

Gap 2.7.3. The simulation-based optimization mechanism developed combines simulation models coded in Anylogic® software and the evolutionary optimization algorithm Non-Sorted Genetic Algorithm II. The reader can address the foundations of the mechanism developed in the literature review (see Subsection 2.4, Figure 2.7) and its application to the two case studies in the appended papers I and IV. This fragment of the thesis research is encompassed within the scope of the first and third sets of research questions (SRQ1 and SRQ3).

2.7.4 Uncertainty assessment in after-sales services

When the impact of long-term decisions, as those required when designing both asset management strategies and product-service systems, are analyzed, risk management is central [16, 131]. Therefore, the different uncertainty sources that affect both the asset management and the designed services have to be identified and quantified. Once these uncertainties are estimated, what is their effect in the final objectives of the organizations can be quantified, i.e. risk can be quantified [132], thus facilitating risk-based decision-making.

As reviewed in Section 2.5, uncertainty assessment has traditionally been the subject of many studies, which have addressed diverse topics, such as uncertainty sources classification, modeling and quantification, as well as their assessment in specific industrial environments [135, 33]. However, there is a lack of studies that specifically address uncertainty assessment in the context of servitization, categorizing the uncertainty sources to be dealt with in the after-sales services and analytically deriving their impact so that the final service-offer design is facilitated.

In order to bridge this literature gap, the framework for assessing uncertainty in practitioner contexts proposed by De Rocquigny et al. [33] has been adapted for the specific case of manufacturers undergoing the servitization process. The adoption of this framework has not only enabled to categorize the uncertainty sources, but also to quantify how they propagate from the problem inputs and the problem model itself, e.g. simulation inputs and developed model, to the variables of interests, e.g. service-level and cost. Likewise, important managerial insights are provided in order to understand the importance of uncertainty assessment when shifting to product-service system business models, as well as to identify what decisions could reduce such uncertainties, and thus mitigate the risk absorbed by manufacturers in product-service-system business models.

Gap 2.7.4. The reader is addressed to the appended paper III to find further details with regards to uncertainty assessment and risk management in the context of after-sales services. The research illustrates through a wind energy case study the significant influence of uncertainty when designing the service to be provided by manufacturers.
This fragment of the thesis research is encompassed within the scope of the third set of research questions (SRQ3).

2.7.5 Asset management optimization towards servitization

Product-service systems represent a potential path to move up the value chain, completely changing the business models at the industrial level. However, there are still many barriers that manufacturers have to overcome in order to successfully undergo the servitization process [9]. Many of these barriers arise due to the ownership shift that most of the product-service system business models require, where manufacturers now own the products that they used to sell and their customers pay them for the use of those products during a period of time [1]. Therefore, the product that used to be sold by manufacturers, becomes an asset to be owned and managed by them [131].

The integration of services within manufacturers' strategic and operative management, besides the management of the assets when products are owned by them, becomes extremely complex [148, 15]. In this context, there is a clear need of models, methods and tools that can systematically help design and manage the product-service system offering [7, 131, 15] and that can easily interact with, or benefit of, existing advanced assets management tools [36], as the ones developed along the present thesis research.

Therefore, the apex of the present thesis research is the outline of theoretical and practical insights regarding the alignment of asset management and product-service system research areas. To this aim, a management framework, understood as a set of tools allowing manufacturers to enhance their decision-making process with regards to the product-service system design and implementation, as well as to the asset management strategies to be adopted within such product-service system scenarios, is developed.

Gap 2.7.5. The reader can address in the appended paper V the theoretical and practical insights regarding the alignment of asset management and product-service system research areas, as well as the management framework proposed, which gathers the solutions developed along the thesis. Analyzed wind energy and railway case studies validate and demonstrate the suitability of the developments for facilitating manufacturers' decision-making process in the context of servitization. This fragment of the thesis research is encompassed within the scope of the first and third sets of research questions (SRQ1 and SRQ3).

Relationship among literature gaps and thesis research

The reader may address in Table 2.3 the specific relation of aforementioned gaps to both the research questions posed in Subsection 1.3.3 and the main contributions of the present thesis (see appended papers in Part II).

Set of research questions				Thesis contributions					
Gap	SRQ1	SRQ2	SRQ3	Paper I [23]	Paper II [24]	Paper III [25]	Reliability App [28]	Paper IV [26]	Paper V [27]
2.7.1	✓	✓		✓	✓			✓	
2.7.2	✓						✓		
2.7.3	✓			✓				✓	
2.7.4			✓			✓			
2.7.5	✓		✓						✓

Table 2.3 Relationship among literature/practitioner gaps and sets of research questions (SRQ) and thesis contributions.

3 Research methodology

The present Chapter describes the research methodology adopted for performing the present research. First it explains the research strategy. It goes on to present the methodology adopted to validate and verify the models developed within the thesis, which ensure models' correctness. Next, the thesis building blocks are introduced, as well as enclosed within a management framework that acts as the thread of the appended papers. Finally, it concludes with a brief summary of each of the appended papers.

3.1 Research strategy

As shown in Figure 3.1, according to Kumar [166], research types can be classified according to 3 different criteria: application, objectives and enquiry mode. These three criteria, as well as where does this thesis research stand with respect to them, are described as follows:

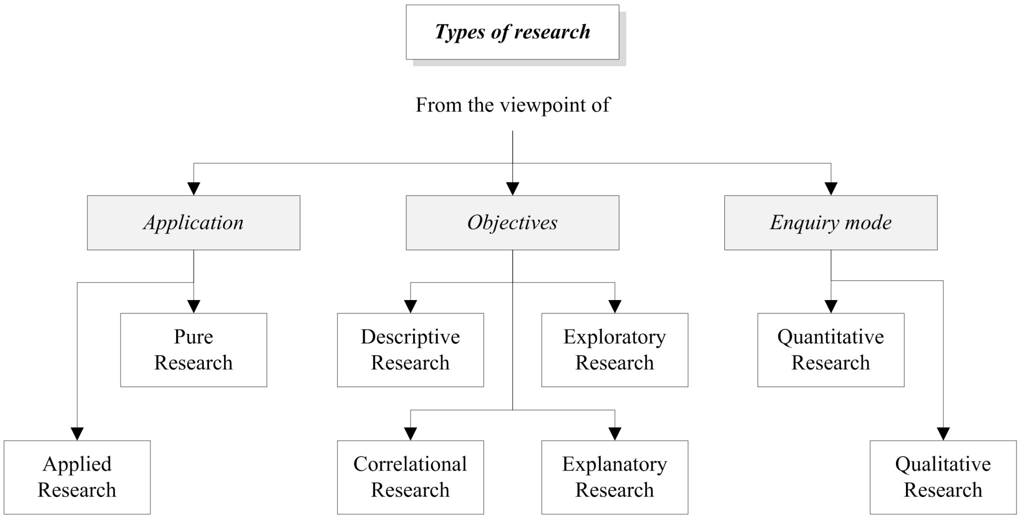


Figure 3.1 Types' of research [166].

- **Application.** Researches might be either pure, when theories that may not have application now nor in the future are tested; or applied, where the enhancement of the understanding of a phenomenon is sought.

  Research position
  The present research mainly lies in the second group, i.e. applied research. The developments presented in the thesis aim to better understand and enhance current asset management solutions so that they better respond to current manufacturers' needs and challenges when they undergo the servitization process. In fact, the development of the thesis in the context of a research technology center, whose main purpose is to generate and transfer knowledge to the industrial network, supports this applied research nature. The development of the two case studies presented in the thesis further reinforce the applied position of the thesis.

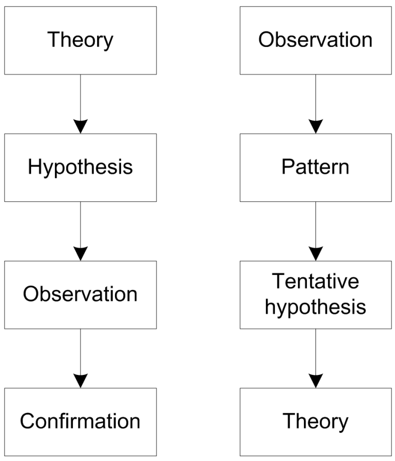
- **Objectives.** Researches might be classified according to their main purpose as follows: descriptive, which describes a situation or problem; correlational, which establishes the relationship between two or more variables; explanatory, which explains why things happen the way they do; or exploratory, which explores a subject area where little is known and/or determine the feasibility of a particular study.

  Research position
  Although in theory researches might be categorized into one of the above cited objectives, they usually have hints of more than one. It is the case of the present research, where both

descriptive and exploratory researches have been performed.
According to the descriptive part of the present research, current problems to be tackled and challenges to be faced by manufacturers, both with regards to the servitization process and the asset management strategies, have been in-depth studied. To this respect, the analysis of current practitioner situation, through the industrial cases studied, as well as the academic one through the comprehensive literature review performed for identifying already existing solutions, have been central.
This descriptive research has set the foundations for the exploratory research, which has led to the development of new theories and algorithms that address cited servitization and asset management needs. Such theories and algorithms have further been studied and validated through two different case studies referring to the railway and wind energy sectors.

- **Enquiry mode.** Researches might be classified as qualitative or quantitative. Qualitative enquiry employs variables measured on nominal or ordinal scales, i.e. it establishes relative variations in a specific phenomenon, whilst quantitative enquiry measures the real magnitude of those variables.

  Research position
  The present research can be classified as quantitative since each of the building blocks of the thesis, e.g. data analysis, simulation-based optimization or risk management, have been defined by quantitative variables. Furthermore, the managerial framework developed, which gathers the main solutions provided along the thesis, aims to base both the asset management and the service-related decision-making processes on quantitative variables, such as life cycle cost or service-level.



(a) Deductive reasoning.

(b) Inductive reasoning.

Figure 3.2 Deductive and inductive research approaches.

Likewise, as shown in Figure 3.2, depending on the scientific reasoning approach adopted for conceiving the researches, they might be considered either deductive or inductive [167]. On deductive research, also called hypothetical framework, a top-down strategy is adopted. Initial statements or theories are proposed and they are afterwards confirmed through gathered results; which should be coherent and consistent with the initial theories (see Figure 3.2a). On the contrary, inductive reasoning, also known as an observational framework, goes from data to knowledge, in a bottom-up strategy. Therefore, patterns are sought in the observations in order to formulate tentative hypotheses, which are then tried to be fit into suitable theories (see Figure 3.2b).

Accordingly, a deductive reasoning approach has been adopted on the present research from a scientific point of view. As aforementioned, a top-down strategy has been followed to design it, first exploring new theories and algorithms that have afterwards been confirmed through the case studies.

3.2 Research validation and verification

The development of mathematical and simulation models during the research in order to aid the decision-making process requires the validation and verification of the correctness of such models. These two concepts are usually defined as follows (see [168, 169]):

- Verification. It ensures that the computer program of the computerized model and its implementation are correct.
- Validation. It confirms that a computerized model within its domain of applicability possesses a satisfactory range of accuracy consistent with the intended application of the model.

Therefore, validation and verification seek to prove the correctness of developed models, ensuring that they provide proper answers to the established questions. In order to study how verification and validation relate to the model development process, the graphical paradigm developed by Sargent [170] can be adopted (see Figure 3.3). This paradigm considers two key aspects: the model development process and the models' validation and verification within such process.

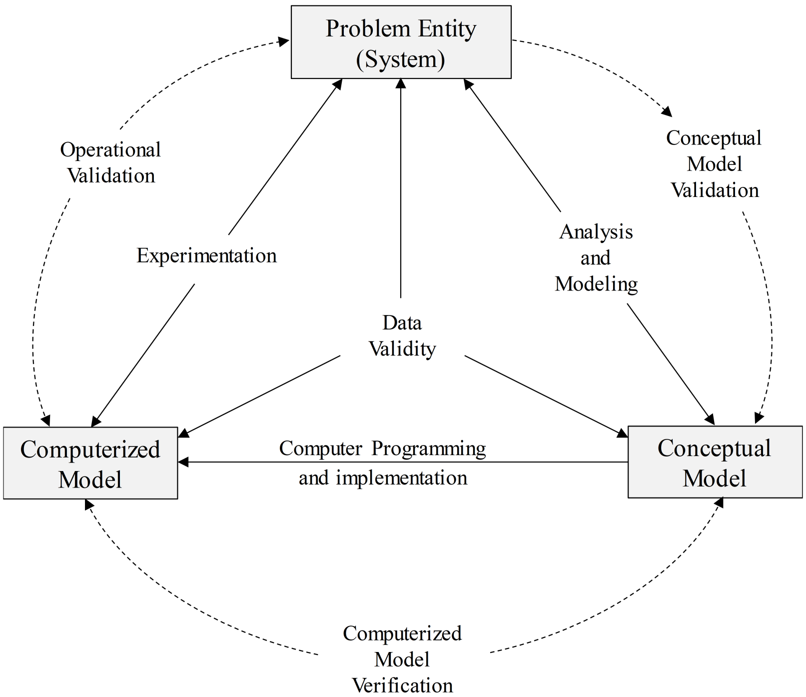


Figure 3.3 Simplified version of model validation and verification proposed by Sargent [170].

Regarding the model development process, the *Problem Entity* refers to the real or proposed system to be modeled, which might represent an idea, situation, mechanism, phenomena, etc. This problem entity is represented by mathematical/logical/verbal model, i.e. the *Conceptual Model*, which is then implemented on a computer as a *Computerized Model* [168].

Following the logic of the validation and verification proposed by Sargent [168], problem entity refers to the asset management and servitization problems to be tackled; the conceptual models are the mathematical representations developed for representing such problems, which might have particularities depending on the case study; and the computerized model is the implementation of the conceptual models in the simulation software (Anylogic®). Accordingly, the conceptual model is developed through the *analysis and modeling* phase and the computerized model is developed through a *computer programming and implementation* phase. Then, experiments on the computerized model (*experimentation* phase) enable to make inferences about the problem entity [168] (see Figure 3.3).

Once the models have been developed, their validation and verification can be performed, emphasizing at three main central aspects (see Figure 3.3). Firstly, *Conceptual Model Validation* confirms that the theories and assumptions underlying the conceptual model are correct, i.e. the model representation of the problem entity is reasonable for its intended purpose. Secondly, *Computerized Model Verification* ensures that the computer programming and implementation of the conceptual model is right. And finally, *Operational Validation* determines whether the model's outputs have enough accuracy for its purpose within its application domain [168].

There are different validation techniques that are commonly used for verifying and validating the simulation model (see Sargent [168]), which have been adopted for validating the models used in the present research:

- **Comparison to other models.** Results obtained by the developed model are compared to the results obtained in other (valid) models. To this respect, several calculations, such as time to failures depending on the assets' virtual age, reliability thresholds variations or maintenance costs among others, have been tested in models developed in different software tools, such as R, Excel or Anylogic®.

- **Degenerate tests.** The model behavior is tested by analyzing the impact that the change of input and internal parameters has in the output. For example, maintenance cost continues to increase as reliability of assets decreases, or maintenance workload increases as the reliability thresholds that determine the maintenance strategy are higher. *Operational graphics* validation technique is usually suggested for studying the outcome of such tests.

- **Parameter Variability - Sensitivity analysis.** Similarly to degenerate tests, this technique suggests changing values of the input and internal parameters of the model to determine their effect in both model's behavior and outputs, which should be consistent with the behavior of the real system. Thus, along with mentioned degenerate tests, specific sensitivity analyses have been performed, for instance for analyzing dynamic opportunistic maintenance approach and for uncertainty assessment.

- **Event validity.** The events happening on the simulation model are compared to those of the real system. For instance, the time-based maintenance strategy should have the same number of maintenance events as in reality.

- **Extreme condition tests.** The model structure and outputs should be logical for any combination of models' inputs and internal parameters, regardless how extreme or unlikely they are. For example, if there is no maintenance team available, no maintenance activity should be performed, and thus, all systems should finish their life-cycle in failure mode; or reliability thresholds equal to 0, should mean that corrective maintenance strategy is adopted (no preventive maintenance activity should be performed), whereas reliability thresholds equal to 1, should trigger maintenance activities constantly.

- **Internal validity.** Several runs of the stochastic model are performed in order to determine the variability of the model. A large amount of variability means that the model is inconsistent, and therefore its results may be questionable. Accordingly, developed model outputs consistency has been validated through different key performance indicators, such as cost, service-level, maintenance teams workload, failure modes' mean time to failures, etc.

- **Traces.** Especially during computerized model verification, traces might be used to follow the behavior of the specific entities in the model, thus studying whether the model's logic is correct and accurate. Traces have played a key role on the simulation model verification, ensuring that all processes born in the model, such as resources allocation, hierarchical propagation of failures, or preventive and corrective maintenance performance, have been properly modeled.

Likewise, as it is remarked in Figure 3.3 and although it is usually not considered within model validation, *Data Validity* should also be discussed within simulation modeling validation and verification [168]. In fact, data validity is central for three main purposes: for building the conceptual model, validating the model, and for conducting experiments with the validated model. Nonetheless, model validation usually concerns with the first two purposes, having often a lack of data that would allow performing experiments that would further validate it [168].

This has also been the case for herein developed models, where data available has allowed building and validating the model, therefore ensuring its suitability for analyzing several decisions impact in the context of asset management and servitization. In both case studies, a significant effort has been placed for gathering and analyzing data regarding maintenance processes and strategies, failures' reliability, maintainability and costs, resources allocation, etc. In particular, data gathered in companies' computerized systems as well as case studies experts' knowledge has been utilized for model development.

Undoubtedly, companies' data collection at proper aggregation levels is central for the application of data-driven models as the ones described in this thesis. Therefore, and although as suggested by Sargent [168], "there is not much that can be done to ensure the data are correct", some good data practices in industrial organizations may be implemented. These good practices may include 1) collecting and maintaining data, 2) testing collected data through consistency checks, and 3) plotting the data for outliers identification [168]. To this respect, the developments of the thesis could help laying the foundations for establishing data requirements, facilitating the implementation and effectiveness of such good practices in the context of asset management and servitization.

3.3 Summary of the appended papers

This Section presents a summary of the five appended papers, sorted in chronological order. It provides the title, the regarded sets of research questions, the purpose, the proposed methodology and the findings of each paper. The reader might address the papers on Part II.

3.3.1 Paper I

Title A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms.

Source Renewable Energy.

Regarded sets of research questions (SRQ) 1 and 2.

Purpose To develop a novel maintenance policy able to adequately adapt the decision-making process according to the conditions under which the wind turbines are operating at each time, thus optimizing their life-cycle performance.

Methodology A novel opportunistic maintenance policy is developed based on the concept of dynamic reliability thresholds. The value of such thresholds, which are responsible for triggering the maintenance activities, fluctuates depending on the specific environmental and operational conditions. Therefore, they foster maintenance activities at low wind energy periods, when the production opportunity cost is lower and safer maintenance conditions are given. Likewise, the dynamic reliability thresholds hinder maintenance during high wind energy periods. After analytically deriving the maintenance problem, considering both multi-level maintenance activities and capacity constraints, the suitability of this novel maintenance policy is tested in an agent-based simulation model. The simulation model enables to consider the several stochastic processes to be dealt with in maintenance problems, as well as the dynamic environmental and operational conditions of wind farms. Likewise, the simulation enables to run experiments for a chosen number of wind turbines, consisting of a number of systems that might fail according to different failure modes. Finally, based on real operation, maintenance and weather field data, results between traditional static opportunistic maintenance and dynamic opportunistic maintenance are compared in terms of life cycle cost and availability.

Findings Results show that dynamic opportunistic maintenance outperforms static opportunistic maintenance, both in terms of life cycle cost and availability. In fact, it is demonstrated that dynamic opportunistic maintenance does take advantage of the specific environmental conditions of the wind farm, systematically triggering maintenance activities during lower wind speed periods than static opportunistic maintenance.

3.3.2 Paper II

Title A novel dynamic opportunistic maintenance modeling approach.

Source European Safety and Reliability Conference 2017 (ESREL)

Regarded sets of research questions (SRQ) 2.

Purpose To propose a framework that extends and formalizes the dynamic opportunistic maintenance modeling approach introduced in paper I in order to align maintenance and organizational strategies in diverse sectors and applications.

Methodology The conflicts that have to be generally faced when aligning maintenance and organizational strategies are studied. Subsequently, a framework that generalizes the dynamic opportunistic maintenance modeling in order to to avoid such conflicts by specifically considering operational and environmental conditions in the maintenance decision-making process is presented. This framework consists of nine phases, comprehended in three different groups, namely *strategy definition*, which seeks to identify how might maintenance activities enhance organizational performance; *dynamic alignment modeling*, which guides the modeling of the dynamic reliability thresholds; and *control and evaluation*, which analyzes the performance of the dynamic opportunistic maintenance model in order to test its suitability. Each of the phases is finally illustrated through the wind energy case study presented in Paper I.

Findings The dynamic opportunistic maintenance modeling is not only able to consider more suitable operational and environmental conditions to perform maintenance, but it can take advantage of them to align maintenance and organizational strategies as well, which is one of the main purposes of asset management. In fact, it allows successfully overcoming the conflicts that might appear on such alignment. Furthermore, the dynamic opportunistic maintenance is proven to be applicable to diverse sectors and applications.

3.3.3 Paper III

Title After-sales services optimization through dynamic opportunistic maintenance: a wind energy case study.

Source Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability

Regarded sets of research questions (SRQ) 1 and 3.

Purpose To design successful after-sales services under uncertain scenarios based on long-term maintenance optimization models.

Methodology The framework proposed by De Rocquigny et al. [33] is adapted in order to assess uncertainty impact in after-sales services scenarios. This framework allows categorizing the different uncertainty sources and identifying how they propagate to the variables of interests. To this respect, it is considered that in after-sales service scenarios a trade-off between several stakeholders' interests has to be found. For this specific research, both the interests of asset users and asset providers have been specifically addressed, respectively in terms of in-service availability and life-cycle cost. In order to deal with such conflicting objectives, a multi-objective simulation-based optimization mechanism is developed, combining the simulation model developed in Paper I and implementing genetic optimization algorithms. The Pareto-Front obtained, along with the theoretical and practical insights provided regarding the impact of the uncertainty sources on the variables of interests, enable to assess both the appeal of the offered service for the asset user and the risks absorbed by manufacturers when offering such services. Finally, the research is illustrated through a wind energy case study.

Findings The foundations for assessing the impact of the uncertainty sources to be dealt with in the after-sales services are provided. Therefore, manufacturers are enabled to make service-related decisions on a risk-based approach, which is also a key pillar from the asset management viewpoint. Results show that the uncertainty assessment is critical for designing successful after-sales services. Likewise, results demonstrate the usefulness of making investments for mitigating the uncertainty sources, which would allow offering less risky and more competitive after-sales services, satisfying both asset users and providers. The multi-objective simulation-based mechanism developed presents itself as an effective tool for facilitating service-related decisions, allowing to balance the stakeholders' objectives.

3.3.4 Paper IV

Title Reliability-based advanced maintenance modeling to enhance rolling stock manufacturers' objectives.

Source Submitted to Reliability Engineering & System Safety

Regarded sets of research questions (SRQ) 1 and 2.

Purpose To propose more flexible maintenance strategies for the railway rolling stock which, based on the concept of dynamic opportunistic maintenance, allow both aligning and enhancing maintenance and organizational strategies.

Methodology The dynamic opportunistic maintenance modeling approach, previously introduced in Paper I and formalized and generalized in Paper II, is adapted for the railway rolling stock sector. Aiming at aligning maintenance and organizational objectives, maintenance activities are not only triggered according to failure modes reliability, but also according to the risk of incurring in penalizations, which would have implications both in terms of cost and business image. The whole maintenance problem is analytically derived, considering both multi-level maintenance activities and capacity constraints. This maintenance problem is then implemented in an agent-based simulation model, which allows handling both the stochastic maintenance scenarios and the specific maintenance processes to be considered in the sector. In order to reach the proper indenture level, three different agents have been modeled in a hierarchical structure: train, system and failure mode. The simulation-based optimization mechanism developed allows systematically evaluating maintenance strategies and finding the non-dominated optimal ones according to three objectives: life cycle costs, downtimes caused by failures and incurred penalizations. Finally, based on real operation and maintenance field data, results between currently adopted time-based preventive maintenance, traditional static opportunistic maintenance and dynamic opportunistic maintenance are compared. Likewise, important managerial insights are provided in order to facilitate decision-makers' choices regarding the maintenance strategy to be adopted.

Findings Results show that opportunistic maintenance strategies outperform currently adopted time-based maintenance strategies. Likewise, it is demonstrated that the dynamic opportunistic maintenance policy proposed succeeds in simultaneously considering both internal factors, i.e. failures, and external factors, i.e. penalizations indicators, to systematically take advantage of more favorable operational contexts to perform maintenance. Therefore, it is confirmed that the dynamic opportunistic maintenance modeling approach leads to the alignment between maintenance and organizational decisions, which is a central within asset management. Likewise, the simulation-based optimization mechanism proves itself to be an effective tool that enables decision-makers to represent their decision preferences on the maintenance program.

3.3.5 Paper V

Title Asset management framework and tools for facing challenges in the adoption of Product Service Systems.

Source Submitted to Computers & Industrial Engineering.

Regarded sets of research questions (SRQ) 1 and 3.

Purpose To help manufacturers overcome some of the main barriers when they undergo the servitization process by providing both theoretical and practical insights regarding the alignment between asset management and product-service systems, further supporting this alignment with specific technologies.

Methodology The importance of asset management when designing and implementing product-service systems is introduced. In particular, it is identified how the asset management capabilities can address some of the main technical challenges faced by manufacturers when adopting product-service system business models, thus overcoming some of the main barriers appearing in the servitization process. Then, a management framework, which follows an IDEF0 representation logic is presented in order to model the decisions and actions to be considered for this alignment. This framework, which consists of three different modules, i.e. data analysis, simulation-based optimization module and analysis and decision support module, gathers the specific technical solutions developed in Papers I, II, III and IV. Finally, the case studies modeled in Papers I and IV are adapted for considering diverse product-service system scenarios. Such applications allow testing, validating and discussing the usefulness of the presented management framework, as well as the importance of asset management when making some of the most challenging decisions in the context of product-service systems.

Findings The foundations for aligning asset management and product-service systems are provided, emphasizing the importance of improving asset management capabilities for enhancing service-related decisions. The two case studies analyzed prove the management framework to be useful both for relating specific technologies that help such alignment and for facilitating manufacturers' decisions regarding product-service systems design. Furthermore, the management framework provided is demonstrated suitable for analyzing diverse product-service system scenarios.

4 Results and discussion

This chapter presents the results obtained and their corresponding discussion ordered by set of research questions.

Firstly, each set of research questions (SRQ) is related to the specific problem(s) to be solved, as well as to the literature gap(s) to be bridged to solve such problem(s), derived from Chapters 1 and 2. This brief introduction lays the foundations to discuss the results of the thesis, based both on the content of the modules that conform the management framework described in Section **??** and on the findings presented in the appended papers (Part II). Likewise, this discussion is supported and exemplified by the computational results of the two case studies analyzed in the appended papers, which based on validated simulation models (see Chapter 3), allow obtaining useful insights regarding each set of research questions.

As the reader may notice, herein presented results and discussion are a summary of the ones in the appended papers, although especially framing them on the context of the thesis and the posed set of research questions. To this respect, it has been emphasized the managerial support that manufacturers undergoing the servitization process would achieve if they implemented the technical solutions that conform the management framework presented. Most of the managerial insights are derived from the analysis of the Pareto-Front provided by the implemented NSGA II algorithm, which has been proven a valuable tool to facilitate manufacturers service-related and asset management decisions.

As reviewed in Section 2.4, the Pareto-Front consists of non-dominated solutions, i.e. solutions that are not outperformed by any other solution in at least one of the objectives optimized (operational expenditure and service-level for the presented case studies). Each of the solutions that conform the Pareto-Front corresponds to a specific maintenance strategy (defined by the reliability thresholds, see appended papers I or IV) within the specific control boundaries defined in the management framework of appended paper V, i.e. product reliability, maintenance processes, resources constraints, etc. Were further details needed for the comprehensive understanding of the results shown, the reader is recommended to address the appended papers mentioned in each of the sections, where the different developments, as well as the case studies, solution details and results are comprehensively described.

4.1 Second set of research questions (SRQ2)

How can the maintenance strategy be optimized in order to consistently align it with the organizations' business strategy? How can assets' internal dependencies and external operational factors be considered in the decision-making process? To which extent should external operational factors vary the maintenance decision-making process?

As introduced in Chapters 1 and 2, the alignment between organizations' maintenance and business strategies is a central pillar when excellence in asset management is sought. This alignment enables manufacturers to consistently enhance their business objectives when making maintenance decisions; opposing to the traditional approach of enhancing the maintenance objectives regardless their explicit impact in the business objectives. Thereby, if the alignment between both strategies was achieved, manufacturers would further ensure through their maintenance decisions that their business, and thus, their stakeholders' interests, are met; consequently guaranteeing product-service systems' success as well.

Whereas this topic has been widely researched from a managerial perspective, and it is in fact a main pillar of the latest asset management standard series ISO 55000, it has yet not been specifically addressed by the maintenance optimization modeling research field. In fact, maintenance optimization models remain focused on triggering maintenance activities according to the main maintenance criteria, such as assets' failure risk, reliability or age; without considering the specific business context and objectives of the organizations (see literature gap 2.7.1).

Not considering the alignment between maintenance and business strategies, along with the scarce knowledge of practitioners regarding how to model and solve maintenance optimization problems, has led to a limited practitioner utilization of maintenance optimization models for making decisions. Furthermore, these models application usually relies on specific data analysis assumptions, such as time-to-failure or reliability models, which are not usually considered by practitioners when they apply them, thus sometimes leading to sub-optimal or even wrong results.

These insights have posed the second set of research questions (SRQ2), which have guided the author to specifically consider the alignment between maintenance and business strategies within the maintenance optimization modeling. This part of the research is particularly addressed in the *simulation-based optimization module* of the presented management framework, which, within the boundaries that characterize manufacturers' service context, provides a set of non-dominated maintenance strategies in an iterative process (see I3$\leftrightarrows$O2 in Figure 4.1).[1]

As discussed in detail in previous Section **??**, choosing the maintenance strategies directly regarding at the specific service business model to be adopted, according to the *optimized PSS*, allows aligning the maintenance strategy with the organizational objectives from a strategic viewpoint. In fact, as illustrated in Figure 4.2, stakeholders' requisites for the product-service system already demarcate the maintenance strategies that are able to satisfy them. Therefore, manufacturers will certainly know what maintenance decisions should be made at the determined indenture levels, being able to balance the profitability and appeal of the product-service system offered (to be addressed in the *analysis and decision support module*).

[1] The reader is addressed to appended paper V for a detailed description of the *simulation-based optimization module*, which aims to bridge practitioner gap 2.7.3, and appended papers I and IV, which exemplify how maintenance and business strategies alignment can be considered in wind energy and railway sectors respectively, bridging literature gap 2.7.1.

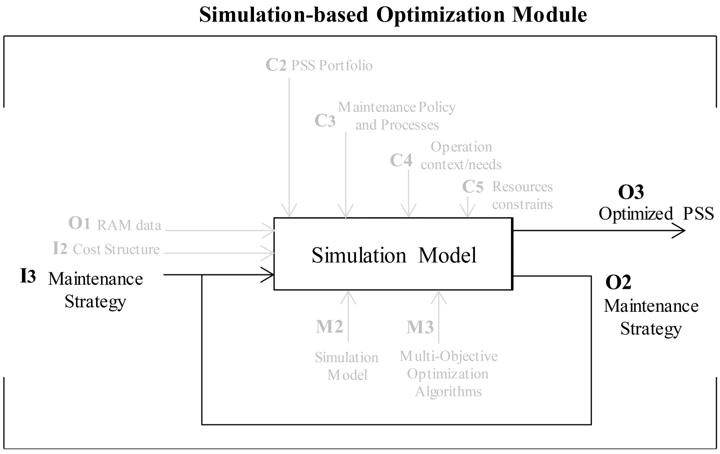


Figure 4.1 Detail of the Simulation-based Optimization Module of the management framework.

Nonetheless, in order to fully align maintenance and business strategies, and thus to fully respond to the second set of research questions (SRQ2) and comprehensively bridge literature gap 2.7.1, the stated strategic alignment provided by the management framework should be complemented at the operational level. Therefore, it is necessary to adopt maintenance strategies that explicitly consider and enhance the alignment between maintenance and business objectives in the short-term decisions as well. To this respect, the novel dynamic opportunistic maintenance modeling approach presented in the thesis makes a major contribution (see appended papers I, II and IV).

In essence, dynamic opportunistic maintenance allows considering and taking advantage of short-term information in order to trigger maintenance activities, balancing maintenance and business objectives in those situations where they might be in conflict. Based on the concept of dynamic reliability thresholds, it fosters maintenance activities when the business context is

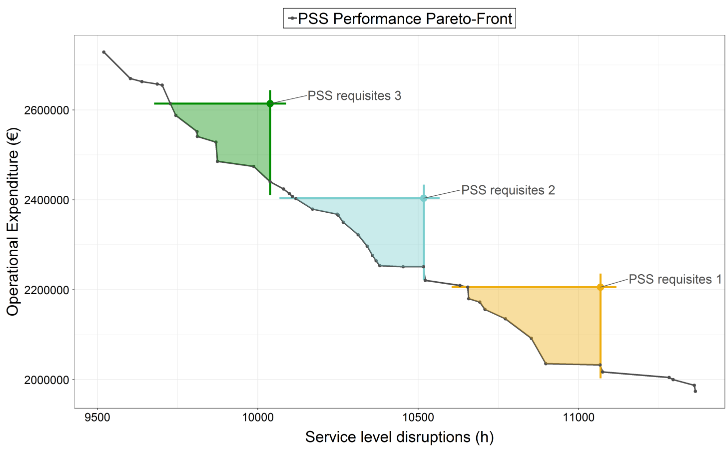


Figure 4.2 Demarcating maintenance decisions according to product-service system requisites.

more favorable, and hinders them when conditions are less favorable. To this aim, the dynamic reliability thresholds allow simultaneously considering assets' internal (e.g. dependencies among failure modes) and external factors (e.g. environmental conditions or organizations' interests). Consequently, the dynamic opportunistic maintenance modeling approach further enhances the results of the *optimized PSS*, outperforming the non-dominated solutions obtained by other traditional maintenance strategies in the specific business objectives considered.

While the interested reader is addressed to appended paper II for the formalization of dynamic opportunistic maintenance and to appended papers I and IV for its application to the wind energy and rolling stock case studies, the main results that demonstrate its suitability for the operational alignment between maintenance and business strategies, are as follows presented and discussed.

4.1.1 Dynamic opportunistic maintenance in Wind Energy Sector

The dynamic opportunistic maintenance was first applied to the wind energy sector, where wind turbines have to be stopped in order to undergo either corrective or preventive maintenance (see case study details in appended paper I). As a consequence, the main business objective, i.e. wind energy production, might be jeopardized by short-term maintenance decisions, especially if maintenance activities are decided to be performed during high-wind speed periods. Likewise, performing maintenance during high wind speed periods is also opposed to another business objective, i.e. workers' safety.

Therefore, the business objectives are partially in conflict with traditional maintenance objectives, such as maintenance cost or assets reliability. For instance, performing maintenance activities only during low wind speed periods may entail to postpone maintenance of certain assets at high-failure risk states. Likewise, the performance of maintenance activities of assets at low-failure risk states may have to be advanced. As a consequence, both situations might lead to economically inefficient solutions and to undesired results in terms of maintenance or business objectives fulfillment.

In order to avoid such conflicts, the dynamic opportunistic maintenance approach aims at systematically performing maintenance activities during low wind speed periods (external factor) whilst considering assets' failure risk (internal factor); seeking a balance between both objectives. Therefore, preventive maintenance activities are to some extent fostered during low wind speed periods and hindered during high wind speeds periods, thus enhancing the operational alignment between maintenance and business objectives.

The reader should notice that it is not the aim of the dynamic opportunistic maintenance to eliminate the preventive maintenance activities, but to plan them at more advantageous business contexts, e.g. at more advantageous weather conditions. To this respect, the dynamism of the reliability thresholds -according to the wind speed as an external factor- should be carefully modeled, otherwise it may lead to an excessive or insufficient maintenance (the reader is referred to appended papers I and II for further details on the thresholds modeling and on the sensitivity analyses).

If results of dynamic opportunistic maintenance are compared to traditional static opportunistic maintenance, where maintenance activities are triggered just based on failure modes' reliability, it is demonstrated that dynamic opportunistic maintenance enhances the operational alignment between maintenance and business objectives, aiding to bridge literature gap 2.7.1. As shown in Table 4.1 and Figure 4.3, dynamic opportunistic maintenance considerably outperforms static opportunistic maintenance in terms of total production losses, i.e. the established business objective (27 % lower losses).

Strategy		Opex (€)	Production Loss (MWh)
Static Opportunistic Maintenance	min Opex	51,856,606	50,239
	min Pr. Loss	52,982,284	48,790
Dynamic Opportunistic Maintenance		50,904,497	36,743

Table 4.1 Main optimization results for each maintenance strategy in wind energy case study.

In fact, it is remarkable that even if static opportunistic maintenance was optimized in order to minimize production losses (in one-objective optimization), the optimal solution would still be far from the optimal result achieved by dynamic opportunistic maintenance (24,7 % lower losses, see Table 4.1). This result is due to the aforementioned fact that wind turbines must be stopped during preventive maintenance. Thus, even if more preventive maintenance implies a better reliability, it is not the key to reduce the wind energy production losses. In other words, more preventive maintenance does not necessarily lead to less production losses. Consequently, production losses can only be reduced if maintenance is performed under lower wind speed periods. It is at this point where the presented dynamic opportunistic maintenance outperforms static opportunistic maintenance, which plans preventive maintenance activities regardless the operational context of the wind turbines.

This result is confirmed in Figure 4.3, where the energy-based and time-based availability of both static and dynamic opportunistic maintenance strategies are compared. Figure 4.3 demonstrates that in static opportunistic maintenance time-based and energy-based availability are coupled -since maintenance is planned regardless the operational context-, whereas in dynamic opportunistic maintenance they are decoupled. In fact, dynamic opportunistic maintenance en-

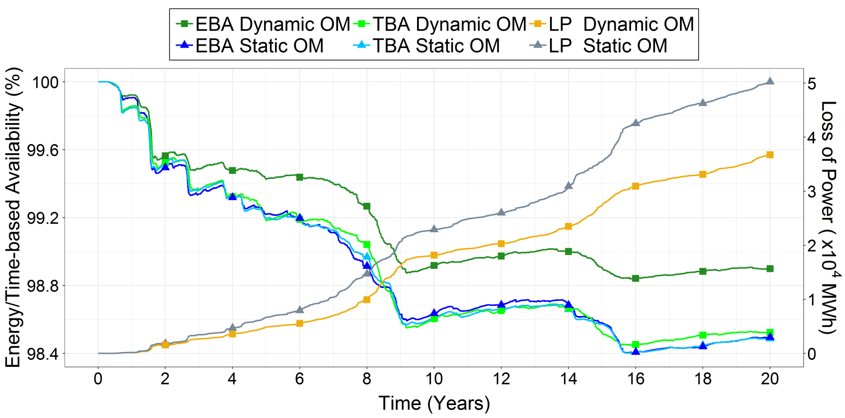


Figure 4.3 Static and Dynamic OM strategies' performance comparison in the wind energy sector.

hances the energy-based availability (over 99,1 %) whilst maintaining the same time-based availability as static opportunistic maintenance.

Consequently, it may be concluded that dynamic opportunistic maintenance does not optimize energy-based availability by performing less maintenance, but by systematically planning maintenance at more advantageous business conditions. In fact, as illustrated in Figure 4.4, dynamic opportunistic maintenance systematically performs maintenance activities under lower wind speeds than static opportunistic maintenance.

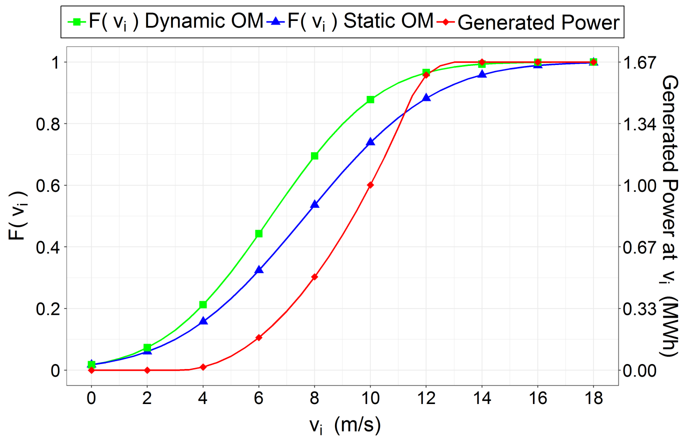


Figure 4.4 Wind speed at which preventive maintenance is performed and accordingly generated power.

This result directly leads to the positive influence of dynamic opportunistic maintenance in terms of workers safety as well. Carlos et al. [171] state that optimal wind speeds for performing maintenance activities are those bellow 5m/s; being generally recommended wind speeds below 12 m/s [172]. As shown in Figure 4.4, if dynamic opportunistic maintenance is adopted, nearly a 35 % of the preventive maintenance activities are performed under ideal conditions and a 97 % under the recommended ones, whereas in static opportunistic maintenance, these percentages decrease to a 22 % and a 88 %, respectively.

Returning to the initially posed objective, it is demonstrated that dynamic opportunistic maintenance helps the operational alignment between maintenance and business decisions, aiding to bridge literature gap 2.7.1. Through the inclusion of both internal and external factors within the decision variables modeling, it allows assessing not only the assets' failure risk, but also the most advantageous weather conditions to perform maintenance, thus enhancing and finding a compromise between business and maintenance objectives. In fact, it achieves as good results as static opportunistic maintenance in the traditional maintenance indicators while outperforming it in the considered business objective.

4.2 Third set of research questions (SRQ3)

How do the different uncertainty sources condition the maintenance strategy and the after-sales services? Which is the risk associated to these uncertainty sources and how can it be managed by the organization? How should the product-service system be designed on an uncertain scenario in order to ensure its success? How could the profitability of reducing the uncertainty of any of the sources be quantified?

As reviewed in Section 2.6, one of the main technical challenges faced by manufacturers undergoing the servitization process is to manage the risks entailed by their decisions, mainly caused by having to own and manage their products during the defined service period. Moreover, due to the long life-cycle of product-service systems, as well as the several stochastic processes that they involve, manufacturers usually strive to identify and to avoid the effect that the different uncertainty sources might have on the objectives that they pursue.

Consequently, lacking a structured risk-based decision-making approach, manufacturers often struggle to make some of the most significant long-term decisions concerning service-oriented business models. Among other examples, it is common to find manufacturers facing difficulties defining the terms of product-service systems contracts, such as the service-level, the price or the stakeholders' responsibilities; which certainly determine their profitability and sustainability as industrial companies offering services (see literature gap 2.7.5).

Given the importance of uncertainty when facilitating and enhancing the decisions on a risk-based approach, not only in the servitization context but also in other industrial contexts, uncertainty assessment has traditionally been the subject of many studies. For instance, there are several researches focused on uncertainty sources classification, modeling and quantification, as well as on uncertainty assessment in industrial contexts. However, there is a lack of studies that specifically address uncertainty assessment in the context of servitization, failing both to categorize the uncertainty sources to be dealt with in the after-sales services and to analytically derive their impact so that the final manufacturers' service-related decisions are facilitated (see literature gap 2.7.4).

In order to bridge this literature gap, and therefore find answers to the third set of research questions posed (SRQ3), the framework proposed by De Rocquigny et al. [33] for assessing the uncertainty in practitioner contexts has been adapted for the case of manufacturers offering services (see appended paper III). This framework allows categorizing both the endogenous and exogenous uncertainty sources affecting the after-sales services. In addition, it lays the foundations for quantifying how such uncertainties propagate from the input variables to be considered in the decision-making process, throughout the system model to, finally, the quantities of interests that guide the final decisions, such as service-level or cost.

The quantification of the propagation of uncertainty to the quantities of interest, which indeed enables to make risk-based decisions and is central for facilitating service-related decisions, is specifically addressed within the *analysis and decision support module* of the management framework proposed in appended paper V (see Figure 4.5). The *strategic decision support* function enables to quantify and to assess the uncertainty within both the input variables and the system model (I4) through a cost-risk-benefit mechanism (M5), determining its affection to the stakeholders' quantities of interest. This analysis complements the *Optimized PSS* (O3) calculated in the *simulation-based optimization module,* which, as discussed in Sections **??** and 4.1, guides manufacturers' asset management and product-service system decisions. Accordingly, it provides the decision-makers with further insights regarding the variability of their decisions' outcome, helping them determine the final *PSS Offer* (O4) in a risk-based approach.

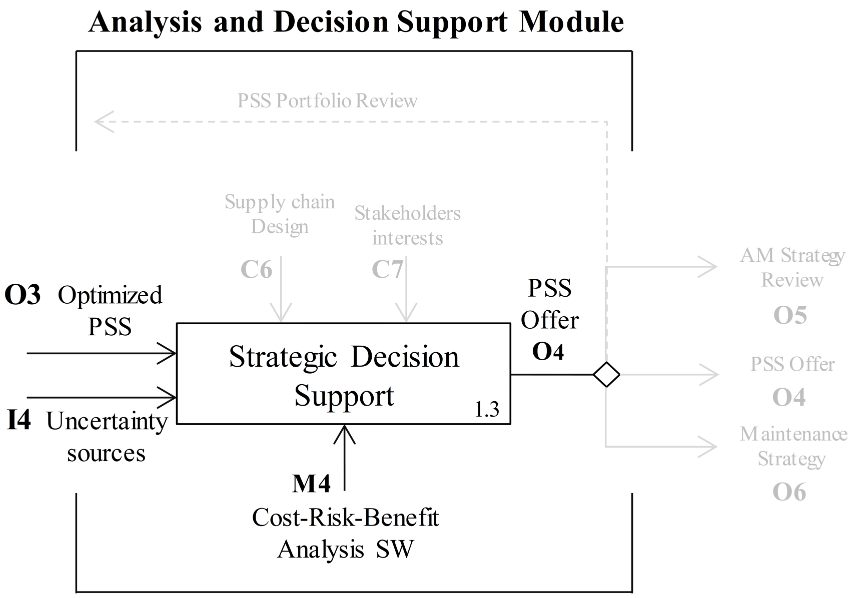


Figure 4.5 Detail of the Simulation-based Optimization Module of the management framework.

In order to illustrate the impact of uncertainty within the specific context of servitization, as well as the role and the managerial benefits of the *strategic decision support* function, the aforementioned wind energy case study has been extended in appended paper III. This case study evaluates the impact of uncertainty in a performance-based contracting (PBC) business model, i.e. result-oriented business model. In particular, it focuses on identifying the influence that uncertainty sources might have in the contract definition, as well as in the managerial insights for assessing the profitability and suitability of mitigating the endogenous uncertainty sources, thus enabling to prove the suitability of the proposed solutions to bridge literature gap 2.7.4.

Due to the several stochastic processes that have to be handled within services, such as failure events, there is an inherent uncertainty in every product-service system. As stated, these uncertainties imply a variability in the outcome of the model, which has been represented in the sensitivity analysis of Figure 4.6. Accordingly, each *optimal PSS* solution (O3 in Figure 4.5), which consists of a specific maintenance strategy within the designed product-service system boundaries (see Section **??**), will have a deviation from the optimal value initially calculated[2].

[2] Given the complexity and detail level of herein described and illustrated results, the reader is recommended to address appended paper III in order to better understand them. Especially, to understand how has been defined the problem, how are shown and discussed solutions defined, how have been the uncertainty sources been considered and how are the service-related decisions conditioned by such uncertainty sources.

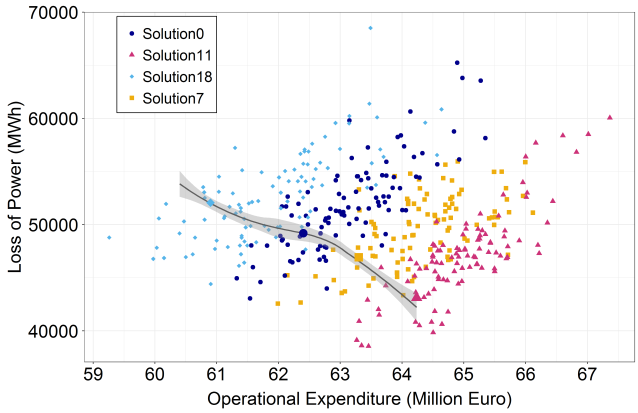
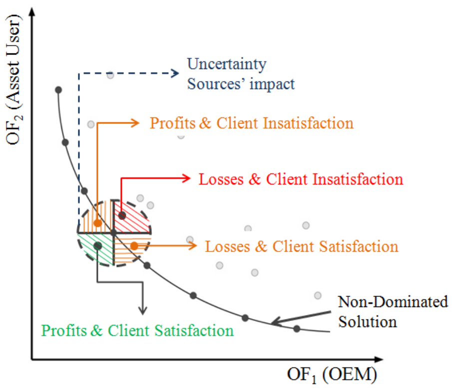
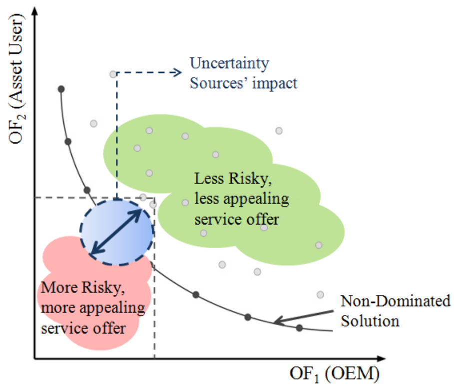


Figure 4.6 Uncertainty impact on the optimized product-service system.

The reader should notice that this variability significantly conditions manufacturers' decision-making process. For instance, if contractual terms of the product-service system were defined according to the output of the *optimal PSS*, there would be a high risk of not meeting those terms due to the effect of uncertainty. In fact, as shown in Figure 4.7a, such effect may lead to different scenarios where the stakeholders' interests fulfillment cannot be guaranteed. Accordingly, if manufacturers wanted to avoid unsuccessful product-service systems, they should determine the product-service system requisites considering the uncertainty impact, achieving lower risk scenarios yet at the expense of a lower product-service system appeal (see Figure 4.7b).



(a) Uncertainty influence on stakeholders interests .



(b) Uncertainty influence on product-service system risk and appeal balancing .

Figure 4.7 Uncertainty influence on product-service systems' stakeholders interests (OEM and Asset-users).

To determine the uncertainty impact and achieve such low-risk scenarios, it is critical to perform a statistical analysis of the outputs' variability. Table 4.2 exemplifies, for the solutions of the present case study, some of the statistical indicators that might be considered for facilita-

	OEMs' Quantity of Interest: Opex (€)					Asset users' Quantity of Interest: LP (MWh)				
	Mean	St	L,CI^{95}_{mean}	U,CI^{95}_{mean}	$F_{U,CI} = 0.95$	Mean	St	L,CI^{95}_{mean}	U,CI^{95}_{mean}	$F_{U,CI} = 0.95$
S. 18	61,7 E6	780 808	61,5 E6	61,9 E6	63,1 E6	51955	3461	51218	52693	58386
S. 0	63,1 E6	687 105	62,9 E6	63,2 E6	64,4 E6	51680	3215	50999	52361	57650
S. 7	64,5 E6	687 806	64,3 E6	64,6 E6	65,8 E6	50377	2741	49800	50955	55465
S. 11	64, 9 E6	652 858	64,8 E6	65,1 E6	66,1 E6	46732	2839	46134	47330	52001

Table 4.2 Confidence Intervals for OEMs' and Asset Users' Quantities of Interest.

ting a risk-based decision-making approach. It presents the mean solution with lower and upper confidence intervals, representing optimistic and pessimistic scenarios $(L,CI; U,CI)$; the standard deviation, representing the variability of the output; and the cumulative probability $\left(F_{U,CI}\right)$, representing the probability of providing a successful service contract a certain amount of times.

In particular, $F_{U,CI}$ provides very useful information for risk management. It guarantees that if decision-makers adopted a particular solution, and they defined the specific price and service-level guided by $F_{U,CI}$, they would succeed in meeting the service terms with such probability. For instance, defining $F_{U,CI} = 0.95$ and adopting the maintenance strategy defined in Solution 7 (S.7), if the contract terms of the PBC were established at a price of 65,8 E6 euros and a maximum production loss -representing the service-level- of 55465 MWh (see Table 4.2), only the 5 % of the times would be either the manufacturer or the asset user dissatisfied. On the contrary, if the price and the maximum production loss were offered at mean values, or without considering the impact of uncertainty sources, there would be a high probability of not providing the committed service-level (implying high penalizations) or/and of exceeding the maintenance cost; thus jeopardizing the service success.

Accordingly, the decision-maker should establish the probability of $F_{U,CI}$ according to the risk level they wanted to assume. Nonetheless, the reader should notice that high $F_{U,CI}$ values lead to more conservative decisions from manufacturers' perspective (higher service cost, lower service-level), consequently leading as well to a less appealing offer for the asset-user (see Figure 4.7b). Therefore, the quantitative analysis provided by the *analysis and decision support module* should be complemented by a qualitative analysis. Decision-makers, according to their own knowledge and experience, should determine a reasonable $F_{U,CI}$ that leads to a low-risk yet appealing product-service system scenario.

As stated by De Weck et al. [135], the mentioned variability of the quantities of interest might be caused either by exogenous or endogenous uncertainty sources (see literature review Section 2.5). On the former case, decision-makers do not have influence over the uncertainty sources, and thus they cannot mitigate the risk that they provoke. On such occasions, decision-makers should be focused on managing such risk according to aforementioned statistical measures and managerial insights.

Nevertheless, when the variability of the quantities of interest is caused by endogenous uncertainty sources, decision-makers are indeed able to mitigate them, lowering the risk of the product-service system. For instance, in the domain of asset management, decision-makers might influence the maintenance logistics, the uncertainty of which might be reduced by making decisions such as maintenance processes optimization or different suppliers or transport means selection.

In this context, it is critical for manufacturers to determine the implications that the mitigation of the endogenous uncertainty sources might have on the profitability of their product-service systems (see literature gap 2.7.4). It will enable them not only to provide more competitive and successful product-service systems, but also to rank and enhance their decision choices, e.g. investment resources assignment.

In order to demonstrate the benefits of the proposed management framework to perform such analysis, the wind energy case study has been once more extended. In particular, the uncertainty provoked by the time to repair has been studied, since it might be influenced by decision-makers at numerous points, such as spare parts supply chain, workers' productivity, maintenance processes design, etc. Four different scenarios have been compared, where the variability of the time to repair has four different levels of uncertainty, from 0 % to 30 % (see the statistical results in Table 4.3).

As illustrated by the density graphs in Figure 4.8, which map the possible (uncertain) outcomes of adopting a particular maintenance solution, the greater the uncertainty level, the greater the after-sales service outcome variability. Thus, according to the statistical measures of the quantities of interest, it may be noticed that in order to provide the same $F_{U,CI} = 0.95$, the contract terms should significantly change, leading to a less appealing service offer in highly uncertain scenarios. Especially in terms of loss of power, the committed service-level should be decreased in more than a 23 % if the scenarios of 0 % and 30 % variability are compared.

Consequently, decision-makers, based on this information, as well as in their own experience, would be able to assess the impact that their decisions for reducing the uncertainties might have in the final service offer. In fact, they would be able to quantify the potential benefits of such decisions, categorizing and ranking the suitability of the investments to be performed. For further details regarding the investment analysis, the interested reader is addressed to the case study described in appended paper III.

In conclusion, as identified in the literature review (see gaps 2.7.4 and 2.7.5), the several risks that manufacturers have to absorb when they shift to product-service system business models present one of the main barriers for undergoing the servitization, and thus, they should be mana-

	OEMs' Quantity of Interest Opex (Euro)				Asset Users' Quantity of Interest LP (MWh)			
Efficiency Uncertainty (%)	Mean	St	$F_{U,CI} = 0.95$	Δ%	Mean	St	$F_{U,CI} = 0.95$	Δ%
0	63,2 E6	687 105	64,4 E6	-	48354	3833	54659	-
10	63,0 E6	1 100 646	64,8 E6	0,6	49719	4921	57814	5,77
20	62,9 E6	1 517 755	65,4 E6	1,55	49481	7865	62419	14,2
30	63,0 E6	2 102 454	66,4 E6	3,1	50097	10789	67418	23,34

Table 4.3 Confidence Intervals for OEMs' and Asset Users' Quantities of Interest given an uncertainty in the efficiency of the time to repair.

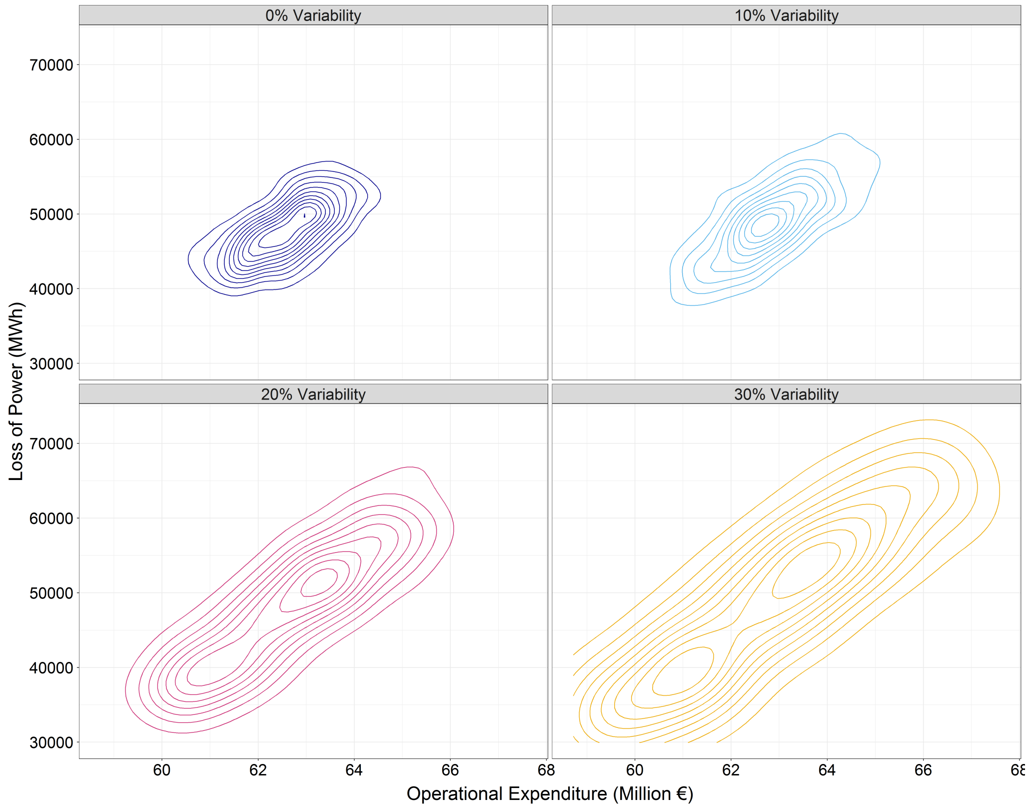


Figure 4.8 The impact of uncertainty in the time to repair.

ged. To this respect, the management framework presented in appended paper V, along with the adoption of the framework proposed by De Rocquigny et al. [33] for understanding and assessing uncertainty in the context of services (appended paper III), provides manufacturers with interesting insights for supporting their decision-making process in a risk-based approach. Therefore, the management framework presented not only guarantees the success of manufacturers' decisions under uncertain business scenarios, but it also lays the foundations for ensuring profitable investment decisions in both quantitative and qualitative terms; answering to some extent to the third set of research questions (SRQ3) while bridging aforementioned gaps.

5 Concluding remarks and future research lines

This last chapter presents the concluding remarks of the research, briefly summarizing, per set of research questions, which are the challenges faced, the contributions of the thesis and its key findings, as well as the guidelines for future research.

5.1 First set of research questions (SRQ1)

Do organizations know how to tackle the asset management? Which steps shall be followed by an organization to achieve excellence levels in asset management? How can the different data sources of an organization be handled in order to improve the decision-making process regarding the asset management? How can the know-how regarding the assets be used to design product-service systems?

Manufacturers are facing a change of paradigm where, if they want to remain competitive, they should "move up the value chain" through the delivery of knowledge-intensive products and services. In fact, although products and services have traditionally been considered separately, during recent years they have converged into the concept of product-service systems; thus conforming a single offer expected to provide advantages at several objectives, such as customer satisfaction, economic viability and environmental sustainability.

In this new paradigm, products containing valuable technical items are reconsidered as services that people/companies might prefer to use rather than own. Therefore, customers would effectively purchase the service of products for a defined use period, neither caring of purchasing, owning nor disposing the products themselves. On the contrary, those products have now to be owned and managed by manufacturers during the defined use period, sometimes the whole life-cycle of the products, which requires the integration of services within the strategic and operative management of manufacturers. In fact, and despite the several advantages that product-service systems can bring to manufacturers, this integration still presents technical barriers that manufacturers have to overcome in order to successfully implement them.

Furthermore, it has to be considered that most original equipment manufacturers are just beginning their servitization process. Thus, they have to satisfy their stakeholders' interests in rather unknown business scenarios, which makes manufacturers' decision-making process concerning the product-service system rather complex, for instance in terms of price and contracts definition, risk and responsibilities definition or stakeholders' requirements fulfillment. In this context, there is a clear need of models, methods and tools that can systematically help to design and manage manufacturers' product-service system offer and that can easily interact with, or benefit of, advanced asset management tools (see research gap 2.7.5).

This need has led to the development of a management framework, understood as a set of technical solutions developed during the thesis research (see appended paper V). This framework is considered to be the apex of the thesis and it seeks to enhance manufacturers' decision-making process with regards both to the product-service system design and implementation, as well as to the asset management strategies to be adopted within such product-service system scenarios. To this aim, the management framework consists of three different modules, which at the same time encompass further contributions of the thesis to the existing literature:

1. *Data analysis module*. It aids converting failure data into useful information for facilitating asset management decisions (registered software [28] answering to practitioner gap 2.7.2).

2. S*imulation-based optimization module*. It allows evaluating specific product-service systems and maintenance strategies considering products' context and characteristics (see appended papers I and IV answering to literature and practitioner gaps 2.7.1 and 2.7.3).

3. A*nalysis and decision support module*. It assesses, in a risk-based approach, the decisions to be made by manufacturers (see appended paper III answering to literature gap 2.7.4).

The management framework follows an IDEF0 representation logic, which formalizes the steps to be adopted by manufacturers in order to optimize their asset management decisions in a servitization context; not only identifying the data requisites and controls to be considered, but also determining and implementing the mechanisms that each of such steps requires. Data flows throughout the three modules, being the output of the former module the input of the following one, further enriching data and information at each module.

The application of the management framework has been proven useful and valuable in its application to the railway and wind energy industries, therefore confirming its suitability (see appended paper V). Within these applications some of the most challenging decisions to be made in the context of product-service systems are analyzed and discussed, such as contracts' pricing, maintenance strategy definition, uncertainty assessment or investment analysis. These results, as well as the managerial insights provided, demonstrate the usefulness of the framework for supporting product-service systems related decisions, despite the diverse nature that such decisions might have.

Therefore, returning to the first set of research questions (SRQ1) posed at the beginning of this study, it is now possible to state that the present thesis, especially through the proposed management framework and the provided technical solutions, enables to enhance asset management capabilities of manufacturers and to facilitate their decision-making processes within service-oriented business models. Nonetheless, in order to fully support manufacturers undergoing the servitization process, some of the topics addressed by the management framework should be further investigated, requiring the following research work:

- Supply chain management appears as a central research area in order to deal with the different stakeholders involved in product-service systems. However, it is out of the scope of the present research. Therefore, the management framework should be complemented with comprehensive supply chain management algorithms and tools that enable firstly, to identify more accurately the operational expenditure entailed by the decisions made, and secondly, to ensure that both asset management and product-service systems' requirements are met.

- The financial implications and/or restrictions that shifting to service-oriented business models has on manufacturers' decision-making processes are as well out of the scope of the present research. However, they are critical for the success of manufacturers' servitization process, and thus, they should be considered within the product-service system design and asset management decisions.

- Whereas developed models and result analysis has been focused on manufacturers' and customers' interests, there are more stakeholders involved within product-service system business models, e.g. investors or providers/suppliers. Therefore, it should be explicitly addressed how the expectations' fulfillment of each stakeholder affects the product-service system design, as well as the asset management decisions.

- Both case studies presented regard to the management of fleets of assets operating in specific operational contexts. However, there can be products which operate isolated within different production processes. Thus, it should be emphasized the considerations that manufacturers managing and offering assets in such circumstances should have when applying the proposed management framework and solutions.

5.2 Second set of research questions (SRQ2)

How can the maintenance strategy be optimized in order to consistently align it with the organizations' business strategy? How can assets' internal dependencies and external operational factors be considered in the decision-making process? To which extent should external operational factors vary the maintenance decision-making process?

Manufacturers interested in implementing service-oriented business models face several technical difficulties entailed by having to manage the products that they used to sell. In this new context, where products become assets to be managed by manufacturers, physical asset management acquires a key role for facilitating several decisions that enhance technical and business performance of assets, ensuring that the interests of product-service systems' stakeholders are met. Particularly, physical asset management seeks to exploit assets finding a balance among cost, service-level and assumed risk in order to satisfy both organizational objectives (e.g. value offer, financial results or clients requirements fulfillment) and asset management objectives (e.g. operational requirements or technical performance).

Due to the several life-cycle processes to be considered in the physical asset management, such as operation, maintenance or decommissioning among others, maintenance management emerges as a pivotal instrument for optimizing assets' exploitation. To this respect, and in line with the latest asset management standard series ISO 55000, it is not only critical to optimize maintenance management, but to ensure that maintenance and organizational strategies are aligned as well. In other words, it is critical to ensure that the maintenance decisions made regarding the assets directly lead to achieve the organizational objectives.

Whereas the alignment between maintenance and organizational objectives has been widely researched from a managerial perspective, it has yet not been specifically addressed by the maintenance optimization modeling research field (see related literature gap 2.7.1). This literature gap has guided the conception of two of the main contributions of the thesis: 1) the management framework itself, which guides the cited alignment at the strategic decision level (see appended paper V); and 2) the dynamic opportunistic maintenance modeling approach, which guides the cited alignment at the operational decision level (see appended papers I, II and IV).

At the strategic decision level, the management framework proposed assesses the maintenance decisions directly regarding at the specific service business model to be adopted and the requisites established by the stakeholders. This feature enables decision-makers to translate the specific objectives they pursue, especially in terms of the product-service systems' profitability and appeal, into specific decisions over the assets; thus aligning asset management and organizational objectives. Furthermore, the risk-based approach considered within the framework allows assessing manufacturers' strategic decisions in the highly uncertain scenarios to be faced when undergoing the servitization process; ensuring, with a certain confidence level, the success of maintenance decisions.

At the operational decision level, the alignment between maintenance and organizational strategies is enhanced through the novel dynamic opportunistic maintenance modeling approach presented, which is specifically considered in the *simulation-based optimization module* of the management framework. Dynamic opportunistic maintenance allows considering and taking advantage of short-term information in order to trigger maintenance activities, balancing maintenance and business objectives in those situations where they might be in conflict. Based on the concept of dynamic reliability thresholds, dynamic opportunistic maintenance fosters maintenance activities when the business context is more favorable, and hinders them when conditions are less favorable; attending both to short-term information regarding assets' internal (e.g. dependencies among failure modes) and external factors (e.g. environmental conditions or organizations' interests).

The two case studies where the management framework and the dynamic opportunistic maintenance have been tested, i.e. wind energy and rolling stock (in appended papers I and IV respectively), demonstrate that both contributions succeed in enhancing mentioned operational and strategic alignment, ensuring that maintenance decisions enable to meet the requisites of the product-service systems. Likewise, they prove that opportunistic maintenance significantly outperforms traditional static opportunistic maintenance strategies in the specific business objectives under consideration, systematically taking advantage of the operational context of the assets.

Despite these promising results, if the second set of research questions (SRQ2) is to be comprehensively answered, future studies on the alignment between maintenance and organizational objectives, especially concerning dynamic maintenance optimization models, are recommended:

- Whereas the dynamic opportunistic maintenance modeling approach has been defined, the specific modeling of the thresholds' dynamism has not been restricted. In fact, modeling possibilities are almost infinite depending on the specific case under study. Therefore, future work should focus on defining the specific factors that should be considered for successfully modeling the thresholds' dynamism depending on the case under study.

- Studied cases have proven the suitability of dynamic opportunistic maintenance in two different sectors, i.e. wind energy and railway sectors. Nonetheless, further applications should be studied in order to identify and accordingly correct the deficiencies it may present for a generalized utilization.

- Developed dynamic opportunistic maintenance models have only considered the economic dependencies of assets. Therefore, future work should focus on studying the inclusion of structural and stochastic dependencies of assets within the dynamic opportunistic maintenance modeling.

- Even though penalization indicators, which have been used for the dynamic thresholds modeling of the rolling stock case study, may be considered as a service-related business variable, it should be further studied and discussed how service-related variables could be included within dynamic opportunistic maintenance. It would enable to align the maintenance strategy to be adopted with the service to be provided.

- Maintenance decisions triggered by the presented dynamic opportunistic maintenance modeling approach are based on assets' reliability, while more advanced maintenance strategies, such as predictive maintenance, might be more suitable for certain assets. Accordingly, it should be addressed how dynamic maintenance strategy may be complemented by other maintenance strategies. Furthermore, similar assets operating in different environments may have a different reliability behavior, so it should be further considered how should dynamic maintenance be applied depending on assets' operational context.

- The fact that dynamic opportunistic maintenance strategy takes advantage of short term information in order to make decisions requires flexible and responsive maintenance operations. Therefore, the managerial implications that the utilization of dynamic opportunistic maintenance would have in manufacturers' operations management should be assessed.

5.3 Third set of research questions (SRQ3)

How do the different uncertainty sources condition the maintenance strategy and the after-sales services? Which is the risk associated to these uncertainty sources and how can it be managed by the organization? How should the product-service system be designed on an uncertain scenario in order to ensure its success? How could the profitability of reducing the uncertainty of any of the sources be quantified?

In spite of the added value that undergoing the servitization strategy can bring to manufacturing companies, there are some barriers that have to be overcome in order to successfully implement an offer based on product-service systems. Many of these barriers are caused by manufacturing companies having to absorb the risks entailed by the product-service system, especially in use-oriented and result-oriented business models, where they have to own and manage their sold products. Even if such risks might be reduced by making specific decisions regarding contract terms, such as determining the price and service-level, or regarding stakeholders' responsibilities definition, these decisions are still difficult to be made in the rather unexplored and uncertain service scenarios that manufacturers have to face.

In this context, manufacturers should build a structured risk-based decision-making approach in order to assess the impact that uncertainty might have on their product-service systems objectives. Did manufacturers have such approach, they would be able to enhance their decisions guaranteeing that both their interests and their stakeholders' interests are not jeopardized by the impact of uncertainty sources, which on some occasions could turn the services into a source of losses instead of a source of incomes. However, due to the long-term and stochastic nature of the processes to be dealt with in services, as well as the aforementioned rather unknown service business scenarios faced, uncertainty assessment and risk management are not trivial issues.

Given the importance of uncertainty when facilitating and enhancing the decisions on a risk-based approach, not only in the servitization context but also in other industrial contexts, uncertainty assessment has been a widely researched topic. However, there is a lack of studies that specifically address uncertainty assessment in the context of servitization, failing both to categorize the uncertainty sources to be dealt with in the after-sales services and to analytically derive their impact so that the final manufacturers' service-related decisions are facilitated (see literature/practitioner gaps 2.7.4 and 2.7.5). Consequently, these literature gaps have led to two main contributions in the context of uncertainty assessment and risk management in service-oriented business models (see appended papers III and V).

1. *Uncertainty assessment in service-oriented business models.* The framework for assessing the uncertainty in industrial practices proposed by De Rocquigny et al. [33] has been adopted and particularized for the after-sales services design. This framework lays the foundations for classifying the uncertainty sources, for quantifying their effect in the final objectives, and for addressing and enhancing the main decision-making processes to mitigate and manage the risks entailed by services.

2. *Risk-based decision-making in service-oriented business models.* A specific cost-risk-benefit mechanism, which ensures the success of made decisions with a certain confidence level, has been developed within the *data analysis and decision support module* of the

management framework proposed. This mechanism enables manufacturers to quantify the uncertainty propagation from the input variables to be considered in the decision-making process, throughout the system model to, finally, the quantities of interests, such as service-level or cost.

The wind energy case study developed (see appended paper III), which evaluates the impact of uncertainty in a performance-based contracting business model, demonstrates the suitability of the contributions for uncertainty assessment and risk management. These contributions are proven successful in enhancing some of the most risk-entailing decisions to be made by manufacturers in the context of servitization, such as contracts definition. Likewise, the contributions lay the foundations for ranking and supporting other decision choices, such as investment resources assignment, both in quantitative and qualitative terms. Therefore, manufacturers are enabled to mitigate absorbed risks, not only enhancing the profitability of their product-service systems, but overcoming some of the main barriers of servitization as well.

Despite these promising results, given the comprehensiveness of the third set of research questions (SRQ3) posed, further work is required to design manufacturers' decisions under the highly uncertain service-oriented business models:

- Similar assets operating in different environments may have a different reliability behavior, and thus the uncertainty associated to them might vary. Since such scenario has not been regarded in the present thesis, further research is required to consider and mitigate the uncertainty that managing assets operating in different operational contexts entails.

- Whereas the framework adapted from De Rocquigny et al. [33] enables to quantify and assess the uncertainty sources to be dealt with in servitization contexts, it does not help manufacturers identify such uncertainty sources. Therefore a procedure to identify the main uncertainty sources to be considered in different sectors' servitization should be researched.

- The present research addresses the implications of uncertainty sources for manufacturers and customers. However, considering the different stakeholders' involved in the product-service system business models, e.g. investors or providers/suppliers, it should be explicitly assessed the implications that the risks adopted by these stakeholders might have in the product-service system design.

References

[1] T.S. Baines, H.W. Lightfoot, S. Evans, A. Neely, R. Greenough, J. Peppard, R. Roy, E. Shehab, A. Braganza, A. Tiwari, J.R. Alcock, J.P. Angus, M. Basti, A. Cousens, P. Irving, M. Johnson, J. Kingston, H. Lockett, V. Martinez, P. Michele, D. Tranfield, I.M. Walton, and H. Wilson. State-of-the-art in product-service systems. *Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture*, 221(10):1543–1552, 2007.

[2] J. Banks. Discrete event simulation. In *Encyclopedia of Information Systems*, pages 663–671. Elsevier BV, 2003.

[3] M. Wong. *Implementation of innovative product service-systems in the consumer goods industry*. PhD thesis, Cambridge University, 2004.

[4] M.J. Goedkoop, C.J.G. Van Halen, H.R.M Te Riele, and P.J.M. Rommens. Product service systems, ecological and economic basics. *Report for Dutch Ministries of environment (VROM) and economic affairs (EZ)*, 36(1):1–122, 1999.

[5] N. Morelli. Product-service systems, a perspective shift for designers: A case study - the design of a telecentre. *Design Studies*, 24(1):73–99, 2003.

[6] A. Tukker. Eight types of product–service system: eight ways to sustainability? experiences from SusProNet. *Business Strategy and the Environment*, 13(4):246–260, 2004.

[7] J.C. Aurich, C. Mannweiler, and E. Schweitzer. How to design and offer services successfully. *CIRP Journal of Manufacturing Science and Technology*, 2(3):136–143, 2010.

[8] N. Maussang, P. Zwolinski, and D. Brissaud. Product-service system design methodology: from the PSS architecture design to the products specifications. *Journal of Engineering Design*, 20(4):349–366, 2009.

[9] F.H. Beuren, M.G.G. Ferreira, and M.P.A. Cauchick. Product-service systems: a literature review on integrated products and services. *Journal of Cleaner Production*, 47:222–231, 2013.

[10] V. González-Prida and A. Crespo Márquez. A framework for warranty management in industrial assets. *Computers in Industry*, 63(9):960 – 971, 2012.

[11] C. Su and X. Wang. Modeling flexible two-dimensional warranty contracts for used products considering reliability improvement actions. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 230(2):237–247, 2016.

[12] M. Bhamra Cook, TA. Bhamra, and M. Lemon. The transfer and application of product service systems: from academia to uk manufacturing firms. *Journal of Cleaner Production*, 14(17):1455–1465, 2006.

[13] M.A. Cohen and S. Whang. Competing in product and service: A product life-cycle model. *Management Science*, 43(4):535–545, 1997.

[14] E. Castellano, P.X. Zubizarreta, G. Pagalday, J. Uribetxebarria, and A. Crespo Márquez. *Optimum Decision Making in Asset Management*, chapter Service 4.0: The Reasons and Purposes of Industry 4.0 within the Ambit of After-Sales Maintenance. IGI-Global.

[15] S. Cavalieri and G. Pezzotta. Product–service systems engineering: State of the art and research challenges. *Computers in Industry*, 63(4):278–288, 2012.

[16] ISO. 55000:2014. asset management-overview, principles and terminology. Technical report, AENOR, 2014.

[17] A. Sola Rosique and A. Crespo Márquez. Principios y marcos de referencia de la gestión de activos, 2016.

[18] EN. 16646:2014. maintenance within physical asset management. Technical report, AENOR, 2014.

[19] A. Crespo Márquez. *The Maintenance Management Framework*. Springer-Verlag GmbH, 2007.

[20] A. Van Horenbeek, L. Pintelon, and P. Muchiri. Maintenance optimization models and criteria. *International Journal of System Assurance Engineering and Management*, 1(3):189–200, 2010.

[21] L.F. Caetano and P.F. Teixeira. Optimisation model to schedule railway track renewal operations: a life-cycle cost approach. *Structure and Infrastructure Engineering*, 11(11):1524–1536, 2015.

[22] C.A.V. Cavalcante and R.S. Lopes. Multi-criteria model to support the definition of opportunistic maintenance policy: A study in a cogeneration system. *Energy*, 80:32–40, 2015.

[23] A. Erguido, A. Crespo Márquez, E. Castellano, and J.F. Gómez Fernández. A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms. *Renewable Energy*, 114:843–856, 2017.

[24] A. Erguido, A. Crespo Márquez, E. Castellano, and J.F. Gómez Fernández. A novel dynamic opportunistic maintenance modelling approach. In *European Safety and Reliability Conference (ESREL) 2017*, 2017.

[25] A. Erguido, A. Crespo Márquez, E. Castellano, and J.L. Flores. After-sales services optimisation through dynamic opportunistic maintenance: a wind energy case study. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 232(4):352–367, 2018.

[26] A. Erguido, A. Crespo Márquez, E. Castellano, J.L. Flores, and J.F. Gómez Fernández. Reliability-based advanced maintenance modelling to enhance rolling stock manufacturers objectives. *Submitted to Reliability Engineering and System Safety*, 2018.

[27] A. Erguido, A. Crespo Márquez, E. Castellano, A.K. Parlikad, and J. Izquierdo. Asset management framework and tools for facing challenges in the adoption of product service systems. *Submitted to Computers & Industrial Engineering*, 2019.

[28] A. Erguido, J. Uribetxebarria, P.X. Zubizarreta, and J. Izquierdo. *Aplicación para el modelado y reporting automático de la fiabilidad*, 2019.

[29] D.M. Louit, R. Pascual, and A.K.S. Jardine. A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data. *Reliability Engineering & System Safety*, 94(10):1618–1628, 2009.

[30] D.J. Teece. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal*, 28(13):1319–1350, 2007.

[31] D. Salazar, C.M. Rocco, and B.J. Galván. Optimization of constrained multiple-objective reliability problems using evolutionary algorithms. *Reliability Engineering & System Safety*, 91(9):1057–1070, 2006.

[32] C.A. Coello Coello, G.B. Lamont, and D.A. Van Veldhuizen. *Evolutionary algorithms for solving multi-objective problems*, volume 5. Springer, 2007.

[33] E. de Rocquigny, N. Devictor, and S. Tarantola. *Uncertainty in industrial practice: a guide to quantitative uncertainty management*. John Wiley & Sons, 2008.

[34] T. Baines and H. Lightfoot. *Made to serve: How manufacturers can compete through servitization and product service systems*. John Wiley & Sons, 2013.

[35] E.L. Silva Teixeira, B. Tjahjono, and S.C. Absi Alfaro. A novel framework to link prognostics and health management and product–service systems using online simulation. *Computers in Industry*, 63(7):669–679, 2012.

[36] N.A.J. Hastings. *Physical asset management*, volume 2. Springer, 2010.

[37] P.A. Jones. *Diamond in the rough? Asset management as a route to value creation*, 2000.

[38] S. Rengarajan and A.K. Parlikad. *Whole-Life Value Based Decision Making in Asset Management [CSIC Series] (Cambridge Centre for Smart Infrastructure & Construction)*. ICE Publishing, 2016.

[39] W. Reim, V. Parida, and D. Örtqvist. Product-service systems (PSS) business models and tactics - a systematic literature review. *Journal of Cleaner Production*, 97:61–75, 2015.

[40] IMEA (Institute of Municipal Engineering Australia). *National Asset Management Manual*, 1994.

[41] IPWEA (Institute of Public Works Engineering Australasia). *International infrastructure management manual*, 2011.

[42] Pas-55 asset management, 2012.

[43] CIEAM. Integrated engineering asset management. *White Paper by the Cooperative Research Centre for Integrated Engineering Asset Management*, 2004.

[44] ANAO (Australian National Audit Office). *Asset Management Handbook*, 1996.

[45] S. Park, S.I. Park, and S. Lee. Strategy on sustainable infrastructure asset management: Focus on korea's future policy directivity. *Renewable and Sustainable Energy Reviews*, 62:710–722, 2016.

[46] A.J. Guillén. *Diseño de soluciones avanzadas de CBM/PHM en sistemas inteligentes de gestión de activos*. PhD thesis, 2018.

[47] Z. Tao, F. Zophy, and J. Wiegmann. Asset management model and systems integration approach. *Transportation Research Record: Journal of the Transportation Research Board*, (1719):191–199, 2000.

[48] Y.C. Wijnia and P.M. Herder. The state of asset management in the netherlands. In *Engineering Asset Lifecycle Management*, pages 164–172. Springer London, 2010.

[49] EN. 13306:2010. maintenance - maintenance terminology. Technical report, European Committee for Standardization, 2010.

[50] U. Leturiondo. *Hybrid Modelling in Condition Monitoring*. PhD thesis, 2016.

[51] J. Lee, Y. Chen, H. Al Atat, M. AbuAli, and E. Lapira. A systematic approach for predictive maintenance service design: methodology and applications. *International Journal of Internet Manufacturing and Services*, 2(1):76, 2009.

[52] A. Crespo Márquez and J.N.D. Gupta. Contemporary maintenance management: process, framework and supporting pillars. *Omega*, 34(3):313–326, 2006.

[53] A. Crespo Márquez, P. Moreu de León, A. Sola Rosique, and J.F. Gómez Fernández. Criticality analysis for maintenance purposes: A study for complex in-service engineering assets. *Qual. Reliab. Engng. Int.*, 32(2):519–533, 2015.

[54] J. F. Gómez Fernández and A. Crespo Márquez. Framework for implementation of maintenance management in distribution network service providers. *Reliability Engineering & System Safety*, 94(10):1639–1649, 2009.

[55] E. Levrat, B. Iung, and A. Crespo Márquez. E-maintenance: review and conceptual framework. *Production Planning & Control*, 19(4):408–429, 2008.

[56] A. Garg and S.G. Deshmukh. Maintenance management: literature review and directions. *Journal of Quality in Maintenance Engineering*, 12(3):205–238, 2006.

[57] H. Wang. A survey of maintenance policies of deteriorating systems. *European Journal of Operational Research*, 139(3):469–489, 2002.

[58] R.P. Nicolai and R. Dekker. A review of multi-component maintenance models. In *Proceedings of European Safety and Reliability Conference*, pages 289–296, 2007.

[59] R. Dekker. Applications of maintenance optimization models: a review and analysis. *Reliability Engineering & System Safety*, 51(3):229–240, 1996.

[60] M.W. Sasieni. A markov chain process in industrial replacement. *OR*, 7(4):148, 1956.

[61] T. Nakagawa and D.N.P. Murthy. Optimal replacement policies for a two-unit system with failure interactions. *Revue française dáutomatique, dínformatique et de recherche opérationnelle. Recherche opérationnelle*, 27(4):427–438, 1993.

[62] T. Nowakowski and S. Werbińka. On problems of multicomponent system maintenance modelling. *International Journal of Automation and Computing*, 6(4):364–378, 2009.

[63] R.C. Vergin and M. Scriabin. Maintenance scheduling for multicomponent equipment. *IIETransactions*, 9(3):297–305, 1977.

[64] P. Ritchken and J.G. Wilson. (m,t) group maintenance policies. *Management Science*, 36(5):632–639, 1990.

[65] H.T. Ba, M.E. Cholette, P. Borghesani, Y. Zhou, and L. Ma. Opportunistic maintenance considering non-homogenous opportunity arrivals and stochastic opportunity durations. *Reliability Engineering & System Safety*, 160:151–161, 2017.

[66] R.E. Wildeman, R. Dekker, and A.C.J.M. Smit. A dynamic policy for grouping maintenance activities. *European Journal of Operational Research*, 99(3):530–551, 1997.

[67] R. Laggoune, A. Chateauneuf, and D. Aissani. Opportunistic policy for optimal preventive maintenance of a multi-component system in continuous operating units. *Computers & Chemical Engineering*, 33(9):1499–1510, 2009.

[68] F. Ding and Z. Tian. Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. *Renewable Energy*, 45:175–182, 2012.

[69] R. Laggoune, A. Chateauneuf, and D. Aissani. Impact of few failure data on the opportunistic replacement policy for multi-component systems. *Reliability Engineering & System Safety*, 95(2):108–119, 2010.

[70] B.R. Sarker and T.I. Faiz. Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy. *Renewable Energy*, 85:104–113, 2016.

[71] W. Zhu, M. F., and C. Bérenguer. A multi-level maintenance policy for a multi-component and multifailure mode system with two independent failure modes. *Reliability Engineering & System Safety*, 153:50–63, 2016.

[72] K.T. Huynh, A. Barros, and C. Berenguer. Multi-level decision-making for the predictive maintenance of -out-of- :f deteriorating systems. *IEEE Transactions on Reliability*, 64(1):94–117, 2015.

[73] K. Nguyen, P. Do, and A. Grall. Multi-level predictive maintenance for multi-component systems. *Reliability Engineering & System Safety*, 144:83–94, 2015.

[74] H. Abdollahzadeh, K. Atashgar, and M. Abbasi. Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups. *Renewable Energy*, 88:247–261, 2016.

[75] K. Atashgar and H. Abdollahzadeh. Reliability optimization of wind farms considering redundancy and opportunistic maintenance strategy. *Energy Conversion and Management*, 112:445–458, 2016.

[76] Y. Zhou, Z. Zhang, T.R. Lin, and L. Ma. Maintenance optimisation of a multi-state series–parallel system considering economic dependence and state-dependent inspection intervals. *Reliability Engineering & System Safety*, 111:248–259, 2013.

[77] A. Van Horenbeek and L. Pintelon. A dynamic predictive maintenance policy for complex multi-component systems. *Reliability Engineering & System Safety*, 120:39–50, 2013.

[78] X. Zhang and J. Zeng. A general modeling method for opportunistic maintenance modeling of multi-unit systems. *Reliability Engineering & System Safety*, 140:176–190, 2015.

[79] M.C.A. Olde Keizer, R.H. Teunter, and J. Veldman. Clustering condition-based maintenance for systems with redundancy and economic dependencies. *European Journal of Operational Research*, 251(2):531–540, 2016.

[80] A. Attar, S. Raissi, and K. Khalili-Damghani. A simulation-based optimization approach for free distributed repairable multi-state availability-redundancy allocation problems. *Reliability Engineering & System Safety*, 157:177–191, 2017.

[81] H. Abdollahzadeh and K. Atashgar. Optimal design of a multi-state system with uncertainty in supplier selection. *Computers & Industrial Engineering*, 105:411–424, 2017.

[82] Z. Tian, T. Jin, B. Wu, and F. Ding. Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy*, 36(5):1502–1509, 2011.

[83] X. Zhou, Z. Lu, and L. Xi. Preventive maintenance optimization for a multi-component system under changing job shop schedule. *Reliability Engineering & System Safety*, 101:14–20, 2012.

[84] V. Babishin and S. Taghipour. Joint maintenance and inspection optimization of a k-out-of-n system. In *2016 Annual Reliability and Maintainability Symposium (RAMS)*. Institute of Electrical and Electronics Engineers (IEEE), 2016.

[85] X. Zhou, L. Xi, and J. Lee. Opportunistic preventive maintenance scheduling for a multi-unit series system based on dynamic programming. *International Journal of Production Economics*, 118(2):361–366, 2009.

[86] H. Shi and J. Zeng. Real-time prediction of remaining useful life and preventive opportunistic maintenance strategy for multi-component systems considering stochastic dependence. *Computers & Industrial Engineering*, 93:192–204, 2016.

[87] C. Zhang, W. Gao, S. Guo, Y. Li, and T. Yang. Opportunistic maintenance for wind turbines considering imperfect, reliability-based maintenance. *Renewable Energy*, 103:606–612, 2017.

[88] E. Zio. Reliability engineering: Old problems and new challenges. *Reliability Engineering & System Safety*, 94(2):125–141, 2009.

[89] T. Shen, F. Wan, W. Cui, and B. Song. Application of prognostic and health management technology on aircraft fuel system. In *2010 Prognostics and System Health Management Conference*. IEEE, 2010.

[90] D. Banjevic. Remaining useful life in theory and practice. *Metrika*, 69(2-3):337–349, 2008.

[91] I.A. Okaro and L. Tao. Reliability analysis and optimisation of subsea compression system facing operational covariate stresses. *Reliability Engineering & System Safety*, 156:159–174, 2016.

[92] T. Bendell. An overview of collection, analysis, and application of reliability data in the process industries. *IEEE Transactions on Reliability*, 37(2):132–137, 1988.

[93] D.F. Percy, K.A.H. Kobbacy, and B.B. Fawzi. Setting preventive maintenance schedules when data are sparse. *International Journal of Production Economics*, 51(3):223–234, 1997.

[94] J.I. Ansell and M.J. Phillips. Practical reliability data analysis. *Reliability Engineering & System Safety*, 28(3):337–356, 1990.

[95] .L.C. Saldanha, E.A. de Simone, and P.F. Frutuoso e Melo. An application of non-homogeneous poisson point processes to the reliability analysis of service water pumps. *Nuclear Engineering and Design*, 210(1-3):125–133, 2001.

[96] H. Feingold. *Repairable systems reliability: Modeling, inference, misconceptions and their causes*. Marcel Dekker, 1984.

[97] H. Pham and H. Wang. Imperfect maintenance. *European Journal of Operational Research*, 94(3):425–438, 1996.

[98] P.A.W. Lewis and D.W. Robinson. Testing for a monotone trend in a modulated renewal process. Technical report, Monterey, California. Naval Postgraduate School, 1973.

[99] M. Kijima and U. Sumita. A useful generalization of renewal theory: Counting processes governed by non-negative Markovian increments. *Journal of Applied Probability*, 23(1):71, 1986.

[100] M. Tanwar, R.N. Rai, and N. Bolia. Imperfect repair modeling using kijima type generalized renewal process. *Reliability Engineering & System Safety*, 124:24–31, 2014.

[101] M. Yañez, F. Joglar, and M. Modarres. Generalized renewal process for analysis of repairable systems with limited failure experience. *Reliability Engineering & System Safety*, 77(2):167–180, 2002.

[102] N. Iyer, K. Goebel, and P. Bonissone. Framework for post-prognostic decision support. In *2006 IEEE Aerospace Conference*. IEEE.

[103] K. Khalili-Damghani, S. Sadi-Nezhad, F.H. Lotfi, and M. Tavana. A hybrid fuzzy rule-based multi-criteria framework for sustainable project portfolio selection. *Information Sciences*, 220:442–462, 2013.

[104] K. Deb, A. Pratap, S. Agarwal, and T. Meyarivan. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation*, 6(2):182–197, 2002.

[105] M. Marseguerra and E. Zio. Optimizing maintenance and repair policies via a combination of genetic algorithms and monte carlo simulation. *Reliability Engineering & System Safety*, 68(1):69–83, 2000.

[106] C.A. Coello Coello. A comprehensive survey of evolutionary-based multiobjective optimization techniques. *Knowledge and Information Systems*, 1(3):269–308, 1999.

[107] A. Sharma, G.S. Yadava, and S.G. Deshmukh. A literature review and future perspectives on maintenance optimization. *Journal of Quality in Maintenance Engineering*, 17(1):5–25, 2011.

[108] A. Konak, D.W. Coit, and A.E. Smith. Multi-objective optimization using genetic algorithms: A tutorial. *Reliability Engineering & System Safety*, 91(9):992–1007, 2006.

[109] C.M. Fonseca and P.J. Fleming. Genetic algorithms for multiobjective optimization: Formulationdiscussion and generalization. In *Icga*, volume 93, pages 416–423, 1993.

[110] J. Rey Horn, N. Nafpliotis, and D.E. Goldberg. A niched pareto genetic algorithm for multiobjective optimization. In *Proceedings of the first IEEE conference on evolutionary computation, IEEE world congress on computational intelligence*, volume 1, pages 82–87, 1994.

[111] N. Srinivas and K. Deb. Muiltiobjective optimization using nondominated sorting in genetic algorithms. *Evolutionary computation*, 2(3):221–248, 1994.

[112] E. Zitzler and L. Thiele. Multiobjective evolutionary algorithms: a comparative case study and the strength pareto approach. *IEEE transactions on Evolutionary Computation*, 3(4):257–271, 1999.

[113] E. Zitzler, M. Laumanns, and L. Thiele. Spea2: Improving the strength pareto evolutionary algorithm. *TIK-report*, 103, 2001.

[114] A. Borshchev. *The big book of simulation modeling: multimethod modeling with AnyLogic 6*.

[115] M. Niazi and A. Hussain. Agent-based computing from multi-agent systems to agent-based models: a visual survey. *Scientometrics*, 89(2):479–499, 2011.

[116] PLE Vensim. Ventana systems, inc. *Avaiable at: http://www. vensim. com*, 2010.

[117] Rockwell Automation. Arena simulation software, 2012.

[118] S. Robinson. *Simulation: The Practice of Model Development and Use*. Wiley, 2004.

[119] D. Meadows and J.M. Robinson. *The electronic oracle: computer models and social decisions*. John Wiley & Sons, 1985.

[120] B. Behdani. Evaluation of paradigms for modeling supply chains as complex socio-technical systems. In *Proceedings Title: Proceedings of the 2012 Winter Simulation Conference (WSC)*. IEEE, 2012.

[121] T. Lorenz and A. Jost. Towards an orientation framework in multi-paradigm modeling. In *Proceedings of the 24th International Conference of the System Dynamics society*, pages 1–18. System Dynamics Society Albany, NY, 2006.

[122] G.P. Richardson. *Feedback thought in social science and systems theory*. University of Pennsylvania, 1991.

[123] J.D. Sterman. *Business dynamics: systems thinking and modeling for a complex world*. Number HD30. 2 S7835 2000. 2000.

[124] J.W. Forrester. Industrial dynamics—after the first decade. *Management Science*, 14(7):398–415, 1968.

[125] T. Šalamon. *Design of agent-based models: developing computer simulations for a better understanding of social processes*. Tomáš Bruckner, 2011.

[126] M.J. North and C.M. Macal. *Managing business complexity: discovering strategic solutions with agent-based modeling and simulation*. Oxford University Press, 2007.

[127] M. Wooldridge and N.R. Jennings. Intelligent agents: Theory and practice. *The knowledge engineering review*, 10(2):115–152, 1995.

[128] M. Wooldridge and N.R. Jennings. Intelligent agents: Theory and practice. *The knowledge engineering review*, 10(2):115–152, 1995.

[129] J.M. Epstein. *Generative social science: Studies in agent-based computational modeling*. Princeton University Press, 2006.

[130] N. Gilbert. *Agent-based models*. Number 153. Sage, 2008.

[131] BSI. Through-life engineering services – adding business value through a common framework – guide, 2018.

[132] 31000:2009 risk management - principles and guidelines.

[133] S.H. Kim, M.A. Cohen, and S. Netessine. Performance contracting in after-sales service supply chains. *Management Science*, 53(12):1843–1858, 2007.

[134] M. Xie, X. Li, and S.H. Ng. Risk-based software release policy under parameter uncertainty. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability*, 225(1):42–49, 2011.

[135] O. De Weck, C. Eckert, and J. Clarkson. A classification of uncertainty for early product and system design. volume DS 42, 2007.

[136] R. De Neufville, O. De Weck, D. Frey, D. Hastings, R. Larson, D. Simchi-Levi, K. Oye, A. Weigel, and R. Welsch. Uncertainty management for engineering systems planning and design. In *Engineering Systems Symposium, MIT, Cambridge, MA*, 2004.

[137] J.Y. Halpern. *Reasoning about uncertainty, vol. 21*. Cambridge: MIT press, 2003.

[138] J.F. Villanueva, A.I. Sanchez, S. Carlos, and S. Martorell. Genetic algorithm-based optimization of testing and maintenance under uncertain unavailability and cost estimation: A survey of strategies for harmonizing evolution and accuracy. *Reliability Engineering & System Safety*, 93(12):1830 – 1841, 2008. 17th European Safety and Reliability Conference.

[139] A. Sanchez, S. Carlos, S. Martorell, and J.F. Villanueva. Addressing imperfect maintenance modelling uncertainty in unavailability and cost based optimization. *Reliability Engineering & System Safety*, 94(1):22 – 32, 2009. Maintenance Modeling and Application.

[140] J.C. Helton. Uncertainty and sensitivity analysis for models of complex systems. In *Computational Methods in Transport: Verification and Validation*, pages 207–228. Springer, 2008.

[141] A. Tan, T. McAloone, and D. Matzen. Service-oriented strategies for manufacturing firms. In *Introduction to Product/Service-System Design*, pages 197–218. Springer London, 2009.

[142] O.K Mont. Clarifying the concept of product–service system. *Journal of Cleaner Production*, 10(3):237–245, 2002.

[143] F. Tonelli, P. Taticchi, and E. Starnini Sue. A framework for assessment and implementation of product-service systems strategies: learning from an action research in the healthcare sector. *WSEAS Trans Bus Econ*, 6(7):303–319, 2009.

[144] S. Evans, P.J. Partidário, and J. Lambert. Industrialization as a key element of sustainable product-service solutions. *International Journal of Production Research*, 45(18-19):4225–4246, 2007.

[145] M. Kang and R. Wimmer. Product service systems as systemic cures for obese consumption and production. *Journal of Cleaner Production*, 16(11):1146–1152, 2008.

[146] K. Besch. Product-service systems for office furniture: Barriers and opportunities on the european market. *Journal of Cleaner Production*, 13(10-11):1083–1094, 2005.

[147] X. Fan and H. Zhang. Aligning product-service systems with market forces: A theoretical framework. In *2010 International Conference on Service Sciences*. IEEE, 2010.

[148] W. Song. Requirement management for product-service systems: Status review and future trends. *Computers in Industry*, 85:11–22, 2017.

[149] A. Richter and M. Steven. On the relation between industrial product-service systems and business models. In *Operations Research Proceedings 2008*, pages 97–102. Springer Berlin Heidelberg, 2009.

[150] E. Sundin and B. Bras. Making functional sales environmentally and economically beneficial through product remanufacturing. *Journal of Cleaner Production*, 13(9):913–925, 2005.

[151] W. Ulaga and W.J. Reinartz. Hybrid offerings: How manufacturing firms combine goods and services successfully. *Journal of Marketing*, 75(6):5–23, 2011.

[152] A. Azarenko, R. Roy, E. Shehab, and A. Tiwari. Technical product-service systems: some implications for the machine tool industry. *Journal of Manufacturing Technology Management*, 20(5):700–722, 2009.

[153] D. Kindström. Towards a service-based business model – key aspects for future competitive advantage. *European Management Journal*, 28(6):479–490, 2010.

[154] T.C. Kuo. Simulation of purchase or rental decision-making based on product service system. *The International Journal of Advanced Manufacturing Technology*, 52(9-12):1239–1249, 2010.

[155] R. Casadesus-Masanell and J.E. Ricart. From strategy to business models and onto tactics. *Long Range Planning*, 43(2-3):195–215, 2010.

[156] D. Nowicki, U.D. Kumar, H.J. Steudel, and D. Verma. Spares provisioning under performance-based logistics contract: Profit-centric approach. *Journal of the Operational Research Society*, 59(3):342–352, 2008.

[157] E. Sundin, A.Ö. Rönnbäck, and T. Sakao. From component to system solution supplier: Strategic warranty management as a key to efficient integrated product/service engineering. *CIRP Journal of Manufacturing Science and Technology*, 2(3):183–191, 2010.

[158] J. Gao, Y. Yao, V.C.Y. Zhu, L. Sun, and L. Lin. Service-oriented manufacturing: a new product pattern and manufacturing paradigm. *Journal of Intelligent Manufacturing*, 22(3):435–446, 2009.

[159] O. Mont, C. Dalhammar, and N. Jacobsson. A new business model for baby prams based on leasing and product remanufacturing. *Journal of Cleaner Production*, 14(17):1509–1518, 2006.

[160] A. Williams. Product service systems in the automobile industry: contribution to system innovation? *Journal of Cleaner Production*, 15(11-12):1093–1103, 2007.

[161] N.M.P. Bocken, S.W. Short, P. Rana, and S. Evans. A literature and practice review to develop sustainable business model archetypes. *Journal of Cleaner Production*, 65:42–56, 2014.

[162] S.W. Lee, M.W. Seong, Y.J. Jeon, and C.H. Chung. Ubiquitin e3 ligases controlling p53 stability. *Animal Cells and Systems*, 16(3):173–182, jun 2012.

[163] V.M. Story, C. Raddats, J. Burton, J. Zolkiewski, and T. Baines. Capabilities for advanced services: A multi-actor perspective. *Industrial Marketing Management*, 60:54–68, 2017.

[164] M. Paiola, N. Saccani, M. Perona, and H. Gebauer. Moving from products to solutions: Strategic approaches for developing capabilities. *European Management Journal*, 31(4):390–409, 2013.

[165] P., L. Pintelon, L. Gelders, and H. Martin. Development of maintenance function performance measurement framework and indicators. *International Journal of Production Economics*, 131(1):295–302, 2011.

[166] R. Kumar. *Research methodology: a step-by-step guide for beginners.* SAGE Publications, London, 3 edition, 2011.

[167] F. Mahootian and T.E. Eastman. Complementary frameworks of scientific inquiry: Hypothetico-deductive, hypothetico-inductive, and observational-inductive. *World Futures: Journal of General Evolution*, 65(1):61–75, 2009.

[168] R.G. Sargent. Verification and validation of simulation models. In *Proceedings of the 2009 Winter Simulation Conference (WSC)*. IEEE, 2009.

[169] S. Schlesinger. Terminology for model credibility. *Simulation*, 32(3):103–104, 1979.

[170] R.G. Sargent. An assessment procedure and a set of criteria for use in the evaluation of'computerized models and computer-based modelling tools'. Technical report, SYRACUSE UNIV NY DEPT OF INDUSTRIAL ENGINEERING AND OPERATIONS RESEARCH, 1981.

[171] S. Carlos, A. Sánchez, S. Martorell, and I. Marton. Onshore wind farms maintenance optimization using a stochastic model. *Mathematical and Computer Modelling*, 57(7-8):1884–1890, 2013.

[172] P. Cobreiro Rodríguez and N. Jiménez Simón. *Wind Turbines: Safety measures in maintenance activities*. Instituto Nacional de Seguridad e Higiene en el Trabajo, 2014.

Part II.

Appended Papers

A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of Wind Farms

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Abstract

Operations and maintenance costs of the wind power generation systems can be reduced through the implementation of opportunistic maintenance policies at suitable indenture and maintenance levels. These maintenance policies take advantage of the economic dependence among the wind turbines and their systems, performing preventive maintenance tasks in running systems when some other maintenance tasks have to be undertaken in the wind farm. The existing opportunistic maintenance models for the wind energy sector follow a static decision making process, regardless of the operational and environmental context. At the same time, on some occasions policies do not refer to practical indenture and maintenance levels. In this paper, a maintenance policy based on variable reliability thresholds is presented. This dynamic nature of the reliability thresholds, which vary according to the weather conditions, provides flexibility to the decision making process. Within the presented model, multi-level maintenance, capacity constraints and multiple failure modes per system have been considered. A comparative study, based on real operation, maintenance and weather data, demonstrates that the dynamic opportunistic maintenance policy significantly outperforms traditional corrective and static opportunistic maintenance strategies, both in terms of the overall wind farm energy production and the Life Cycle Cost.

Keywords: Opportunistic maintenance model, Dynamic reliability thresholds, Life Cycle Cost, Wind energy, Weather conditions

1. Introduction

The growing importance of renewable energy in terms of installed capacity and technological advances has been remarkable during the last years. This growth has been particularly notorious within the wind energy sector, which occupies a leading position among renewable energies [1]. Furthermore, the sector has not only suffered a great development for the last two decades but it is expected to continue its expansion during the following years, being firmly reinforced by the main World Powers energy plans [2].

Along with this progress new challenges have arisen, especially in terms of new technologies' reliability [3] and logistics associated to wind farms' (WF) maintenance [4]. Moreover, due to the trend of WFs' location shift towards offshore sites [5, 6], to deal with these challenges is getting even more difficult. As a result, operations and maintenance costs can rise to a 32% or a 12-30% of the total life cycle cost (LCC) in offshore or in onshore WFs respectively [7, 5].

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Table 1: Nomenclature and Acronyms definition

Nomenclature

LCC	Life Cycle Cost
WF	Wind Farm
WT	Wind Turbine
FM	Failure Mode
$O\&M$	Operations and Maintenance
CM	Corrective Maintenance
PM	Preventive Maintenance
CBM	Condition Based Maintenance
CMS	Condition Monitoring System
TTF	Time To Failure
MT	Maintenance Team
v_t	Average wind speed in period t
v^i	Cut in wind speed
v^o	Cut out wind speed
v^r	Wind speed at which Rated Power is obtained
GP_t	Generated Power in period t
RP	Rated Power of the WT
$R_{ik}(VA)$	Reliability of system i and FM k at virtual age VA
SRT_{ikj}	Fixed Reliability Threshold for applying perfect or imperfect PM j on system i and FM k
SRT_{ikjt}	System Reliability Threshold in period t for applying perfect or imperfect PM j system i and FM k
DRT_{ik}	Fixed Dispatch Reliability Threshold
DRT_{ikt}	Dispatch Reliability Threshold in period t
V	Wind speed threshold for determining reliability thresholds variation
p	Periods of time considered for wind speed forecasting
w_{ik}	Weight that determines reactivity of SRT_{ikj} and DRT_{ik} to wind speed
K	Number of FM considered for each system
J	Levels of PM types considered for each FM
GRP	Generalized Renewal Process
VA_{hikt}	Virtual age associated to FM k in system i in WT h in period t
α_{ik}	Weibull scale parameter of FM k of system i
β_{ik}	Weibull shape parameter of FM k of system i
q^{pr}_{ikj}	Restoration factor of j PM level on system i for FM k
q^{c}_{ik}	Restoration factor of CM on system i for FM k
NT	Number of MTs
C	Capacity of each MT (in hours)
c^{na}	cost of No Availability or opportunity cost
c^{p}	Penalty cost due to unplanned maintenance
c^{c}_{ik}	Cost of tools and materials needed for performing CM of FM k in system i
c^{pr}_{ikj}	Cost of tools and materials needed for performing PM j of FM k in system i
c^{team}	Cost of MT
c^{et}	Extra time cost
NT^{max}	Maximum number of MTs
NT^{c}	Number of MTs working on CM
c^{disp}	cost of maintenance dispatch
m^{c}_{ik}	Maintainability of CM for FM k in system i
m^{pr}_{ik}	Maintainability of PM for FM k in system i
OT	Total operating time
D^{t}	Required WF time-based availability
D^{o}	Required WF energy-based availability
T	Maximum iteration periods

Within this context, asset management acquires high relevance in the sector since it is crucial to search optimal maintenance strategies that allow to improve wind turbines' (WT) reliability and to reduce maintenance cost while raising availability [8, 9]. In spite of its importance, asset management strategies are not optimised in practice nowadays, being corrective maintenance (CM) and time-based minor preventive maintenance (PM) such as routing checks for minimizing degradation effects [10], the most applied maintenance strategies [11].

In addition to these two maintenance policies, Condition Based Maintenance (CBM), enhanced by the several Condition Monitoring Systems (CMS) available for wind energy installations [12, 13], is the third maintenance method currently applied to the wind power systems [11]. In fact, based on their ability to prevent failures [14], CBM strategies have been proved to be cost effective [15, 16] and have been widely researched [17, 18].

Nevertheless, maintenance strategies based uniquely on WTs' health condition monitoring do not take into account that the WTs are multi-component systems composed by a number of subsystems, with dependencies among them that directly affect to the adequacy of the maintenance strategies [19, 20]. According to Nicolai and Dekker [21] these dependencies can be classified as: economic, when performing maintenance activities in different systems simultaneously have different economic consequences than implementing them individually [22]; structural, when a maintenance activity in a system implies performing further actions in other systems [23]; and stochastic, when the risk of failure of two different systems is not independent [24].

When any of the mentioned dependencies exist among subsystems, the optimal maintenance strategies are not those that consider the subsystems separately in the maintenance decision process [p. 479, 25]:

"Obviously, the optimal maintenance action for a given subsystem at any time point depends on the states of all subsystems in the system: the failure of one subsystem results in the possible opportunity to undertake maintenance on other subsystems (opportunistic maintenance)."

In such circumstances, both group maintenance policies and opportunistic maintenance policies are the most suitable maintenance policies, and thus, the most studied ones [19]. On the one hand, group maintenance strategies establish different groups of systems that will undergo maintenance activities attending to the number of failures suffered by the systems, their age or their operation time [26, 27]. However, group maintenance policy is especially cost effective when disassemble and reassembly costs are high [25], which is not particularly the case in the wind energy sector. On the other hand, opportunistic maintenance policy takes advantage of short term circumstances, performing maintenance in non-failed systems when a failure has already happened in another one; making the maintenance decision according to different thresholds regarding systems' age, reliability or health condition. Several models have demonstrated the suitability of opportunistic maintenance policy in diverse sectors following varied strategies, such as age limits [28, 29], combined failure distribution of the systems [30] or accumulated operated periods of the systems [19].

Although opportunistic maintenance policies have not been traditionally implemented in the wind power systems [31], more recently some authors have studied and demonstrated their suitability in the sector [32, 31, 20, 11, 33, 34, 35, 36]; mainly due to the positive economic dependence among WTs [33]. Furthermore, they allow handling some of the main conflicting objectives concerning the decision making process of the wind energy sector: the maximization of revenue, power and reliability and the minimization of operations and maintenance costs [37].

1.1. Previous research

According to the reviewed opportunistic maintenance models for the wind energy sector (see Table 2), Besnard et al. [32] demonstrate that it is possible to reduce the maintenance cost and the opportunity cost due to failures by taking advantage of both low wind speed periods and the dispatches for CM in order to perform some prearranged PM.

Tian et al. [31] focus their research on developing an opportunistic maintenance policy based on the condition monitoring data. Aided by this data, the authors identify the useful remaining life of the systems and they calculate the WT's reliability. So, if the reliability of the WT does not surpass a determined threshold, systems within the WT are replaced.

Ding and Tian [20] propose an opportunistic maintenance model where both imperfect and perfect maintenance levels are considered. This is, systems will not always return to a status as good as new after a repair (the reader is addressed to [38] for further information). In this research, the authors set two different age thresholds for each system, which are based on their Mean Time To Failure (MTTF), in order to make the maintenance decision. The same authors extended their research in Ding and Tian [11] considering different age thresholds for systems belonging to failed and running WTs.

The main focus of the research performed by Sarker and Faiz [35] is to find an opportunistic maintenance strategy that optimises maintenance cost following a multilevel preventive maintenance policy. With this purpose the authors establish several age thresholds for the systems, which determine the PM activities to be performed.

Atashgar and Abdollahzadeh [34] go a step further as they find multi-objective optimal maintenance strategies for minimizing both maintenance cost and loss of production in WFs with redundant WTs. Within this research the WTs are grouped into blocks and opportunistic repairs are performed to WTs of the same block, according to the reliability thresholds associated to perfect or imperfect maintenance.

Table 2: Comparative analysis of the reviewed opportunistic maintenance models for the wind energy sector

Reference	Main Focus	Restoration Effect: Effect of maintenance activities ①②③④ (1. Not Considered 2. According to the system 3. According to the maintenance task 4. According to the system and maintenance task)	Restoration Effect: Method ①② (1. Not Considered 2. Virtual Age model)	Opportunistic maintenance policy: Nature ①② (1. Static 2. Dynamic)	Opportunistic maintenance policy: Maintenance levels ①②③④ (1. Not Considered 2. One level 3. Two Level (Perfect/Imperfect repairs) 4. Several levels)	Opportunistic maintenance policy: Failed/Running turbines ①②③ (1. Only for failed WTs 2. Equal for Failed/Running (F/R) WTs 3. Different for F/R WTs)
Besnard et al. [32]	Weather Conditions	●○○○	●○	●○	●○○○	○●○
Tian et al. [31]	CMS	●○○○	●○	●○	○●○○	○●○
Ding and Tian [20]	Two-level PM	○○●○	○●	●○	○○●○	○●○
Ding and Tian [11]	Two-level PM in F/R WTs	○○●○	○●	●○	○○●○	○○●
Abdollahzadeh et al. [33]	Bi-objective model	○○○●	○●	●○	○○●○	○○●
Atashgar and Abdollahzadeh [34]	Redundancies	○○●○	○●	●○	○○●○	○○●
Sarker and Faiz [35]	Multi-level PM	○○●○	○●	●○	○○○●	○●○
Zhu et al. [36]	Imperfect prediction signal	●○○○	●○	●○	○●○○	●○○

(a)

Reference	Optimisation process: Objective Function ①② (1. Cost 2. Cost & Prod)	Maintenance task consideration: Severity of Failures ①② (1. Not Considered 2. Considered)	Maintenance task consideration: Maintenance Time ①② (1. Not Considered 2. Considered)	Characteristics of WF, WTs and Systems: WF Location ①②③ (1. Onshore 2. Offshore 3. Not specified)	Characteristics of WF, WTs and Systems: Models of WTs considered ①② (1. One 2. Several)	Characteristics of WF, WTs and Systems: Number of systems ①② (1. None (WT as a whole) 2. Several)
Besnard et al. [32]	○●	●○	○●	○●○	●○	●○
Tian et al. [31]	●○	●○	○●	○○●	●○	○●
Ding and Tian [20]	●○	●○	●○	○○●	●○	○●
Ding and Tian [11]	●○	●○	●○	○○●	●○	○●
Abdollahzadeh et al. [33]	○●	●○	○●	○○●	○●	○●
Atashgar and Abdollahzadeh [34]	○●	●○	○●	○○●	○●	○●
Sarker and Faiz [35]	●○	●○	●○	○●○	●○	○●
Zhu et al. [36]	●○	○●	○●	○●○	●○	○●

(b)

In Abdollahzadeh et al. [33], reliability thresholds that determine optimal maintenance activities are set for each component. Both in [33] and [34], maintenance teams (MT) can be preventively dispatched to the WF, instead of having to wait for a failure to happen.

Finally, Zhu et al. [36] study three different maintenance strategies for an offshore WF: periodic routine, reactive maintenance and opportunistic maintenance. In this research each system can only have a failure mode (FM), which can be either hard or soft according to the consequences. Moreover, in this research the impact of the CMS accuracy on opportunistic maintenance is also analysed.

1.2. Proposed approach

It is remarkable that the reviewed researches present static opportunistic maintenance policies that base the decision making process on fixed age, reliability or health thresholds. However, WTs operate under non-stationary conditions that highly condition the repair jobs [39, 40, 41]. So, ideally, the maintenance models should be able to adequately fit the decision making process to the conditions under which the WTs are operating at each time.

In order to deal with this challenge, a dynamic opportunistic maintenance model is presented in this paper. This model adjusts the decision making process according to the weather conditions, pursuing a double objective: 1) the optimisation of the total LCC due to maintenance and 2) the improvement of the WF energy-based availability.

With this purpose, the decision making process is determined by variable reliability thresholds, that change according to the wind speed conditions; fostering the performance of maintenance activities during low wind speed periods and hindering them during high wind speed periods. This dynamic nature, in addition to lead to a better performance of the maintenance strategies both in terms of energy-based availability and LCC, will also allow handling some of the most conflicting factors that appear in the wind power industry [37]:

1. Maximization of revenue and power while maximization of reliability [37].
2. MTs' safety while maintenance performance [10].
3. Minimization of the opportunity cost [42, 43, 44].
4. Improvement of reliability within high velocity wind periods [41].

In order to ensure a realistic approach of the model, several constraints have been included in the study, such as capacity limitations due to the available MTs and systems' maintainability. Furthermore, several FMs are considered per system, bearing their different impact on cost and availability. In fact, although the different FMs within each system directly condition the WT's performance and hence, the resources deployed in the maintenance strategy [45], in the reviewed opportunistic maintenance models only a FM is considered per system.

Finally, in order to prove the suitability of the model for establishing the adequate maintenance strategy, an agent-based simulation has been developed, taking advantage of the ability of simulation techniques to handle the stochastic nature of the sector [33]. The simulation results have been obtained from real operational and reliability data about WFs located in the north of Spain, provided by a leading company in the sector. Likewise, in order to search as realistic scenarios as possible, the simulation has also been fed with real wind data, according to the WF location.

The paper is organized as follows: in section 2 the problem is defined and the presented dynamic opportunistic maintenance policy is explained and analytically derived; in section 3 the simulation process is explained; in section 4 computational results are shown and discussed for a specific case study, comparing both traditional and presented approaches; finally, in section 5, concluding remarks are presented and future research lines are established.

2. Problem definition and model description

2.1. Problem definition

The WF consists of H WTs of similar characteristics that have N critical systems connected in series. Each system might fail in k different FMs, classified according to their severity (k = 1,2,...,K). Consequently, after a failure, corresponding k CM will be performed. Likewise, systems can also undergo different PM levels associated to the different FMs, prior to their occurrence (j = 1,2,...,J).

Generally, the repairs return the systems to an operational condition worse than the new one but better than just before the maintenance task is performed. This concept leads to a classification of maintenance as perfect or imperfect, according to the ability of each maintenance activity to restore the system [38]. Accordingly, in this work both perfect and imperfect repairs have been considered, being $j = J$ a perfect repair and $j = 1$ the most imperfect repair.

Among the several methods that treat the restoration effect of maintenance (see [38]), in this work the Generalized Renewal Process (GRP) proposed by Yañez et al. [46] is used. This method has been specifically utilised in the presented model due to its flexibility for modelling both the behaviour of the systems before failures and the quality of repairs during the different life stages of the systems. To do so, GRP considers a q_{ij} rejuvenation parameter [0,1] associated to the efficiency of the restoration effect of the maintenance activity j on the system i ($q = 0$ for the most imperfect maintenance and $q = 1$ for perfect maintenance). Consequently, after a maintenance activity j, Eq.1 is followed to update the virtual age of the system i (the reader is addressed to [46] for further information). Then, in order to identify systems' reliability after an imperfect repair, failure probability distribution conditioned to the survival of the new virtual age is calculated in Eq.2 (adopted from [46]):

$$VA_i^{new} = VA_i^{old}(1 - q_{ij}) \tag{1}$$

$$F\left(t|VA_i^{new}\right) = P\left[T_{ij} \leq t|T_{ij} > VA_i^{new}\right] = \frac{F\left(t\right) - F\left(VA_i^{new}\right)}{1 - F\left(VA_i^{new}\right)} \tag{2}$$

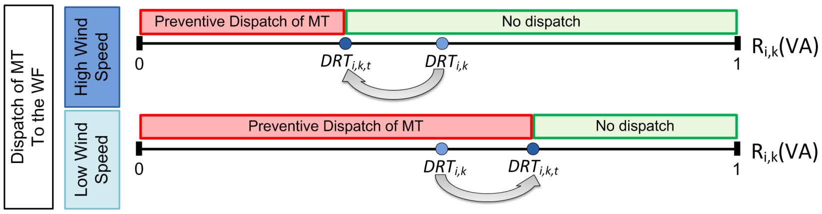
In the wind energy sector, Weibull and Exponential distributions have been respectively utilised for modelling the reliability of mechanical and electrical systems [47]. Since Exponential distribution is also contemplated by Weibull distribution as a particular case, Eq.2 is particularized ad hoc for Weibull distribution in Eq.3, according to the scale (α_{ik}) and shape parameters (β_{ik}) that define the Weibull distribution for each FM k of system i (see [33]):

$$R\left(t|VA_{hik}^{new}\right) = 1 - F\left(t|VA_{hik}^{new}\right) = exp\left[\left(\frac{VA_{hik}^{new}}{\alpha_{ik}}\right)^{\beta_{ik}} - \left(\frac{t}{\alpha_{ik}}\right)^{\beta_{ik}}\right] \tag{3}$$

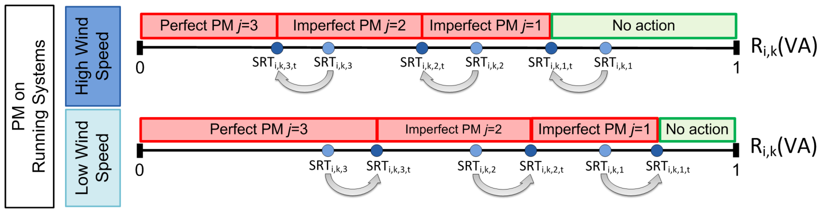
Finally, every failure occurrence or PM involves some fixed and variable maintenance costs that have to be considered in the model. Every maintenance activity implies dispatching a MT to the WF, which involves a relevant cost (c^{disp}). Likewise, each maintenance task will require a material cost (c_{ik}^{c}, c_{ik}^{pr}) and a time to repair (m_{ik}^{c}, m_{ik}^{pr}). However, since in the wind energy sector there are some failures caused by sensors' false alarms, each system has been provided with a FM $k = 1$ that has an impact in terms of availability, but not in terms of material, human resources nor dispatch cost. The time to repair is the source of the opportunity and penalty costs (c^{na}, c^{p}) and the human resources' need, which can be either internal or external. According to internal resources a number of MTs are hired (NT^{max}) and are considered to be constant through the whole analysis. The MTs have a certain annual cost (c^{team}) and capacity (C). Finally, whereas when no own resources are available to perform required CM activities extra time (ET) is externally hired at an extra cost (c^{et}), PM will only be performed with own resources.

2.2. Dynamic opportunistic maintenance policy

Two different maintenance decisions are considered within the presented dynamic opportunistic maintenance policy according to respective dynamic reliability thresholds: the MT dispatch to the WF, based on DRT_{ik}, and the PM decision, based on SRT_{ikj}. Accordingly, on the one hand, if the reliability of any FM ($R_{ik}\left(VA\right)$) does not reach the DRT_{ik}, the decision of preventively dispatching a MT to the WF will be made, ensuring a minimum reliability for every system and FM. On the other hand, once the decision of dispatching a MT to the WF has been made -either preventively or correctively-, the imperfect PM decision is made according to SRT_{ikj} (see Figures 1 and 2).



(a) Decision-making structure for the dispatch of the maintenance teams



(b) Decision-making structure for performing PM. Example with 3 PM levels per FM

Figure 1: Decision-making structure for the dynamic opportunistic maintenance model

As stated, whereas in the reviewed researches these thresholds are static, in the presented model they are dynamic. Both DRT_{ik} and SRT_{ikj} will vary with regards to wind speed conditions according to Eq.4-6; being increased in low wind speed periods and decreased in high speed periods. Thus, PM will be fostered during low wind periods and hindered during high wind speeds periods (see Figure 1). As shown in Eq.4-6 the variation of the thresholds -and hence, the maintenance strategy- is determined by the following factors:

1. Wind speed threshold (V): during wind speed periods above this value, the reliability thresholds will decrease, hindering the PM activities; and on the contrary during low wind speed periods. Wind speed during the next p periods of time is forecasted and compared to V in order to determine if reliability thresholds should decrease or increase (Eq.6).
2. Generated power (GP_t) and reactivity weight (w_{ik}): determine to which extent the reliability thresholds should be reactive to wind conditions. The gradient of both DRT_{ik} and SRT_{ikj} is proportional to the difference between the generated power at each time period (GP_t) and the rated power of WTs (RP).

$$SRT_{ikjt} = SRT_{ikj} + (2W_t - 1) \cdot SRT_{ikj} \cdot w_{ik} \cdot \left(\frac{RP}{GP_t + RP \cdot W_t}\right)^{(2W_t-1)} \tag{4}$$

$$DRT_{ikt} = DRT_{ik} + (2W_t - 1) \cdot DRT_{ik} \cdot w_{ik} \cdot \left(\frac{RP}{GP_t + RP \cdot W_t}\right)^{(2W_t-1)} \tag{5}$$

$$W_t = \begin{cases} 1 & \sum_{l=t}^{t+p} \frac{v_l}{p} \leq V \\ 0 & \sum_{l=t}^{t+p} \frac{v_l}{p} > V \end{cases} \tag{6}$$

It is not the aim of the dynamic opportunistic maintenance to eliminate the PM activities, but to plan them when weather conditions are more advantageous. Since WTs should be stopped during maintenance, downtime periods (time-based availability) will be similar in both dynamic and static maintenance strategies. However, energy losses will be reduced through dynamic opportunistic maintenance, maximizing WF's production and energy-based availability and minimizing opportunity cost derived from the unavailability periods. In other words, the WTs will be available during the most profitable periods. Likewise, as maintenance activities will be prone to be planned within low wind speed periods, safety of maintenance teams will also be improved [10].

Furthermore, on some occasions WFs must be stopped due to different reasons, such as for substation maintenance. Since no power can be generated during these periods, maintenance managers usually take the opportunity of performing PM. In order to consider such situations within the model, and help the manager on the maintenance decision to be made during these periods as well, they should be considered as no-wind periods ($\sum_{l=t}^{t+P} \frac{v_l}{p} = 0$), since no power can be generated. Consequently, according to the established maintenance policy, the thresholds will be increased during these periods, fostering PM.

2.3. Mathematical model

In this section the mathematical formulation of the dynamic opportunistic maintenance model is developed according to the maintenance process shown in Figure 2. To this aim, the standard approach of discretising the time in order to formulate stochastic programming models ($T = \{0, 1, 2, ..., T\}$) has been considered. Without loss of generality, some assumptions have been made for its formulation:

1. Degradation processes of the systems are considered independent from each other and they are associated to the operation time (ageing systems).
2. As commonly done in ageing systems, Increasing Failure Rate (IFR) is considered.
3. Installed WTs are the same model, composed by similar systems. Therefore, reliability distribution of the FMs of the systems is irrespective of the WT that contains them.
4. Reliability of the FMs follows the Weibull distribution, with scale parameter α and shape parameter β.
5. Maintenance activities should be finished during the period of time in which they are started.
6. A maintenance dispatch is considered per period of time, where several MTs can be dispatched.
7. The wake effect affection to WTs' production has been considered to be minimised during the WF layout design optimisation [48] and thus neglected.
8. PM is assumed to be less resource-consuming than CM since
    (a) extra damages in other systems because of failures reduction;
    (b) stock management can be planned in advance;
    (c) resources can be allocated to maintenance tasks in a balanced way.
9. WF maintenance managers make decisions in discrete time and frequently [39].

The principal objective of the model is to minimize the LCC due to O&M while providing the maximum WF energy-based availability. Accordingly, the optimal reliability thresholds that define the dynamic opportunistic maintenance policy (SRT_{ikjt}, DRT_{ikt}), i.e. the decision variables of the model, should be found.

Table 3: Intermediate Binary variables utilised in the model

$z_{hikt} = \begin{cases} 1 & if\, CM\, k\, is\, performed\, in\, system\, i\, of\, WT\, h\, in\, period\, t \\ 0 & otherwise \end{cases}$	$\gamma_t = \begin{cases} 1 & if\, a\, MT\, is\, preventively\, dispatched\, to\, WF\, in\, period\, t \\ 0 & otherwise \end{cases}$
$y_{hikjt} = \begin{cases} 1 & if\, PM\, j\, is\, performed\, in\, FM\, k\, of\, system\, i\, of\, WT\, h\, in\, period\, t \\ 0 & otherwise \end{cases}$	$\sigma_{hikjt} = \begin{cases} 1 & if\, PM\, j\, should\, be\, performed\, in\, FM\, k\, of\, system\, i\, of\, WT\, h\, in\, period\, t \\ 0 & otherwise \end{cases}$
$\theta_t = \begin{cases} 1 & if\, a\, MT\, is\, correctively\, dispatched\, to\, WF\, in\, period\, t \\ 0 & otherwise \end{cases}$	$\varphi_t = \begin{cases} 1 & if\, there\, are\, available\, resources\, for\, performing\, PM\, in\, period\, t \\ 0 & otherwise \end{cases}$

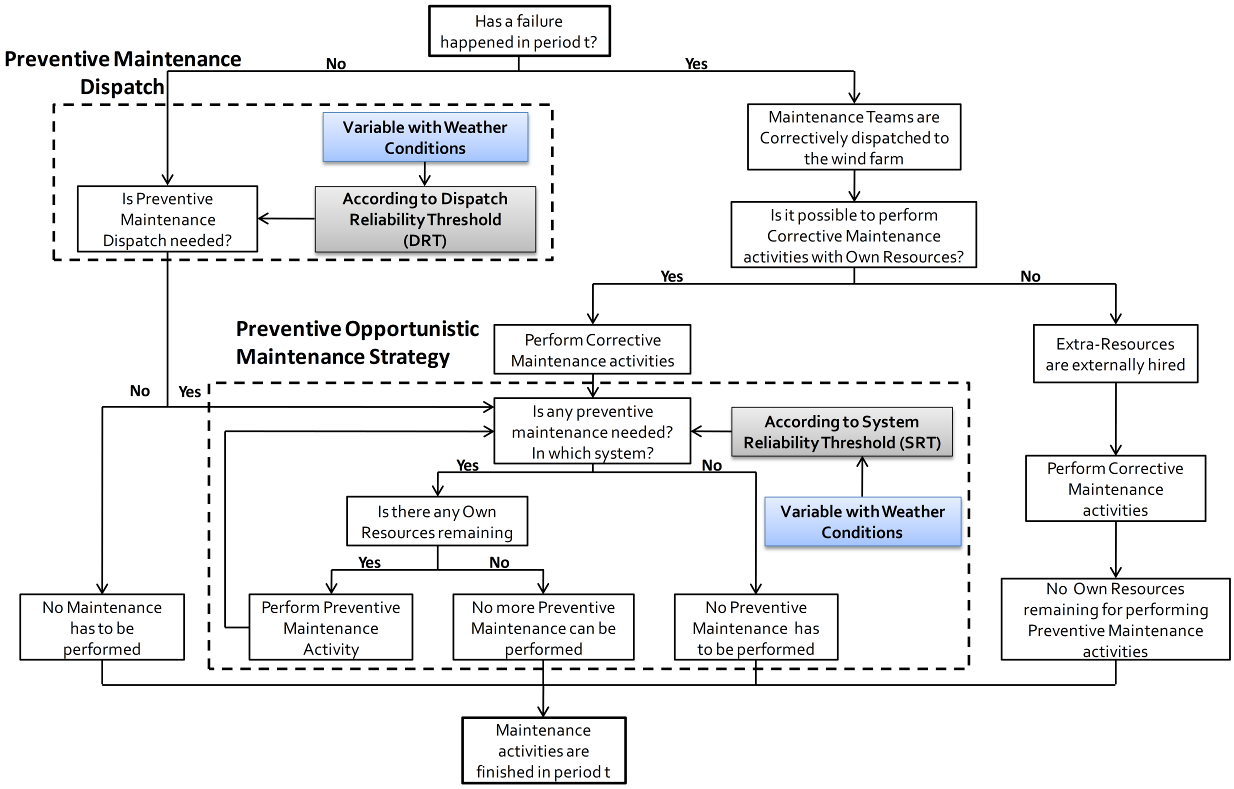


Figure 2: Flowchart of the Dynamic Opportunistic Maintenance Model

To this aim, the objective function (see Eq.7) of the model bears the main O&M costs to be faced in a WF, related to the failure ocurrence (z_{hikt}) and the PM decision (y_{hikjt}): 1) own and externally hired human resources needs, both in terms of own maintenance teams (NT, c^{team}) and extra time needed (ET, c^{et}); 2) dispatching of MTs to the WF (c^{disp}); 3) material and tools requirements $\left(c^{c}_{ik}, c^{pr}_{ikj}\right)$; and 4) production losses (c^{na}) and penalty costs (c^{p}) due to WTs unavailability during maintenance, directly proportional to maintenance tasks duration $\left(m^{c}_{ik}, m^{pr}_{ikj}\right)$ and the lost power during maintenance (GP_t). The cost of the imperfect maintenance has been defined as a function of the restoration factor $\left(q^{c}_{ik}, q^{pr}_{ik,j}\right)$ (as in [11]), as well as the maintainability. Due to the long term nature of the study the maintenance cost at each period t has to be updated to present value according to an interest rate (k_a):

$$min\, LCC\left(DRT_{ikt}, SRT_{ikjt}\right) = \Bigg[\sum_t ET_t \cdot c^{et} + \sum_t NT \cdot c^{team} + \sum_t (\gamma_t + \theta_t) \cdot c^{disp} +$$
$$\sum_h \sum_i \sum_{k \neq 1} \sum_t z_{hikt} \cdot c^{c}_{ik} \cdot \left(q^{c}_{ik}\right)^2 + \sum_h \sum_i \sum_k \sum_t z_{hikt} \cdot m^{c}_{ik} \cdot \left(q^{c}_{ik}\right)^2 \cdot GP_t \cdot \left(c^{na} + c^{p}\right) +$$
$$\sum_h \sum_i \sum_k \sum_j \sum_t y_{hikjt} \cdot \left(q^{pr}_{ikj}\right)^2 \cdot \left(m^{pr}_{ikj} \cdot GP_t \cdot \left(c^{na} + c^{p}\right) + c^{pr}_{ikj}\right)\Bigg] \cdot (1 + k_a)^{-t} \quad (7)$$

The objective of maximizing WFs' energy-based availability -calculated attending to the lost power during maintenance tasks duration and total available power ($H \cdot \sum_t GP_t$)- is ensured through the establishment of a minimum energy-based availability requirement (Eq.8). The time-based availability -calculated attending to the tasks duration and total operating time (OT)- is also calculated through Eq.9.

$$\frac{H\cdot\sum_t GP_t - \left[\sum_h\sum_i\sum_k\sum_t m^c_{ik}\cdot z_{hikt}\cdot\left(q^c_{ik}\right)^2\cdot GP_t + \sum_h\sum_i\sum_k\sum_j\sum_t m^{pr}_{ikj}\cdot y_{hikjt}\cdot\left(q^{pr}_{ikj}\right)^2\cdot GP_t\right]}{H\cdot\sum_t GP_t}\geq D^o \tag{8}$$

$$\frac{OT - \left[\sum_h\sum_i\sum_k\sum_j\sum_t m^{pr}_{ikj}\cdot y_{hikjt}\cdot\left(q^{pr}_{ikj}\right)^2 + \sum_h\sum_i\sum_k\sum_t m^c_{ik}\cdot z_{hikt}\cdot\left(q^c_{ik}\right)^2\right]}{OT} \tag{9}$$

The generation of power is modelled regarding the average wind speed at each period. Power is only generated in wind speeds between cut in $\left(v^i\right)$ and cut out (v^o) wind speeds, increasing non linearly until the wind speed in which the rated power (RP) is reached (v^r). The mathematical relationship has been defined as in Karki and Patel [49]:

$$GP_t = \begin{cases} 0, & 0\leq v_t < v^i \\ RP\cdot\left(a+b\cdot v_t + c\cdot v_t^2\right) & v^i\leq v_t < v^r \\ RP & v^r\leq v_t < v^o \\ 0, & v^o \leq v_t \end{cases} \qquad \forall t\epsilon T \tag{10}$$

where the parameters in Eq.10 are obtained as follows [49]:

$$a = \frac{1}{\left(v^i - v^r\right)^2}\left[v^i\left(v^i+v^r\right) - 4v^i v^r\left(\frac{v^i+v^r}{2v^r}\right)^3\right] \tag{11}$$

$$b = \frac{1}{\left(v^i - v^r\right)^2}\left[4\left(v^i+v^r\right)\left(\frac{v^i+v^r}{2v^r}\right)^3 - \left(3v^i+v^r\right)\right] \tag{12}$$

$$c = \frac{1}{\left(v^i - v^r\right)^2}\left[2 - 4\left(\frac{v^i+v^r}{2v^r}\right)^3\right] \tag{13}$$

As stated, the decision of preventively dispatching a MT to the WF relies on DRT_{ikt}, which varies according to the wind speed forecasting (see Eq.5,6) between [0,1] (Eq.14). When the reliability of any FM of a system (R_{ik}) does not reach its required threshold (DRT_{ikt}), MTs are preventively dispatched to the WF (Eq.15). Likewise, if a failure happens in t ($z_{hikt} = 1$), the dispatch of the MT is compulsory (Eq.16). Furthermore, dispatches of MTs are limited to one per period (Eq.17), being able to send several teams in the same dispatch.

$$0\leq DRT_{ikt}\leq 1 \qquad \forall i\epsilon I, \forall k\epsilon K, \forall t\epsilon T \tag{14}$$

$$\gamma_t = \begin{cases} 1 & R_{ik}(VA_{hikt}) \leq DRT_{ikt} \\ 0 & otherwise \end{cases} \qquad \forall h\epsilon H, \forall i\epsilon I, \forall k\epsilon K, \forall t\epsilon T \quad (15)$$

$$\theta_t = \begin{cases} 1 & \sum_h \sum_i \sum_{k\neq 1} z_{hikt} \geq 1 \\ 0 & otherwise \end{cases} \qquad \forall t\epsilon T \quad (16)$$

$$\theta_t + \gamma_t \leq 1 \qquad \forall t\epsilon T \quad (17)$$

The decision of performing PM activities is based on SRT_{ikjt} [0,1] (see Eq.4,6,18). When the reliability of a system does not reach the required reliability threshold (Eq.19) a system is susceptible of being preventively maintained; however, more conditions have to be met in order to perform PM (see Figure 2): 1) only the most comprehensive maintenance is performed, i.e. if both imperfect and perfect maintenance are needed, perfect maintenance will be performed (Eq.20); 2) a MT must have been previously dispatched to the WF (Eq.21); 3) own human resources have to be available for performing PM (Eq.25,26); and 4) only a maintenance activity is performed at each time on the WT (Eq.22).

$$0 \leq SRT_{ikjt} \leq 1 \qquad \forall i\epsilon I, \forall j\epsilon J, \forall k\epsilon K, \forall t\epsilon T \quad (18)$$

$$\sigma_{hikjt} = \begin{cases} 1 & R_{ik}(VA_{hikt}) \leq SRT_{ikjt} \\ 0 & otherwise \end{cases} \qquad \forall h\epsilon H, \forall i\epsilon I, \forall k\epsilon K, \forall j\epsilon J, \forall t\epsilon T \quad (19)$$

$$y_{hikjt} \leq \sigma_{hikjt} - \sigma_{hik(j+1)t} \qquad \forall h\epsilon H, \forall i\epsilon I, \forall k\epsilon K, \forall j\epsilon J, \forall t\epsilon T \quad (20)$$

$$y_{hikjt} \leq \theta_t + \gamma_t \qquad \forall h\epsilon H, \forall i\epsilon I, \forall k\epsilon K, \forall j\epsilon J, \forall t\epsilon T \quad (21)$$

$$\sum_i \sum_k \sum_j y_{hikjt} + \sum_i \sum_k z_{hikt} \leq 1 \qquad \forall h\epsilon H, \forall t\epsilon T \quad (22)$$

In fact, with regard to human resource limitations, some capacity constraints have been set (Eq.23-26). As shown in Figure 2, each CM must be performed, and if no resources are available, extra time (ET) is externally hired at a higher cost (Eq.23). Eq.24 ensures that no more than the maximum available MTs (MT^{max}) are used for CM at each time ($NT_t^c \epsilon \{1, 2, ..., NT^{max}\}$). Since PM can only be performed with own resources, Eq.25 analyses if there are still own resources available after CM; and if so, PM is performed if needed (Eq.26).

$$\sum_h \sum_i \sum_{k\neq 1} z_{hikt} \cdot m_{ik}^c \cdot (q_{ik}^c)^2 \leq C \cdot NT_t^c + ET_t \qquad \forall t\epsilon T \quad (23)$$

$$NT_t^c \leq NT^{max} \qquad \forall t\epsilon T \quad (24)$$

$$\varphi_t = \begin{cases} 1 & \sum_h \sum_i \sum_{k\neq 1} z_{hikt} \cdot m_{ik}^c \cdot (q_{ik}^c)^2 \leq C \cdot NT^{max} \\ 0 & \sum_h \sum_i \sum_{k\neq 1} z_{hikt} \cdot m_{ik}^c \cdot (q_{ik}^c)^2 > C \cdot NT^{max} \end{cases} \qquad \forall t\epsilon T \quad (25)$$

$$\sum_h \sum_i \sum_k \sum_j y_{hikjt} \cdot m_{ikj}^{pr} \cdot \left(q_{ikj}^{pr}\right)^2 \leq C \cdot (NT^{max} - NT_t^c) \cdot \varphi_t \qquad \forall t\epsilon T \quad (26)$$

When PM or CM are performed ($y_{hikjt} = 1$, $z_{ikht} = 1$), the system's virtual age associated to FM k (VA_{hikt}) is reduced according to the restoration factor (q_{ikj}^{pr}, q_{ik}^c). If no action is performed in a system during a period, the virtual age should be increased by a period (Eq.27).

$$VA_{hikt} = (VA_{hik(t-1)} + 1) \cdot \left(1 - z_{hikt} \cdot q_{ik}^c - y_{hikjt} \cdot q_{ikj}^{pr}\right)$$
$$\forall h\epsilon H, \forall i\epsilon I, \forall k\epsilon K, \forall j\epsilon J, \forall t\epsilon T \quad (27)$$

3. Simulation Process

As shown in the analytical model, expected maintenance cost and production of the WF depend on the followed opportunistic maintenance policy, which is determined by the dynamic reliability thresholds. Therefore, in order to find profitable maintenance strategies, it is necessary to establish the correct set of thresholds (SRT_{ikj}, DRT_{ik}) and their variation according to the forecasted wind conditions (w_{ik}, V, p).

Due to the different stochastic processes that have to be considered within this complex system model, such as failure occurrence, repair processes, weather conditions, etc., it is hard to handle it analytically [11, 33]. Therefore, although most part of the problem has been analytically derived, simulation techniques have been used to handle the many random scenarios that can appear for each set of reliability thresholds, as commonly done in other researches about the topic [35, 33, 34, 11, 31]. Particularly, an agent-based simulation has been developed due to its suitability to handle engineering problems with multi-agent systems [50]. The simulation process developed follows 6 different steps (see Figure 3).

Step 1. In the initialization of the simulation all the parameters needed for the simulation process are specified: the parameters needed for the dynamic reliability thresholds modelling, costs related to maintenance, reliability and maintainability distributions, number of MTs, maximum iteration period, etc.

Step 2. The simulation clock and virtual age of the FMs of the systems are updated, identifying their new reliability according to their age. Wind speed is also forecasted and reliability thresholds are accordingly updated.

Step 3. If any failure has happened, needed CM is applied and the virtual age of the system is updated. After the CM, the new time to failure (TTF) is obtained through the Inverse Transform Technique [51], according to Eq.28 (adopted from [33]), in which R is uniformly distributed between [0,1). If no failure occurs, whether a MT has to be preventively dispatched or not is also decided in this step.

$$TTF_{hik} = \alpha_{ik} \left[\left(\frac{VA_{hik}}{\alpha_{ik}} \right)^{\beta_{ik}} - ln\,(1-R) \right]^{\frac{1}{\beta_{ik}}} - VA_{hik} \qquad (28)$$

Step 4. If a MT has been dispatched to the WF, PM decision is made according to the reliability thresholds. The virtual age and the new time to failure (TTF_{hik}) are updated for the maintained systems, according to Eq.28.

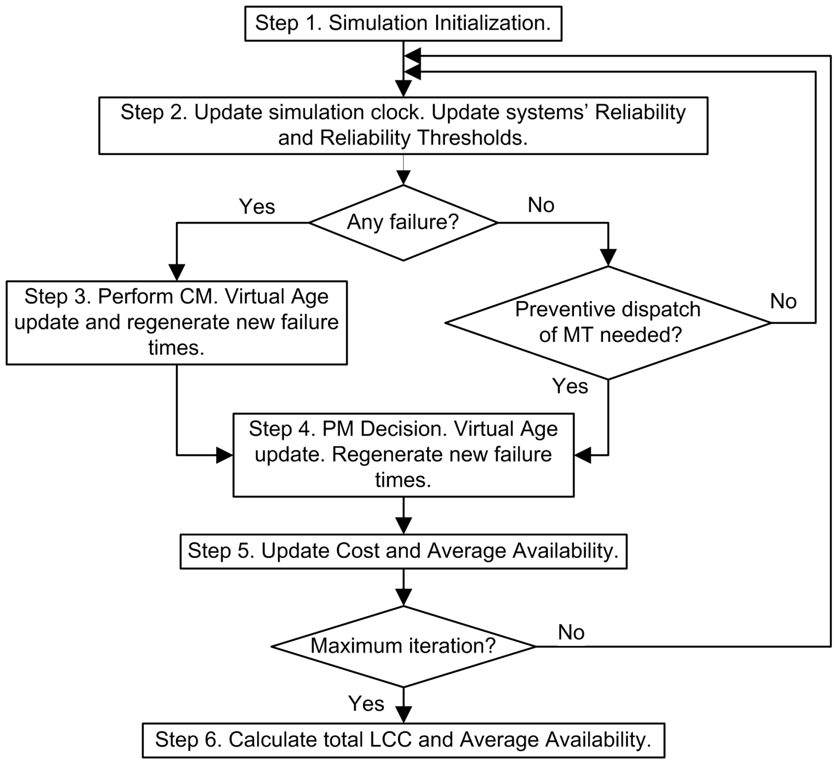


Figure 3: Simulation process for LCC and Energy-based availability evaluation

Step 5. LCC and energy-based availability are updated. If actual period is equal to the maximum iteration period, step 6 is followed. Otherwise, steps 2,3, 4 and 5 are repeated.

Step 6. The total expected LCC and the average energy-based availability are calculated for the established opportunistic maintenance policy, $LCC = f\left[SRT_{ikj}, DRT_{ik}, w_{ik}, V, p\right]$.

4. Case study & Computational results

An onshore application has been considered to test the efficiency of the dynamic opportunistic maintenance policy, since all the operation and reliability data provided by the wind energy company belonged to this type of WFs. The data available has been on more than 300 WTs over a time span of more than 12 years. These WTs are all the same-model and they are located in the North of Spain, working at similar operational conditions. Although this data is confidential and therefore no detailed numbers can be provided neither for the systems' reliability nor maintainability, the final results obtained are shown and explained in this section.

Three have been the strategies compared in the computational results shown below:

- *Strategy 1.* CM and minor PM are performed, as commonly done in the industry [11].

  $LCC = f\left[SRT_{ikj} = 0, DRT_{ik} = 0, w_{ik} = 0, V = 0, p = 0\right]$

- *Strategy 2.* CM and PM are performed, according to the static opportunistic maintenance policy established by the reliability thresholds. In this strategy, thresholds will not vary according to the wind conditions.

  $LCC = f\left[SRT_{ikj},\ DRT_{ik}, w_{ik} = 0, V = 0, p = 0\right]$

- *Strategy 3.* CM and PM are performed, according to the presented dynamic opportunistic maintenance policy established by the reliability thresholds and their variation degree regarding the wind conditions.

  $LCC = f\left[SRT_{ikj}, DRT_{ik}w_{ik}, V, p\right]$

Finally, a sensitivity analysis has been performed in order to discuss the most influential parameters within the model and to evaluate the different assumptions made. Despite the fact that the methodology has been applied to an Onshore WF, it could also be applied to an Offshore WF.

4.1. WF profile

A recently installed virtual WF that consists of 40 WTs (H = 40*)* of a rated power of 1,67 megawatt (MW) is considered. For each WT the 4 most critical systems are considered (N= 4), regarding both their reliability and the consequences of their failures, according to the data available for the study. These 4 systems are: gearbox, blades, pitch system and yaw system. For each system three independent FMs are analyzed (K = 3). As stated in Subsection 2.1, the k = 1 FM does not have material requirements nor need of field-maintenance, since they are provoked by sensors' false alarms. The systems can also undergo two different PM levels (J = 2) associated to the FMs *(*k = 2,3), with a restoration factor associated to the maintenance routine (q^{pr}_{ik1}= 0.75 and q^{pr}_{ik2}= 1) (see [11]).

The access cost to the WF is assumed to be 5000€, own resources 800€/day per maintenance team, 2 maintenance teams, extra resources 250€/hr per maintenance team, the total opportunity cost 105€/MWh, the penalization cost 35€/MWh, the interest rate 5% and the lead time to the WF one hour. Finally, the cost for the materials and the maintainability of PM has been set a 30% lower than for CM. Further information about material cost for the WT under study can be found on Martin-Tretton et al. [52].

Since wind conditions are a key factor within the methodology, real wind data has been utilised in order to feed the simulation and obtain as much realistic scenarios as possible. The wind turbines cut-in, cut-out and rated speeds are assumed to be 3 m/s, 25 m/s and 13 m/s, respectively. Finally, daily wind average forecasting potential has been established to 5 periods (p = 5).

4.2. Sensitivity analysis

In this section the different parameters that condition the dynamic reliability thresholds, and hence, the presented dynamic opportunistic maintenance model, are discussed through a sensitivity analysis, considering the following base scenario: $SRT_{i1j} = 0.0$, $SRT_{i21} = 0.8$, $SRT_{i22} = 0.4$, $SRT_{i31} = 0.8$, $SRT_{i32} = 0.4$, $DRT_{i2} = 0.2$, $DRT_{i3} = 0.2$, $w_{ik} = 0.5$, $V = 2.0$, $p = 5$.

Wind speed threshold (V). The opportunistic maintenance strategy, both in terms of LCC and loss of production, shows a better performance when the wind speed threshold is established at low values. If higher values are established, the reactivity of the reliability thresholds is higher and maintenance is prone to be over-sized, increasing LCC and production losses.

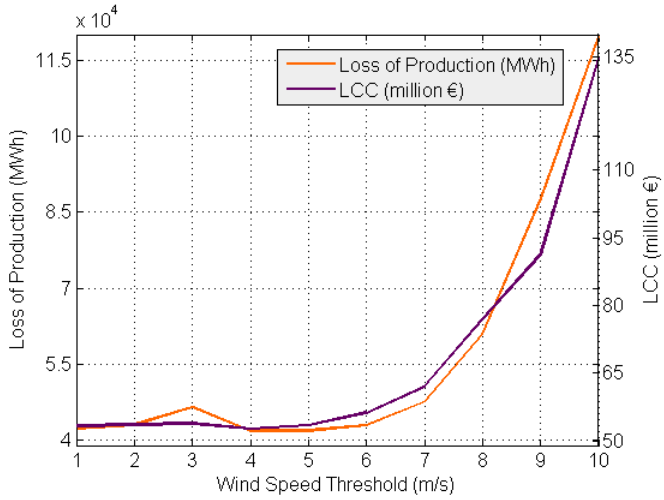


Figure 4: Expected LCC and Production Losses with different Wind Speed Thresholds

Number of periods for which average wind speed can be forecasted (p). It is expected that if the average wind speed was forecasted for more periods of time, the performance of the maintenance strategy would show better results. However, the results show that the performance of the dynamic opportunistic maintenance model is quite regular from $p = 3$ on.

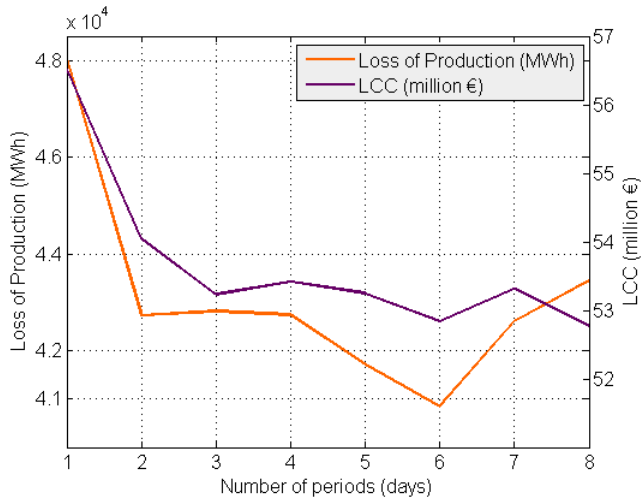


Figure 5: Sensitivity analysis according to predicted periods

Reactivity weight (w_{ik}). It helps determining the variation degree of the thresholds associated to each FM according to wind and it is expected that the optimal value will be different for each FM. For the defined base scenario, the best performance, both according to LCC and Production losses, is found at $w_{ik} = 0.5$.

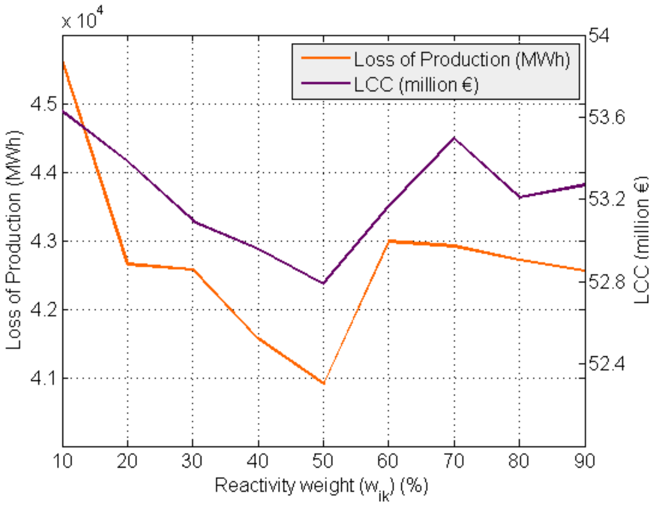


Figure 6: Expected LCC and Production Losses with different reactivities to wind (w_{ik})

4.3. Optimisation results and discussion

The optimisation results presented in this section have been obtained through the OptQuest Engine, a commercial optimisation software developed by Fred Glover in OptTek Systems Inc. (Opttek Systems Inc. 2000) that has been proved to be robust and efficient on finding high-quality solutions [53]. The OptQuest Engine is based on scatter search and it also integrates successfully Tabu search, integer programming, and a procedure to configure and train neural networks for the optimisation of stochastic problems [54]. Especially, neural networks play an important role in order to avoid getting trapped in local minima, since they are able to remember good solutions and recombine them to guide the search towards the best solutions [55]. For further information about scatter search and the OptQuest Engine the reader is addressed to [56, 53, 57].

	Gearbox			**Pitch**			**Yaw**			**Blades**		
	Dec. Var	Str.2	Str.3	Dec. Var	Str.2	Str.3	Dec. Var	Str.2	Str.3	Dec. Var	Str.2	Str.3
FM1	SRT_{11j}	0.0	0.0	SRT_{21j}	0.0	0.0	SRT_{41j}	0.0	0.0	SRT_{41j}	0.0	0.0
	DRT_{11}	0.0	0.0	DRT_{21}	0.0	0.0	DRT_{31}	0.0	0.0	DRT_{41}	0.0	0.0
	w_{11}	0.0	0.0	w_{21}	0.0	0.0	w_{31}	0.0	0.0	w_{41}	0.0	0.0
	V	0.0	0.5	V	0.0	0.5	V	0.0	0.5	V	0.0	0.5
FM2	SRT_{121}	0.725	0.775	SRT_{221}	0.9	0.925	SRT_{321}	0.825	0.875	SRT_{421}	0.775	0.825
	SRT_{122}	0.175	0.675	SRT_{222}	0.175	0.225	SRT_{322}	0.0	0.125	SRT_{422}	0.675	0.6
	DRT_{12}	0.0	0.1	DRT_{22}	0.175	0.15	DRT_{32}	0.0	0.125	DRT_{42}	0.675	0.6
	w_{12}	0.0	0.55	w_{22}	0.0	0.2	w_{32}	0.0	1.0	w_{42}	0.0	0.6
	V	0.0	0.5	V	0.0	0.5	V	0.0	0.5	V	0.0	0.5
FM3	SRT_{131}	0.725	0.75	SRT_{231}	0.925	0.975	SRT_{331}	0.9	0.90	SRT_{431}	0.8	0.875
	SRT_{132}	0.3	0.325	SRT_{232}	0.575	0.525	SRT_{332}	0.6	0.55	SRT_{432}	0.45	0.575
	DRT_{13}	0.175	0.3	DRT_{23}	0.175	0.225	DRT_{33}	0.475	0.5	DRT_{43}	0.0	0.125
	w_{13}	0.0	0.35	w_{23}	0.0	0.15	w_{33}	0.0	0.7	w_{43}	0.0	0.45
	V	0.0	0.5	V	0.0	0.5	V	0.0	0.5	V	0.0	0.5

Table 4: Optimised values for the Decision Variables

In order to compare the different strategies that are analyzed within the research, optimal values have been found for each one (see Table 4). The most remarkable results are:

LCC & Production Losses. Opportunistic maintenance strategies, both based on static and dynamic reliability thresholds, are proven to be economically effective compared to strategy 1. In fact, according to the obtained results, opportunistic maintenance policies can reduce LCC by a 25% (see Table 5 and Figure 7). Likewise, optimisation results show that the use of the dynamic reliability thresholds (strategy 3) considerably outperforms the use of static reliability thresholds (strategy 2), minimizing the total production losses by almost a 27% and slightly improving the LCC as well. Furthermore, it is remarkable that the results in terms of production losses for strategy 3 are not achievable through strategy 2. In fact, if the static reliability thresholds of strategy 2 were optimised for minimizing production losses instead of being optimised for minimizing the LCC, production losses would still be a 24,7% lower for strategy 3 than 2, additionally increasing the LCC (see Table 5).

Strategy		LCC (€)	Production Loss (MWh)
1		67,544,964	66,895
2	min LCC	51,856,606	50,239
	min Pr. Loss	52,982,284	48,790
3		50,904,497	36,743

Table 5: Main optimisation results for each strategy

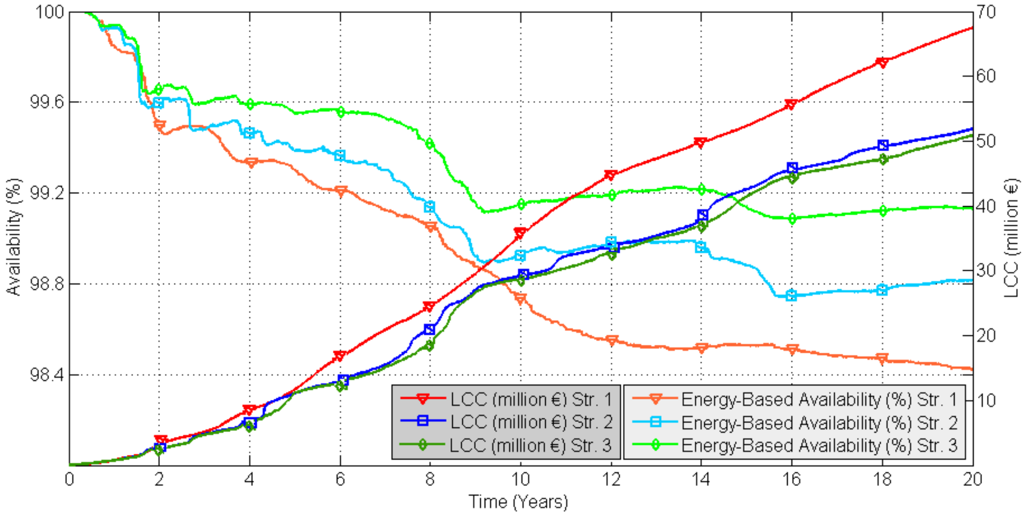


Figure 7: Strategies' performance comparison according to Energy-based Availability and LCC

This result is mainly due to the fact that WTs must be stopped during PM. Thus, even if more PM implies a better reliability, it is not the key to reduce the wind energy production losses. Consequently, if production losses are to be minimized, PM should be planned during low wind energy periods. It is at this point where the presented dynamic opportunistic maintenance, which systematically takes advantage of the low wind energy periods for performing maintenance, maximizes the total production and outperforms strategy 2, where the PM is planned regardless of the operational context of the WTs.

Energy-based availability & Time-Based availability. If energy-based and time-based availability of strategies 2 and 3 are compared (Figure 8), it is observed that the dynamic reliability thresholds improve the overall energy-based availability. Whereas following strategy 2 implies that maintenance activities have almost the same impact in both time-based and energy-based availability, through the dynamic reliability thresholds, the impact of maintenance activities on the energy-based availability is minimized, reaching an energy-based availability over 99,1%. This fact, along with the slight difference regarding LCC between strategies 2 and 3, reaffirms that whereas the dynamic opportunistic maintenance policy does not reduce PM, it achieves to find more suitable maintenance opportunities with regards to the wind conditions than static opportunistic maintenance policy.

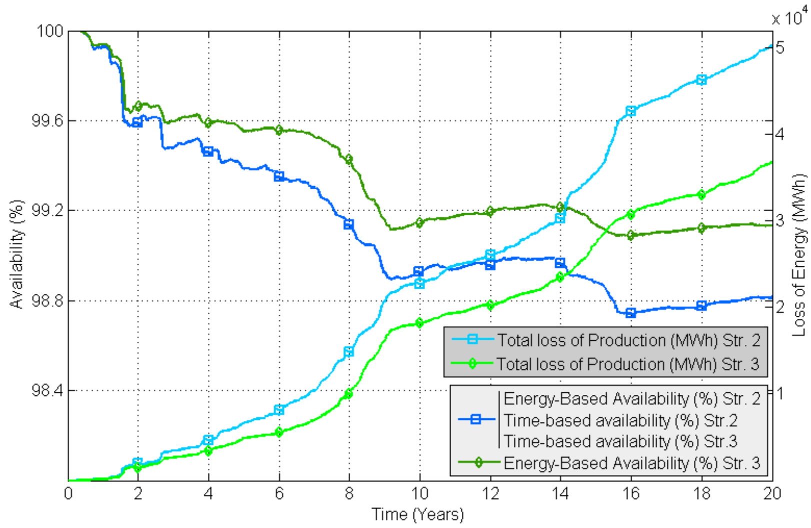


Figure 8: Strategies' performance comparison according to Energy-based and Time-based Availability

Wind speed during PM. As stated in Carlos et al. [10] optimal wind speeds for performing maintenance activities are those bellow 5m/s, not only in terms of production, but also in terms of workers' safety. In fact, regarding workers' safety, maintenance in WTs is generally recommended to be performed under wind speeds bellow 12 m/s [58]. As shown in Figure 9, following the strategy based on the dynamic reliability thresholds (strategy 3), nearly a 35% of the PM activities are performed under ideal conditions and a 97% under the recommended ones, whereas in strategy 2, with the static reliability thresholds, these percentages decrease to a 22% and a 88%, respectively. Moreover, according to power generation, these results show that whereas in strategy 2 more than a 10% of the PM activities are performed during maximum generation periods, in strategy 3 this figure falls to a 2%.

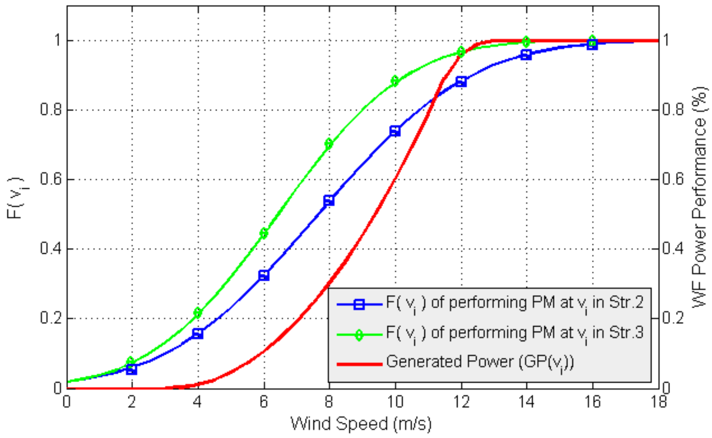


Figure 9: Wind speed at which PM is applied

Static and Dynamic opportunistic maintenance policies under stochastic wind speeds. The obtained results are based on real wind data according to the location of the wind farm. However, since wind predictions might be inaccurate and tendencies might change during the life cycle of the wind farm, the effect of wind speed variability both in LCC and loss of production has been analyzed (see Figures 10 and 11). To this aim, the wind data used to feed the simulation has been stochastically calculated at each time period based on the real wind data and a variability factor. According to the results shown in Figures 10 and 11, it can be noticed that the impact of wind speed variation in the static opportunistic maintenance is minor, since the reliability thresholds are optimised without considering the wind speed as an input. On the contrary, the wind speed variability directly affects the dynamic opportunistic maintenance, mostly in environments where the variability is higher than 60%. However, strategy 3 still outperforms strategy 2, excluding the most variable environment, where the results of strategies 2 and 3 are similar.

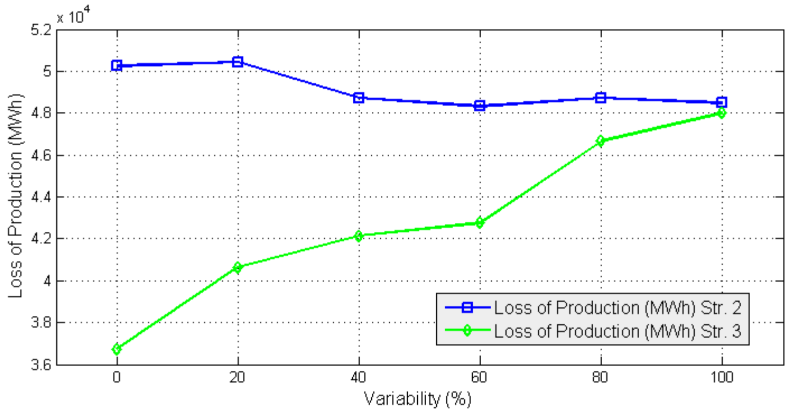


Figure 10: Loss of Production Variability

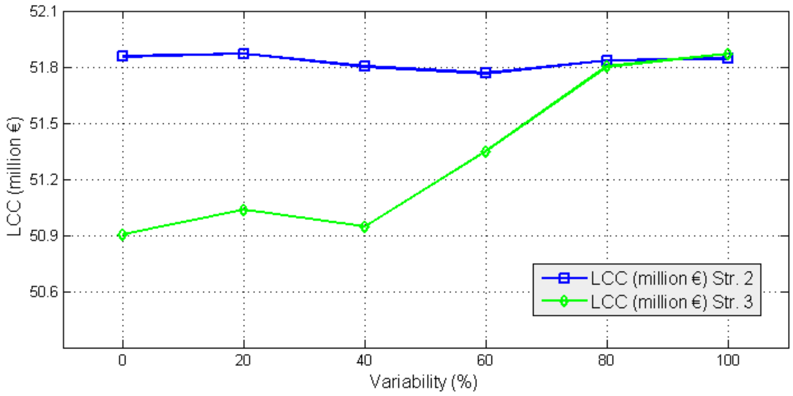


Figure 11: LCC variability

5. Concluding Remarks

Different opportunistic maintenance policies have been proposed for the wind power industry during the past few years, with different focus, objectives and assumptions. However, all these studies meet at a point: decision making process is always based on static reliability or age thresholds. On the contrary, the reliability thresholds proposed in the presented opportunistic maintenance model are allowed to vary according to the weather conditions. Thus, a dynamic nature has been provided to the maintenance decision making process, allowing it to be more adaptable to the specific environment circumstances.

The results obtained show that the performance of the strategies established by the dynamic reliability thresholds improve the ones proposed by the static reliability thresholds, both according to wind farm production and life cycle cost. Likewise, the dynamic opportunistic maintenance policy presented in this paper also allows to improve workers' safety, since the preventive maintenance activities are performed under the recommended weather conditions. Furthermore, as far as the authors are concerned, this opportunistic maintenance model is the first one for the sector that bears so many factors at the same time, i.e. multiple components systems with multiple failure modes, multilevel maintenance with perfect and imperfect maintenance, utilisation of own and outsourced maintenance resources, repair times for each failure mode, etc.

Future efforts will concentrate on the integration of the condition based maintenance strategies in the presented dynamic opportunistic maintenance policy. Likewise, further research will be performed to address the challenge of optimising simultaneously the maintenance strategies for several wind farms through dynamic opportunistic maintenance policies. Finally, in the case study presented there was not a remarkable wind speed seasonality, which might condition the wind farm's production, and thus, the dynamic opportunistic maintenance policy adopted. The authors will further investigate the dynamic opportunistic maintenance behaviour in wind farms where this effect is more relevant.

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[1] T. Ackermann, Wind Power in Power Systems, Wiley-Blackwell, 2005. doi:10.1002/0470012684.
URL http://dx.doi.org/10.1002/0470012684

[2] Anon., Global status of wind power in 2014, Global wind energy Council (2015).
URL http://www.gwec.net/wp-content/uploads/2015/03/GWEC_Global_Wind_2014_Report_LR

[3] P. J. Tavner, J. Xiang, F. Spinato, Reliability analysis for wind turbines, Wind Energy 10 (1) (2007) 1–18. doi:10.1002/we.204.
URL http://dx.doi.org/10.1002/we.204

[4] M. Shafiee, Maintenance logistics organization for offshore wind energy: Current progress and future perspectives, Renewable Energy 77 (2015) 182–193. doi:10.1016/j.renene.2014.11.045.
URL http://dx.doi.org/10.1016/j.renene.2014.11.045

[5] J. Kaldellis, M. Kapsali, Shifting towards offshore wind energy—recent activity and future development, Energy Policy 53 (2013) 136–148. doi:10.1016/j.enpol.2012.10.032.
URL http://dx.doi.org/10.1016/j.enpol.2012.10.032

[6] Anon., The European offshore wind industry - key trends and statistics 2014, The European Wind Energy Association, EWEA (2015).
URL http://www.ewea.org/fileadmin/files/library/publications/statistics/EWEA-European-Offshore-Statistics-2014.pdf

[7] E. Byon, Wind turbine operations and maintenance: a tractable approximation of dynamic decision making, IIE Transactions 45 (11) (2013) 1188–1201. doi:10.1080/0740817x.2012.726819.
URL http://dx.doi.org/10.1080/0740817X.2012.726819

[8] H. Krokoszinski, Efficiency and effectiveness of wind farms—keys to cost optimized operation and maintenance, Renewable Energy 28 (14) (2003) 2165–2178. doi:10.1016/s0960-1481(03)00100-9.
URL http://dx.doi.org/10.1016/S0960-1481(03)00100-9

[9] Z. Sen, Statistical investigation of wind energy reliability and its application, Renewable Energy 10 (1) (1997) 71–79. doi:10.1016/0960-1481(96)00021-3.
URL http://dx.doi.org/10.1016/0960-1481(96)00021-3

[10] S. Carlos, A. Sánchez, S. Martorell, I. Marton, Onshore wind farms maintenance optimization using a stochastic model, Mathematical and Computer Modelling 57 (7-8) (2013) 1884–1890. doi:10.1016/j.mcm.2011.12.025.
URL http://dx.doi.org/10.1016/j.mcm.2011.12.025

[11] F. Ding, Z. Tian, Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds, Renewable Energy 45 (2012) 175–182. doi:10.1016/j.renene.2012.02.030.
URL http://dx.doi.org/10.1016/j.renene.2012.02.030

[12] F. P. G. Márquez, A. M. Tobias, J. M. P. Pérez, M. Papaelias, Condition monitoring of wind turbines: Techniques and methods, Renewable Energy 46 (2012) 169–178. doi:10.1016/j.renene.2012.03.003.
URL http://dx.doi.org/10.1016/j.renene.2012.03.003

[13] W. Yang, P. J. Tavner, C. J. Crabtree, Y. Feng, Y. Qiu, Wind turbine condition monitoring: technical and commercial challenges, Wind Energy 17 (5) (2014) 673–693. doi:10.1002/we.1508.
URL http://dx.doi.org/10.1002/we.1508

[14] M. C. Garcia, M. A. Sanz-Bobi, J. del Pico, Simap: Intelligent system for predictive maintenance, Computers in Industry 57 (6) (2006) 552–568. doi:10.1016/j.compind.2006.02.011.
URL http://dx.doi.org/10.1016/j.compind.2006.02.011

[15] A. V. Horenbeek, J. V. Ostaeyen, J. R. Duflou, L. Pintelon, Quantifying the added value of an imperfectly performing condition monitoring system—application to a wind turbine gearbox, Reliability Engineering & System Safety 111 (2013) 45–57. doi:10.1016/j.ress.2012.10.010.
URL http://dx.doi.org/10.1016/j.ress.2012.10.010

[16] Anon., Managing the wind, Refocus 6 (2005) 48–51. doi:10.1016/s1471-0846(05)70402-9.
URL http://dx.doi.org/10.1016/S1471-0846(05)70402-9

[17] Y. Amirat, M. Benbouzid, E. Al-Ahmar, B. Bensaker, S. Turri, A brief status on condition monitoring and fault diagnosis in wind energy conversion systems, Renewable and Sustainable Energy Reviews 13 (9) (2009) 2629–2636. doi:10.1016/j.rser.2009.06.031.
URL http://dx.doi.org/10.1016/j.rser.2009.06.031

[18] A. Kusiak, Z. Zhang, A. Verma, Prediction, operations, and condition monitoring in wind energy, Energy 60 (2013) 1–12. doi:10.1016/j.energy.2013.07.051.
URL http://dx.doi.org/10.1016/j.energy.2013.07.051

[19] H. Wang, H. Pham, Optimal preparedness maintenance of multi-unit systems with imperfect maintenance and economic dependence, in: Springer Series in Reliability Engineering, Springer, 2006, pp. 135–150. doi:10.1007/1-84628-325-6_7.
URL http://dx.doi.org/10.1007/1-84628-325-6_7

[20] F. Ding, Z. Tian, Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions, International Journal of Reliability, Quality and Safety Engineering 18 (05) (2011) 463–481. doi:10.1142/s0218539311004196.
URL http://dx.doi.org/10.1142/S0218539311004196

[21] R. Nicolai, R. Dekker, A review of multi-component maintenance models, in: Proceedings of European Safety and Reliability Conference, 2007, pp. 289–296.
URL http://www.dimat.unina2.it/marrone/dwnld/Proceedings/ESREL/2007/Pdf/CH036.pdf

[22] R. Dekker, R. E. Wildeman, F. A. van der Duyn Schouten, A review of multi-component maintenance models with economic dependence, Mathematical Methods of Operations Research 45 (3) (1997) 411–435. doi:10.1007/bf01194788.
URL http://dx.doi.org/10.1007/BF01194788

[23] M. W. Sasieni, A markov chain process in industrial replacement, OR 7 (4) (1956) 148. doi:10.2307/3007561.
URL http://dx.doi.org/10.2307/3007561

[24] T. Nakagawa, D. Murthy, Optimal replacement policies for a two-unit system with failure interactions, Revue française d'automatique, d'informatique et de recherche opérationnelle. Recherche opérationnelle 27 (4) (1993) 427–438.
URL http://archive.numdam.org/ARCHIVE/RO/RO_1993__27_4/RO_1993__27_4_427_0/RO_1993__27_4_427_0.pdf

[25] H. Wang, A survey of maintenance policies of deteriorating systems, European Journal of Operational Research 139 (3) (2002) 469–489. doi:10.1016/s0377-2217(01)00197-7.
URL http://dx.doi.org/10.1016/S0377-2217(01)00197-7

[26] P. Ritchken, J. G. Wilson, (m,t) group maintenance policies, Management Science 36 (5) (1990) 632–639. doi:10.1287/mnsc.36.5.632.
URL http://dx.doi.org/10.1287/mnsc.36.5.632

[27] R. C. Vergin, M. Scriabin, Maintenance scheduling for multicomponent equipment, IIETransactions 9 (3) (1977) 297–305. doi:10.1080/05695557708975158.
URL http://dx.doi.org/10.1080/05695557708975158

[28] J. Crocker, U. Kumar, Age-related maintenance versus reliability centred maintenance: a case study on aero-engines, Reliability Engineering & System Safety 67 (2) (2000) 113–118. doi:10.1016/s0951-8320(99)00052-6.
URL http://dx.doi.org/10.1016/S0951-8320(99)00052-6

[29] J. S. Dagpunar, A maintenance model with opportunities and interrupt replacement options, The Journal of the Operational Research Society 47 (11) (1996) 1406. doi:10.2307/3010206.
URL http://dx.doi.org/10.2307/3010206

[30] X. Zheng, N. Fard, A maintenance policy for repairable systems based on opportunistic failure-rate tolerance, IEEE Transactions on Reliability 40 (2) (1991) 237–244. doi:10.1109/24.87134.
URL http://dx.doi.org/10.1109/24.87134

[31] Z. Tian, T. Jin, B. Wu, F. Ding, Condition based maintenance optimization for wind power generation systems under continuous monitoring, Renewable Energy 36 (5) (2011) 1502–1509. doi:10.1016/j.renene.2010.10.028.
URL http://dx.doi.org/10.1016/j.renene.2010.10.028

[32] F. Besnard, M. Patrikssont, A.-B. Strombergt, A. Wojciechowskit, L. Bertling, An optimization framework for opportunistic maintenance of offshore wind power system, in: IEEE Bucharest PowerTech, IEEE Institute of Electrical & Electronics Engineers, 2009. doi:10.1109/ptc.2009.5281868.
URL http://dx.doi.org/10.1109/PTC.2009.5281868

[33] H. Abdollahzadeh, K. Atashgar, M. Abbasi, Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups, Renewable Energy 88 (2016) 247–261. doi:10.1016/j.renene.2015.11.022.
URL http://dx.doi.org/10.1016/j.renene.2015.11.022

[34] K. Atashgar, H. Abdollahzadeh, Reliability optimization of wind farms considering redundancy and opportunistic maintenance strategy, Energy Conversion and Management 112 (2016) 445–458. doi:10.1016/j.enconman.2016.01.027.
URL http://dx.doi.org/10.1016/j.enconman.2016.01.027

[35] B. R. Sarker, T. I. Faiz, Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy, Renewable Energy 85 (2016) 104–113. doi:10.1016/j.renene.2015.06.030.
URL http://dx.doi.org/10.1016/j.renene.2015.06.030

[36] W. Zhu, M. Fouladirad, C. Bérenguer, A multi-level maintenance policy for a multi-component and multifailure mode system with two independent failure modes, Reliability Engineering & System Safety 153 (2016) 50–63. doi:10.1016/j.ress.2016.03.020.
URL http://dx.doi.org/10.1016/j.ress.2016.03.020

[37] M. Iqbal, M. Azam, M. Naeem, A. Khwaja, A. Anpalagan, Optimization classification, algorithms and tools for renewable energy: A review, Renewable and Sustainable Energy Reviews 39 (2014) 640–654. doi:10.1016/j.rser.2014.07.120.
URL http://dx.doi.org/10.1016/j.rser.2014.07.120

[38] H. Pham, H. Wang, Imperfect maintenance, European Journal of Operational Research 94 (3) (1996) 425–438. doi:10.1016/s0377-2217(96)00099-9.
URL http://dx.doi.org/10.1016/S0377-2217(96)00099-9

[39] E. Byon, L. Ntaimo, Y. Ding, Optimal maintenance strategies for wind turbine systems under stochastic weather conditions, IEEE Transactions on Reliability 59 (2) (2010) 393–404. doi:10.1109/tr.2010.2046804.
URL http://dx.doi.org/10.1109/TR.2010.2046804

[40] P. Tavner, D. M. Greenwood, M. W. G. Whittle, R. Gindele, S. Faulstich, B. Hahn, Study of weather and location effects on wind turbine failure rates, Wind Energy 16 (2) (2012) 175–187. doi:10.1002/we.538.
URL http://dx.doi.org/10.1002/we.538

[41] G. Wilson, D. McMillan, Modeling the relationship between wind turbine failure modes and the environment, Gas (CCGT) 22 (2014) 6–4.
URL https://pure.strath.ac.uk/portal/files/30166175/Modeling_the_relationship_between_wind_turbine_failure_modes_and_the_environment.pdf

[42] S. Kahrobaee, S. Asgarpoor, A hybrid analytical-simulation approach for maintenance optimization of deteriorating equipment: Case study of wind turbines, Electric Power Systems Research 104 (2013) 80–86. doi:10.1016/j.epsr.2013.06.012.
URL http://dx.doi.org/10.1016/j.epsr.2013.06.012

[43] J. Andrawus, J. Watson, M. Kishk, A. Adam, The selection of a suitable maintenance strategy for wind turbines, Wind Engineering 30 (6) (2006) 471–486. doi:10.1260/030952406779994141.
URL http://dx.doi.org/10.1260/030952406779994141

[44] E. Byon, Y. Ding, Season-dependent condition-based maintenance for a wind turbine using a partially observed Markov

decision process, IEEE Trans. Power Syst. 25 (4) (2010) 1823–1834. doi:10.1109/tpwrs.2010.2043269.
URL http://dx.doi.org/10.1109/TPWRS.2010.2043269

[45] J. Carroll, A. McDonald, D. McMillan, Failure rate, repair time and unscheduled o&m cost analysis of offshore wind turbines, Wind Energy (2015) n/a–n/adoi:10.1002/we.1887.
URL http://dx.doi.org/10.1002/we.1887

[46] M. Yañez, F. Joglar, M. Modarres, Generalized renewal process for analysis of repairable systems with limited failure experience, Reliability Engineering & System Safety 77 (2) (2002) 167–180. doi:10.1016/S0951-8320(02)00044-3.
URL http://www.sciencedirect.com/science/article/pii/S0951832002000443

[47] A. Karyotakis, On the optimisation of operation and maintenance strategies for offshore wind farms, Ph.D. thesis, University College London (UCL) (2011).
URL http://discovery.ucl.ac.uk/id/eprint/1302066

[48] J. S. González, A. G. G. Rodriguez, J. C. Mora, J. R. Santos, M. B. Payan, Optimization of wind farm turbines layout using an evolutive algorithm, Renewable Energy 35 (8) (2010) 1671–1681. doi:10.1016/j.renene.2010.01.010.
URL https://doi.org/10.1016%2Fj.renene.2010.01.010

[49] R. Karki, J. Patel, Reliability assessment of a wind power delivery system, Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 223 (1) (2008) 51–58. doi:10.1243/1748006xjrr218.
URL http://dx.doi.org/10.1243/1748006XJRR218

[50] M. Niazi, A. Hussain, Agent-based computing from multi-agent systems to agent-based models: a visual survey, Scientometrics 89 (2) (2011) 479–499. doi:10.1007/s11192-011-0468-9.
URL http://dx.doi.org/10.1007/s11192-011-0468-9

[51] J. Banks, Discrete event simulation, in: Encyclopedia of Information Systems, Elsevier BV, 2003, pp. 663–671. doi:10.1016/b0-12-227240-4/00045-9.
URL http://dx.doi.org/10.1016/B0-12-227240-4/00045-9

[52] M. Martin-Tretton, M. Reha, M. Drunsic, M. Keim, Data collection for current us wind energy projects: Component costs, financing, operations, and maintenance, Contract 303 (2012) 275–3000.

[53] M. Laguna, R. Martí, The optquest callable library, in: Optimization Software Class Libraries, Springer, 2003, pp. 193–218. doi:10.1007/0-306-48126-X_7.
URL http://link.springer.com/chapter/10.1007/0-306-48126-X_7

[54] F. Glover, J. P. Kelly, M. Laguna, The optquest approach to crystal ball simulation optimization, Graduate school of Business, University of Colorado 16.
URL https://www.researchgate.net/profile/Fred_Glover/publication/267771945_THE_OPTQUEST_APPROACH_TO_CRYSTAL_BALL_SIMULATION_OPTIMIZATION/links/545d0a330cf295b5615e665f.pdf

[55] I. Yun, B. Park, Application of stochastic optimization method for an urban corridor, in: Proceedings of the 2006 Winter Simulation Conference, Institute of Electrical & Electronics Engineers (IEEE), 2006. doi:10.1109/wsc.2006.322918.
URL http://dx.doi.org/10.1109/WSC.2006.322918

[56] F. Glover, A template for scatter search and path relinking, Lecture notes in computer science 1363 (1998) 13–54. doi:10.1007/BFb0026589.
URL http://link.springer.com/chapter/10.1007/BFb0026589

[57] M. Laguna, R. Martí, Experimental testing of advanced scatter search designs for global optimization of multimodal functions, Journal of Global Optimization 33 (2) (2005) 235–255. doi:10.1007/s10898-004-1936-z.
URL http://link.springer.com/article/10.1007/s10898-004-1936-z

[58] P. C. Rodríguez, N. J. Simón, Wind Turbines: Safety measures in maintenance activities, Instituto Nacional de Seguridad e Higiene en el Trabajo (2014).

A novel dynamic opportunistic maintenance modelling approach

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ABSTRACT: The necessity of the alignment between the maintenance strategies and the business strategies has been widely researched to date. Nevertheless, it is difficult to find maintenance optimization models that specifically take into account the global business criteria within the definition of the maintenance strategies. This fact usually hinders the use of the theoretical maintenance optimisation models in the industrial applications. The present research provides new insights into this issue through a novel maintenance modelling approach based on the opportunistic maintenance policies. The main novelty of this approach relies on the use of dynamic decision variables, which will be defined regarding both the business needs and the specific operational context; leading to a better maintenance and business performance. In this paper, the framework followed for implementing this approach is presented; being also illustrated through a real case study, devoted to optimise the maintenance strategies in the wind energy sector.

1 INTRODUCTION

In the actual business environment, where there is a fierce competition and the business dynamism is a real challenge, organizations have not only the need to improve their manufacturing performance, but also to make it sustainable. In this context, maintenance management has a pivotal role in the organizations' success, since it allows managing the risk of failures, finding a trade-off between the dependability and the life cycle cost of the organizations' assets. Consequently, the role of the maintenance management has evolved during the last years, from a "necessary evil" to a real value adding activity; indeed, to a business issue.

With this in mind, it is a key aspect to align the maintenance and the business strategies, ensuring that the business goals are specifically regarded within the maintenance strategies. Although this problem has extensively been studied from a management perspective (Márquez et al. 2015), it is quite difficult to find in the literature maintenance optimisation models that explicitly take into account the business global objectives (Horenbeek et al. 2010). Actually, this fact considerably complicates the utilization of the maintenance optimisation models in the industrial organizations (Garg & Deshmukh 2006, Dekker 1996).

One of the main challenges to deal with when the business and the maintenance strategies are to be aligned is the business environment dynamism. Organizations are opened to global markets and competition, so business objectives and goals might be changeable (Teece 2007). In order to manage this dynamism, the maintenance optimisation models should be able to integrate short term information within the decision making process.

With this respect, opportunistic maintenance (OM) policies can provide valid solutions, since they allow including short term information within the maintenance optimisation models (Wildeman et al. 1997). However, if the literature is reviewed, little work can be found that studies a better business performance through the utilization of the OM policies (Horenbeek et al. 2010).

The present research provides new insights into this issue, establishing a novel OM modelling approach that specifically considers the main business strategy and the short-term information about the assets' operational context. It is not the intention of this paper to study the whole mathematical formulation of the optimisation model (further detailed in (Erguido et al., unpubl.)), but to address the definition and implementation of the proposed approach. To this end, a comprehensive framework that embraces all the phases to be followed for its modelling and application in any sector is presented. Furthermore, all the phases defined in the framework are illustrated through a real case study, devoted to optimise the maintenance strategies in the wind energy sector.

The paper has been organised as follows: in section 2 a brief overview of the literature is presented; in section 3 the proposed approach is explained; in section 4 the approach is illustrated through a real case study; and in section 5 some concluding remarks are pointed out.

2 STATE OF THE ART

Over the past decades, wide research in maintenance has emphasized the importance of developing maintenance optimisation models in order to improve the systems' reliability (Horenbeek et al. 2010, Wang 2002), and consequently reduce the risk of failure and the maintenance cost.

Wang's comprehensive review (2002) about the maintenance optimisation models classifies them into two main categories: single-unit systems and multiple-unit systems. However, beyond the differences between these two categories, the maintenance decision making process, and accordingly the maintenance strategy, usually relies on (Wang 2002):

- The age of the assets (age based).
- The time between the maintenance activities (time based).
- The number of failures (failure based).
- The cost of the maintenance activities (cost limit based).
- The maintainability of the assets (repair time limit based).

Whereas the decision making-process principles are similar in both the single-unit and the multiple-unit maintenance policies, the formers tend to overlook the fact that systems are complex. That is, systems are composed by several subsystems and components with dependencies among them. According to Nicolai & Dekker (2007), these dependencies can be classified into: economic, when performing maintenance activities in different systems simultaneously have different economic consequences than implementing them individually; structural, when a maintenance activity in a system implies performing another action in other systems; and stochastic, when the risk of failure of two different systems is not independent. Hence, since the single-unit maintenance policies do not consider these dependencies, they might lead to suboptimal solutions (Wang 2002).

On the other hand, multiple-unit maintenance policies do consider the dependencies among the multi-component systems, potentially being able to find better maintenance solutions than the single-unit maintenance policies. Among these maintenance policies, OM policies have particularly acquired wide relevance during the last years, being an extensively researched topic.

OM policies try to optimize the maintenance performance through the planning of preventive maintenance activities in non-failed components when a failure has already happened in any other component of the system (Wang 2002); reducing both the economic and the failure risk of the non-failed components (Dekker, 1996). To this aim, OM policies take advantage of the short term information -e.g. asset degradation or production scheduling (Horenbeek & Pintelon 2013, Zhou et al. 2012)-, in order to efficiently manage the maintenance resources.

In analytical modelling terms, the OM strategy is generally defined according to certain thresholds –decision variables (DV), to be optimised- related to the reliability of the assets $(X = (\varepsilon_1, \dots, \varepsilon_i, \dots, \varepsilon_n))$ (Wang 2002). Therefore, whenever the opportunity of maintenance arises, if the reliability of the asset is beyond its threshold, then the preventive maintenance activity should be triggered.

Traditionally, the general analytical formulation of the OM models has been composed by an objective function (z) to be maximized or minimized (e.g. production or cost) and the constraints related to the thresholds or DVs; additionally adding, some further constraints $(C(X))$ related to maintenance criteria (e.g. production schedule). If the formulation is particularized for the case of the reliability-based OM strategy, it can be summarized as follows:

$$\max imize \;\; z(X) \tag{1}$$

$$subjected \;\; to$$

$$0 \le \varepsilon_i \le 1 \quad \forall i = 1,2,\dots,n \tag{2}$$

$$c(X) \le C \tag{3}$$

Literature devoted to the OM has grown exponentially during the last years, especially focusing on minimizing the maintenance cost. Additionally, the researches reviewed usually focus on some further maintenance criteria beyond the cost, such as: the remaining useful life of the components (Shi & Zeng 2016, Huynh et al. 2015, Tian et al. 2011), the degradation of the systems (Horenbeek & Pintelon 2013, Hou & Jiang, 2013), the systems' configuration (Keizer et al. 2016, Zhou et al. 2013), the production schedule (Iung et al. 2016, Zhou et al. 2012), the data uncertainty (Laggoune et al. 2010), etc. However, as long as the authors are concerned, there is not any OM model that particularly emphasizes in consistently aligning the maintenance and the business strategies, specifically considering the business goals within the decision making process; which is indeed a key aspect (Horenbeek et al. 2010).

3 DYNAMIC OPPORTUNISTIC MAINTENANCE MODELLING APPROACH

In essence, the set of thresholds provided by the OM models allows efficiently managing the economic and the failure risk of the components. However, according to the reviewed OM models, once the set of thresholds is established through the optimisation process, it usually remains static over time. Therefore, if the organization's context -for which the model has been ad hoc developed- changes, the maintenance strategy adopted might lead to suboptimal solutions.

This fact is a drawback if the maintenance strategy has to remain aligned with the business strategy, since business environments are changeable (Teece 2007). With the aim of bridging this gap, a novel OM model based on dynamic thresholds has been defined. These dynamic thresholds will vary in accordance with the business needs and the operational context: fostering the preventive maintenance when the business context is favourable and hindering it when it is not. Therefore, the maintenance and the business strategies will remain aligned even if the business context or objectives vary over time.

The main principle underpinned in the defined approach is that depending on the specific business environment, business and maintenance interests might diverge, leading to two possible conflicts (see Figure 1):

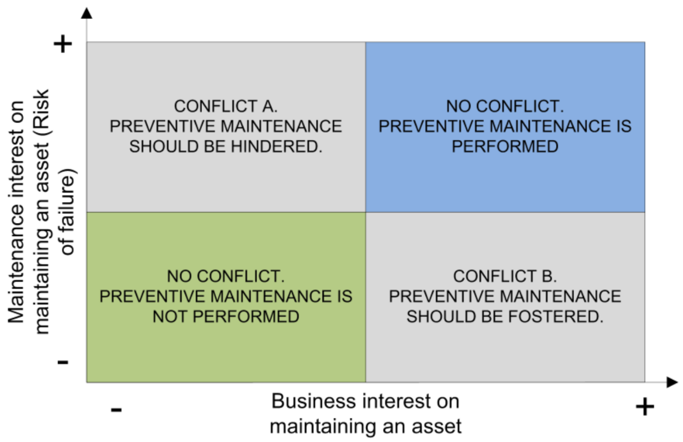

Figure 1. Maintenance and Business Interest relation according to preventive maintenance performance.

– *Conflict A: the business manager is not interested in preventively maintaining an asset although its risk of failure is high.* This situation might happen when there is a peak of demand, the asset is about to be disposed, etc. If a static threshold-based OM was followed, the reliability of the asset would probably be below its threshold, and the preventive maintenance would be performed, dismissing the main business objectives. On the contrary, if a dynamic threshold-based OM was followed, the threshold would go down ($\varepsilon_t = \varepsilon - \Delta\varepsilon_t$), hindering the preventive maintenance and trying to keep the main business interest (see Figure 2).

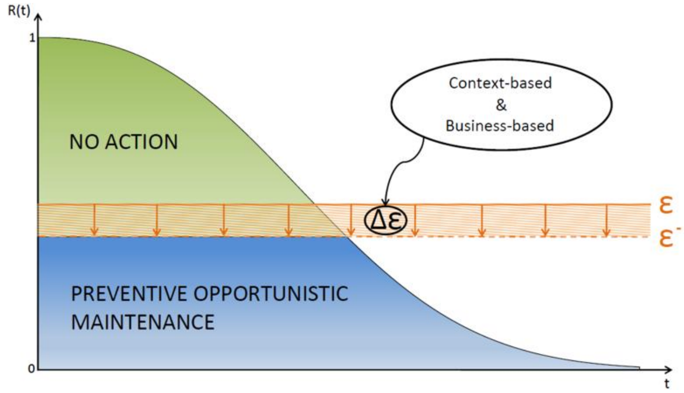

Figure 2. Solution provided by dynamic OM to Conflict A.

– *Conflict B: the business manager is interested in maintaining an asset although its risk of failure is low.* This situation might happen when a peak of demand is forecasted, a balancing of the maintenance/production workload is sought, some extra budget is available for investments, etc. In this case, if a static threshold-based OM was followed, the reliability of the asset would probably be over its threshold, and the preventive maintenance would not be performed, probably at the expense of the business future interest. On the contrary, if a dynamic threshold-based OM was followed, the threshold would go up ($\varepsilon_t = \varepsilon + \Delta\varepsilon_t$), fostering the preventive maintenance and trying to keep the main business interest (see Figure 3).

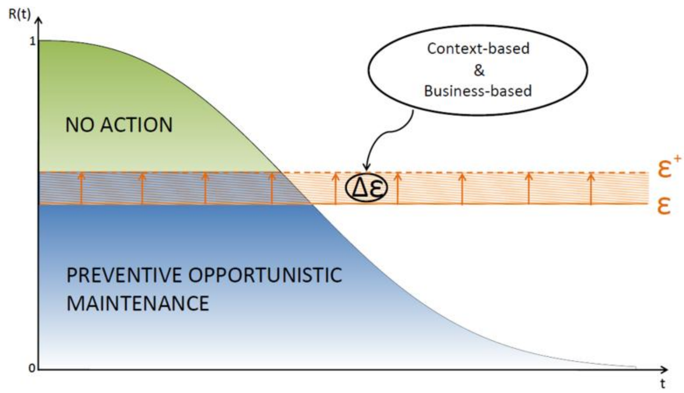

Figure 3. Solution provided by dynamic OM to Conflict B.

As stated, the reliability thresholds, which define the dynamic OM approach, should be function of the operational and business context. The general analytical formulation can be summarized as follows:

$$\max imize \quad z(X) \tag{4}$$

$$subjected \quad to$$

$$0 \leq \varepsilon_i\,(op\ context,\ bness\ objec) \leq 1 \qquad \forall i = 1,2,\ldots,n \tag{5}$$

$$c(X) \leq C \tag{6}$$

3.1 *Framework for dynamic opportunistic maintenance*

As stated, the dynamic OM can allow handling both A and B conflicts. However, some challenges arise when the dynamic OM has to be defined, mainly summarized in the following research questions (RQ):

- RQ1. Which/How many business strategic factors should be directly considered within the maintenance strategy?
- RQ2. How can the maintenance strategy facilitate the fulfilment of each business factor?
- RQ3. To which extent should each business factor affect the maintenance strategy?

On the one hand, RQ1 and RQ2 can be considered at the strategic decision level. If these questions were not correctly answered, the business and maintenance strategies could not be aligned. On the other hand, RQ3 regards the tactical decision level. In fact, if RQ3 was misled, the maintenance model could lead the maintenance manager to an excessive or an insufficient maintenance planning, provoking either an inadmissible maintenance cost or a too high failure rate. In order to properly answer these research questions, a framework based on 9 different phases divided into 3 different levels is presented (see Figure 4).

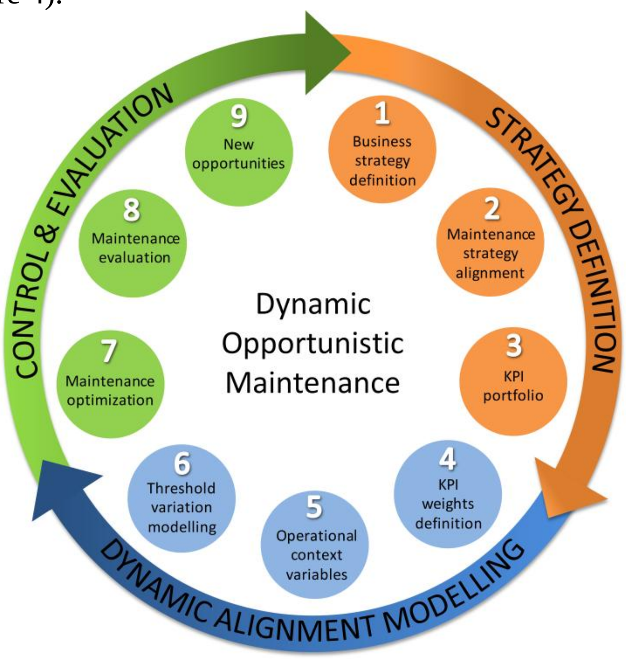

Figure 4. Framework for the dynamic OM application.

3.1.1 *Strategy definition*

The main aim of the 3 phases defined within this level is to assure the maintenance and business strategies' suitable definition and alignment (RQ1, RQ2).

- *Phase 1- Business strategy definition*. It is a key point to accurately establish the main business strategy, setting the main goals and the KPIs to measure them.
- *Phase 2- Maintenance strategy alignment*. In this phase the maintenance strategy should be defined, bearing in mind the main business strategy and goals, in order to facilitate their fulfillment and to assure the alignment between the maintenance and the business strategies. At this phase, special emphasis should be done on identifying the conflicts A and B, in order to hinder them through the dynamic OM optimisation model.
- *Phase 3- KPI portfolio*. In Phase 2 several KPIs might be identified for measuring the maintenance performance. However, in Phase 3, the most relevant maintenance KPIs related to the main business strategy should be identified and listed. Thereafter, these KPIs will be essential for the dynamism of the thresholds and the avoidance of conflicts A and B.

3.1.2 *Dynamic alignment modelling*

This level aims to translate the business and maintenance strategies' definition into the analytical modelling of the dynamic OM optimisation model, fostering the avoidance of A and B conflicts. With this purpose, the three phases of this level are devoted to the modelling of the dynamic thresholds (RQ3).

- *Phase 4- KPI weights definition*. When more than one maintenance KPI is identified as critical for the business strategy in Phase 3, they have to be categorised according to their relevance to the business; that is, according to their capacity to hinder the established A and B conflicts. Subsequently, in order to reflect these differences within the optimisation model, they should be weighted. Thereafter, these weights will determine to which extent each maintenance KPI will affect to the variation of the reliability thresholds, responsible for preventing the conflicts A and B.
- *Phase 5- Operational context variables*. Maintenance and business performance might be influenced by different operational context variables, such as, workload or stock buffers, which will provide the opportunity to efficiently manage the preventive maintenance activities. Therefore, these variables should be identified in order to plan the maintenance activities under more favourable business conditions and to hinder the stated A and B conflicts; aligning the business and maintenance strategies.
- *Phase 6- Threshold variation modelling*. The aim of this phase is to analytically derive to which extent should the dynamic thresholds vary with regard to the KPIs and the operational context variables determined in phases 4 and 5. The correct definition of this variation will avoid to oversize or undersize the preventive maintenance activities.

3.1.3 *Control & Evaluation*

The main goal of this level is to define the whole dynamic OM strategy, regarding the maintenance resources and constraints, and to evaluate it both according to the maintenance and business performance; seeking afterwards for further improvement opportunities.

- *Phase 7- Maintenance optimisation.* The whole analytical model should be derived (in addition to the already defined reliability thresholds), including the objective function and the maintenance constraints. Additionally, through optimisation methods, an optimal set of dynamic thresholds should be identified, which will promote the avoidance of the conflicts A and B, without over-sizing or under-sizing the maintenance activities.
- *Phase 8- Maintenance evaluation*. The followed maintenance strategy should be evaluated according both to the main maintenance and business KPIs, identifying if the objectives established during the *Strategy Definition* level have been achieved and the conflicts A and B are sufficiently avoided.
- *Phase 9- New opportunities*. In this phase further opportunities to enhance both the business and the maintenance strategies should be sought. Special attention should be paid to the business environment changes, in order to keep the maintenance and business conflicts (A and B) identified and, thus, the maintenance and the business strategies aligned.

4 A WIND FARM CASE STUDY

The growing importance of the renewable energy in terms of installed capacity has been remarkable during the last years, which has lead to an increment of the interest in wind farms' (WF) maintenance research. Particularly, OM literature regarding the wind energy sector has grown significantly during the last years, mainly due to the economic dependencies among the wind turbines (WT) installed in the WF (Abdollahzadeh et al. 2016).

The reviewed OM studies for the wind energy sector have obtained very relevant results according to different maintenance criteria, such as: minimizing maintenance cost and maximizing production (Abdollahzadeh et al. 2016), utilization of condition monitoring systems (Zhu et al. 2016, Tian et al. 2011), redundancies management (Atashgar & Abdollahzadeh 2016), etc. Despite the fact that these studies focus primarily on the maintenance criteria, they are also very likely to imply an improvement on the business results. Nevertheless, since it is not the main aim of these researches to consistently align the business and the maintenance strategies, they might lead to suboptimal solutions in global business terms.

Due to the proven suitability of the OM strategies in the wind energy sector, it has been considered as the case study for the application of the presented dynamic maintenance modelling approach. Precisely, an onshore application has been considered, based on real field data provided by a leading company in the sector. Although neither reliability nor cost data are provided due to confidentiality issues, final results are shown. Furthermore, a comparison between the traditional static opportunistic approach and the dynamic opportunistic approach has been performed.

4.1 *Energy-based availability driven dynamic opportunistic maintenance for the wind energy sector*

In order to illustrate the methodology, the framework defined in section 3.1 is going to be followed, exemplifying each phase with the wind energy case study. Since it is not the intention of this paper to study the whole mathematical formulation of the optimisation model (further detailed in (Erguido et al., unpubl.)), only the key parts of the model, regarding the dynamic OM approach, are detailed.

4.1.1 *Strategy definition*

Due to the nature of the wind energy sector, the benefits are mainly provided by the operational availability of the WTs. Furthermore, before providing the energy, the companies usually have to take the commitment of predicting how much energy are they going to be able to provide into the network within the next period of time; having to pay penalties if the pre-established figure is not reached. Therefore, due to this double challenge, the productivity of the wind farm is a cornerstone within the business definition strategy (phase 1).

Accordingly, in order to be aligned with the business strategy, the maintenance strategy should be highly focused on improving the availability (phase 2). Two different availability indicators can be considered in the wind energy sector: Time-based Availability (TBA) and Energy-based Availability (EBA). Since the EBA takes into account both the real energy production and the actual energy available (see Equation 7), it is considered a more comprehensive indicator for evaluating the WFs' productivity than the TBA (González et al. 2016). Furthermore, the EBA also provides relevant information regarding the penalty costs related to the not provided but committed energy. Thus, the EBA is set as a very relevant maintenance KPI (phase 3).

$$EBA = \frac{Generated\ \ Power}{Actual\ \ Energy\ \ Available} \tag{7}$$

It should be remarked that during the maintenance activities the WTs should be stopped. Therefore, if the EBA has to be increased, following the logic underneath the dynamic OM approach (see Figure 2), the aim of the model should focus on fostering the maintenance activities during the low wind speed periods (solution for Conflict B), while hindering them during the high wind speed periods (solution for conflict A). In consequence, this fact will lead to perform the preventive maintenance activities during low energy periods, reducing the total energy losses and increasing the EBA.

4.1.2 *Dynamic alignment modelling*

Only the EBA has been considered as a critical KPI in the present case study, so no weight is necessary to be established in the phase 4. According to the phase 5, the main operational context variables affecting the EBA indicator are those related to the generated power (GP). With this respect, since the GP is directly proportional to the wind speed (v_t) (for further information the reader is addressed to (Karki & Patel 2008)), v_t it is the main operational variable to take into account.

According to the dynamic threshold modelling (phase 6) used in the present case study, it should be remarked that it has been defined according to:

- The wind speed (v_t).
- The Generated Power (GP).
- The Rated Power (RP).
- A reactivity weight (w_i) to determine to which extent should the reliability threshold be reactive to the wind speed.
- A wind speed threshold (V) to determine if the wind speed is low enough to perform preventive maintenance or not.

$$\varepsilon_{t,i} = \varepsilon_i + (2 \cdot W_t - 1) \cdot w_i \left(\frac{RP}{GP_t + RP \cdot W_t} \right)^{(2 \cdot W_i - 1)} \quad (8)$$

where

$$W_t = \begin{cases} 1 & v_t \leq V \\ 0 & v_t > V \end{cases} \quad (9)$$

It should also be noted that when the wind speed (v_t) is below the wind speed threshold (V), the reliability threshold ($\varepsilon_{t,i}$) will increase, fostering the preventive maintenance performance (Conflict B solution). On the contrary, when the wind speed (v_t) is over the wind speed threshold (V), the preventive maintenance performance will be hindered (conflict A solution). Furthermore, it is worth it to remark that the reliability threshold is proportional to the generated power. Consequently, the final solution will be determined by $[\varepsilon_i, V, w_i]$.

4.1.3 *Control and Evaluation*

In addition to the modelling of the dynamic thresholds, further constraints are defined within the whole dynamic OM for the wind energy sector. The model developed by the authors allows optimising both the Life Cycle Cost (LCC) and the EBA (objective function), taking into account several maintenance constraints, mainly related to the maintenance teams' capacity (phase 7).

In order to optimise and evaluate the defined OM strategies simulation techniques have been utilized, mainly due to the stochastic processes that have to be considered within the WF maintenance optimisation models (failure occurrence, repair processes, weather conditions, etc.). Particularly, the optimisation software used for this case study has been Opttek Systems Inc. 2000, developed by Fred Glover in OptTek Systems Inc. Furthermore, this software provides an optimisation engine that allows finding high-quality solutions (phase 7), successfully integrating scatter search, tabu search, integer programming and a procedure to configure and train neural networks for the optimization of stochastic problems (Laguna & Martí 2003).

Within the developed simulation environment different maintenance strategies can be tested according to the LCC and the EBA indicators (f $[\varepsilon_i, V, w_i]$). Consequently, the maintenance and business managers are able to evaluate them (phase 8) and seek for further solutions that enhance the maintenance performance and its alignment with the business strategies (phase 9).

4.2 *Computational Results*

In order to prove the suitability of the dynamic OM approach, it has been compared to the widespread static OM policies.

For the computational results shown in this section, a recently installed virtual WF that consists of 40 WTs of a rated power of 1,67 megawatt (MW) each has been considered. Particularly, the four most critical systems have been taken into account, regarding their reliability, maintainability and cost data: gearbox, blades, pitch and yaw system.

It should be highlighted that the simulation has been fed with real operational and failure data, provided by a leading company of the sector. Furthermore, data according to the wind speed, a key aspect for implementing the dynamic OM in the wind energy sector, have also been collected from real field data.

If the maintenance strategies' results are evaluated according to the EBA, which has been established as the KPI to be optimised (Phase 3), one can notice that the results provided by the dynamic OM are quite promising (see Figure 5). In fact, production losses are reduced a 27%, leading to an EBA of 99.1%.

It is interesting to compare the differences between the TBA and the EBA indicators (see Figure 6). Whereas TBA remains the same for both the static and the dynamic approaches, the EBA increa-

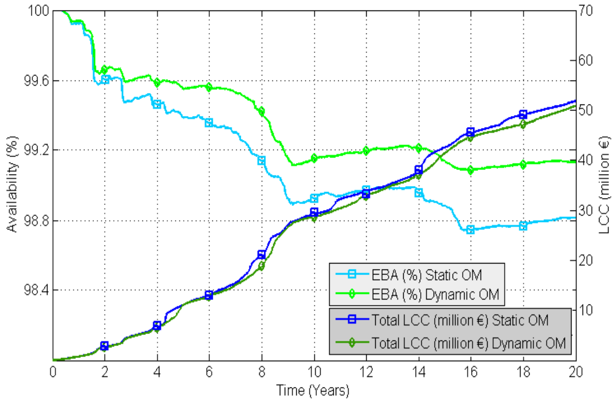

Figure 5. Results for Optimal Static and Dynamic OM strategies

ses in the dynamic opportunistic approach. This result is in line with the expected results for the dynamic OM strategy. As sought within the strategy definition (Phases 1-3), the EBA has been increased by performing the preventive maintenance activities during low wind speed periods, avoiding the conflicts A and B.

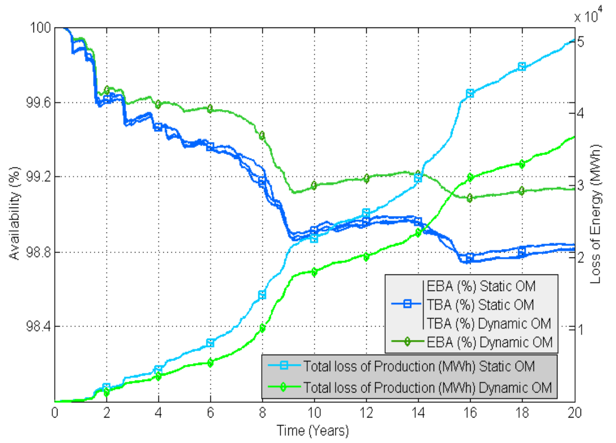

Figure 6. TBA and EBA comparison

In fact, if the wind speed at which the preventive maintenance is performed is analysed, one can notice that it is lower for the dynamic OM (see Figure 7), implying, as stated, an increase in the generated power.

Finally, it is a further significant finding that the improvement in the EBA is not at the expense of a higher LCC. On the contrary, LCC is also slightly improved, near a 2%, mainly due to the avoided penalty costs and the opportunity costs related to the committed but not provided energy amount.

5 CONCLUDING REMARKS

Different opportunistic maintenance optimisation models have been proposed during the last years in order to find a more efficient maintenance management. However, it is difficult to find opportunistic maintenance optimisation models that consistently align the maintenance and the business objectives.

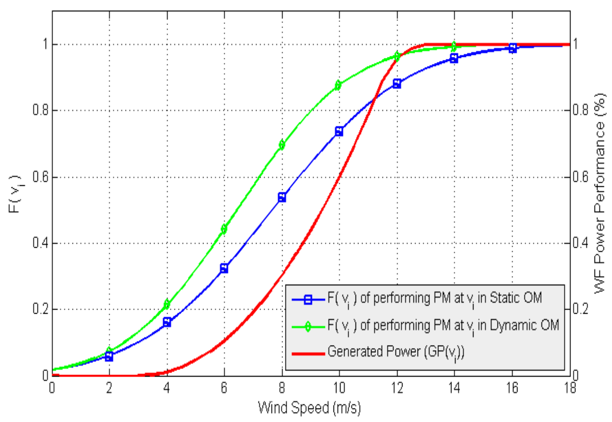

Figure 7. Wind speed during PM performance

In this paper, a novel dynamic opportunistic maintenance approach that allows the systematic alignment between the maintenance and the business strategies is presented. To this aim, the thresholds that define the opportunistic maintenance strategies have been set dynamic. Therefore, depending on the specific operational and business context, the thresholds vary in order to foster or hinder the preventive opportunistic maintenance activities, according to the main business interest. Due to the difficulties that might arise during the implementation of the defined approach, a framework that bears all the phases to be followed during the definition and the application of the methodology is also presented; further illustrating it through a real wind energy case study.

Results obtained in the case study demonstrate that the dynamic opportunistic maintenance improve the results provided by the traditional static opportunistic maintenance strategies, both in terms of productivity and cost. Furthermore, the dynamic opportunistic maintenance allows to consistently aligning the maintenance and business strategies, improving the main business KPI considered in almost a 30%.

Nevertheless, the authors are aware of the limitations of the defined approach, and thus, further research lines will be conducted. According to the limitations, the actions will be focused on studying the most suitable methodologies and tools to be used in each of the phases set in the framework, making especial emphasis on the modelling of the dynamic thresholds. Moreover, the dynamic opportunistic maintenance will also be applied to different sectors, with different features and goals, in order to test its suitability and flexibility for aligning the maintenance and business strategies in different contexts.

REFERENCES

Abdollahzadeh, H., Atashgar, K., Abbasi, M. 2016. Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups. *Renewable Energy* 88, 247-261. http://dx.doi.org/10.1016/j.renene.2015.11.022

Atashgar, K., Abdollahzadeh, H. 2016. Reliability optimization of wind farms considering redundancy and opportunistic maintenance strategy. *Energy Conversion and Management* 112, 445-458. http://dx.doi.org/10.1016/j.enconman.2016.01.027

Dekker, R. 1996. Applications of maintenance optimization models: a review and analysis. *Reliability Engineering & System Safety* 51 (3), 229-240. http://dx.doi.org/10.1016/0951-8320(95)00076-3

Erguido A., Crespo Márquez A., Castellano E., Gómez Férnandez J.F. A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of Wind Farms. *Paper submitted under review*

Garg, A., Deshmukh, S. 2006. Maintenance management: literature review and directions. *Journal of Quality in Maintenance Engineering* 12 (3), 205-238. http://dx.doi.org/10.1108/13552510610685075

González E., Nanos E. M., Seyr H., Valldecabres L., Yurusen N. Y. 2016. Key performance indicators for wind farm operation and maintenance. *1st Joint Industry Workshop – Scientific Report*

Horenbeek, A. V., Pintelon, L. 2013. A dynamic predictive maintenance policy for complex multi-component systems. *Reliability Engineering & System Safety* 120, 39-50. http://dx.doi.org/10.1016/j.ress.2013.02.029

Horenbeek, A. V., Pintelon, L., Muchiri, P. 2010. Maintenance optimization models and criteria. *International Journal of System Assurance Engineering and Management 1* (3), 189-200. http://dx.doi.org/10.1007/s13198-011-0045-x

Hou, W., Jiang, Z. 2013. An opportunistic maintenance policy of multi-unit series production system with consideration of imperfect maintenance. *Applied Mathematics and Information Sciences* 7 (1L), 283-290.

Huynh, K. T., Barros, A., Berenguer, C. 2015. Multi-level decision-making for the predictive maintenance of k-out-of-n deteriorating systems. *IEEE Transactions on Reliability* 64 (1), 94-117. http://dx.doi.org/10.1109/TR.2014.2337791

Iung, B., Do, P., Levrat, E., Voisin, A. 2016. Opportunistic maintenance based on multi-dependent components of manufacturing system. *CIRP Annals - Manufacturing Technology* 65 (1), 401-404. http://dx.doi.org/10.1016/j.cirp.2016.04.063

Karki, R., Patel, J. 2008. Reliability assessment of a wind power delivery system. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 223 (1), 51-58. http://dx.doi.org/10.1243/1748006XJRR218

Keizer, M. C. O., Teunter, R. H., Veldman, J. 2016. Clustering condition-based maintenance for systems with redundancy and economic dependencies. *European Journal of Operational Research* 251 (2), 531-540. http://dx.doi.org/10.1016/j.ejor.2015.11.008

Laggoune, R., Chateauneuf, A., Aissani, D. 2010. Impact of few failure data on the opportunistic replacement policy for multi-component systems. *Reliability Engineering & System Safety* 95 (2), 108-119. http://dx.doi.org/10.1016/j.ress.2009.08.007

Laguna, M., Martí, R. 2003. The optquest callable library. In: *Optimization Software Class Libraries. Springer*, pp. 193-218. http://link.springer.com/chapter/10.1007/0-306-48126-X_7

Márquez, A. C., de León, P. M., Rosique, A. S., Fernández, J. F. G. 2015. Criticality analysis for maintenance purposes: A study for complex in-service engineering assets. *Qual. Reliab. Engng. Int*. 32 (2), 519-533. http://dx.doi.org/10.1002/qre.1769

Nicolai, R., Dekker, R. 2007. A review of multi-component maintenance models. In: *Proceedings of European Safety and Reliability Conference*. pp. 289-296. URL http://www.dimat.unina2.it/marrone/dwnld/Proceedings/ESREL/2007/Pdf/CH036.pdf

Shi, H., Zeng, J. 2016. Real-time prediction of remaining useful life and preventive opportunistic maintenance strategy for multi-component systems considering stochastic dependence. *Computers & Industrial Engineering* 93, 192-204. http://dx.doi.org/10.1016/j.cie.2015.12.016

Teece, D. J. 2007. Explicating dynamic capabilities: the nature and microfoundations of (sustainable) enterprise performance. *Strategic Management Journal* 28 (13), 1319-1350. http://dx.doi.org/10.1002/smj.640

Tian, Z., Jin, T., Wu, B., Ding, F. 2011. Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy* 36 (5), 1502-1509. URL http://dx.doi.org/10.1016/j.renene.2010.10.028

Wang, H. 2002. A survey of maintenance policies of deteriorating systems. *European Journal of Operational Research* 139 (3), 469-489. URL http://dx.doi.org/10.1016/S0377-2217(01)00197-7

Wildeman, R., Dekker, R., Smit, A. 1997. A dynamic policy for grouping maintenance activities. *European Journal of Operational Research* 99 (3), 530-551. http://dx.doi.org/10.1016/S0377-2217(97)00319-6

Zhou, X., Lu, Z., Xi, L. 2012. Preventive maintenance optimization for a multi-component system under changing job shop schedule. *Reliability Engineering & System Safety* 101, 14-20. http://dx.doi.org/10.1016/j.ress.2012.01.005

Zhou, Y., Zhang, Z., Lin, T. R., Ma, L. 2013. Maintenance optimisation of a multi-state series parallel system considering economic dependence and state-dependent inspection intervals. *Reliability Engineering & System Safety* 111, 248-259. http://dx.doi.org/10.1016/j.ress.2012.10.006

Zhu, W., Fouladirad, M., Bérenguer, C. 2016. A multi-level maintenance policy for a multi-component and multifailure mode system with two independent failure modes. *Reliability Engineering & System Safety* 153, 50-63.

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After-sales services optimisation through dynamic opportunistic maintenance. A Wind energy case study.

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Abstract

After-sales maintenance services can be a very profitable source of income for original equipment manufacturers (OEM) due to the increasing interest of assets' users on performance-based contracts. However, when it concerns the product value-adding process, OEM have traditionally been more focused on improving their production processes, rather than on complementing their products by offering after-sales services; consequently leading to difficulties in offering them efficiently. Furthermore, due to both the high uncertainty of the assets' behaviour and the inherent challenges of managing the maintenance process (e.g. maintenance strategy to be followed or resources to be deployed), it is complex to make business out of the supply of after-sales services. With the aim of helping the business and maintenance decision makers at this point, this paper proposes a framework for optimising the income of after-sales maintenance services through: 1) implementing advanced multi-objective opportunistic maintenance strategies that systematically consider the assets' operational context in order to perform preventive maintenance during most favourable conditions, 2) considering the specific OEMs' and users' needs, and 3) assessing both endogenous and exogenous uncertainties that might condition the after-sales services' success. The developed case study for the wind energy sector demonstrates the suitability of the presented framework for optimising the after-sales services.

Keywords

After-Sales Services, Life Cycle Cost, Uncertainty Assessment, Dynamic Opportunistic Maintenance, Multi-Objective Optimisation, Wind Energy Sector

1 Introduction

After-sales service is fast becoming a key instrument in the relationship between the Original Equipment Manufacturers (OEM) and the asset users. In general, asset users are more frequently asking for such services, and the OEMs are willing to satisfy them due to the several benefits that they are able to obtain, such as: recurrent stream of revenues generated throughout the life cycle of the assets, which usually exceeds the profit margins of new equipment sales[1]; extra value added to sold equipment, used as a competitive differentiating feature[2]; increase of the asset users' satisfaction and loyalty[3,4], etc.

Accordingly, many OEMs have already successfully integrated the after-sales services within their business, having transformed it in a business core[2]. Nevertheless, some others, such as machinery fabrication companies, have traditionally been more focused on new equipment design and sale rather than on offering after-sales services to their clients; having now difficulties in properly deploying such services[5].

The main problems when defining the after-sales services arise when the key factors that drive the system performance have to be identified and their influence on operational availability has to be measured[6]. Furthermore, there are several uncertainty sources that have to be dealt with during the after-sales services' deployment, such as cost or repair processes, which make it difficult to guarantee a determined service level and a price for providing it[7,8].

In this context, the development of maintenance models plays a key role, since they enable to calculate the quality of the after-sales service (through reliability, availability and maintainability analysis), and the cost associated to that service (through life cycle cost (LCC) analysis); allowing to find a trade-off between the service level to be offered and its price. Moreover, when such maintenance models are developed, the impact of uncertainty sources can also be measured, accurately providing the decision-maker with the necessary information to anticipate the risks to be handled within the after-sales service contracting. Accordingly, the after-sales service success and the satisfaction of every stakeholder involved in the contract will be fostered.

To the best of the authors' knowledge, there is not previous research that 1) categorises the uncertainty sources to be dealt with in the after-sales services, 2) analytically derives

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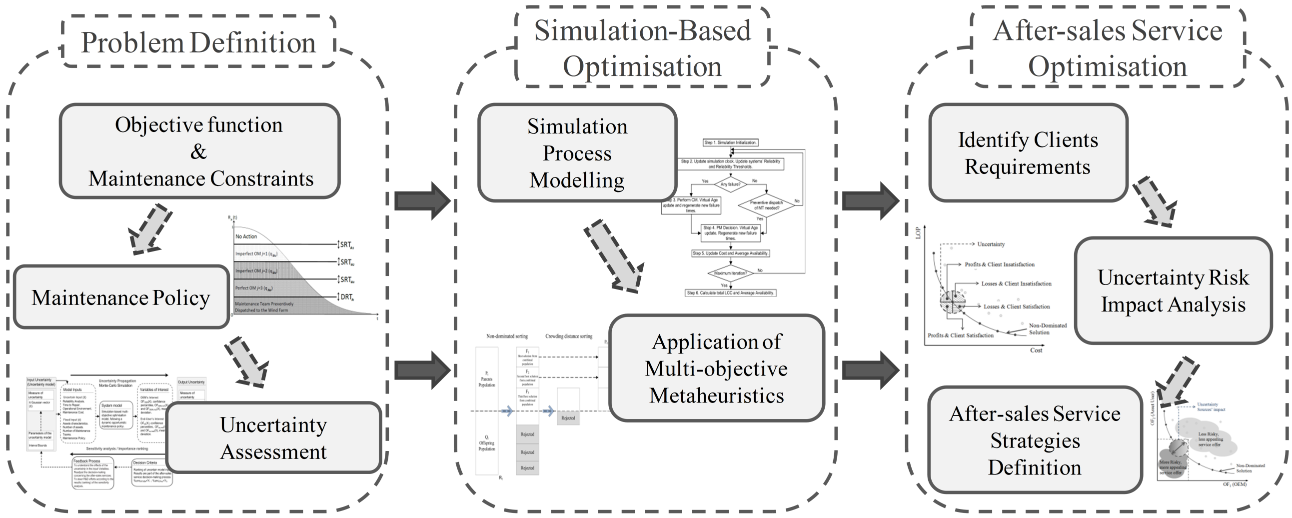


Figure 1. Proposed approach (figures are shown in detail during the paper)

their impact in terms of both the after-sales service level and its profitability and 3) provides managerial insights illustrated through a numerical experiment based on real-field data, enriching its practitioner approach.

Therefore, it is the aim of this paper to address these specific issues, for which different steps have been taken, classified into 3 main phases (see Figure 1):

1. Problem definition. Within this phase the maintenance problem is defined, identifying the maintenance constraints for deploying the after-sales service and the main objectives of both the OEM and the asset user. Likewise, the maintenance policy to be followed during the after-sales service is established and the main uncertainty sources are identified.
2. Simulation-based optimisation. Simulation techniques are used in order to handle the several stochastic processes to be born within the after-sales maintenance services and to evaluate the different strategies [9,10]. Since both the interests of the OEM and asset users should be met by the defined after-sales maintenance services, a multi-objective meta-heuristic is implemented for finding the efficient frontier of the service level vs cost curve (non-dominated optimal maintenance strategies), in a simulation-based optimisation approach [11].
3. After-sales Service optimisation. Before offering the after-sales service, the asset users are characterised and their requirements are identified. Based on the two previous phases and with the aid of a sensitivity analysis, the impact of uncertainty sources on the after-sales service is analyzed, in order to be able to assess the economical risk of the after-sales service to be offered.

The paper is organized as follows. In section 2 a brief summary of the literature is performed. Section 3 addresses the uncertainty impact and assessment on the after-sales service. In section 4 the system model for managing the after-sales services in the wind energy sector is developed. In section 5 the computational results based on real field data are shown. Finally, section 6 summarizes the main conclusions of the research and establishes future research lines.

2 State of the art

The present work is associated with multiple literatures, but the three most directly related literatures are on after-sales services, uncertainty assessment and maintenance optimisation models (specifically applied to the wind energy sector).

2.1 *After-sales services*

To date, the literature has distinguished two different types of after-sales services [6,7]: material contract and Performance Based Contracting (PBC). While under a material contract the asset users pay to the OEM the services related to the maintenance activity (i.e. spare parts or labour time), under the PBC a service level of the assets is ensured by the OEM at the asset user site.

Traditionally, most of the service agreements have been related to material contracts. However, the paradigm is currently changing to PBC due to the interest of asset users on the availability of their systems rather than on the resources used for maintaining them [7]. Therefore, on this new context, the asset users will explicitly define the service level that they require, and the OEMs will determine how to fulfil that requirement [13], i.e. defining their after-sales maintenance strategy.

The most widely used PBC payment forms can be classified as fixed or variable price:

1. Fixed payment method. There are two basic approaches depending on the uncertainty related to the sold asset [14]: fixed price, where the OEM assumes all the risk of the contract (asset with lower uncertainty), and cost plus fixed price, where the risk is assumed by the asset user (asset with higher uncertainty). In both cases, the OEMs will prefer to minimize the LCC of the committed service in order to maximize their profits [15].
2. Variable payment methods. The OEMs will be rewarded if certain goals related to the service level are

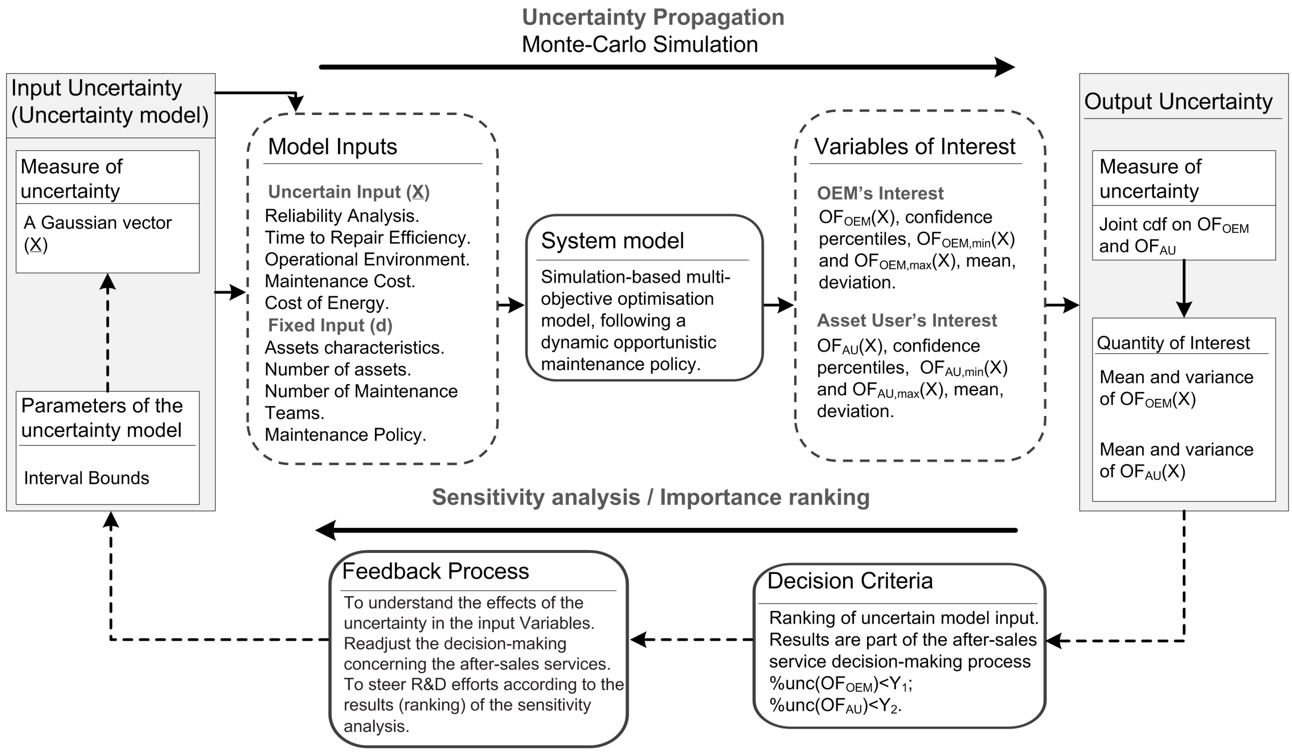


Figure 2. Uncertainty framework for after-sales services, adapted from [12]

achieved. Thus, OEMs will be focused on maximizing both their interests and the asset users' interests [16].

In the wind power industry, maintenance activities are usually performed by the OEM under a material contract, which implies lucrative revenues for the OEM. Nevertheless, such contract model generates financial pressures on the wind farmers and does not ensure the OEMs' efforts on improving their assets' reliability, which suggests that a change of paradigm to PBC will be given [14]. Under the PBC, the asset users would be able to focus on their core business (delivering reliable and clean energy), while the OEMs would keep longer service agreements [14].

2.2 *Uncertainty assessment*

There are plenty of uncertainty sources that might condition the after-sales service, jeopardising its success, and thus, the OEMs' profits and asset users' service level [7]. These uncertainty sources might be classified in endogenous, when the OEM has influence over the uncertainty source to a greater extent, and exogenous, when there is lesser influence over them [17]. Whereas the formers are mainly related to product and organization factors, such as technology, data quality or system model accuracy; the latters are provoked by forces outside from the control of the organizations, such as, changes in environmental conditions, market evolution (new competitors/products arrival, innovations, financial changes, etc.) or political and cultural context (products regulations, protocols, etc.).

Both endogenous and exogenous uncertainties should be considered within the uncertainty analysis. However, the decision-makers' efforts should be rather focused on minimising the formers [12] in order to reduce the risk of the after-sales service deployment; understanding the risk as the effect of the uncertainty impact on OEMs' and asset users' objectives [18].

Generally, these uncertainties, which are quantified through statistical analysis and confidence or tolerance intervals [19,20], should be assessed in industrial practice at different levels [12] (see Figure 2):

1. The system model, which aims to numerically describe the real industrial problem and obtain some outputs (variables of interest) according both to fixed and uncertain inputs (developed in Section 4).
2. Uncertainty sources, which might appear both in the inputs parameters and in the system model, and will propagate the uncertainty until the output (respectively studied in Sections 3 and 5).
3. Actions related to the decision making process regarding the feedback process based on the analysis of the uncertainty impact on the quantities of interest (see Section 5).

Likewise, the general goals when assessing the uncertainty can be classified in [12]: to understand its influence on the model in order to improve the decision making-process; to accredit a certain level of uncertainty for accepting the use of a model; to compare relative performance and select the best maintenance policy or operation of the system; and to comply or demonstrate that a certain criterion regarding uncertainty is met.

For the present research, the main goals will be related to the identification and assessment of the main uncertainty sources regarding the after-sales services, mainly due to the maintenance processes and strategies adopted [7]. Therefore, it will be possible to measure the risk of the different after-sales services to be deployed, comparing them and selecting the most appropriate one. Likewise, as a further result, the

Table 1. Nomenclature and Acronyms definition

Nomenclature			
LCC	Life Cycle Cost	w_{ik}	Reactivity weight
LP	Loss of Power	K	Number of FM considered for each system
OF	Objective Function	J	Levels of PM types considered for each FM
WF	Wind Farm	GRP	Generalized Renewal Process
WT	Wind Turbine	VA_{hikt}	Virtual age associated to FM k in system i in WT h in period t
FM	Failure Mode		
CM	Corrective Maintenance	α_{ik}	Weibull scale parameter of FM k of system i
PM	Preventive Maintenance	β_{ik}	Weibull shape parameter of FM k of system i
OEM	Original Equipment Manufacturer	q^{pr}_{ikj}	Restoration factor of j PM level on system i for FM k
AU	Asset user	q^{c}_{ik}	Restoration factor of CM on system i for FM k
TTF	Time To Failure	NT	Number of MTs
MT	Maintenance Team	c^{c}_{ik}	Cost of tools and materials needed for performing CM of FM k in system i
v_t	Average wind speed in period t		
GP_t	Generated Power in period t	c^{pr}_{ikj}	Cost of tools and materials needed for performing PM j of FM k in system i
RP	Rated Power of the WT		
$R_{ik}(VA)$	Reliability of system i and FM k at virtual age VA	c^{team}	Cost of MT
SRT_{ikj}	Fixed Reliability Threshold for applying perfect or imperfect PM j on system i and FM k	c^{et}	Extra time cost
		c^{disp}	cost of maintenance dispatch
SRT_{ikjt}	System Reliability Threshold in period t for applying perfect or imperfect PM j system i and FM k	c^{na}	cost of No Availability or opportunity cost
		c^{p}	Penalty cost due to unplanned maintenance
DRT_{ik}	Fixed Dispatch Reliability Threshold	m^{c}_{ik}	Maintainability of CM for FM k in system i
DRT_{ikt}	Dispatch Reliability Threshold in period t	m^{pr}_{ik}	Maintainability of PM for FM k in system i
V	Wind speed threshold for determining reliability thresholds variation	C	Capacity of each MT (in hours)
		NT^{max}	Maximum number of MTs
p	Periods of time considered for wind speed forecasting	T	Maximum iteration periods

decision-maker will be able to rank the uncertainty sources, and thereby, guide their decisions in order to reduce them.

2.3 Maintenance optimisation models

As stated, in order to successfully structure the after-sales service, it is necessary to develop adequate maintenance models that find the efficient frontier of the service quality vs cost curve [2].

Wang's comprehensive review [21] about the maintenance optimisation models classifies them into two main categories: single-unit systems and multiple-unit systems. In both cases, the maintenance decision making process relies on the usual indicators, such as, assets' age, reliability, number of failures, etc. However, the formers tend to overlook the fact that the assets are very complex, consisting of several systems and subsystems, which can present economical, structural or stochastic dependencies among them that condition the maintenance performance (see [22]).

In this context, multiple-unit maintenance policies, which consider such dependencies, enable to find more suitable maintenance solutions [21]. Accordingly, there has been a growing interest in the utilisation, modelling and optimisation of such maintenance policies.

It is the case of opportunistic maintenance policy, which due to its capacity for including short term information in order to improve maintenance performance [23], has been widely researched lately [24]. According to Ba et al. [25], the short term information included within the opportunistic maintenance can be both regarding internal, e.g. assets' dependencies, and external factors, e.g. production schedule. In the specific context of the after-sales service offer, external factors play a key role, since beyond the dependencies among the assets, the needs of the asset users should be continuously regarded within the maintenance decision making process.

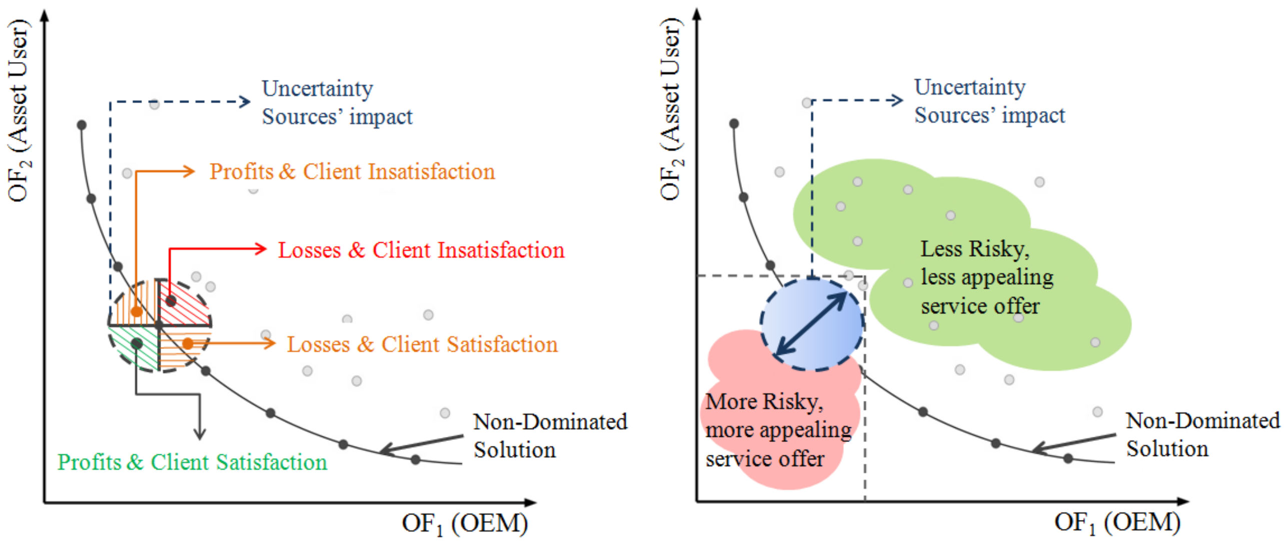
On the particular case of the wind energy sector, opportunistic maintenance policies have been widely researched as well, mainly favoured by the economical dependencies among the wind turbines [26]. Nevertheless, to date, researches on opportunistic maintenance in the wind energy sector have been mainly related to the internal factors, rather than to the external factors: redundancies [27], condition monitoring systems [26,28,29], multi-level maintenance [30,31], etc.

Therefore, on this specific research, the novel dynamic opportunistic maintenance proposed by the authors has been adopted, since it enables to consider both internal and external factors [32], more suitable for the after-sales service context.

3 Uncertainty assessment on the after-sales service

In order to be able to manage the several uncertainty sources that might jeopardize the success of the after-sales service deployment, the framework for assessing the uncertainty in industrial practices proposed by Rocquigny et al. [12] has been adopted and particularised for this specific application in Figure 2.

In the particular case of the after-sales services, the propagation and impact of the uncertainty sources in the variables of interest should have a double perspective, since the output of the model should consider both the OEMs' and the asset users' interests, which could respectively be the minimization of service cost and service disruptions (see Figure 2).



(a) Uncertainty influence on OEMs' and Asset Users' Interests

(b) Service Appeal for the asset user VS Risk of the after-sales service success

Figure 3. Uncertainty impact on the after-sales service

Figure 3 illustrates the impact that the uncertainty sources might have in practice: whereas the model should give an after-sales strategy that optimises both the OEMs' and the asset users' interests (non-dominated solution), in the practice, this solution will not be so accurate -due to the uncertainty sources-, being probable to provide a final output that does not meet stakeholders' interests.

Accordingly, the uncertainty might lead to different scenarios depending on the output variables' results: both the OEM and the asset user are satisfied, neither of them is satisfied, or only one of them is satisfied (see Figure 3a). Since every stake has to be satisfied by the after-sales service in order to consider it successful, it is essential to measure the impact of the uncertainty sources within the interest variables; otherwise the success of the after-sales service will be jeopardised. This impact, which in Figure 3 has been represented through the diameter of the circle, can be measured by analyzing the joint probability distribution function of the interest variables (see Figure 2).

The OEM should be aware of this uncertainty impact within the definition of the after-sales service, in order to search a scenario where both the OEM and the asset user are satisfied. In fact, decisions very conservative from the OEM perspective (higher service cost, lower service level) might lead to an after-sales service less appealing for the asset users, and vice versa (see Figure 3b). Thus a trade-off should be found between offering an appealing service for the asset users and a successful after-sales service.

Furthermore, once the OEM is able to quantify the uncertainty impact, they will be able to rank the uncertainty sources according to their impact on the variables of interest through a sensitivity analysis. Consequently, they will be able to focus their research efforts on reducing these uncertainties and their impact, especially regarding the endogenous uncertainties, and offering more appealing and less risky after-sales services in the future.

4 System model for managing after-sales services in the wind energy sector

On this section, the whole system for managing the after-sales service in the wind energy sector is modelled, defining the specific problem, maintenance policy to be followed, deriving the analytical formulation of OEMs and asset users' quantities of interest and the optimisation problem.

4.1 Problem definition

The wind farm (WF) consists of H wind turbines (WTs) of similar characteristics that have N critical systems connected in series. Each system might fail in k different failure modes (FMs) classified according to their severity (k = 1,2,...,K), for which in case of failure, k corrective maintenance (CM) will be performed. Likewise, prior to a failure occurrence, systems can undergo different preventive maintenance (PM) levels, either perfect or imperfect (j = 1,2,...,J).

When the PM activity restores the system to an operational condition worse than the new one but better than just before the maintenance task is performed, it will be considered an imperfect action. However, if the PM restores the system to an operational condition as good as the new one, i.e. replacement, it will be considered a perfect action (see[33] for further information). Accordingly, in this research $j = J$ is considered a perfect repair and $j = 1$ the most imperfect repair.

Among the several studies that have investigated the restoration effect of maintenance (see[33]), the Generalized Renewal Process (GRP) proposed by Yañez et al.[34] is specifically utilised in the present problem. The GRP provides flexibility for modelling both the behaviour of the systems before failures and the quality of repairs during the different life stages of the systems by the definition of two main concepts (see Eq.1):

- Rejuvenation parameter ($q_{ij} = [0, 1]$), which is associated to the efficiency of the restoration effect of the maintenance activity j on the system i ($q = 0$ for the most imperfect maintenance and $q = 1$ for perfect maintenance)

- Virtual age (VA), which identifies the system's age after being repaired, and thus, it's reliability.

$$VA_i^{new} = VA_i^{old}(1 - q_{ij}) \quad (1)$$

Accordingly, after an imperfect repair, failure probability distribution conditioned to the survival of the new virtual age is calculated through Eq.2. Due to the suitability of the Weibull distribution when modelling the WTs' systems' reliability[35,36], Eq.2 has been ad hoc particularized in Eq.3 according to the scale (α_{ik}) and shape parameters (β_{ik}) that define the Weibull distribution for each FM k of system i (the reader is addressed to[34] for further information):

$$F\left(t|VA_i^{new}\right) = P\left[T_{ij} \leq t | T_{ij} > VA_i^{new}\right] = \frac{F(t) - F\left(VA_i^{new}\right)}{1 - F\left(VA_i^{new}\right)} \quad (2)$$

$$R\left(t|VA_{hik}^{new}\right) = 1 - F\left(t|VA_{hik}^{new}\right) = exp\left[\left(\frac{VA_{hik}^{new}}{\alpha_{ik}}\right)^{\beta_{ik}} - \left(\frac{t}{\alpha_{ik}}\right)^{\beta_{ik}}\right] \quad (3)$$

Likewise, both fixed and variable maintenance costs are considered in the problem. According to the formers, performing any maintenance implies a relevant dispatch cost (c^{disp}), a material cost (c_{ik}^c, c_{ik}^{pr}), an opportunity cost (c^{na}) in terms of not produced energy, a penalty cost (c^p) in case a failure hinders the distribution of committed energy, and an extra cost (c^{et}) regarding outsourced maintenance activities if there are not own resources available for performing CM. In fact, own human resources, which consist of a number of maintenance teams (NT^{max}) with a certain capacity (C), are considered to be the main fixed cost (c^{team}). Both own and outsourced resources will directly depend on the required time to repair the systems, according to the maintainability of each FM (m_{ik}^c, m_{ik}^{pr}).

Finally, without loss of generality, some assumptions have been made for the problem formulation:

1. Degradation processes of the systems are considered independent from each other and they are associated to the operation time (ageing systems, with increasing failure rate).
2. Data pooling procedure has been followed for performing the reliability analysis, since the fleet of WTs within a WF can be considered identical according to the coupling factors proposed by Stamatelatos et al.[37]
3. Reliability of the FMs follows the Weibull distribution, with scale parameter α and shape parameter β.
4. Maintenance activities should be finished during the period of time in which they are started.
5. A maintenance dispatch is considered per period of time, where several maintenance teams (MTs) can be dispatched.
6. PM is assumed to be less resource-consuming than CM.
7. WF maintenance managers make decisions in discrete time and frequently[38].

4.2 Dynamic opportunistic maintenance policy

In this study, the dynamic opportunistic maintenance policy proposed by the authors[39] is followed, since it enables the consideration of short term information, regarding both internal and external factors, within the maintenance decision making process. In particular, the internal factors are considered through the economic dependence among the WTs[40,41] and the external factors through their specific operational context. To this aim, the maintenance decision making process relies on two different dynamic reliability thresholds levels, which will release the maintenance activities based on the reliability of the FMs (see Figure 4):

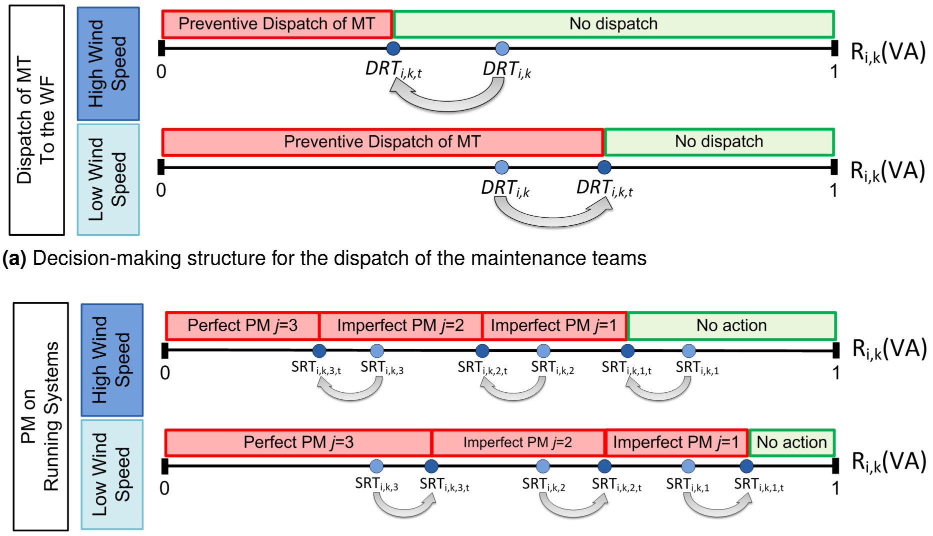
- Dispatch reliability threshold (DRT_{ikt}): it determines whether a maintenance team should be preventively dispatched to the WF for performing PM, ensuring a minimum reliability for each FM and system. Consequently, if the reliability of any FM is below DRT_{ikt}, a maintenance team is dispatched to the WF (see Figure 4a).
- System reliability threshold (SRT_{ikjt}): once a maintenance team has been dispatched to the WF, it determines whether PM level j should be performed during period t for preventing FM k of system i. Accordingly, if the reliability of any FM is below SRT_{ik2t} and above SRT_{ik3t}, imperfect PM j=2 should be performed (see Figure 4b).

The novelty of the dynamic maintenance policy remains on systematically considering the operational context of the assets, dynamically recalculating the reliability thresholds' value in order to release the maintenance activities during the most suitable operational contexts. In the particular case of the wind energy case study, there are several reasons for trying to avoid the performance of PM during high wind speed periods:1) WTs must be stopped during PM, 2) the profits of the WF are directly related to the wind speed[42] and 3) maintenance activities should be released during low wind speed periods for workers' safety[43].

Accordingly, the dynamic maintenance policy proposed is focused on fostering the PM activities during low wind speed periods and hindering them during high wind speed periods. To this aim, as shown in Figure 4, DRT_{ikt} and SRT_{ikjt} are increased during low wind speed periods (preventive maintenance is fostered) and are decreased during high wind speed periods (preventive maintenance is hindered). Therefore, two of the most conflicting objectives to be born in the wind energy sector are achieved[44]: to reduce the wind energy power losses while reducing the total maintenance cost.

In order to define the thresholds variation with regards to the specific operational context, it will be determined by the following factors (see Eq.4-6):

1. Wind speed threshold (V): it determines if the reliability threshold should be decreased or increased according to the forecasted wind speed during the next



(a) Decision-making structure for the dispatch of the maintenance teams

(b) Decision-making structure for performing PM. Example with 3 PM levels per FM

Figure 4. Decision-making structure for the dynamic opportunistic maintenance model

p periods. If the forecasted wind speed average is above V, W_t will acquire value 0, and according to the block $(2W_t - 1)$ in Eq.4 and 5, the thresholds will be decreased in order to hinder PM. Otherwise, when the wind speed forecast is below V, the thresholds will be increased in order to foster PM. (Eq.6).

2. Generated power (GP_t) and reactivity weight (w_{ik}): they determine the gradient of the reliability thresholds. On the one hand, the reactivity weight $(0 \leq w_{ik} \leq 1)$ directly balances the impact of the wind speed on the reliability thresholds. On the other hand, the use of W_t in block $(\frac{RP}{GP_t + RP \cdot W_t})^{(2W_t - 1)}$ (Eq.4 and 5) ensures that the gradient is proportional to the difference between the generated power at each time period (GP_t) and the rated power of the WTs (RP). Accordingly, the greater the difference between GP_t and RP, the greater the thresholds variation. Furthermore, the inclusion of W_t in this block ensures that the gradient is normalized in a [0,1] interval both in high and low wind speed periods.

$$SRT_{ikjt} = SRT_{ikj} + (2W_t - 1) \cdot SRT_{ikj} \cdot w_{ik} \cdot (\frac{RP}{GP_t + RP \cdot W_t})^{(2W_t - 1)} \quad (4)$$

$$DRT_{ikt} = DRT_{ik} + (2W_t - 1) \cdot DRT_{ik} \cdot w_{ik} \cdot (\frac{RP}{GP_t + RP \cdot W_t})^{(2W_t - 1)} \quad (5)$$

$$W_t = \begin{cases} 1 & \sum_{l=t}^{t+p} \frac{v_l}{p} \leq V \\ 0 & \sum_{l=t}^{t+p} \frac{v_l}{p} > V \end{cases} \quad (6)$$

4.3 LCC and LP analysis

In order to make profits out of the after-sales service, the OEMs should be able to accurately estimate both the LCC of their assets and the service level that they are able to offer to the asset users, concerning among others: reliability, availability and maintainability (RAM). Accordingly, the main costs to be born in the wind energy sector regarding maintenance and after-sales service, i.e. CM, PM, dispatch and human resources costs, and the offered service level, through the lost power ((LP), have been analytically derived in this Subsection.

According to the CM and PM cost (see Eq.7 and Eq.8 respectively), material and tools requirements $\left(c^c_{ik}, c^{pr}_{ikj}\right)$ and costs due to the non availability caused by maintenance have been considered, according to the downtime $\left(m^c_{ik}, m^{pr}_{ikj}\right)$ and the non-generated power during the maintenance period (GP_t), modelled as in Karki and Patel[42]. Whereas in the CM a penalty cost should be considered for committed but not provided power (c^p), in the PM the unique cost associated to the non-available periods is the opportunity cost of not being producing energy (c^{na}). As in other reviewed studies[45,46], the cost of imperfect maintenance has been associated to the restoration factor of the maintenance activity (q).

$$z_{hikt} \cdot \left[c^c_{ik} \cdot (q^c_{ik})^2 + m^c_{ik} \cdot GP_t \cdot (c^{na} + c^p)\right] \quad (7)$$

$$y_{hikjt} \cdot \left[c^{pr}_{ikj} \cdot \left(q^{pr}_{ikj}\right)^2 + m^{pr}_{ikj} \cdot GP_t \cdot c^{na}\right] \quad (8)$$

Likewise, every time that maintenance has to be performed, a maintenance team should be dispatched to the WF (Eq.9), which implies a cost $\left(c^{disp}\right)$. Accordingly, a number of maintenance teams (NT) will be internally hired at a cost (c^{team}) by the company in order to perform maintenance. However, if a failure happens and there are no own maintenance teams available for maintenance, external resources (ET_t) should be hired at an extra cost (c^{et}) (Eq.10).

$$(\gamma_t + \theta_t) \cdot c^{disp} \quad (9)$$

Table 2. Intermediate Binary variables utilised in the model

$z_{hikt} = \begin{cases} 1 & if\, CM\, k\, is\, performed\, in\, system\, i\, of\, WT\, h\, in\, period\, t \\ 0 & otherwise \end{cases}$	$y_{hikjt} = \begin{cases} 1 & if\, PM\, j\, is\, performed\, in\, FM\, k\, of\, system\, i\, of\, WT\, h\, in\, period\, t \\ 0 & otherwise \end{cases}$
$\theta_t = \begin{cases} 1 & if\, a\, MT\, is\, correctively\, dispatched\, to\, WF\, in\, period\, t \\ 0 & otherwise \end{cases}$	$\gamma_t = \begin{cases} 1 & if\, a\, MT\, is\, preventively\, dispatched\, to\, WF\, in\, period\, t \\ 0 & otherwise \end{cases}$

$$ET_t \cdot c^{et} + NT \cdot c^{team} \tag{10}$$

Thereby, considering the long term nature of the LCC analysis, for which the cost has to be properly updated to present value according to the interest rate (k_a), the LCC can be defined as follows (Eq.11).

$$LCC\,(DRT_{ik,}SRT_{ikj}) = \Bigg[\sum_t (\gamma_t + \theta_t) \cdot c^{disp}$$
$$\sum_h \sum_i \sum_k \sum_t z_{hikt} \left[c^c_{ik}\,(q^c_{ik})^2 + m^c_{ik} \cdot GP_t\,(c^{na} + c^p)\right] +$$
$$\sum_h \sum_i \sum_k \sum_j \sum_t y_{hikjt} \left[c^{pr}_{ikj}\left(q^{pr}_{ikj}\right)^2 + m^{pr}_{ikj} \cdot GP_t \cdot c^{na}\right]$$
$$\sum_t ET_t \cdot c^{et} + \sum_t NT \cdot c^{team}\Bigg] \cdot (1 + k_a)^{-t} \tag{11}$$

As stated, the OEM should as well be aware of the service level that is able to provide at the mentioned cost. Particularly, in the wind energy sector the service level can be measured according to the lost power[47] (Eq.12).

$$LP = \sum_t GP_t \cdot \Bigg(\sum_h \sum_i \sum_k m^c_{ik} \cdot z_{hikt} +$$
$$\sum_h \sum_i \sum_k \sum_j m^{pr}_{ikj} \cdot y_{hikjt}\Bigg) \tag{12}$$

4.4 Dynamic opportunistic maintenance optimisation model

The general mathematical formulation of the considered dynamic OM policy (see Figure 4) will take the following form, considering the DRT and SRT modelling (Eq.15-17); only a maintenance per WT at a time Eq.18); and the overall long term maintenance strategy performance according to LCC (Eq.11) and Lost Power (LP) (Eq.14):

$$OF_{OEM} = Minimize\ LCC(X) \tag{13}$$

$$OF_{AU} = Minimize\ LP(X) \tag{14}$$

$S.T.$

$$0 \leq DRT_{ik} \leq SRT_{ik1} \leq ... \leq SRT_{ikj} \leq$$
$$\leq ... \leq SRT_{ikJ} \leq 1\ i\epsilon I, k\epsilon K, j\epsilon J; t\epsilon T \tag{15}$$

$$0 \leq w_{ik} \leq 1\ i\epsilon I, k\epsilon K \tag{16}$$

$$0 \leq DRT_{ikt} \leq SRT_{ik1t} \leq ... \leq SRT_{ikjt} \leq$$
$$\leq ... \leq SRT_{ikJt} \leq 1\ i\epsilon I, k\epsilon K, j\epsilon J; t\epsilon T \tag{17}$$

$$\sum_j y_{hikjt} + z_{hikt} \leq 1\ h\epsilon H, i\epsilon I, k\epsilon K, t\epsilon T \tag{18}$$

$$z_{hikt}, y_{hikjt} \epsilon \{0,1\}\ h\epsilon H, i\epsilon I, k\epsilon K, t\epsilon T, \forall j = 1,2$$

4.5 Multi-objective Simulation-based Optimisation: NSGA II

Several stochastic processes have to be born within the maintenance model, such as failure occurrence, repair processes and weather conditions; which difficult to analytically solve the presented maintenance problem[30,45]. Thus, in order to accurately evaluate the different maintenance strategies and find optimal solutions, most of the problem has been firstly analytically derived, and secondly implemented in simulation techniques, as commonly done in other researches[31,45,48].

Particularly, an agent-based simulation has been modelled due to its suitability to handle engineering problems with multi-agent systems[49], such as the wind energy sector. The simulation process modelled can be summarized in 6 main steps (see Figure 5):

Step 1. In the simulation initialization the parameters needed for the selection of the maintenance policy and the solution of the maintenance problem are specified. On the one hand, the formers will be determined by the after-sales service manager, namely: reliability and wind speed thresholds, number of maintenance teams, etc. On the other hand, the latters will condition the maintenance solution, but they are not under the influence of the decision-maker, such as: FMs' failure and maintainability distributions or costs related to maintenance.

Step 2. The simulation clock and virtual age of each FM of the systems are updated, and their new reliability according to their age is identified (Eq.3). Likewise, the dynamic reliability thresholds are updated according to the wind speed prediction (Eq.4-6).

Step 3. If a failure happens a MT is preventively dispatched to the wind farm to perform CM. If there are not own resources available, maintenance should be outsourced

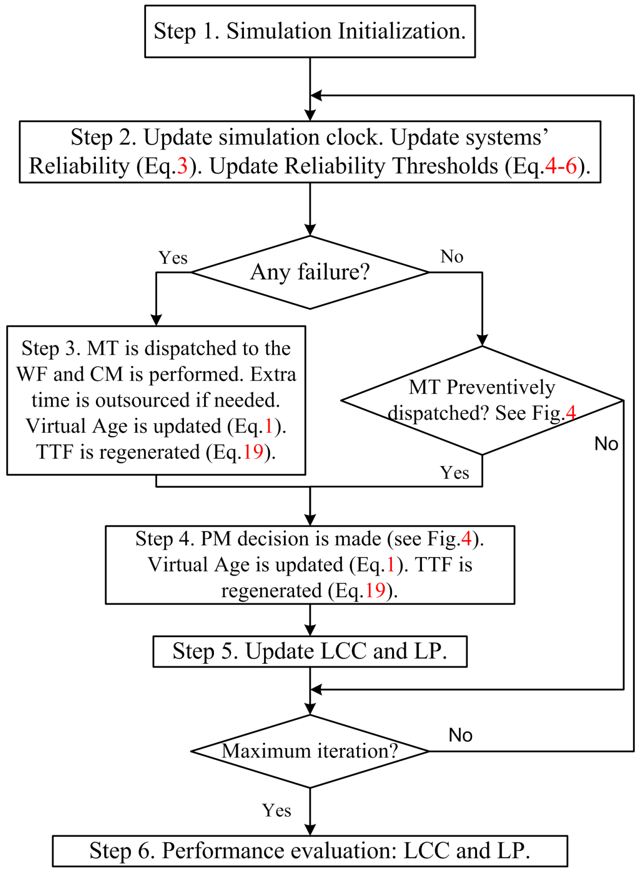


Figure 5. Simulation process for LCC and Energy-based availability evaluation

at an extra cost. After restoring the FM, its virtual age is updated and the new time to failure (TTF) is calculated through the Inverse Transform Technique[50], according to Eq.19, in which R is uniformly distributed between [0,1) (adopted from[45]).

$$TTF_{hik} = \alpha_{ik} \left[\left(\frac{VA_{hik}}{\alpha_{ik}} \right)^{\beta_{ik}} - ln\left(1 - R\right) \right]^{\frac{1}{\beta_{ik}}} - VA_{hik} \tag{19}$$

When there is not a failure in the WF, whether a MT should be preventively dispatched to the WF should be decided, according to DRT_{ikt} (Eq.4). In the case a preventive dispatch of a MT is not needed, it should be analyzed whether it is the maximum iteration period or not.

Step 4. PM decision is made according to the reliability thresholds SRT_{ikjt} (Eq.5) and the available capacity of the own resources. Virtual age of the repaired FMs is updated (Eq.3) and the new time to failure (TTF_{hik}) is calculated (Eq.19).

Step 5. LCC and Energy-based availability are updated. If the actual period is equal to the maximum iteration period, step 6 is followed. Otherwise, steps 2,3, 4 and 5 are repeated.

Step 6. The total expected LCC and the average energy-based availability are calculated for the established opportunistic maintenance policy, $LCC = f\left[SRT_{ikj}, DRT_{ik}, w_{ik}, V, p, MT\right]$.

In order to find an optimal set of dynamic reliability thresholds, and since in the after-sales service a trade-off between OEMs' and asset users' objectives should be found, the well known multi-objective meta-heuristic NSGA II[51] has been implemented for the simulation-based optimisation. The NSGA II has already been used for solving several maintenance problems[11,52] due to the high quality non-dominated solutions and the diversity on the Pareto front that it provides[53].

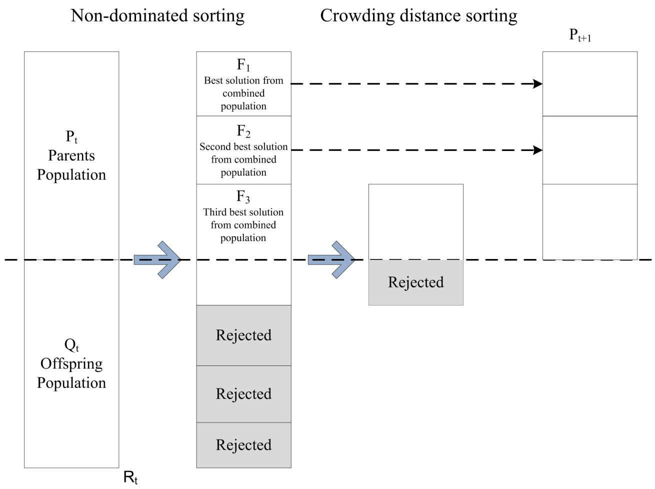


Figure 6. NSGA II procedure adopted from[51]

Figure 6 illustrates the general procedure of NSGA II, which is based on building a population of competing individuals, ranking and sorting each individual according to their non-domination level and creating a new pool of offsprings through Evolutionary Operations. Then, parents and offsprings are combined before partitioning the new combined pool into fronts. The diversity of the population is ensured through the called crowding distance, which evaluates how far is each solution from its neighbours in the front[51,54].

5 Wind Energy case study

5.1 Wind farm profile

It is considered the case in which the OEM installs a new WF consisting of 50 WTs (H = 50) of a rated power of 1,67 megawatt (MW); and the after-sales service will be based on a PBC during the whole life cycle of the assets.

For each WT the 4 most critical systems are considered (N= 4), regarding both their reliability and the consequences of their failures, according to the data available for the study. These 4 systems are: blades, gearbox, yaw system and pitch system. For each system three independent FMs are analyzed (K = 3). Particularly, k = 1 FMs of each system are assigned to sensors' false alarms, so they do not have material requirements nor need of field-maintenance. The systems can also undergo two different PM levels (J = 2) associated to the FMs (k = 2,3), with a restoration factor associated to the maintenance routine (q^{pr}_{ik1}= 0.75 and q^{pr}_{ik2}= 1) (see[30]).

The access cost to the WF is assumed to be 5000€, own resources 800€/day per maintenance team, extra resources 250€/hr per maintenance team, the total opportunity cost 105€/MWh, the penalization cost 35€/MWh, the interest rate 5% and the lead time to the WF one hour. Finally,

	OEMs' Quantity of Interest: LCC (€)					Asset users' Quantity of Interest: LP (MWh)				
	Mean	St	L, CI^{95}_{mean}	U, CI^{95}_{mean}	$F_{U,CI} = 0.95$	Mean	St	L, CI^{95}_{mean}	U, CI^{95}_{mean}	$F_{U,CI} = 0.95$
S. 18	61,7 E6	780 808	61,5 E6	61,9 E6	63,1 E6	51955	3461	51218	52693	58386
S. 0	63,1 E6	687 105	62,9 E6	63,2 E6	64,4 E6	51680	3215	50999	52361	57650
S. 7	64,5 E6	687 806	64,3 E6	64,6 E6	65,8 E6	50377	2741	49800	50955	55465
S. 11	64, 9 E6	652 858	64,8 E6	65,1 E6	66,1 E6	46732	2839	46134	47330	52001

Table 3. Confidence Intervals for OEMs' and Asset Users' Quantities of Interest

the cost for the materials and the maintainability of PM has been set a 30% lower than for CM. Further information about material cost for the WT under study can be found on Martin-Tretton et al.[55].

Real wind data has been utilised in order to feed the simulation and obtain as much realistic scenarios as possible. The wind turbines cut-in, cut-out and rated speeds are respectively assumed to be 3 m/s, 25 m/s and 13 m/s.

5.2 Optimisation Results and Discussion

20 different optimal after-sales maintenance strategies have been found through the previous multi-objective optimisation. Nevertheless, 4 different strategies have been selected in order to 1) illustrate their usefulness for properly deploying an after-sales service, 2) measure the uncertainty propagation and its consequences and 3) offer a successful PBC. (The reader can address the results in Table 3 and the decision variables in Table 5 within Appendix A).

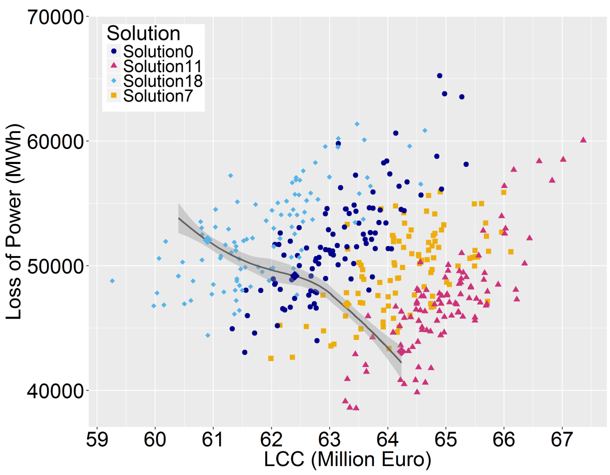


Figure 7. Sensitivity analysis for measuring optimal results uncertainty due to the system model

As stated in Subsection 2, due to the several stochastic processes that have to be handled within the after-sales services[7] such as failure events, there is an inherent uncertainty in the system model that cannot be avoided. These system uncertainties imply variability in the results of the model and a deviation from the optimal solution, which is represented in the sensitivity analysis of figure 7.

If a statistical analysis is performed to measure the uncertainty propagation to the quantities of interest, the decision maker will be able to assess the risk that implies following certain maintenance strategy, and thus, to manage it[12]. Moreover, the decision-maker will be able to decide whether they should be more or less cautious when establishing the cost and the service level of the after-sales service.

These results are shown in Table 3, where the mean (with lower and upper confidence intervals (CI)), the standard deviation and the cumulative probability of providing a successful service the 95% of the times are analyzed. As an example, following the maintenance strategy defined in Solution 7 (S.7), if the life cycle PBC was priced at 65,8 E6 euros and the service level was established at 55465 MWh (during the 20 years of the life cycle), only the 5% of the times would be either the OEM or the asset user dissatisfied. If the price and the service level were offered at mean values, or without considering the impact of uncertainty sources, there would be a high probability of not providing the committed service level (implying high penalizations) or to exceed the maintenance cost, jeopardizing the after-sales service success.

Therefore, according to the requirements of each asset user, regarding both service-level and cost, the after-sales service decision maker should define the maintenance strategy to be followed (attending to the optimal solutions), and the price and service level to be offered (attending to the statistical analysis of the uncertainty).

Furthermore, as defined in Section 3, uncertainty sources of the input variables can also condition the success of the deployed service. Likewise, this impact should be quantified and managed as well. With the purpose of analyzing such impact, the uncertainty on the efficiency of the time to repair has been measured, since it might be conditioned by several factors: problems in the spare parts supply chain, workers' productivity, maintenance processes design, etc.

The density graphs in Figure 8 confirm how the greater the uncertainty level, the greater the variability on the results of the after-sales service. Thus, if a statistical analysis is performed (see Table 4), it can be noticed that in order to provide an after-sales service within the 95% confidence level, its quality will considerably decrease, especially in the asset user quantity of interest, where the committed service-level should be decreased in more than a 23%. Therefore, the greater the uncertainty sources the less appealing service and PBC that the OEM will be able to offer.

Consequently, and according to the feedback process shown in Figure 2, the after-sales service decision makers should focus their efforts and investments, firstly, on the reduction of the endogenous uncertainty sources that condition the after-sales inputs, and secondly, on further improving these inputs.

Such investments will have both a qualitative benefit for the OEM, in terms of offered service level and good corporate image ensuring and enhancing the sales of new

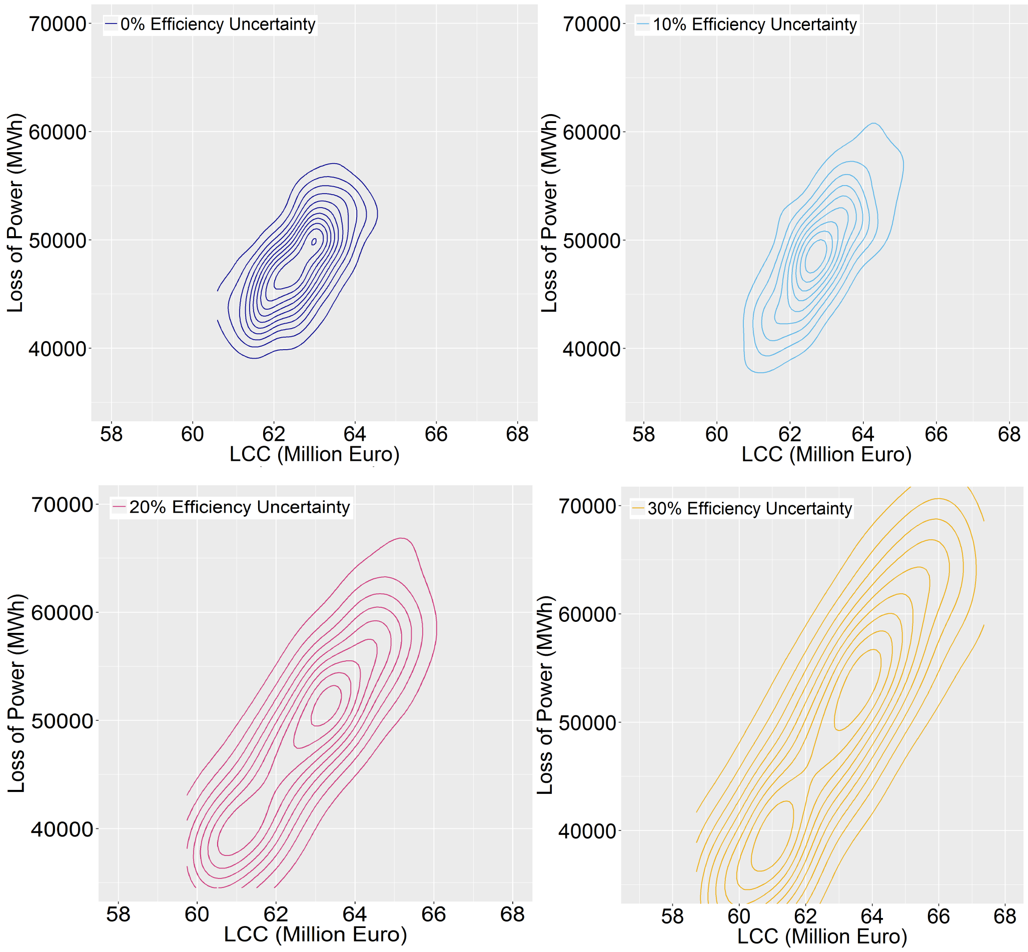


Figure 8. The impact of uncertainty in the efficiency of the time to repair

	OEMs' Quantity of Interest LCC (Euro)				Asset Users' Quantity of Interest LP (MWh)			
Efficiency Uncertainty (%)	Mean	St	$F_{U,CI} = 0.95$	$\Delta\%$	Mean	St	$F_{U,CI} = 0.95$	$\Delta\%$
0	63,2 E6	687 105	64,4 E6	-	48354	3833	54659	-
10	63,0 E6	1 100 646	64,8 E6	0,6	49719	4921	57814	5,77
20	62,9 E6	1 517 755	65,4 E6	1,55	49481	7865	62419	14,2
30	63,0 E6	2 102 454	66,4 E6	3,1	50097	10789	67418	23,34

Table 4. Confidence Intervals for OEMs' and Asset Users' Quantities of Interest given an uncertainty in the efficiency of the time to repair

assets in the future; and in quantitative terms, due to the saved maintenance cost and the greater price of the PBC.

In particular, the quantitative impact of the investment can be further analyzed through the well known return of investment (ROI) indicator. Since these investments benefit the asset users as well, variable payment methods are usually established, where both the OEM and the asset users increase their profits [15]. A common approach is to assume a linear function in order to allocate the revenues obtained by the investment [14] (see Eq.20): a, the price to be paid by the asset user for the provided service; LCC, the cost of providing the service for the OEM; b, the variable revenue from improving the service level $(LP \leq LP_{committed})$. Therefore, the profit difference (ΔB^o) between scenarios with different uncertainty levels can be obtained through Eq.21.

$$B^o = (a - LCC) + b(LP_{committed} - LP) \tag{20}$$

$$\Delta B^o = B_2^o - B_1^o = (LCC_1 - LCC_2) + b(LP_1 - LP_2) \tag{21}$$

Accordingly, if the variable revenue from improving the service level (b) was established at a 20% of the generated power price, and it is considered that the OEM manage 10 different wind farms (N^{WF}), the break even of the ROI analysis for the scenario where the efficiency of the time to repair is improved a 10%, e.g. from the mid scenario of 20% to 10% (see Table 4), can be defined as follows:

$$ROI = \frac{\Delta B^o - Invest.}{Invest.} = 0$$
$$[(LCC_1 - LCC_2) + b(LP_1 - LP_2)] \cdot N^{WF} = Invest. \tag{22}$$

$$Investment = [(65,4E6 - 64,8E6) + 0,2{\cdot}105{\cdot}(62419 - 57814)]\ 10 \simeq 7.000.000 \quad (23)$$

Therefore, under the cited circumstances, investments under 7.000.000 euros would be economically justified for the OEM. Furthermore, the asset users would not only have a better service availability, but they would also increase their profits through the extra-generated power (Eq.24).

$$B_{AU}^{o} = 0,8{\cdot}105{\cdot}(62419 - 57814) \simeq 390.000 \quad (24)$$

Finally, further investments can be performed for improving the efficiency of the input variables, such as the time to repair, which would considerably improve the offered service level (see Figure 9). Likewise, as in the previous case, the break even of the ROI could be analyzed according to Eq.20-22 in order to identify the suitability of the investments.

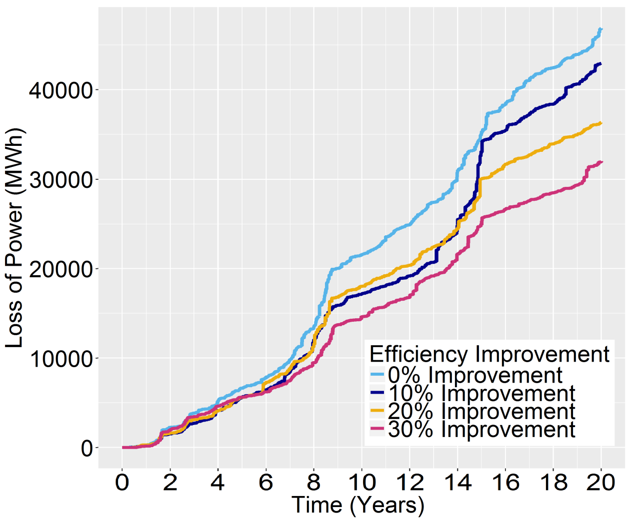


Figure 9. Impact of improving the efficiency of the time to repair on the offered service level

6 Concluding remarks

After-sales services can be a great source of profits for OEMs. However, OEMs have usually difficulties in properly defining the after-sales service due to the several factors that have to be considered, such as: services' targets, maintenance policy definition, maintenance strategy optimisation, etc. Furthermore, there are multiple uncertainty sources that might condition the performance of the after-sales services, which are both related to the input variables and the developed system model itself.

Therefore, the present paper provides methodological insights for properly categorising the impact of the uncertainty sources and offering successful after-sales service contracts. To this aim, the whole system modelling is covered, from the maintenance problem modelling to the after-sales service definition, illustrating it for the wind-energy case study.

The results obtained demonstrate that when these uncertainty sources are not suitably identified and quantified, there is a high risk of both not being able to provide the offered service level and exceeding the cost of the service; consequently, turning the after-sales services into a source of losses instead of a source of incomes.

Future efforts will focus on how the uncertainty due to random inputs that directly affect the after-sales service should be addressed. Likewise, further research might concentrate on the development of a more generic system modelling that allows managing the after-sales maintenance service regardless the sector under study.

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References

1. Öner K, Kiesmüller G and van Houtum G. Optimization of component reliability in the design phase of capital goods. *European Journal of Operational Research* 2010; 205(3): 615–624. DOI:10.1016/j.ejor.2010.01.030.
2. Cohen M and Whang S. Competing in product and service: A product life-cycle model. *Management Science* 1997; 43(4): 535–545.
3. González-Prida V and Márquez AC. A framework for warranty management in industrial assets. *Computers in Industry* 2012; 63(9): 960 – 971. DOI:http://dx.doi.org/10.1016/j.compind.2012.09.001.
4. Su C and Wang X. Modeling flexible two-dimensional warranty contracts for used products considering reliability improvement actions. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 2016; 230(2): 237–247. DOI:10.1177/1748006X15627395.
5. Sagarna I, Uribetxebarria J, Castellano E et al. After-sales maintenance service strategies optimization. an offshore wind farm case study. *IFAC-AMEST PapersOnLine* 2016; 49(28): 156–161. DOI:10.1016/j.ifacol.2016.11.027.
6. Kim SH, Cohen MA and Netessine S. Reliability or inventory? contracting strategies for after-sales product support. In *Proceedings of 2007 International Conference on Manufacturing & Service Operations Management*.
7. Kim SH, Cohen M and Netessine S. Performance contracting in after-sales service supply chains. *Management Science* 2007; 53(12): 1843–1858. DOI:10.1287/mnsc.1070.0741.
8. Xie M, Li X and Ng S. Risk-based software release policy under parameter uncertainty. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 2011; 225(1): 42–49. DOI:10.1177/1748006XJRR286.
9. Laggoune R, Chateauneuf A and Aissani D. Impact of few failure data on the opportunistic replacement policy for multi-component systems. *Reliability Engineering & System Safety* 2010; 95(2): 108–119. DOI:10.1016/j.ress.2009.08.007.
10. Zhu W, Fouladirad M and Bérenguer C. A multi-level maintenance policy for a multi-component and multifailure mode system with two independent failure modes. *Reliability*

Engineering & System Safety 2016; 153: 50–63. DOI:10.1016/j.ress.2016.03.020.
11. Attar A, Raissi S and Khalili-Damghani K. A simulation-based optimization approach for free distributed repairable multi-state availability-redundancy allocation problems. *Reliability Engineering & System Safety* 2017; 157: 177–191. DOI: 10.1016/j.ress.2016.09.006.
12. de Rocquigny E, Devictor N and Tarantola S. *Uncertainty in industrial practice: a guide to quantitative uncertainty management*. John Wiley & Sons, 2008.
13. Macfarlan W and Mansir B. Supporting the warfighter through performance-based contracting. defense standardization program j.(july/september) 38-43, 2004.
14. Jin T, Ding Y, Guo H et al. Managing wind turbine reliability and maintenance via performance-based contract. DOI:10.1109/PESGM.2012.6344739.
15. Jin T and Wang P. Planning performance based contracts considering reliability and uncertain system usage. *Journal of the Operational Research Society* 2012; 63(10): 1467–1478. DOI:10.1057/jors.2011.144.
16. Nowicki D, Kumar U, Steudel H et al. Spares provisioning under performance-based logistics contract: Profit-centric approach. *Journal of the Operational Research Society* 2008; 59(3): 342–352. DOI:10.1057/palgrave.jors.2602327.
17. De Weck O, Eckert C and Clarkson J. A classification of uncertainty for early product and system design.
18. 31000:2009 risk management - principles and guidelines.
19. Villanueva J, Sanchez A, Carlos S et al. Genetic algorithm-based optimization of testing and maintenance under uncertain unavailability and cost estimation: A survey of strategies for harmonizing evolution and accuracy. *Reliability Engineering & System Safety* 2008; 93(12): 1830 – 1841. DOI:http://dx.doi.org/10.1016/j.ress.2008.03.014. 17th European Safety and Reliability Conference.
20. Sanchez A, Carlos S, Martorell S et al. Addressing imperfect maintenance modelling uncertainty in unavailability and cost based optimization. *Reliability Engineering & System Safety* 2009; 94(1): 22 – 32. DOI:http://dx.doi.org/10.1016/j.ress.2007.03.022. Maintenance Modeling and Application.
21. Wang H. A survey of maintenance policies of deteriorating systems. *European Journal of Operational Research* 2002; 139(3): 469–489. DOI:10.1016/s0377-2217(01)00197-7.
22. Nicolai R and Dekker R. A review of multi-component maintenance models. In *Proceedings of European Safety and Reliability Conference*. pp. 289–296.
23. Shi H and Zeng J. Real-time prediction of remaining useful life and preventive opportunistic maintenance strategy for multi-component systems considering stochastic dependence. *Computers & Industrial Engineering* 2016; 93: 192–204. DOI: 10.1016/j.cie.2015.12.016.
24. Keizer MCO, Teunter RH and Veldman J. Clustering condition-based maintenance for systems with redundancy and economic dependencies. *European Journal of Operational Research* 2016; 251(2): 531–540. DOI:10.1016/j.ejor.2015.11.008.
25. Ba HT, Cholette M, Borghesani P et al. Opportunistic maintenance considering non-homogenous opportunity arrivals and stochastic opportunity durations. *Reliability Engineering & System Safety* 2017; 160: 151–161. DOI:10.1016/j.ress.2016.12.011.
26. Tian Z, Jin T, Wu B et al. Condition based maintenance optimization for wind power generation systems under continuous monitoring. *Renewable Energy* 2011; 36(5): 1502–1509. DOI:10.1016/j.renene.2010.10.028.
27. Atashgar K and Abdollahzadeh H. Reliability optimization of wind farms considering redundancy and opportunistic maintenance strategy. *Energy Conversion and Management* 2016; 112: 445–458. DOI:10.1016/j.enconman.2016.01.027.
28. Hameed Z and Vatn J. Role of grouping in the development of an overall maintenance optimization framework for offshore wind turbines. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 2012; 226(6): 584–601. DOI:10.1177/1748006X1246461.
29. Shafiee M and Finkelstein M. A proactive group maintenance policy for continuously monitored deteriorating systems: Application to offshore wind turbines. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 2015; 229(5): 373–384. DOI:10.1177/1748006X15598915.
30. Ding F and Tian Z. Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. *Renewable Energy* 2012; 45: 175–182. DOI:10.1016/j.renene.2012.02.030.
31. Sarker BR and Faiz TI. Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy. *Renewable Energy* 2016; 85: 104–113. DOI:10.1016/j.renene.2015.06.030.
32. Erguido A, Crespo Márquez A, Castellano E et al. A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms. *Renewable Energy* 2017; 114: 843–856. DOI:10.1016/j.renene.2017.07.017.
33. Pham H and Wang H. Imperfect maintenance. *European Journal of Operational Research* 1996; 94(3): 425–438. DOI: 10.1016/s0377-2217(96)00099-9.
34. Yañez M, Joglar F and Modarres M. Generalized renewal process for analysis of repairable systems with limited failure experience. *Reliability Engineering & System Safety* 2002; 77(2): 167–180. DOI:10.1016/S0951-8320(02)00044-3.
35. Karyotakis A. *On the optimisation of operation and maintenance strategies for offshore wind farms*. PhD Thesis, University College London (UCL), 2011.
36. Andrawus JA. *Maintenance optimisation for wind turbines*. PhD Thesis, The Robert Gordon University, 2008.
37. Stamatelatos M, Dezfuli H, Apostolakis G et al. Probabilistic risk assessment procedures guide for nasa managers and practitioners. Technical report, NASA, 2011.
38. Byon E, Ntaimo L and Ding Y. Optimal maintenance strategies for wind turbine systems under stochastic weather conditions. *IEEE Transactions on Reliability* 2010; 59(2): 393–404. DOI: 10.1109/tr.2010.2046804.
39. Erguido A, Márquez AC, Castellano E et al. A novel dynamic opportunistic maintenance modelling approach. In *European Safety and Reliability Conference (ESREL) 2017*.
40. Abdollahzadeh H and Atashgar K. Optimal design of a multi-state system with uncertainty in supplier selection. *Computers & Industrial Engineering* 2017; 105: 411–424. DOI:10.1016/j.cie.2017.01.019.
41. Shafiee M and Finkelstein M. A proactive group maintenance policy for continuously monitored deteriorating systems: Application to offshore wind turbines. *Proceedings of the*

Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 2015; 229(5): 373–384. DOI:10.1177/1748006x15598915.
42. Karki R and Patel J. Reliability assessment of a wind power delivery system. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 2008; 223(1): 51–58. DOI:10.1243/1748006xjrr218.
43. Carlos S, Sánchez A, Martorell S et al. Onshore wind farms maintenance optimization using a stochastic model. *Mathematical and Computer Modelling* 2013; 57(7-8): 1884–1890. DOI:10.1016/j.mcm.2011.12.025.
44. Iqbal M, Azam M, Naeem M et al. Optimization classification, algorithms and tools for renewable energy: A review. *Renewable and Sustainable Energy Reviews* 2014; 39: 640–654. DOI:10.1016/j.rser.2014.07.120.
45. Abdollahzadeh H, Atashgar K and Abbasi M. Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups. *Renewable Energy* 2016; 88: 247–261. DOI:10.1016/j.renene.2015.11.022.
46. Ding F and Tian Z. Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions. *International Journal of Reliability, Quality and Safety Engineering* 2011; 18(05): 463–481. DOI:10.1142/s0218539311004196.
47. González E, Nanos EM, Seyr H et al. Key performance indicators for wind farm operation and maintenance. Scientific report, 1st Joint Industry Workshop, 2016.
48. Zille V, Bérenguer C, Grall A et al. Modelling multicomponent systems to quantify reliability centred maintenance strategies. *Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability* 2011; 225(2): 141–160. DOI:10.1177/1748006X11402269.
49. Niazi M and Hussain A. Agent-based computing from multi-agent systems to agent-based models: a visual survey. *Scientometrics* 2011; 89(2): 479–499. DOI:10.1007/s11192-011-0468-9.
50. Banks J. Discrete event simulation. In *Encyclopedia of Information Systems*. Elsevier BV, 2003. pp. 663–671. DOI:10.1016/b0-12-227240-4/00045-9.
51. Deb K, Pratap A, Agarwal S et al. A fast and elitist multiobjective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* 2002; 6(2): 182–197. DOI:10.1109/4235.996017.
52. Safari J. Multi-objective reliability optimization of series-parallel systems with a choice of redundancy strategies. *Reliability Engineering & System Safety* 2012; 108: 10–20. DOI:10.1016/j.ress.2012.06.001.
53. Salazar D, Rocco CM and Galván BJ. Optimization of constrained multiple-objective reliability problems using evolutionary algorithms. *Reliability Engineering & System Safety* 2006; 91(9): 1057–1070. DOI:10.1016/j.ress.2005.11.040.
54. Coello CAC, Lamont GB, Van Veldhuizen DA et al. *Evolutionary algorithms for solving multi-objective problems*, volume 5. Springer, 2007.
55. Martin-Tretton M, Reha M, Drunsic M et al. Data collection for current us wind energy projects: Component costs, financing, operations, and maintenance. *Contract* 2012; 303: 275–3000.

Appendix A

Numerical experiments illustrated through the paper correspond to the following solutions.

	Gearbox										
Sol.	SRT_{121}	SRT_{122}	DRT_{12}	w_{12}	SRT_{131}	SRT_{132}	DRT_{13}	w_{13}	MT	p	V
S. 0	0.86	0.42	0.35	0.60	0.98	0.61	0.24	0.99	2	4	0.5
S. 7	0.77	0.43	0.40	0.76	0.76	0.47	0.03	0.34	3	5	0.5
S. 11	0.84	0.44	0.15	0.56	0.98	0.43	0.05	0.34	3	4	1
S. 18	0.85	0.56	0.03	0.51	0.74	0.38	0.25	0.13	2	3	0.5

	Pitch							
Sol.	SRT_{221}	SRT_{222}	DRT_{22}	w_{22}	SRT_{231}	SRT_{232}	DRT_{23}	w_{23}
S. 0	0.82	0.61	0.44	0.39	0.98	0.65	0.48	0.22
S. 7	0.93	0.65	0.08	0.80	0.98	0.62	0.05	0.2
S. 11	0.96	0.67	0.30	0.66	0.98	0.70	0.33	0.44
S. 18	0.96	0.59	0.38	0.4	0.97	0.62	0.45	0.16

	Yaw							
Sol.	SRT_{321}	SRT_{322}	DRT_{32}	w_{32}	SRT_{331}	SRT_{332}	DRT_{33}	w_{33}
S. 0	0.79	0.62	0.10	0.31	0.93	0.16	0.01	0.49
S. 7	0.92	0.26	0.10	0.95	0.93	0.40	0.10	0.96
S. 11	0.90	0.68	0.12	0.83	0.93	0.71	0.16	0.60
S. 18	0.79	0.51	0.725	0.33	0.94	0.73	0.09	0.37

	Blades							
Sol.	SRT_{421}	SRT_{422}	DRT_{42}	w_{42}	SRT_{431}	SRT_{432}	DRT_{43}	w_{43}
S. 0	0.95	0.49	0.27	0.68	0.92	0.39	0.05	0.54
S. 7	0.91	0.50	0.43	0.53	0.88	0.62	0.23	0.37
S. 11	0.91	0.56	0.35	0.15	0.86	0.37	0.14	0.46
S. 18	0.92	0.54	0.01	0.49	0.84	0.30	0.09	0.01

Table 5. Decision Variables of the solutions presented in the Optimisation Results

Reliability-based advanced maintenance modelling to enhance rolling stock manufacturers' objectives

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Abstract

The light rail is gaining relevance within cities' transportation network due to its adequate balance among sustainability, economic and safety factors. Nevertheless, there is still a gap for improvement in those factors through the optimisation of rolling stock maintenance strategies. The development of new and more flexible maintenance strategies at proper indenture levels will aid to improve the reliability and availability of the light rail during operation phase, as well as to reduce its life cycle cost. Accordingly, the present research develops a multi-objective maintenance model that adopts a novel reliability-based advanced maintenance policy; whose aim is to consistently evaluate short-term information in order to enhance both traditional maintenance and organisational key performance indicators. The proposed multi-objective mathematical model is solved through a simulation-based optimisation (SBO), which by means of iteration evaluates different maintenance strategies according to the non-dominated sorting genetic algorithm (NSGA II). Empirical results, based on real data obtained from a light rail fleet operating in Spain, demonstrate that the proposed maintenance model for the rolling stock can significantly improve the light rail performance regarding both maintenance and organisational objectives.

Keywords: Reliability, Opportunistic maintenance, Life cycle cost, External variables, Multi-objective optimisation, Rolling stock

1. Introduction

Being concerned about the environmental and health matters derived from the gas emissions of conventionally fuelled vehicles, the European Commission is determined to suppress the most pollutant transport means from cities by 2050 [1, 2]. In fact, some of the most important European cities have already been forced to set traffic restrictions due to their high pollution levels. Thereby, the use of alternative, environmentally friendly and sustainable transport means is becoming mandatory for most of the cities. In this context, and after being relegated from the streets during the 1960s by the cars, the modern light rail is again gaining relevance and arising as a solution for the main urban transport problems, namely air pollution, road congestion and uneven access to mobility [3, 4]. In fact, many important cities in Europe such as Amsterdam or Flanders, have recently invested great amounts of money in this mean of transport.

The light rail, though, is not only claimed to satisfy environmental and urban sustainability requirements, but also reliability, safety and economic requirements [5, 6]. Consequently, and due to the fierce competitiveness existing in the railway sector [7], technical, reliability and economic requirements for being awarded with the light rail projects' tenders are very challenging. Among these requirements, special emphasis is lately being made with regards to the Life Cycle Cost (LCC) and the Reliability, Availability, Maintainability and Safety (RAMS) of the light rail during the operation phase [8, 9, 10, 11], deriving to high penalization costs if the committed contractual terms are not met.

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In this context, developing suitable asset management and maintenance strategies becomes crucial in order to meet both sustainability and competitiveness challenges [12, 13]. Nevertheless, to date, Time Based Preventive Maintenance (TBPM) strategies, based on periodic inspections and interval replacements (i.e. every 15 days, 3 months, 1 year, etc.), tend to survive in the sector [7]. These maintenance programs, which are mainly based on experience and suppliers' information, tend to be quite conservative, replacing components prior to their end of life cycle. As a result, they usually lead to sub-optimal and inefficient maintenance solutions which spend resources in non-critical maintenance activities [7, 14].

Therefore, the improvement of rolling stock's maintenance strategies through maintenance optimisation models provides an important opportunity to bring additional value in the railway sector [15]. However, according to the literature, research regarding the railway sector mainly focuses on railways' infrastructure maintenance and rolling stock circulation optimisation models (e.g. scheduling or assignment) [16, 17], whereas maintenance optimisation models for the rolling stock are still scarce [18].

In fact, both the literature and the case study experts who the authors have been working with, have emphasized the need for more flexible and efficient rolling stock maintenance models, with the ability to dynamically decide the maintenance to be performed [19, 7, 20]. Accordingly, in this paper a novel reliability-driven dynamic opportunistic maintenance (OM) modelling approach is presented and applied to the railway rolling stock with a double objective: 1) to optimise rolling stock operation performance, regarding LCC and in-service reliability, and 2) to propose more flexible maintenance programs able to align maintenance and organisational objectives.

The remainder of the paper is organised as follows. In section 2 the literature review, the advances to the state of the art and the research methodology are presented. Section 3 describes the novel dynamic OM policy presented and applied to the case study. Section 4 and 5 respectively derive and develop the analytical maintenance model for the light rail rolling stock and the simulation-based optimisation mechanism to solve it. In section 6 the numerical examples, analysis and results are presented, based on real field data provided by a leading company in the sector. Finally, section 7 summarizes the main conclusions of the research and establishes the future research lines.

2. State of the art - Opportunistic Maintenance Optimisation Models

2.1. Literature review

The light rail is a multi-unit asset that consists of several systems, subsystems and components that are continuously interacting. Thus, maintenance dependencies appear among the different systems, which increase the complexity of the rolling stock maintenance optimisation [21]. According to Nicolai and Dekker [22], these dependencies can be classified into: *economic*, when performing maintenance activities in several systems simultaneously leads to potential cost savings compared to performing them separately; *structural*, when performing a maintenance activity in a system implies further maintenance activities in other systems; and *stochastic*, when the risk of failure of two different systems is not independent.

On such occasions, multi-unit maintenance solutions are necessary due to their capacity of making decisions in a changing planning horizon, according to the short-term information regarding the assets' status and their environmental context [23]. Nevertheless, to date, the few existing rolling stock maintenance models, which are mostly related to minimize costs through optimal preventive maintenance intervals and spare parts supply, mainly develop single-unit maintenance models.

More precisely, in Yun and Ferreira [50] the replacement period for the railway sleepers was analyzed through a simulation model. In Cheng and Tsao [18] the authors identified both the best ratio between Corrective Maintenance (CM) and Preventive Maintenance (PM) through the evaluation of non-metric and metric factors and the replacement intervals and spare parts quantities. Dou et al. [51] optimised rolling stock maintenance efficiency through a reliability-centred maintenance analysis and Ruijters et al. [52] optimised compressors' maintenance strategies using a fault maintenance tree.

Other single-unit maintenance modelling researches related to the rolling stock, such as Conradie et al. [10], have made an effort to quantify the reliability of rolling stock through lifetime data and the inter-dependencies of the systems in order to be able to adopt reliability-based maintenance instead of time-based maintenance. Fourie and Tendayi [53] have also developed and tested a life cycle costing framework for railway rolling stock, according to their maintenance, operations and failure history. Likewise, Eisenberg and Fink [54] have investigated condition-based maintenance models where maintenance decisions are supported by Petri nets.

However, regarding the stated literature, as a multi-unit system, rolling stock maintenance models should integrate short term information concerning the whole assets' context within the decision-making process. Accordingly, the utilisation, modelling and optimisation of OM policies, which are able to favour

Source	Focus	OM Policy					Repairability		Resources		Optimisation	
		Threshold		DV	Dependence							
		S	D		In	Ex	Non-Rep	Rep	Inf	Lim	OF	Algorithm
Zhou et al. [24]	Economies of Scale	■	□	R(t)	■	□	□	■	■	□	C	DP
Laggoune et al. [25]	Economies of Scale	■	□	Age	■	□	■	□	■	□	C	MC
Laggoune et al. [26]	Data Uncertainty	■	□	Age	■	□	■	□	■	□	C	MC
Tian et al. [27]	Predictive Maintenance	■	□	Health	■	□	■	□	■	□	C	MC
Ding and Tian [28]	Economies of Scale	■	□	Age	■	□	□	■	□	■	C	MC
Zhou et al. [29]	Changes in Job Schedule	■	□	Job schedule	□	■	■	□	■	□	C	DP
Zhou et al. [30]	Series-Parallel systems	■	□	State	■	□	■	□	■	□	R	SO
Horenbeek and Pintelon [23]	Degradation monitoring	■	□	Health	■	□	□	■	■	□	C	Sim
Cavalcante and Lopes [31]	Multi-criteria decision	■	□	Age	■	□	■	□	■	□	C	Sim
Nguyen et al. [32]	Multi-level PM	■	□	R(t)	■	□	■	□	■	□	C	MC
Huynh et al. [33]	Redundancies and CBM	■	□	R(t)	■	□	■	□	■	□	C	GPS
Zhang and Zeng [34]	Structural dependencies	■	□	Health	■	□	■	□	■	□	Det	Exact
Caetano and Teixeira [35]	Degradation monitoring	■	□	Health	■	□	■	□	■	□	LCC	MILP
Sarker and Faiz [36]	Multi-level PM	■	□	Age	■	□	□	■	■	□	C	ES
Abdollahzadeh et al. [37]	Multi-level PM	■	□	R(t)	■	□	□	■	□	■	C & LOLP	MOPSO
Shi and Zeng [38]	Predictive Maintenance	■	□	Health	■	□	■	□	□	■	C	PSO
Babishin and Taghipour [39]	Redundancies	■	□	Repair Num	■	□	■	□	■	□	C	Sim
Keizer et al. [40]	Redundancies and CBM	■	□	Health	■	□	■	□	■	□	C	DP
Zhu et al. [41]	Uncertainty in PhM	■	□	Age	■	□	■	□	■	□	C	MC
Atashgar and Abdollahzadeh[42]	Redundancies	■	□	R(t)	■	□	□	■	□	■	C & LOLP	MOPSO
Abdollahzadeh and Atashgar[43]	Redundancies	■	□	Health	■	□	□	■	□	■	C & LOLP	MOACO
Ba et al. [44]	External Opp.	■	□	M(t)	□	■	■	□	■	□	C	GA
Attar et al. [45]	Redundancies	■	□	Health	■	□	■	□	■	□	C & A	NSGA II
Zhang et al. [46]	Multi-level PM	■	□	R(t)	■	□	□	■	■	□	C	FFO
Kang and Subramaniam [47]	Production control	■	□	Age	□	■	□	■	□	■	C	VI
Zhou and Lu [48]	Product quality	■	□	Time to PM	■	□	□	■	■	□	C	Exact
Poppe et al. [49]	Degradating components	■	□	Health	■	□	■	□	■	□	C	FE
Present Study	Dynamic OM	□	■	R(t)	■	■	□	■	□	■	C & FD & ND	NSGA II

S: Static; D: Dynamic; In: Internal; DV: Decision Variable; Ex: External; Rep: Repairable; Inf: Infinite; Lim: Limited ; OF: Objective Function; C: Cost; LOLP: Loss of Load Probability; R: Revenue; A: Availability; FD: Failure Downtime; ND: Number of Delays; Det: Deterioration; DP: Dynamic Programming; MC: Monte Carlo; SO: Stochastic Ordering;GPS: Generalized Pattern Search; MILP: Mixed Integer Linear Problem; ES: Exhaustive Search; PSO: Particle Swarm Optimisation; MOPSO: Multi-objective Particle Swarm Optimisation Algorithm; MOACO: Multi-Objective and Colony Optimisation; VI: Value Iteration; NSGA II: Non-dominated Sorting Genetic Algorithm; FE: Full Enumeration

Table 1: A review of the recent researches in opportunistic maintenance optimisation models

or bother the maintenance performance according to the specific needs of the assets [55, 38], acquire high relevance in the sector [21]. In fact, due to the structural complexity of new assets, there has been a growing research interest in the utilisation of OM in varied sectors (see Table 1).

In essence, the OM paradigm seeks to take advantage of the events caused either by internal or external factors that are potentially favourable for maintenance [56, 44], leading to a dynamic decision-making process. On the one hand, the internal opportunities are directly related to the maintenance decisions and are provoked by the cited dependencies among the systems of the assets. On the other hand, the external factors are related to the environmental or context situations that foster the arrival of opportunities, without being directly influenced by maintenance, such as customer requirements or production schedule [44].

When these opportunities arise, either internally or externally, the decision of maintenance is usually made according to the traditional maintenance variables, such as time intervals, age, reliability, condition state (e.g. degradation) or number of repairs [56]. In particular, in the OM optimisation models the maintenance decision is usually made according to certain thresholds -acting as decision variables (DV)- related to these maintenance variables (see Table 1). The following classification helps distinguish the latest OM models:

- **Age-based OM.** They assume that the risk of failure is proportional to the age of the components. Thus, if the opportunity of maintenance arises and the age of any component is over its established age-threshold, it will undergo maintenance. Age-based OM studies have explored the impact of different factors on this policy, namely: uncertainty caused by the lack of failure data [26], imperfect maintenance influence [36], imperfect prediction of failures [41], multi-criteria optimisation [31] or its integration with production control [47].

- **Reliability-based OM.** Reliability of the systems is estimated according to varied methods, such as failure data analysis or degradation models. This reliability is then compared to a reliability threshold and it is decided whether the maintenance task should be triggered or not. Reviewed reliability-based OM models deal with several topics: economic and structural dependencies [33], multi-level maintenance [32], multi-objective optimisation considering imperfect maintenance and capacity constraints [37], redundancies [42], etc.

- **Condition-based OM.** Maintenance decision is directly made according to the health state or the remaining useful life (RUL) of the systems, which can be identified through either condition monitoring systems (CMS) or inspections. Condition-based OM reviewed, address several research fields, such as: multi-state series–parallel systems [30], simultaneous consideration of structural, stochastic and economic dependencies [23], degradating multi-unit systems [34, 49], redundancies [40, 45], impact of uncertain suppliers behaviour [43] or integration of OM and failure prediction based on neural networks [27].

Although most of the reviewed researches implement the above mentioned OM policies, other OM policies might be considered as well. In Zhou et al. [29] maintenance is determined by the changes in job shop schedule, whilst in other studies, maintenance decision is made according to the number of times that the system has been minimally repaired [39], to the next time to PM [48] or to the maintenance activity duration [44].

2.2. Motivation and Literature Gap

As reviewed, a considerable amount of literature has been published on OM during the last years, particularly on new optimisation models dealing with internal opportunities (see Table 1). However, there is still an important gap between the complex models developed in the literature and their application in real world problems [31, 57]. According to the literature and the best knowledge of the authors, this gap can be solved by promoting researches in two key domains [57, 19, 58, 59]: **(1)** maintenance models should not only seek maintenance optimisation, but also the alignment between maintenance and organisational objectives; and **(2)** mechanisms that facilitate the decision-making process, based on data analysis and decision-making optimisation models, should be integrated within industrial companies.

Therefore, it is the aim of this study to provide new insights into both domains by specifically contributing in:

1. Presenting a novel dynamic OM policy able to simultaneously combine internal and external maintenance opportunities in order to consistently align maintenance and organisational objectives in changing contexts.

2. Modelling the cited dynamic OM for a real rolling stock case study, testing and evaluating its results.
3. Developing a multi-objective maintenance model for the rolling stock that considers several real maintenance constraints, such as, imperfect maintenance or finite maintenance resources.
4. Developing a realistic simulation-based optimisation mechanism that allows both making optimal decisions and providing maintenance decision-makers with the opportunity of representing their decision preferences on the maintenance program.

2.3. Research methodology

According to the best practices found in the literature review, the research methodology shown in Figure 1 has been adopted in order to achieve each of the presented contributions.

Firstly, the proposed dynamic OM policy for aligning maintenance and organisational objectives is defined. Secondly, the maintenance model for the rolling stock case study is mathematically modelled. And, finally, it is solved through a specifically developed simulation-based optimisation mechanism, as recommended in the literature [41, 26, 45]. Likewise, these three steps and their contributions have been evaluated in a case study based on real field data.

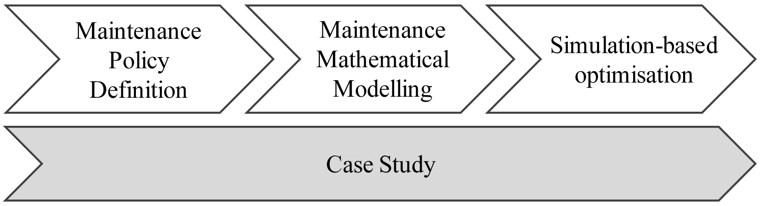


Figure 1: Research methodology

In particular, a reliability-based OM model is developed since it does not necessarily assume that the failure risk is proportional to the age of the components. Likewise, although condition-based OM approach is more precise than reliability-based OM, it presents some complexities that difficult its application when the number of systems under study increases; complexities mainly due to the technology to be deployed, the algorithms to be developed or each systems' particularities [60].

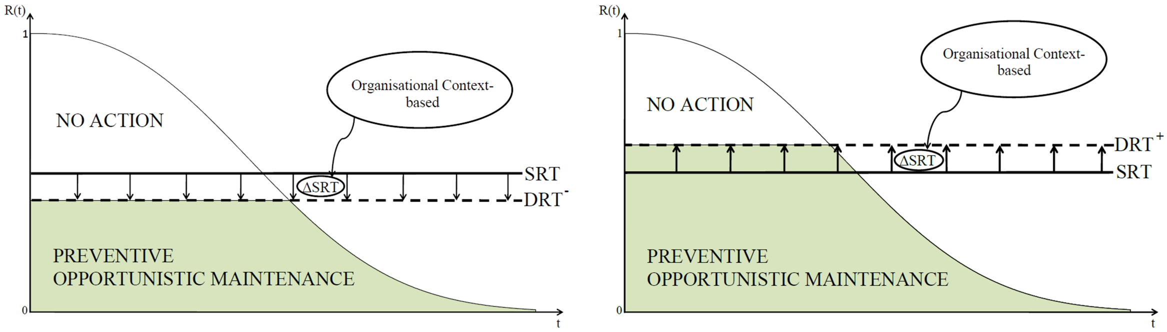
This is the case of rolling stock condition-based maintenance, where the variable operational context and the intrinsic nature of the components difficult the prediction of their pf interval [61]. In this context, condition-based maintenance is valuable for modelling especially critical maintenance activities related to safety factors [62], but not for modelling the impact of alternative maintenance strategies on the fleet performance simultaneously regarding several components, which is indeed required by manufacturers [54].

3. Reliability-based dynamic opportunistic maintenance

As reviewed in Section 2, OM models usually base the maintenance decision-making process on thresholds that allow efficiently managing the economic and failure risk of systems. However, most of the models base this decision on a static set of thresholds (see Table 1). On such occasions, the set of static thresholds provided by OM models assumes a unique context, for which the model has been developed and solved. Thus, since opportunities that arise from specific changes in the context over time (new customer requirements, specific targets, production schedule, etc.) are not being considered, static OM might lead to sub-optimal solutions that entail a misalignment between maintenance and organisational objectives.

If an alignment of maintenance and organisational objectives is sought in OM models, two main conflicts regarding both fields have to be considered [63]:

1. *The reliability of a system is getting low (higher risk of failure) and thus from the exclusive maintenance perspective it should be maintained. However, the specific organisational context is not favourable for maintenance.*
2. *The reliability of a system is quite high (lower risk of failure) and thus from the exclusive maintenance perspective it should not be maintained. However, the specific organisational context is favourable for maintenance.*



(a) Dynamic OM: hindering preventive maintenance

(b) Dynamic OM: fostering preventive maintenance

Figure 2: Dynamic opportunistic maintenance approach

In contrast to static OM, the dynamic OM suggests to dynamically vary the thresholds that trigger the maintenance activities, so that opportunities arisen from the context changes are taken and a trade-off between maintenance and organisational objectives is found. Accordingly, when there is not specific interest in maintaining a system due to the organisational context, the reliability thresholds will be decreased ($DRT^{-} = SRT - \Delta SRT$), hindering maintenance to some extent (see Figure 2a). However, if the organisational context is favourable, the reliability threshold should increase ($DRT^{+} = SRT + \Delta SRT$), fostering preventive maintenance when possible (see Figure 2b).

The dynamic reliability thresholds modelling consists of three building blocks (see Eq.1):

1. Static Reliability Threshold ($SRT, [0, 1]$). It sets the base maintenance policy, as well as the dynamism with regards to context changes.
2. Context-alignment weight ($w, [0, 1]$). It determines to which extent should the maintenance thresholds vary with regards to the organisational context changes.
3. Context evaluation function ($f\,[external\,variables, t]\,, [-1, 1]$). It determines both whether the opportunity is favourable or unfavourable (threshold increase or decrease) and how (un)favourable it is (threshold gradient).

$$DRT_t = SRT_{ik} + SRT_{ik} \cdot w_{ik} \cdot f(ext\,var, t) \tag{1}$$

Although the dynamic OM leads to more flexible maintenance programs able to align maintenance and organisational objectives, special attention should be paid to the DRT modelling, since an excessive dependence of the thresholds on the organisational context changes might lead to an excessive or insufficient maintenance planning [63]. Likewise, it is remarkable that compared to static OM, maintenance is not suppressed nor increased by dynamic OM; it is performed within more favourable conditions from the organisational interests' perspective. Therefore, whereas results regarding the organisations' performance indicators will be outperformed, the traditional maintenance indicators (e.g. LCC or availability) will be similar both in static and dynamic OM.

4. Advanced maintenance modelling for the light rail

This section analytically derives the maintenance optimisation problem for optimising both the maintenance strategy LCC and the in-service reliability of the railway rolling stock. Likewise, for testing the performance of dynamic OM maintenance modelling, the organisational objective of avoiding service penalizations has been considered as well. Especial emphasize has been made to consider a realistic maintenance scenario, including maintenance resources constraints and imperfect maintenance.

4.1. System description

The light rail considered in the present problem consists of L trams of similar characteristics that have N systems. Likewise, each system might have $K^n = \{1, ..., k^n\}$ failure modes (FM). After a FM happens, depending on its severity, i.e. soft-failure or hard-failure [41], planned or immediate corrective maintenance will be performed respectively (see subsection 5.1). In contrast to soft failures, hard failures usually entail penalizations.

Table 2: Nomenclature utilised in the model

Nomenclature			
L	Number of trams considered.	m^{c}_{ik}	Maintainability of CM for FM k in system i
I	Number of systems considered in the tram.	m^{pr}_{ikj}	Maintainability of PM j for FM k in system i
K_i	Number of FM considered for each system i.		
G^m	Maintenance Group	MT	Number of maintenance teams
VA_{likt}	Virtual age of FM k of system i in tram l in period t	T^{wt}	Available working time per maintenance team
q^{pr}_{ikj}	Restoration factor of PM j on system i for FM k	MTr	Number of maintenance tracks
		CPT	Penalization contractual target
q^{c}_{ik}	Restoration factor of CM on system i for FM k	PI_t	Penalization indicator in period t
		PI^{del}_t	Delays' penalization indicator in period t
α_{ik}	Weibull scale parameter of FM k of system i	P	Number of periods for which the reliability indicators are evaluated.
β_{ik}	Weibull shape parameter of FM k of system i		
		ND_{lt}	Number of delays of tram l in period t
c^{c}_{ik}	Corrective maintenance cost of FM k in system i	NMS_t	Number of measured stations for delays checking in period t
c^{pr}_{ikj}	Maintenance cost for performing PM j of FM k in system i	MDT_{ik}	Minimum Dynamic reliability Threshold for FM k in system i
$c^{c,mat}_{ik}$	Cost of tools and materials needed for performing CM of FM k in system i	PDT_{ik}	Perfect Dynamic reliability Threshold for FM k in system i
$c^{pr,mat}_{ik}$	Cost of tools and materials needed for performing PM of FM k in system i	IDT_{ik}	Imperfect Dynamic reliability Threshold for FM k in system i
C^{insp}_{ikt}	Inspection cost of FM k in system i per period t	TPI	Target Penalization Indicator
		w_{ik}	Context-alignment weight for FM k in system i
c^{s}_{ik}	Set up cost for FM k in system i		
c^p	Penalty cost	k_a	Interest rate
c^{mt}	Maintenance teams' cost	OT	Total operating time
c^{wt}	Maintenance teams' working time cost	T	Maximum iteration periods

Likewise, systems can also undergo preventive maintenance in order to avoid the occurrence of the FMs. According to Pham and Wang [64], maintenance activities might be classified as either imperfect ($j = 1$) or perfect ($j = 2$); whereas the formers return the systems to a condition worse than the new one but better than just before the maintenance task is performed, the latters restore the systems to an operational condition as good as new (AGAN). There are several methods that treat the restoration factor of maintenance activities (see [64]). Nevertheless, due to its flexibility for modelling both the behaviour of the systems before failure and the quality of the repairs during the different life stages of the systems, the *General Renewal Process* (GRP) proposed by Yañez et al. [65] has been utilized. The GRP modelling is based on two main concepts:

1. Virtual Age (VA). The calculated age of the system immediately after repair process.
2. Rejuvenation parameter (q). The effect of the repair process in the virtual age of the systems.

A value of $q = 1$ leads to a perfect maintenance ($VA = 0$, AGAN), whereas $0 < q < 1$ leads to an imperfect maintenance (Eq.2). Accordingly, after an imperfect repair, failure probability distribution conditioned to the survival of the new virtual age should be estimated (Eq.3). Eq.3 is particularized for Weibull distribution (Eq.4) due to its flexibility and applicability in the rolling stock reliability modelling [18, 10].

$$VA^{new}_{lik} = VA^{old}_{lik}(1 - q_{ik}) \tag{2}$$

$$F\left(t|VA^{new}_{i}\right) = P\left[T_{ij} \leq t|T_{ij} > VA^{new}_{i}\right] = \frac{F\left(t\right) - F\left(VA^{new}_{i}\right)}{1 - F\left(VA^{new}_{i}\right)} \tag{3}$$

$$F\left(t|VA^{new}_{lik}\right) = exp\left[\left(\frac{VA^{new}_{lik}}{\alpha_{ik}}\right)^{\beta_{ik}} - \left(\frac{t}{\alpha_{ik}}\right)^{\beta_{ik}}\right] \tag{4}$$

Without loss of generality, some common assumptions have been made for the OM modelling and solution [33, 26, 38]:

1. Degradation processes of the systems and their FMs are considered independent from each other and they are associated to the trams' production (ageing systems with Increasing Failure Rate).
2. Data pooling procedure is used for performing the reliability analysis since trams belonging to the same fleet can be considered as identical, according to the checklist of coupling factors proposed by Stamatelatos et al. [66]: same location, design, hardware, environment, etc.
3. Each maintenance task has a specified duration and an associated deadline which occurs before the end of the maintenance window.
4. Inspections are considered to be mandatory (not to be optimised), thus they are considered as a fix cost for each FM per unit time in the present model $\left(C_{ikt}^{ins}\right)$.
5. Rail services managers make decisions in discrete time and frequently.

4.2. Calculation of rolling stock maintenance cost

The main preventive and corrective maintenance costs (see Eq.5-6) in the light rail rolling stock are related to tools and materials $\left(c_{ik}^{c,mat}, c_{ikj}^{pr,mat}\right)$, manpower (c^{mt}), which is directly proportional to maintenance teams' working time and cost $\left(m_{ikj}^{pr}, m_{ik}^{c}, c^{wt}\right)$, set-up cost (c_{ik}^{s}) and penalty costs (c^{p}), in the case that failures entailing penalizations occur.

$$c_{ik}^{c} = c_{ik}^{s} + m_{ik}^{c} \cdot c^{wt} + c_{ik}^{c,mat} + c^{p} \tag{5}$$

$$c_{ikj}^{pr} = c_{ik}^{s} + m_{ikj}^{pr} \cdot c^{wt} + c_{ikj}^{pr,mat} \tag{6}$$

In contrast to manpower or materials cost, set-up cost and penalty cost are not directly proportional to maintenance time or number of repairs, and might vary depending on the maintenance policy adopted.

On the one hand, there are positive economic dependencies among some of the systems and FMs within the light rail, mainly due to their location [67, 21]. Thus, set-up cost (c_{ik}^{s}) might be reduced if FMs belonging to the same systems or maintenance groups $G^{m} = \{i, j, ..., l\}$ are maintained together. For instance, if set-up costs were completely shared, it would be consider a unique c_{ik}^{s} for every maintained FM in the group (e.g. $f(G^{m} = p, o, ..., q) = S$; $c_{p}^{s} = c_{o}^{s} = c_{o}^{s} + c_{p}^{s} = S$).

On the other hand, penalty cost (c^{p}) depend on the established penalization targets in the light rail tenders, which without loss of generality usually refer to transport offer, service availability, delays, failure rate and accidents. These indicators are generally periodically measured (every p periods), and if the contractual penalization targets (CPT) established in the light rail tenders are not met, a penalty cost should be paid (see Eq. 7). Eq. 8 represents the delay penalization indicator (PI^{del}), which compares the number of incurred delays (ND_{lr}) and the number of measured stations (NMS_{r}).

$$c_{t}^{p} = \begin{cases} c^{p} & PI_{t} < CPT \\ \\ 0 & PI_{t} \geq CPT \end{cases} \tag{7}$$

where

$$PI_{t}^{del} = 1 - \frac{\sum_{l} \sum_{r=t-P}^{t} ND_{lr}}{L \cdot \sum_{r=t-P}^{t} NMS_{r}} \tag{8}$$

4.3. Dynamic OM policy for the light rail

For the specific case study developed in the present paper, the dynamism of the reliability thresholds has been defined as a function of the penalizations, since the objectives of rolling stock OEMs do not only refer to LCC and availability, but also to a good service quality, i.e. a good organisational image. Therefore, the $f(ext\,var, t)$ that defines the dynamic OM is focused on avoiding penalizations for a low service quality, fostering or hindering preventive maintenance depending on the evolution of the penalization indicators over time.

In particular, the $f(ext\,var, t)$ compares the actual penalization indicator (PI) for the period considered, with a Target Penalization Indicator (TPI), which will determine the suitability of the maintenance opportunity (see Eq.9). Thus, when the penalization indicator is below this TPI, the dynamic reliability threshold will increase in order to foster preventive maintenance and avoid to incur in penalizations. On the contrary, when the indicator is below the TPI, the dynamic reliability threshold will decrease, hindering preventive maintenance.

$$f(ext\,var,t) = \frac{TPI - PI_t^{del}}{TPI} \tag{9}$$

Likewise, as defined in section 4.3, $f(ext\,var,t)$ should be normalized between [-1,1]. This normalization, has to be performed in two steps, between [-1,0] and [0,1], in order to suitably handle the dynamic thresholds' increase and decrease (see Eq.10). For finding the required f_{max} and f_{min} for the normalization, the minimum and maximum values that can acquire PI_t^{del} have been empirically identified, being 0.9 and 1 respectively.

$$f_{norm}(ext\,var,t) = \begin{cases} -1 + \frac{[f(ext\,var,t) - f_{min}(ext\,var,t)]\cdot(0+1)}{[0 - f_{min}(ext\,var,t)]} & f(ext\,var,t) \leq 0 \\ 0 + \frac{[f(ext\,var,t) - 0]\cdot(1-0)}{[f_{max}(ext\,var,t) - 0]} & f(ext\,var,t) > 0 \end{cases} \tag{10}$$

where

$$f_{max}(ext\,var,t) = \frac{TPI - 0.9}{TPI} \tag{11}$$

$$f_{min}(ext\,var,t) = \frac{TPI - 1}{TPI} \tag{12}$$

In particular, the dynamic OM policy adopted in the present maintenance model consists of three different reliability thresholds for each FM, which trigger the following maintenance decisions (see Figure 3):

1. Minimum Dynamic Threshold (MDT_{ikt}). When the reliability of a certain FM goes below this threshold, it should undergo perfect preventive maintenance, regardless whether the tram is undergoing maintenance or not. Thus, this threshold ensures a minimum reliability for each FM.
2. Perfect Dynamic Threshold (PDT_{ikt}). When either preventive or corrective maintenance is being performed in the tram, the PDT_{ikt} helps decide if perfect preventive maintenance should be performed to other FMs in the same tram. Accordingly, this threshold facilitates opportunistic replacement decision.
3. Imperfect Dynamic Threshold (IDT_{ikt}). When either preventive or corrective maintenance is being performed in the tram, the IDT_{ikt} is used to decide if imperfect preventive maintenance should be applied to other FMs in the same tram. Therefore, this threshold facilitates opportunistic repair decision, where the FM does not return to as good as new. Whereas the model described in Subsection 4.4 allows establishing several imperfect maintenance thresholds, with different repair activities related to them, a unique imperfect repair activity has been considered to simplify the maintenance policy.

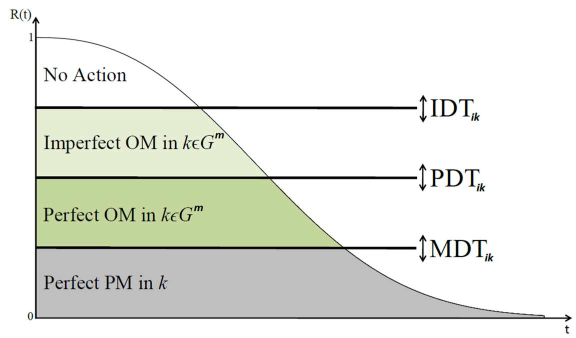


Figure 3: Defined dynamic opportunistic maintenance policy

Table 3: Binary variables utilised in the mathematical model

Decision variables	***Intermediate binary variables***
$MST_{ik} = Minimum\, Static\, Threshold\, of\, FM\, k\, of\, system\, i$	$y_{likjt} = \begin{cases} 1 & if\, PM\, j\, is\, performed\, in\, FM\, k\, of\, system\, i \\ & of\, Tram\, l\, in\, period\, t \\ 0 & otherwise \end{cases}$
$PST_{ik} = Perfect\, Static\, Threshold\, of\, FM\, k\, of\, system\, i$	
$IST_{ik} = Imperfect\, Static\, Threshold\, of\, FM\, k\, of\, system\, i$	$z_{likt} = \begin{cases} 1 & if\, FM\, k\, of\, system\, i\, of\, Tram\, l\, happens \\ & in\, period\, t\ (PI < PCT) \\ 0 & otherwise \end{cases}$
$w_{ik} = Reactivity\, weight\, of\, FM\, k\, of\, system\, i$	
$TPI = Target\, Penalization\, Indicator$	$\gamma_t = \begin{cases} 1 & if\, delay\, penalization\, target\, is\, not\, met \\ & in\, period\, t \\ 0 & otherwise \end{cases}$

Accordingly, the maintenance solution considers both different maintenance levels and the organisational context to make decisions. In particular, the dynamic OM solution to be optimised, which will directly determine the light rail operational performance during its life cycle, is defined by the set of static thresholds, the context-alignment weights and TPI established for each FM k of each system i.

$$\begin{aligned} X(MST_{ik}, PST_{ik}, IST_{ik}, w_{ik}, TPI) = \big[& MST_{11}, PST_{11}, IST_{11}, w_{11}, ..., \\ & MST_{ik}, PST_{ik}, IST_{ik}, w_{ik}, ..., \\ & MST_{IK_I}, PST_{IK_I}, IST_{IK_I}, w_{IK_I}, TPI \big] \end{aligned}$$

4.4. Mathematical Formulation

The overall long term maintenance strategy performance, which is directly determined by the adopted dynamic OM strategy, is evaluated according to two of the main light rail operation indicators, such as LCC of the maintenance strategy (Eq.13) and in-service reliability (through downtime due to failures), and the organisational indicator penalizations due to delays (Eqs.13-15). Likewise, the general mathematical formulation considers:

1. DRT modelling, according to $X\,[MST_{ik}, PST_{ik}, IST_{ik}, w_{ik}, TPI]$, which should be between [0,1] (Eq.16-18).
2. Human resources capacity constraints, where performed maintenance should not be longer than the available working time ($NT{\cdot}T^{wt}$) (Eq.19).
3. Workshop resources capacity constraints, where the time spent by the trams in the maintenance tracks should not be longer than the available working time in the tracks ($NTr{\cdot}T^{wt}$) (20).
4. Maintenance constraints, where only one maintenance activity per FM and period of time can be performed (Eq.21).

$$\begin{aligned} Minimize\, LCC\,(X) = \Bigg[\sum_l \sum_i \sum_k \sum_t \Bigg(& z_{likt} \cdot \left(c^s_{ik} + m^c_{ik}{\cdot}c^{wt} + c^{c,mat}_{ik}\right) + \sum_j y_{likjt}{\cdot} \left(c^s_{ik} + m^{pr}_{ikj}{\cdot}c^{wt} + c^{pr,mat}_{ikj}\right) \Bigg) + \\ & + \sum_t c^p{\cdot}\gamma_t + L{\cdot} \sum_i \sum_k \sum_t C^{insp}_{ikt} \Bigg] \cdot (1+k_a)^{-t} \end{aligned} \tag{13}$$

$$Minimize\ Failure\ Downtime\,(X) = \sum_l \sum_i \sum_k \sum_t m^c_{ik} \cdot z_{likt} \tag{14}$$

$$Minimize\ Delays\ Penalizations\,(X) = \sum_t \gamma_t \tag{15}$$

$S.T.$

$$0 \leq MST_{ik} \leq PST_{ik} \leq IST_{ik} \leq 1 \ \ \forall i \epsilon I, \forall k \epsilon K \tag{16}$$

$$0 \leq w_{ik} \leq 1 \ \ \forall i \epsilon I, \forall k \epsilon K \tag{17}$$

$$0 \leq TPI \leq 1 \tag{18}$$

$$\sum_l \sum_i \sum_k \sum_j m_{ikj}^{pr} \cdot y_{likjt} + \sum_l \sum_i \sum_k m_{ik}^{c} \cdot z_{likt} \leq NT \cdot T^{wt} \quad \forall t \epsilon T \tag{19}$$

$$\sum_l max(m_{ikj}^{pr} \cdot y_{likjt} + m_{ik}^{c} \cdot z_{likt}) \leq NTr \cdot T^{wt} \quad \forall i \epsilon I, \forall k \epsilon K, \forall j \epsilon J, \forall t \epsilon T \tag{20}$$

$$\sum_j y_{likjt} + z_{likt} \leq 1 \quad \forall l \epsilon L, \forall i \epsilon I, \forall k \epsilon K, \forall t \epsilon T \tag{21}$$

$$z_{likt}, y_{likjt}, \gamma_t \epsilon \{0,1\} \; \forall l \epsilon L, \forall i \epsilon I, \forall k \epsilon K, \forall j = \{1,2\}, \forall t \epsilon T \tag{22}$$

5. Simulation-based Optimisation. NSGA II

As shown in the analytical model, the expected performance of the light rail during its life cycle depends on the adopted maintenance strategy, which is at the same time determined by the dynamic reliability thresholds. Therefore, the simulation-based optimisation mechanism described in this section allows systematically evaluating different maintenance strategies ($X\,[MST_{ik}, PST_{ik}, IST_{ik}, w_{ik}, TPI]$) in order to find optimal solutions that will help the decision-maker achieve their objectives. This mechanism consists of two separate modules that continuously interact between them:

- Maintenance strategy performance evaluation model. It evaluates the performance indicators of the rolling stock during its life cycle for a given maintenance strategy.
- Multi-objective optimisation process. It explores the space of different maintenance strategies guided by a multi-objective evolutionary algorithm in order to achieve optimal solutions.

5.1. Maintenance strategy performance evaluation model

The stochastic processes to be handled within this complex model, such as failure occurrence or repair processes, make it difficult to solve it analytically [41, 45]. Therefore, although most part of the problem has been analytically derived, simulation techniques have been used to handle the many random scenarios that can appear for each maintenance strategy, as commonly done in other researches in the field [45, 43]. In particular, an agent-based simulation model has been developed in Anylogic® simulation environment [68], due to its previous success dealing with engineering problems with multi-unit systems hierarchically organized [69].

In order to reach the indenture level established within the light rail hierarchical structure (maintainable item), three different agents have been defined: trams, systems and failure modes. Accordingly, depending on the specific systems, the FM might regard either to the subsystem or component failure; and thus, reliability analyses and maintenance strategies are studied with regards to them.

Figure 4 shows the modelled simulation processes to handle the four different maintenance events at FM indenture level (see subsection 4.1), which are as follows:

1. Hard failure event management (Figure 4a). The light rail should be removed from the line, brought to the repair shop and repaired as soon as the maintenance resources are available (Eq. 19). Once it is repaired the need of soft failure and/or OM management is analyzed.
2. Soft failure event management (Figure 4b). Failures that do not have affection to the service are repaired at the end of the service, as long as maintenance resources are available (Eq. 19). Once it is repaired the need of OM is analyzed.
3. OM management (Figure 4c). The decision of opportunistically maintaining a FM is made based on the established maintenance strategy, according to the reliability thresholds defined and the resources availability.
4. TBPM management (Figure 4d). Scheduled maintenance is performed according to the time interval defined in the time-based preventive maintenance strategy (specifically modelled in order to compare actual maintenance strategy to proposed opportunistic maintenance).

Therefore, in line with the analytical model presented in subsection 4.4, maintenance performance, both in terms of corrective and preventive maintenance, is directly determined by the reliability thresholds

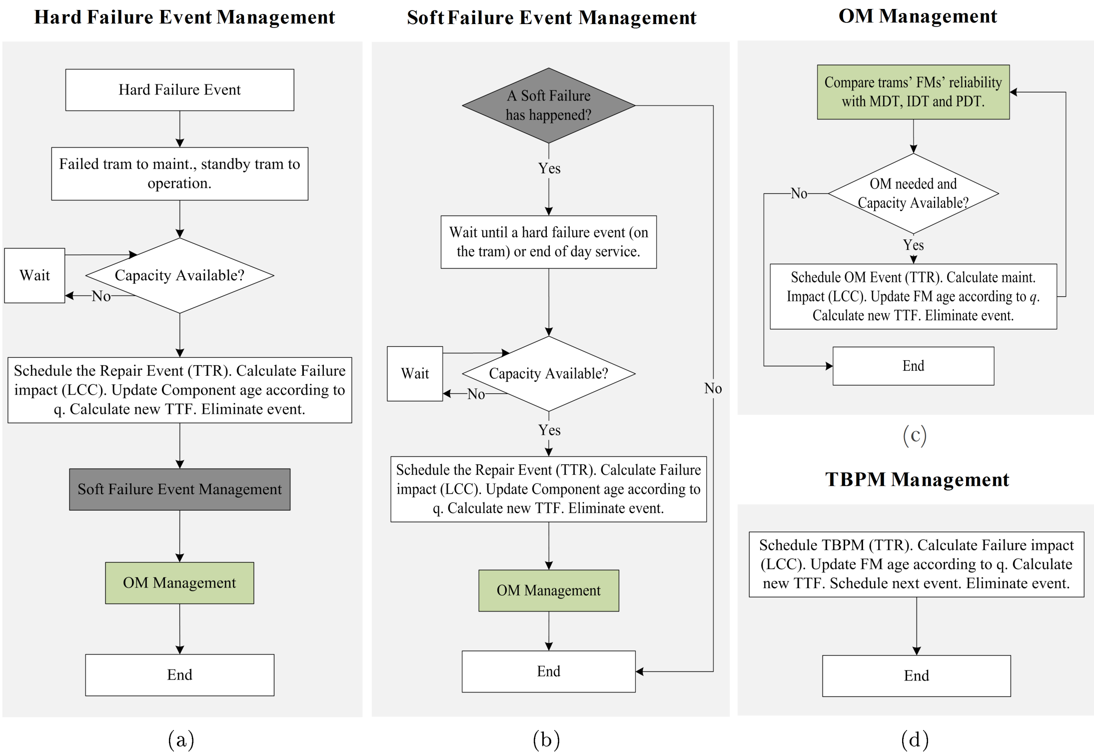


Figure 4: Flowcharts for maintenance events triggering processes

and the available resources. The following steps describe the simulation iteration process for evaluating the maintenance performance during the life cycle (see Figure 5):

Step 1. The parameters and decision variables required for the simulation process (see Tables 2 and3) are initialized: maintenance policy, costs related to maintenance, failure and maintainability distributions, number of MT and working hours, maximum iteration period, etc.

Step 2. The simulation clock and virtual age of the FMs are updated, identifying their new reliability according to their age. Likewise, the reliability thresholds are updated according to the external variables as well.

Step 3. If maintenance has to be performed according to the events triggering processes defined in Figure 4, then the Time To Repair is calculated (TTR) and the needed resources are allocated. Once the maintenance activity is finished, the virtual age of the system is updated. The new Time To Failure (TTF) is calculated through the Inverse Transform Technique (Eq.23) [70], in which R is uniformly distributed between [0,1).

$$TTF_{hik} = \alpha_{ik} \left[\left(\frac{VA_{hik}}{\alpha_{ik}} \right)^{\beta_{ik}} - ln\,(1-R) \right]^{\frac{1}{\beta_{ik}}} - VA_{hik} \tag{23}$$

Step 4. LCC, failure downtime and number of penalizations are updated (Eqs.13-14). If actual period is equal to the maximum iteration period, then step 5 is followed. Otherwise, steps 2, 3 and 4 are repeated.

Step 5. The total expected LCC, failure downtime and number of penalizations are calculated for the established OM policy (Eqs. 13-14).

5.2. Multi-objective Optimisation Process

The maintenance model described in subsection 4.4 has to deal with conflicting objectives as maintenance cost and failure downtime; this is, decreasing one of them implies increasing the other one. On such occasions, multi-objective optimisation algorithms are required to achieve a trade-off between the objectives. These algorithms allow finding the Pareto optimal front, that is, the feasible solutions for which there is not any other feasible solution that improves one criterion without causing a simultaneous worsening of at least one other criterion [71]. Thus, once obtained the Pareto-front, the decision-maker

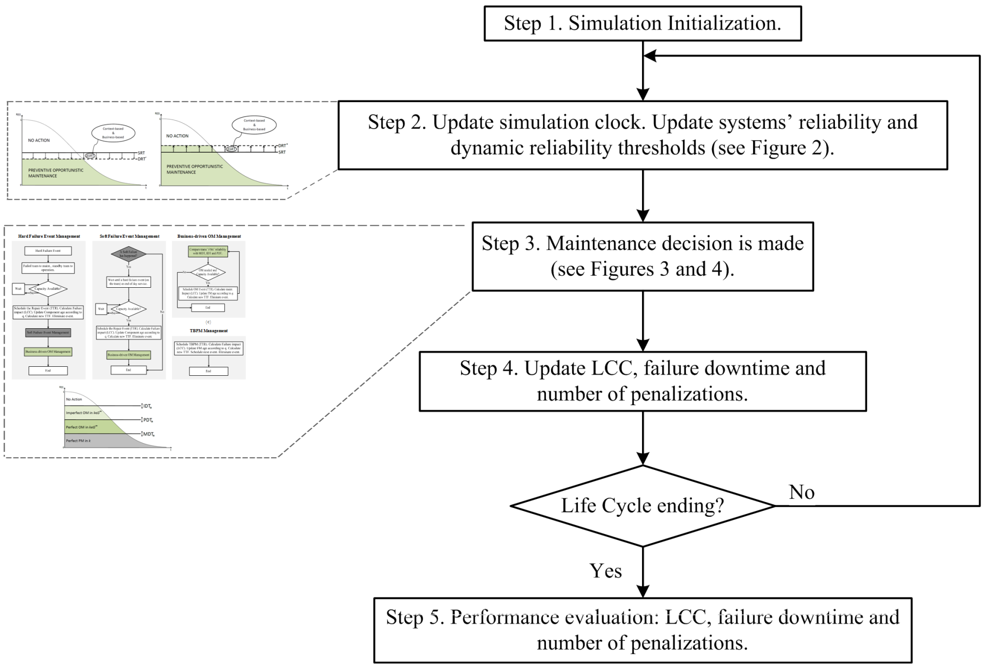


Figure 5: Simulation process for LCC, failure downtime and number of penalizations evaluation

will easily identify what solution should be pursued for achieving the compromise between the conflicting targets.

In the context of multi-objective combinatorial optimisation problems, meta-heuristic algorithms have been proven very useful to find high-quality optimal solutions; being several algorithms available in the literature, such as genetic or particle swarm optimisation algorithms [71]. Since it is not the aim of this paper to further research optimisation algorithms, but to use them in the context of rolling stock maintenance optimisation, genetic algorithms are adopted for developing the present simulation-based optimisation mechanism.

In particular, the Non-dominated Sorting Genetic Algorithm II (NSGA II) introduced by Deb et al. [72] is adopted due to its previous successful implementation in maintenance optimisation problems [45, 73]; considering the success in terms of providing both high quality non-dominated solutions and a proper diversity on the Pareto front [73]. NSGA II is based on the previous evolutionary Non-dominated Sorting Genetic Algorithm (NSGA), which finds optimal solutions based on several layers of classification and ranking of individuals [71]. Notwithstanding, NSGA II also includes elitism and a crowded distance sorting to ensure the diversity of the population without specifying any additional parameter, making it more efficient [71].

In the present optimisation problem, genes consist of the variables that define the dynamic reliability thresholds, and thus the dynamic OM. Subsequently, each individual is evaluated through the simulation model (see Figure 5), and then ranked and sorted based on their non-domination level regarding the objective functions. Out of this sorting, a new pool of offsprings is created through evolutionary operations, namely crossover and mutation, which respectively combine solutions (genes of two desirable individuals are crossed) or alter them (some genes are mutated) in an iterative process that leads to global optimal solutions.

6. Case study & computational results

In this section a light rail fleet case study is considered in order to test the efficiency of both the proposed dynamic OM model for the railway rolling stock and the simulation-based optimisation mechanism developed. To this aim, data provided by a leading company in the sector on a light rail fleet consisting of 21 same-model trams operating at the same operational conditions in Spain has been utilised.

In particular, 18 failure modes belonging to 6 different systems selected by the experts of the company were initially analyzed. Nevertheless, either because of indenture level issues (i.e. not specific preventive maintenance was performed for a particular failure mode) or because of data scarcity, the case study has had to be restricted to the analysis of 10 failure modes. These failure modes belong to the brake, gates, heating and ventilation air conditioning (HVAC) and traction systems. However, due to confidentiality issues, neither detailed association between analyzed failure modes/systems and their maintenance LCC and downtime figures, nor specific reliability and maintainability statistical analyses' results can be provided in the paper.

Three have been the maintenance strategies studied and compared in the computational results shown below (see optimised decision variables in Table 6 in Annex A):

- *Time-based preventive maintenance.* Preventive maintenance is performed according to certain time intervals depending on the specific FM (i.e. preventive maintenance every 2-4-6... years); which is the standard approach in the sector.
  $LCC,\, TTR,\, Delays\, pen = f[time\, intervals]$

- *Traditional/static OM.* The optimal static OM strategy is adopted. Thus, maintenance activities are triggered based on failure modes' reliability (internal factors).
  $LCC,\, TTR,\, Delays\, pen = f[MST_{ik}, PST_{ik}, IST_{ik}, w_{ik} = -, TPI = -]$

- *Dynamic OM.* The optimal dynamic OM strategy is adopted. Thus, maintenance activities are triggered based on both failure modes' reliability (internal) and organisational (external) factors.
  $LCC,\, TTR,\, Delays\, pen = f[MST_{ik}, PST_{ik}, IST_{ik}, w_{ik}, TPI]$

Likewise, a sensitivity analysis has been performed in order to discuss the impact and suitability of the parameters selected for the dynamic OM modelling.

6.1. Light rail fleet profile

A recently installed virtual fleet of light rail that consists of 21 trams ($L = 21$) is considered, being 18 of them in service, 2 ready to undergo preventive maintenance and 1 in standby, in case any in-service tram suffers a hard failure. As previously stated, for each tram four systems have been considered ($I = 4$): brake, traction, heating and ventilation air conditioning (HVAC) and gates.

Likewise, each of systems has between 2 and 3 independent failure modes ($k_i = 2\, or\, k_i = 3$), for which the Weibull distribution properly fits (α_{ik}, β_{ik}); identified after implementing the practical procedure for identifying statistical reliability models proposed in Louit et al. [74]. Furthermore, in order to bear the impact of a more real imperfect maintenance in the case study [65], it is considered that failure modes can undergo either imperfect ($q_{ik1} = 0.75$) or perfect preventive maintenance ($q_{ik2} = 1$).

There are 2 maintenance tracks and 2 maintenance operators teams per shift ($NT = 2$, $NTr = 2$), being the working time per shift 12 hours (T^{wt}), and the maintenance operator cost 38€/hr (c_{NT}). Preventive maintenance material cost is ranged between 1200 and 7250€ $\left(c_{ik}^{pr,mat}\right)$ and maintainability between 4 and 12hrs $\left(m_{ikj}^{pr}\right)$, depending on the failure mode. On the contrary, according to the field data, corrective maintenance material cost is ranged between 50 and 150€ $\left(c_{ik}^{c,mat}\right)$ and its maintainability between 1 and 4,5hrs (m_{ik}^{c}). Despite that it is less expensive to correctively maintain the failure modes, according to the experts knowledge, it is considered not to have a restoration factor in the tram ($q_{ik}^{c} = 0$).

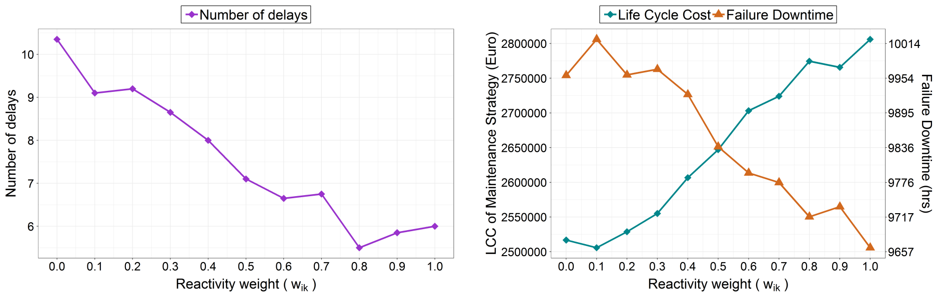
Set-up cost for maintenance has been established in 30€ (c_{ik}^{s}) per tram maintained, mainly due to the set-up time, considering a unique c_{ik}^{s} when more than a FM is simultaneously maintained. Penalizations are evaluated every 3 months according to the contract requirements, and assumed cost per penalization has been established in 500€ (c^{pen}). Finally, the life cycle of the light rail fleet is 36 years (OT) and the interest rate 3% (k_a).

6.2. Sensitivity analysis

In this section the impact of the parameters that condition the dynamic OM policy is evaluated. To this aim, a base maintenance strategy is chosen (obtained from the optimal solutions gathered in Subsection 6.3 and establishing ($w_{ik} = 0.5$) and($TPI = CPT$)) and changes in context-alignment weight and target penalization indicator are analyzed.

Context-alignment weight (w_{ik}). The bigger the context-alignment weight, the more it is fostered preventive maintenance during the periods when there is a high risk of incurring in penalizations; and the more it is hindered during low risk periods. Accordingly, in the base scenario where $TPI = CPT$, there are less penalizations at high context-alignment weights (see Figure 6a). However, if the context-alignment weight is not optimised, it can lead to over-maintenance, entailing an increase of the LCC (see Figure 6b).

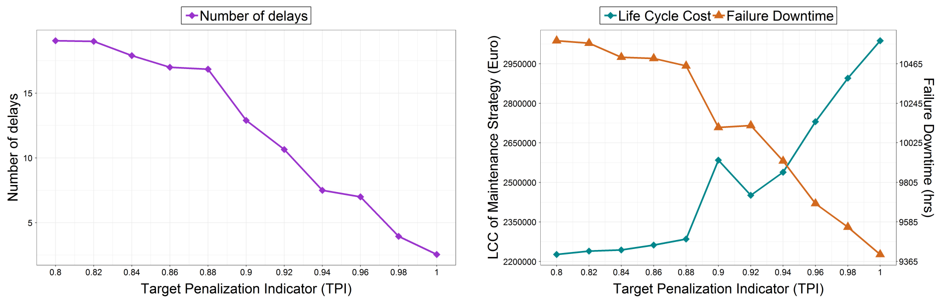
Target Penalization Indicator (TPI). Low TPI will hinder preventive maintenance, since the penalization indicator will be easily over the target (see Eq. 9). Thus, the lower TPI , the more difficult it will



(a) Number of delays (b) LCC and failure downtime

Figure 6: Context-alignment weight sensitivity analysis

be to avoid penalizations (see Figure 7a). However, for high TPI values, preventive maintenance can be excessively fostered, entailing an over-maintenance (see Figure 7b).



(a) Number of delays (b) LCC and failure downtime

Figure 7: Target Penalization Indicator sensitivity analysis

6.3. Optimisation results and discussion

The simulation-based optimisation mechanism developed allows the decision maker to obtain a Pareto-front where optimal maintenance strategies are compared with regards to the objectives established in the maintenance problem. Thus, they will not only be able to identify how optimal maintenance strategies can outperform their current maintenance strategy (TBPM), but also to decide which maintenance strategy they should adopt in order to achieve their objectives.

For instance, guided by Figure 8, where both maintenance strategy LCC and failure downtime are represented in the Pareto-front, the decision-maker can identify the range of maintenance strategies that outperform their current strategy either in terms of LCC, failure downtime or both (see specific results of analyzed maintenance strategies in Table 4). Accordingly, if the decision-maker is satisfied with the reliability of the rolling stock (i.e. failure downtime), the LCC can be decreased from $2.45E6$ to $2.11E6$ € (14% of improvement) without entailing a higher failure downtime (see Figure 8). On the contrary, if the decision-maker is satisfied with their LCC, they can improve the overall reliability of the fleet, from $11E3$ to near $10E3$ hours (9% of improvement).

Maintenance Strategy	LCC (x10^6 €)	Fail. Down. (x10^3 hrs)	Delays
TBPM	2.45	11.1	21
Static OM ($\sim fail.down.$)	2.11	11.1	17.0
Static OM($\sim LCC$)	2.45	10.1	14.0
Dynamic OM ($\sim fail.down.$)	2.12	11.0	13.7
Dynamic OM ($\sim LCC$)	2.45	10.2	11.3

Table 4: Mean values of analyzed maintenance strategies' performance regarding the objective functions

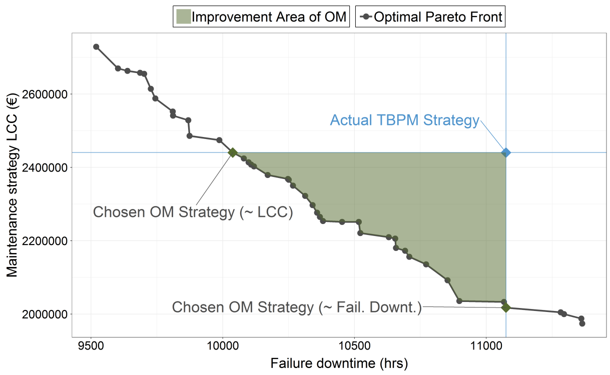
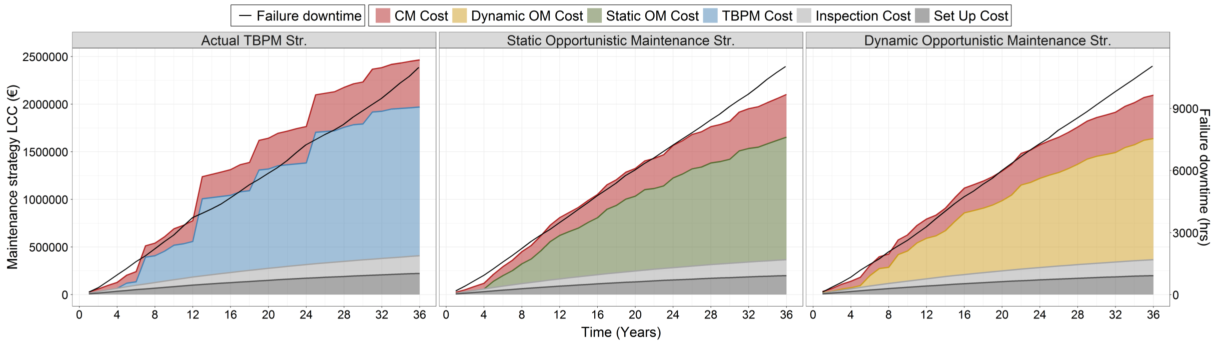
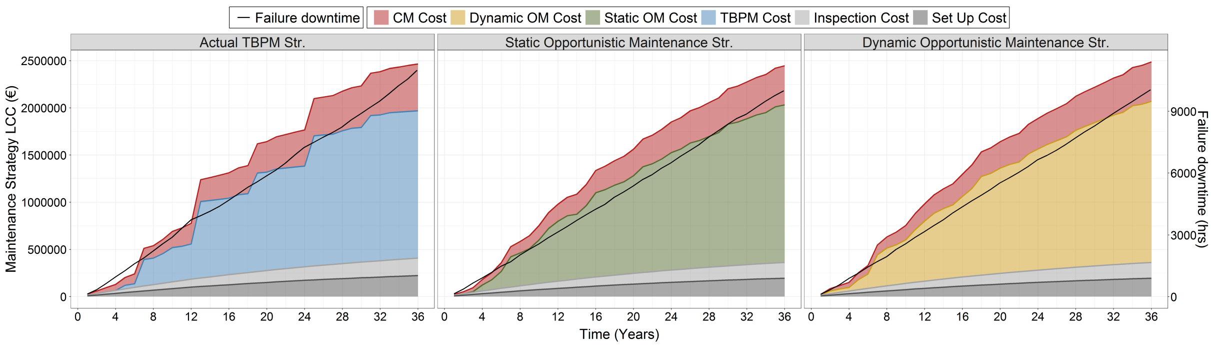


Figure 8: Pareto Optimal & chosen OM strategies

Furthermore, once the maintenance strategy to be adopted has been chosen, the decision-maker can analyze in detail its performance by using the simulation model. As an example, OM strategies identified in Table 4, have been further analyzed in Figures 9 and 10.



(a) Comparison for similar failure downtime

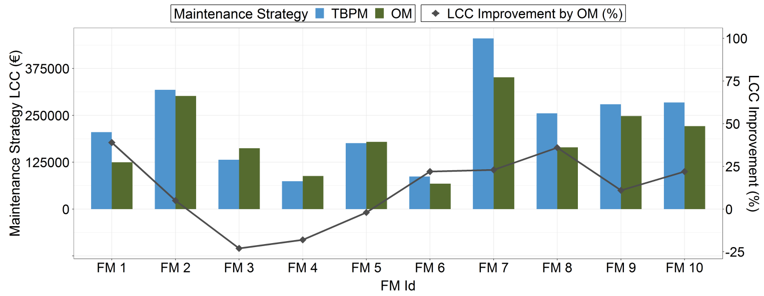


(b) Comparison for similar LCC

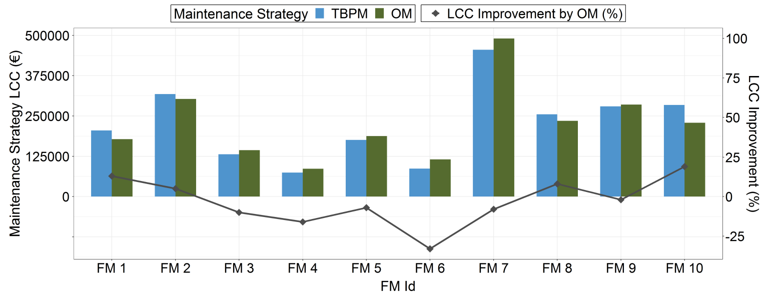
Figure 9: Comparison between maintenance strategies' performance according to LCC and failure downtime

On the one hand, Figure 9 shows the evolution of the LCC classified according to the different maintenance activities, such as corrective maintenance, preventive maintenance, inspections or set-up, as well as their entailed failure downtime. Consequently, obtained results allow confirming the inefficiencies of the current maintenance strategy. In fact, the same failure downtime can be achieved even if preventive maintenance cost is significantly reduced (18%) (see Figure 9a). Likewise, through a reallocation of the maintenance resources (preventive maintenance cost increase of 7%), a better reliability can be achieved, respectively reducing corrective maintenance costs and failure downtime in a 16% and a 9% (see Figure 9b).

On the other hand, these inefficiencies can be further analyzed according to the maintenance strategy cost per failure mode, which will let the decision-maker know what failure modes are being over or under-maintained. For the specific case study, this information can be specifically addressed in Figure 10, where the maintenance LCC per failure mode is compared between current (TBPM) and static OM. As shown in Figure 10a, current maintenance strategy properly allocates resources in failure modes 2 or 5; however, failure modes 1,7 and 8 are being over-maintained while 3 and 4 require more maintenance. Therefore, aided by the simulation module developed and just changing the reliability thresholds that define the OM strategy, the decision-maker will be able to identify the expected impact of the changes in the specific FMs.



(a) Similar Failure Downtime strategies



(b) Similar LCC strategies

Figure 10: LCC comparison between OM and TBPM per failure mode

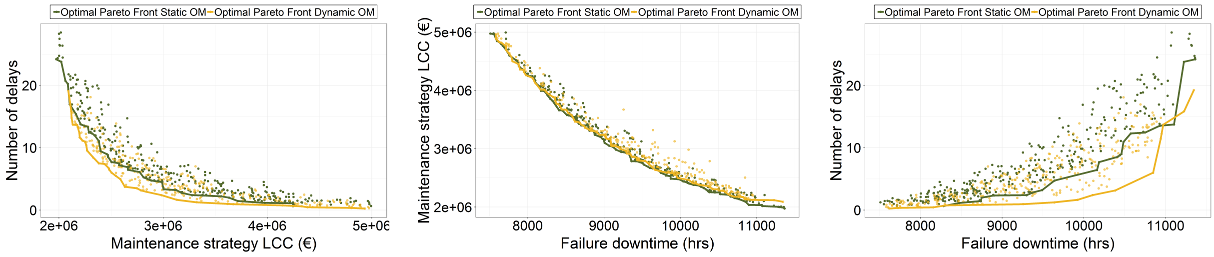
The presented result analysis so far, however, does not differentiate between static and dynamic OM modelling, which is one of the main contributions of the paper. This is due to the fact that, as stated in Section 3, dynamic OM does not outperform static OM in the traditional maintenance indicators. In fact, as shown in Figure 11b, Pareto-optimal fronts for LCC and downtime achieved with both OM strategies are quite similar, with less than 1% of failure downtime variance for the different LCC intervals analyzed (see Table 5 and Figure 11b).

LCC Interval ($x10^6$ €)	ΔDelays (%)	ΔFail. Down. (%)
2.1-2.7	23.2	-0.5
2.7-3.3	22.4	-1.0
3.3-3.9	19.2	-0.8
3.9-4.5	30.5	0.8
4.5-5.1	30.5	-0.3

Fail. Down. Interval ($x10^3$ hrs)	ΔDelays (%)
7.5-8.3	38.4
8.3-9.1	13.5
9.1-9.9	23.3
9.9-10.7	32.3
10.7-11.5	35.8

Table 5: Delays % improvement for same failure downtime and LCC intervals

Nevertheless, if the organisational objective considered for modelling the dynamic OM is analyzed, i.e. number of penalizations during the light rail fleet life cycle, results of dynamic OM considerably outperform those obtained by Static OM. Actually, the comparison of the two Pareto-fronts in Figures 11a and 11c, which show the number of delays against maintenance strategies LCC and downtime, reveals that results are significantly improved. For instance, specifically considering the dynamic and static OM optimal strategies' results for the chosen objective function values (see Figure 8 and Table 4), the number of delays in the mean values decreases a 19% in both cases; from 17 to 13,7, and from 14 to 11,3, respectively.



(a) LCC vs delays (b) LCC vs failure downtime (c) Failure downtime vs delays

Figure 11: Comparison of Pareto-fronts between static and dynamic OM

Likewise, if the number of delays decrease is analyzed per different LCC and failure downtime intervals, results show that in mean values, the number of delays is decreased between 20-30% in the former case and between 13-38% in the latter case. Thus, in general terms, for same LCC or failure downtime, results for the considered organisational objective are significantly improved by dynamic OM compared to static OM; which implies that maintenance opportunities from an organisational perspective are systematically better assessed by dynamic OM.

7. Concluding remarks

The present paper sheds new light in optimising rolling stock maintenance strategies, which as studied, can significantly improve railway fleets' performance in terms of life cycle cost and reliability. In particular, with the aim of providing the rolling stock manufacturers with more flexible maintenance programs, a novel dynamic opportunistic maintenance model is presented and validated in a computational case study based on real field data.

Results obtained show that the novel dynamic opportunistic maintenance policy proposed, in contrast to traditionally adopted maintenance strategies, succeeds in simultaneously considering both internal and external variables to systematically take advantage of more favourable contexts to perform maintenance; leading to align maintenance and organisational decisions. Furthermore, as far as the authors are concerned, the maintenance model developed, which not only considers the railway fleet as a multi-unit system that can undergo multi-level maintenance, but also establishes capacity constraints such as maintenance teams and tracks, is one of the most comprehensives in the sector.

Likewise, the simulation-based optimisation mechanism developed, which incorporates multi-objective optimisation genetic algorithms hooked on simulation analysis, enables the decision-maker to 1) identify optimal maintenance strategies that find a compromise between conflicting objectives and 2) in detail analyze the performance of specific maintenance strategies. Thus, it is considered an effective tool that enables decision-makers to represent their decision preferences on the maintenance program.

Finally, in a future context where the rolling stock is not going to be sold as an equipment, but as a service, the application of the proposed research appears to be very valuable for manufacturers willing to undergo the servitization process. As a consequence, future research will be focused on both exploiting the presented methodologies in the context of servitization and generalizing current work to comprehend other railway platforms. Likewise, failure modes under study have been limited due to available data at proper indenture levels; thus, in order to properly undergo the servitization process, data gathering and filtering efforts to include more systems in the study will be made.

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References

[1] EC, White Paper on Transport: Roadmap to a Single European Transport Area: Towards a Competitive and Resource-efficient Transport System, Publications Office of the European Union, 2011.

[2] L.-Y. He, L.-Y. Qiu, Transport demand, harmful emissions, environment and health co-benefits in China, Energy Policy 97 (2016) 267–275. doi:10.1016/j.enpol.2016.07.037.
URL https://doi.org/10.1016%2Fj.enpol.2016.07.037

[3] M. Siemiatycki, Return to the Rails: The Motivations for Building a Modern Tramway in Bilbao, Spain, Citeseer, 2009.

[4] EC, Eu transport in figures (2016).
URL https://ec.europa.eu/transport/sites/transport/files/pocketbook2016.pdf

[5] C. A. Kennedy, A comparison of the sustainability of public and private transportation systems: Study of the greater toronto area, Transportation 29 (4) (2002) 459–493. doi:10.1023/a:1016302913909.
URL https://doi.org/10.1023%2Fa%3A1016302913909

[6] B. Firlik, B. Czechyra, A. Chudzikiewicz, Condition monitoring system for light rail vehicle and track, Key Engineering Materials 518 (2012) 66–75. doi:10.4028/www.scientific.net/kem.518.66.
URL https://doi.org/10.4028%2Fwww.scientific.net%2Fkem.518.66

[7] T. Nilsen, R. Syvertsen, RCM and barrier modelling—application of barrier analysis to railway rolling stock maintenance optimization, in: Safety and Reliability of Complex Engineered Systems, Informa UK Limited, 2015, pp. 1039–1045. doi:10.1201/b19094-137.
URL https://doi.org/10.1201%2Fb19094-137

[8] R. Yaping, Z. Xingchen, Baiyun, L. Lu, C. Yao, S. Yiwei, Life cycle cost analysis of urban rail transit vehicle, in: 8th International Conference on Measuring Technology and Mechatronics Automation (ICMTMA), Institute of Electrical and Electronics Engineers (IEEE), 2016. doi:10.1109/icmtma.2016.96.
URL https://doi.org/10.1109%2Ficmtma.2016.96

[9] P. Dersin, A. Peronne, C. Arroum, Selecting test and maintenance strategies to achieve availability target with lowest life-cycle cost, in: 2008 Annual Reliability and Maintainability Symposium, Institute of Electrical and Electronics Engineers (IEEE), 2008. doi:10.1109/rams.2008.4925812.
URL https://doi.org/10.1109%2Frams.2008.4925812

[10] P. Conradie, C. Fourie, P. Vlok, N. Treurnicht, Quantifying system reliability in rail transportation in an ageing fleet environment, South African Journal of Industrial Engineering 26 (2) (2015) 128–142, cited By 0.
URL https://www.scopus.com/inward/record.uri?eid=2-s2.0-84943514966&partnerID=40&md5=301e7ccf94034eccc59a95ad46c12b7c

[11] Une-en 50126-1:2005. rairail applications. the specifications and demonstration of reliability, availability, maintainability and safety (rams) (2005).

[12] M. Asjad, M. S. Kulkarni, O. P. Gandhi, A life cycle cost based approach of o&m support for mechanical systems, International Journal of System Assurance Engineering and Management 4 (2) (2013) 159–172. doi:10.1007/s13198-013-0156-7.
URL https://doi.org/10.1007%2Fs13198-013-0156-7

[13] J. Fang, L. Ji, Life cycle cost prediction for rolling stocks in maintenance phase based on VBA language program, International Journal of Smart Home 9 (3) (2015) 239–252. doi:10.14257/ijsh.2015.9.3.22.
URL https://doi.org/10.14257%2Fijsh.2015.9.3.22

[14] B. Schlake, C. Barkan, J. Edwards, Train delay and economic impact of in-service failures of railroad rolling stock, Transportation Research Record: Journal of the Transportation Research Board 2261 (2011) 124–133. doi:10.3141/2261-14.
URL https://doi.org/10.3141%2F2261-14

[15] G. L. Giacco, D. Carillo, A. D'Ariano, D. Pacciarelli, Á. G. Marín, Short-term rail rolling stock rostering and maintenance scheduling, Transportation Research Procedia 3 (2014) 651–659. doi:10.1016/j.trpro.2014.10.044.

[16] Y.-C. Lai, S.-W. Wang, K.-L. Huang, Optimized train-set rostering plan for Taiwan high-speed rail, IEEE Transactions on Automation Science and Engineering 14 (1) (2017) 286–298. doi:10.1109/tase.2016.2526039.
URL https://doi.org/10.1109%2Ftase.2016.2526039

[17] Y.-C. Lai, D.-C. Fan, K.-L. Huang, Optimizing rolling stock assignment and maintenance plan for passenger railway operations, Computers & Industrial Engineering 85 (2015) 284–295. doi:10.1016/j.cie.2015.03.016.
URL https://doi.org/10.1016%2Fj.cie.2015.03.016

[18] Y.-H. Cheng, H.-L. Tsao, Rolling stock maintenance strategy selection, spares parts' estimation, and replacements' interval calculation, International Journal of Production Economics 128 (1) (2010) 404–412. doi:10.1016/j.ijpe.2010.07.038.
URL https://doi.org/10.1016%2Fj.ijpe.2010.07.038

[19] A. V. Horenbeek, L. Pintelon, P. Muchiri, Maintenance optimization models and criteria, International Journal of System Assurance Engineering and Management 1 (3) (2010) 189–200. doi:10.1007/s13198-011-0045-x.
URL http://dx.doi.org/10.1007/s13198-011-0045-x

[20] P. Umiliacchi, D. Lane, F. Romano, A. S.p.A, Predictive maintenance of railway subsystems using an ontology based modelling approach, 2011.

[21] H. Ghamlouch, A. Grall, Opportunistic maintenance strategy for a train fleet under safety constraints and inter-system dependencies, in: Safety and Reliability. Safe societies in a changing world., 2018.

[22] R. Nicolai, R. Dekker, A review of multi-component maintenance models, in: Proceedings of European Safety and Reliability Conference, 2007, pp. 289–296.
URL http://www.dimat.unina2.it/marrone/dwnld/Proceedings/ESREL/2007/Pdf/CH036.pdf

[23] A. V. Horenbeek, L. Pintelon, A dynamic predictive maintenance policy for complex multi-component systems, Reliability Engineering & System Safety 120 (2013) 39–50. doi:10.1016/j.ress.2013.02.029.
URL http://dx.doi.org/10.1016/j.ress.2013.02.029

[24] X. Zhou, L. Xi, J. Lee, Opportunistic preventive maintenance scheduling for a multi-unit series system based on dynamic programming, International Journal of Production Economics 118 (2) (2009) 361–366. doi:10.1016/j.ijpe.2008.09.012.
URL http://dx.doi.org/10.1016/j.ijpe.2008.09.012

[25] R. Laggoune, A. Chateauneuf, D. Aissani, Opportunistic policy for optimal preventive maintenance of a multi-component system in continuous operating units, Computers & Chemical Engineering 33 (9) (2009) 1499–1510.

doi:10.1016/j.compchemeng.2009.03.003.
URL http://dx.doi.org/10.1016/j.compchemeng.2009.03.003

[26] R. Laggoune, A. Chateauneuf, D. Aissani, Impact of few failure data on the opportunistic replacement policy for multi-component systems, Reliability Engineering & System Safety 95 (2) (2010) 108–119. doi:10.1016/j.ress.2009.08.007.
URL http://dx.doi.org/10.1016/j.ress.2009.08.007

[27] Z. Tian, T. Jin, B. Wu, F. Ding, Condition based maintenance optimization for wind power generation systems under continuous monitoring, Renewable Energy 36 (5) (2011) 1502–1509. doi:10.1016/j.renene.2010.10.028.
URL http://dx.doi.org/10.1016/j.renene.2010.10.028

[28] F. Ding, Z. Tian, Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds, Renewable Energy 45 (2012) 175–182. doi:10.1016/j.renene.2012.02.030.
URL http://dx.doi.org/10.1016/j.renene.2012.02.030

[29] X. Zhou, Z. Lu, L. Xi, Preventive maintenance optimization for a multi-component system under changing job shop schedule, Reliability Engineering & System Safety 101 (2012) 14–20. doi:10.1016/j.ress.2012.01.005.
URL http://dx.doi.org/10.1016/j.ress.2012.01.005

[30] Y. Zhou, Z. Zhang, T. R. Lin, L. Ma, Maintenance optimisation of a multi-state series–parallel system considering economic dependence and state-dependent inspection intervals, Reliability Engineering & System Safety 111 (2013) 248–259. doi:10.1016/j.ress.2012.10.006.
URL http://dx.doi.org/10.1016/j.ress.2012.10.006

[31] C. A. Cavalcante, R. S. Lopes, Multi-criteria model to support the definition of opportunistic maintenance policy: A study in a cogeneration system, Energy 80 (2015) 32–40. doi:10.1016/j.energy.2014.11.039.
URL https://doi.org/10.1016%2Fj.energy.2014.11.039

[32] K.-A. Nguyen, P. Do, A. Grall, Multi-level predictive maintenance for multi-component systems, Reliability Engineering & System Safety 144 (2015) 83–94. doi:10.1016/j.ress.2015.07.017.
URL http://dx.doi.org/10.1016/j.ress.2015.07.017

[33] K. T. Huynh, A. Barros, C. Berenguer, Multi-level decision-making for the predictive maintenance of -out-of- :f deteriorating systems, IEEE Transactions on Reliability 64 (1) (2015) 94–117. doi:10.1109/tr.2014.2337791.
URL http://dx.doi.org/10.1109/TR.2014.2337791

[34] X. Zhang, J. Zeng, A general modeling method for opportunistic maintenance modeling of multi-unit systems, Reliability Engineering & System Safety 140 (2015) 176–190. doi:10.1016/j.ress.2015.03.030.
URL http://dx.doi.org/10.1016/j.ress.2015.03.030

[35] L. F. Caetano, P. F. Teixeira, Optimisation model to schedule railway track renewal operations: a life-cycle cost approach, Structure and Infrastructure Engineering 11 (11) (2015) 1524–1536. doi:10.1080/15732479.2014.982133.
URL https://doi.org/10.1080%2F15732479.2014.982133

[36] B. R. Sarker, T. I. Faiz, Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy, Renewable Energy 85 (2016) 104–113. doi:10.1016/j.renene.2015.06.030.
URL http://dx.doi.org/10.1016/j.renene.2015.06.030

[37] H. Abdollahzadeh, K. Atashgar, M. Abbasi, Multi-objective opportunistic maintenance optimization of a wind farm considering limited number of maintenance groups, Renewable Energy 88 (2016) 247–261. doi:10.1016/j.renene.2015.11.022.
URL http://dx.doi.org/10.1016/j.renene.2015.11.022

[38] H. Shi, J. Zeng, Real-time prediction of remaining useful life and preventive opportunistic maintenance strategy for multi-component systems considering stochastic dependence, Computers & Industrial Engineering 93 (2016) 192–204. doi:10.1016/j.cie.2015.12.016.
URL http://dx.doi.org/10.1016/j.cie.2015.12.016

[39] V. Babishin, S. Taghipour, Joint maintenance and inspection optimization of a k-out-of-n system, in: 2016 Annual Reliability and Maintainability Symposium (RAMS), Institute of Electrical and Electronics Engineers (IEEE), 2016. doi:10.1109/rams.2016.7448039.
URL https://doi.org/10.1109%2Frams.2016.7448039

[40] M. C. O. Keizer, R. H. Teunter, J. Veldman, Clustering condition-based maintenance for systems with redundancy and economic dependencies, European Journal of Operational Research 251 (2) (2016) 531–540. doi:10.1016/j.ejor.2015.11.008.
URL http://dx.doi.org/10.1016/j.ejor.2015.11.008

[41] W. Zhu, M. Fouladirad, C. Bérenguer, A multi-level maintenance policy for a multi-component and multifailure mode system with two independent failure modes, Reliability Engineering & System Safety 153 (2016) 50–63. doi:10.1016/j.ress.2016.03.020.
URL http://dx.doi.org/10.1016/j.ress.2016.03.020

[42] K. Atashgar, H. Abdollahzadeh, Reliability optimization of wind farms considering redundancy and opportunistic maintenance strategy, Energy Conversion and Management 112 (2016) 445–458. doi:10.1016/j.enconman.2016.01.027.
URL http://dx.doi.org/10.1016/j.enconman.2016.01.027

[43] H. Abdollahzadeh, K. Atashgar, Optimal design of a multi-state system with uncertainty in supplier selection, Computers & Industrial Engineering 105 (2017) 411–424. doi:10.1016/j.cie.2017.01.019.
URL https://doi.org/10.1016%2Fj.cie.2017.01.019

[44] H. T. Ba, M. Cholette, P. Borghesani, Y. Zhou, L. Ma, Opportunistic maintenance considering non-homogenous opportunity arrivals and stochastic opportunity durations, Reliability Engineering & System Safety 160 (2017) 151–161. doi:10.1016/j.ress.2016.12.011.
URL https://doi.org/10.1016%2Fj.ress.2016.12.011

[45] A. Attar, S. Raissi, K. Khalili-Damghani, A simulation-based optimization approach for free distributed repairable multi-state availability-redundancy allocation problems, Reliability Engineering & System Safety 157 (2017) 177–191. doi:10.1016/j.ress.2016.09.006.
URL https://doi.org/10.1016%2Fj.ress.2016.09.006

[46] C. Zhang, W. Gao, S. Guo, Y. Li, T. Yang, Opportunistic maintenance for wind turbines considering imperfect, reliability-based maintenance, Renewable Energy 103 (2017) 606–612. doi:10.1016/j.renene.2016.10.072.

URL https://doi.org/10.1016%2Fj.renene.2016.10.072

[47] K. Kang, V. Subramaniam, Joint control of dynamic maintenance and production in a failure-prone manufacturing system subjected to deterioration, Computers & Industrial Engineering 119 (2018) 309–320. doi:10.1016/j.cie.2018.03.001.

[48] X. Zhou, B. Lu, Preventive maintenance scheduling for serial multi-station manufacturing systems with interaction between station reliability and product quality, Computers & Industrial Engineering 122 (2018) 283–291. doi:10.1016/j.cie.2018.06.009.

[49] J. Poppe, R. N. Boute, M. R. Lambrecht, A hybrid condition-based maintenance policy for continuously monitored components with two degradation thresholds, European Journal of Operational Research 268 (2) (2018) 515–532. doi:10.1016/j.ejor.2018.01.039.

[50] W. Y. Yun, L. Ferreira, Prediction of the demand of the railway sleepers: A simulation model for replacement strategies, International Journal of Production Economics 81-82 (2003) 589–595. doi:10.1016/s0925-5273(02)00299-2.
URL https://doi.org/10.1016%2Fs0925-5273%2802%2900299-2

[51] F. Dou, W. Zhou, Z. Long, A maintenance strategy for urban maglev train based on RCM, in: 2014 IEEE International Conference on Information and Automation (ICIA), Institute of Electrical and Electronics Engineers (IEEE), 2014. doi:10.1109/icinfa.2014.6932839.
URL https://doi.org/10.1109%2Ficinfa.2014.6932839

[52] E. Ruijters, D. Guck, P. Drolenga, M. Peters, M. Stoelinga, Maintenance analysis and optimization via statistical model checking, in: Quantitative Evaluation of Systems, Springer Nature, 2016, pp. 331–347. doi:10.1007/978-3-319-43425-4_22.
URL https://doi.org/10.1007%2F978-3-319-43425-4_22

[53] C. J. Fourie, T. G. Tendayi, A DECISION-MAKING FRAMEWORK FOR EFFECTIVE MAINTENANCE MANAGEMENT USING LIFE CYCLE COSTING (LCC) IN a ROLLING STOCK ENVIRONMENT, South African Journal of Industrial Engineering 27 (4). doi:10.7166/27-4-1526.
URL https://doi.org/10.7166%2F27-4-1526

[54] D. Eisenberger, O. Fink, Assessment of maintenance strategies for railway vehicles using petri-nets, Transportation Research Procedia 27 (2017) 205–214. doi:10.1016/j.trpro.2017.12.012.

[55] R. Wildeman, R. Dekker, A. Smit, A dynamic policy for grouping maintenance activities, European Journal of Operational Research 99 (3) (1997) 530–551. doi:10.1016/s0377-2217(97)00319-6.
URL http://dx.doi.org/10.1016/S0377-2217(97)00319-6

[56] H. Wang, A survey of maintenance policies of deteriorating systems, European Journal of Operational Research 139 (3) (2002) 469–489. doi:10.1016/s0377-2217(01)00197-7.
URL http://dx.doi.org/10.1016/S0377-2217(01)00197-7

[57] A. Garg, S. Deshmukh, Maintenance management: literature review and directions, Journal of Quality in Maintenance Engineering 12 (3) (2006) 205–238. doi:10.1108/13552510610685075.
URL http://dx.doi.org/10.1108/13552510610685075

[58] A. C. Márquez, P. M. de León, A. S. Rosique, J. F. G. Fernández, Criticality analysis for maintenance purposes: A study for complex in-service engineering assets, Qual. Reliab. Engng. Int. 32 (2) (2015) 519–533. doi:10.1002/qre.1769.
URL http://dx.doi.org/10.1002/qre.1769

[59] J. F. G. Fernández, A. C. Márquez, Framework for implementation of maintenance management in distribution network service providers, Reliability Engineering & System Safety 94 (10) (2009) 1639–1649. doi:10.1016/j.ress.2009.04.003.
URL http://dx.doi.org/10.1016/j.ress.2009.04.003

[60] J. Lee, Y. Chen, H. A. Atat, M. AbuAli, E. Lapira, A systematic approach for predictive maintenance service design: methodology and applications, International Journal of Internet Manufacturing and Services 2 (1) (2009) 76. doi:10.1504/ijims.2009.031341.

[61] McKinsey, The rail sector changing maintenance game, Tech. rep., Digital McKinsey (2017).

[62] U. Leturiondo, Hybrid modelling in condition monitoring, Ph.D. thesis, Luleå University of Technology (2016).

[63] A. Erguido, A. C. Márquez, E. Castellano, F. G. Fernández, A novel dynamic opportunistic maintenance modelling approach, in: Safety and Reliability. Theory and Applications, 2017.

[64] H. Pham, H. Wang, Imperfect maintenance, European Journal of Operational Research 94 (3) (1996) 425–438. doi:10.1016/s0377-2217(96)00099-9.
URL http://dx.doi.org/10.1016/S0377-2217(96)00099-9

[65] M. Yañez, F. Joglar, M. Modarres, Generalized renewal process for analysis of repairable systems with limited failure experience, Reliability Engineering & System Safety 77 (2) (2002) 167–180. doi:10.1016/S0951-8320(02)00044-3.
URL http://www.sciencedirect.com/science/article/pii/S0951832002000443

[66] M. Stamatelatos, H. Dezfuli, G. Apostolakis, C. Everline, S. Guarro, D. Mathias, A. Mosleh, T. Paulos, D. Riha, C. Smith, et al., Probabilistic risk assessment procedures guide for nasa managers and practitioners.

[67] W. Derigent, E. Thomas, E. Levrat, B. Iung, Opportunistic maintenance based on fuzzy modelling of component proximity, CIRP Annals - Manufacturing Technology 58 (1) (2009) 29–32. doi:10.1016/j.cirp.2009.03.079.
URL https://doi.org/10.1016%2Fj.cirp.2009.03.079

[68] A. Borshchev, The big book of simulation modeling: multimethod modeling with AnyLogic 6.

[69] M. Niazi, A. Hussain, Agent-based computing from multi-agent systems to agent-based models: a visual survey, Scientometrics 89 (2) (2011) 479–499. doi:10.1007/s11192-011-0468-9.
URL https://doi.org/10.1007%2Fs11192-011-0468-9

[70] J. Banks, Discrete event simulation, in: Encyclopedia of Information Systems, Elsevier BV, 2003, pp. 663–671. doi:10.1016/b0-12-227240-4/00045-9.
URL https://doi.org/10.1016%2Fb0-12-227240-4%2F00045-9

[71] C. A. C. Coello, G. B. Lamont, D. A. Van Veldhuizen, et al., Evolutionary algorithms for solving multi-objective problems, Vol. 5, Springer, 2007.

[72] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation 6 (2) (2002) 182–197. doi:10.1109/4235.996017.
URL https://doi.org/10.1109%2F4235.996017

[73] D. Salazar, C. M. Rocco, B. J. Galván, Optimization of constrained multiple-objective reliability problems using evolutionary algorithms, Reliability Engineering & System Safety 91 (9) (2006) 1057–1070. doi:10.1016/j.ress.2005.11.040.
URL https://doi.org/10.1016%2Fj.ress.2005.11.040

[74] D. Louit, R. Pascual, A. Jardine, A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data, Reliability Engineering & System Safety 94 (10) (2009) 1618–1628. doi:10.1016/j.ress.2009.04.001.
URL https://doi.org/10.1016%2Fj.ress.2009.04.001

Annex A

Optimised decision variables for the different maintenance strategies analysed are as follows:

System 1 - Brake System								
	FM1				FM2			
	MST_{11}	PST_{11}	IST_{11}	w_{11}	MST_{12}	PST_{12}	IST_{12}	w_{12}
Static OM ($\sim fail.down.$)	0.06	0.26	0.35	-	0.03	0.32	0.35	-
Static OM($\sim LCC$)	0	0.50	0.58	-	0.08	0.29	0.35	-
Dynamic OM ($\sim fail.down.$)	0.07	0.32	0.34	0.0	0.08	0.38	0.42	0.42
Dynamic OM ($\sim LCC$)	0.12	0.36	0.52	0.0	0.06	0.39	0.41	0.57

System 2 - HVAC								
	FM1				FM2			
	MST_{21}	PST_{21}	IST_{21}	w_{21}	MST_{22}	PST_{22}	IST_{22}	w_{22}
Static OM ($\sim fail.down.$)	0.33	0.49	0.61	-	0.4	0.5	0.51	-
Static OM($\sim LCC$)	0.05	0.22	0.52	-	0.19	0.44	0.5	-
Dynamic OM ($\sim fail.down.$)	0.19	0.26	0.49	0.0	0.07	0.34	0.56	0.0
Dynamic OM ($\sim LCC$)	0.11	0.34	0.47	0.0	0.06	0.38	0.62	0.0

System 3 - Gates												
	FM1				FM2				FM3			
	MST_{31}	PST_{31}	IST_{31}	w_{31}	MST_{32}	PST_{32}	IST_{32}	w_{32}	MST_{33}	PST_{33}	IST_{33}	w_{33}
Static OM ($\sim fail.down.$)	0.14	0.28	0.58	-	0.03	0.49	0.82	-	0.06	0.2	0.28	-
Static OM($\sim LCC$)	0.2	0.33	0.64	-	0.36	0.57	0.94	-	0.1	0.19	0.31	-
Dynamic OM ($\sim fail.down.$)	0.13	0.47	0.52	0.26	0.15	0.46	0.91	0.0	0.05	0.19	0.39	0.63
Dynamic OM ($\sim LCC$)	0.02	0.32	0.68	0.15	0.0	0.52	0.96	0.0	0.06	0.31	0.36	0.42

System 4 - Traction System													
	FM1				FM2				FM3				
	MST_{41}	PST_{41}	IST_{41}	w_{41}	MST_{42}	PST_{42}	IST_{42}	w_{42}	MST_{43}	PST_{43}	IST_{43}	w_{43}	TPI
Static OM ($\sim fail.down.$)	0.04	0.26	0.39	-	0.23	0.25	0.28	-	0.04	0.29	0.46	-	-
Static OM($\sim LCC$)	0.03	0.18	0.57	-	0.08	0.36	0.55	-	0.12	0.48	0.53	-	-
Dynamic OM ($\sim fail.down.$)	0.08	0.36	0.43	0.02	0.07	0.15	0.24	0.0	0.04	0.22	0.3	0.0	0.91
Dynamic OM ($\sim LCC$)	0.1	0.36	0.62	0.28	0.02	0.17	0.57	0.0	0.03	0.19	0.29	0.0	0.92

Table 6: Optimised decision variables

Asset management framework and tools for facing challenges in the adoption of Product Service Systems

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Abstract

Servitization is recognized as a key business strategy for Original Equipment Manufacturers willing to move up the value chain. However, several barriers have to be overcome in order to successfully integrate products and services. Many of these barriers are caused by the technical challenges associated with the design and management of the product-service systems, such as life-cycle service level and cost estimation, risk management, or the system design and pricing. Asset management presents itself as a key research area in order to overcome these barriers as well as to integrate product-service systems within the manufacturers' operations management. It is the scope of this paper to provide theoretical and practical insights regarding the alignment of asset management and product-service system research areas. To support the alignment between both areas, a management framework which gathers specific technologies, including reliability analysis, simulation modelling and multi-objective optimization algorithms, is presented. The purpose of the framework is to provide manufacturers with a decision-support tool that facilitates the main managerial challenges faced when implementing a servitization strategy. The paper contributions are successfully applied to case studies in the railway and wind energy sectors based on real field data, thereby demonstrating their suitability for both facilitating manufacturer's decision-making process and better satisfying stakeholders' interests.

Keywords: Servitization, Asset management, Product-Service System, Management framework, Simulation modelling, Multi-objective optimization

1. Introduction

Original Equipment Manufacturers (OEMs) have traditionally been focused on adding value to their products through improvements in terms of quality and cost. Thus, their investments in research and development have mainly been oriented towards products and production processes' design. Nonetheless, manufacturing industries have been undergoing a severe shift of paradigm over the last years, being increasingly challenged by new producers able to offer acceptable quality standards at a low-cost labour base [1]. Therefore, if OEMs want to retain their manufacturing competitiveness, they are advised to "move up the value chain", avoiding to compete uniquely in product and quality offer [1].

In this context, an offer based on the delivery of knowledge-intensive products and services can provide several advantages from a competitiveness point of view [1, 2]. This fact has led to the emergence of Product-Service System (PSS), where both product and services conform a single offer [3, 4], and the business model is no longer selling "only product" but selling an "integration of product and services" [5, 6]. In this new business model, the ownership of the product and its use are decoupled, thus customers (a more suitable term for the users of these products) will not typically buy the product, but its availability or capability [7].

The use of PSSs is expected to bring additional value to an organisation's stakeholders, providing advantages such as: recurrent incomes exceeding the profit margins of new equipment sales [8]; customized

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and differentiating products [9], and increased customers' satisfaction and loyalty [10, 11]. Nonetheless, and besides the cultural and financial challenges related to the ownerless consumption of products, manufacturers have to face technical challenges associated to the management of PSSs within their operations [1]. Such technical challenges are usually a consequence of having to own and manage their advanced and complex products as own assets in rather unknown and risky scenarios; and they are often the reason of the PSS adoption barriers [12–14]. In this context, physical asset management (AM) can acquire a key role in order to facilitate the management of such products (now assets) and maximize their value [15], facilitating PSS design and its performance.

Whereas PSS and AM have been widely researched as independent topics, the impact that the development of accurate AM strategies might have when integrating PSSs in manufacturers' operations has not been previously studied yet. Consequently, the present paper aims to fill this gap in the literature by exploring how developing and improving AM capabilities might help overcome some of the traditional barriers that hinder PSSs' adoption. To this aim, the paper presents a novel management framework, supported by analytical and simulation models, as well as optimization algorithms, which allows manufacturers optimize their AM decisions and achieve successful PSS scenarios.

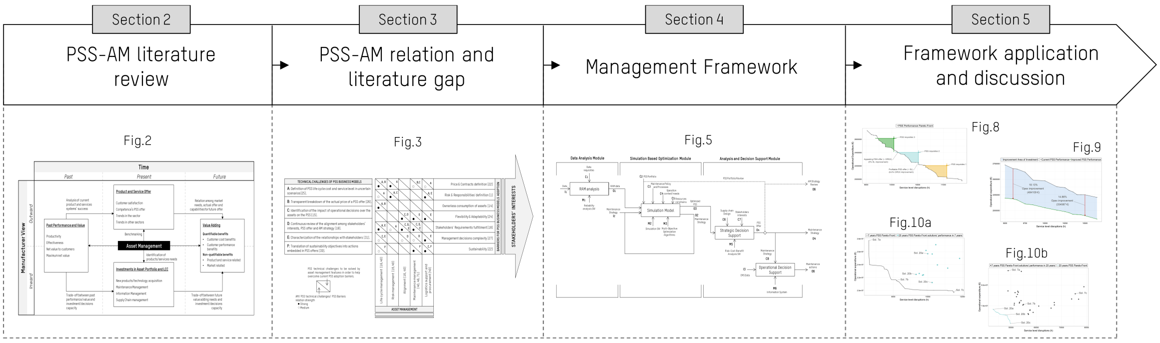


Figure 1: Research Methodology

The paper has been developed following the research methodology shown in Figure 1, which is a graphic guiding line for the remainder of the paper. In section 2 a summary of the exhaustive literature review is presented. Section 3 presents the proposed management framework and describes its main modules and their implementation. Section 4 demonstrates the suitability of the framework through two different case studies based on real field data, regarding two leading sectors such as wind energy and railway. Finally, Section 5 summarizes the concluding remarks and future research lines.

2. Literature Review

2.1. PSS and barriers for its adoption

The integration of products and services has emerged as a new manufacturing strategy for organisations in order to become more competitive, particularly aiming at three objectives: (1) customer satisfaction, (2) economic viability and (3) sustainability [1]. In this context, Tukker [16] highlights that the economy based on purchasing products (*"pure products"*) converges in an economy based on the use of those products (*"pure services"*). This shift, known as *servitization*, has led to the creation of PSSs, where product ownership and use are decoupled in order to sell the result of their combination [17]. Accordingly, the products provide the technical functions to the customers [12], while the services ensure that customers' demands are met [18]. PSS might be classified into three different PSS business models [16]:

- Product-oriented, where some services to be provided by the manufacturer are included within the product sale (e.g. warranties) [12].
- Use-oriented, where the business model is to sell the availability of the product whilst the product ownership remains within the manufacturer (e.g. car renting services) [12, 19].
- Result-oriented: where the business model is to sell the outcome or capability provided by the product, again owned by manufacturers (e.g. pay-per-print) [16].

The choice of the business model will directly determine *how* value is delivered by the manufacturer and perceived by the customer [20], which will lead to different results in terms of competitiveness and differentiation [21]. Likewise, depending on the PSS business model pursued, products and services will have to be differently combined and implemented by manufacturers within their operations management. To this respect, manufacturers will have to make decisions in several tactics that will determine *how much* value is delivered by the chosen business model [21].

Reim et al. [20] categorize these tactics as follows: i) *contracts*, to define the responsibilities of the stakeholders, for instance in terms of asset's downtimes [22–24]; ii) *marketing*, to guide the decisions related to the communication between the stakeholders [22, 25]; iii) *network*, to define the interactions with the stakeholders involved in the PSS, such as suppliers, dealers, customers or service partners [22]; iv) *product and service design*, to identify how manufacturers should design both their products and services portfolio to successfully implement the PSS [26, 27] and v) *sustainability*, to meet legal and market environmental conditions through new technologies and solutions [28, 29].

The complexity of making decisions in such diverse domains has translated into several barriers which hinder PSS business models adoption. These barriers (BA) are summarized as follows:

BA1. Price and contracts definition, requiring to handle and fulfil the interests of each involved stakeholder in a long-term relationship [20].

BA2. Risk and responsibilities definition, requiring to guarantee the product performance along its life cycle and the role of each stakeholder within the PSS [1].

BA3. Ownerless consumption of assets, requiring to transparently design the PSS terms, avoiding the conflicts of interests that may appear among the stakeholders [13].

BA4. Flexibility and adaptability, requiring to ensure that service or/and product specifications satisfy the needs of the stakeholders during the whole contractual relationship [22].

BA5. Stakeholders' requirements fulfilment, requiring both to translate customers' requisites into PSS requisites and to align physical products' characteristics to the service [17]

BA6. Management decisions complexity, requiring non-traditional business networks and changes in relationships with actual stakeholders, identifying how decisions made affect them [25],

BA7. Sustainability, requiring to ensure a compromise between economic and environmental benefits [30].

2.2. Asset management and related capabilities

The complexity of making decisions in such diverse tactics in order to overcome the barriers, entails that manufacturers striving for offering a successful PSS have to develop several capabilities ranging from relationship building to technical or management capabilities [31]. Particularly, regarding the latters, manufacturers often struggle to realize value from the products that they have to manage as own assets in PSS scenarios [14]. To this respect, AM can provide manufacturers with useful insights for enhancing the value that assets can provide to the organization and its stakeholders [32]. In fact, AM is considered to sit the needed meeting point between technical and business performance of assets, making especial emphasis on balancing assets' costs, risks and benefits, over different timescales [32].

Especially when managing products -as assets- in a servitization context, it becomes strategically critical to assess the four AM perspectives proposed by Tao et al. [33]. The perspectives in Tao et al. [33] have been further complemented and adapted in order to address the case of manufacturers facing a PSS scenario. In Figure 2, the aforementioned perspectives are classified according to their timing, i.e. past, present or future, and their position with regards to the manufacturer, i.e. inward or outward:

- **Past performance and value.** Performance history of products and services are measured in order to analyze whether stakeholders' expectations are being met in terms of effectiveness, efficiency or/and created value.

- **Investments in asset portfolio and LCC.** Products' and services' needs are assessed in order to make decisions either about investments, such as new technology acquisition or development, or about management, such as supply chain or maintenance.

- **Product and service offer.** Stakeholders' interests, as well as competitors and markets' trends are assessed in order to guide future decisions.

- **Value adding.** New products and/or services developments are sought in order to add value to the organisation's offer, both in quantifiable (e.g. cost or service level) and non-quantifiable terms (e.g. market leading image). Future value adding seeks a compromise between internal capabilities and external trends and demands.

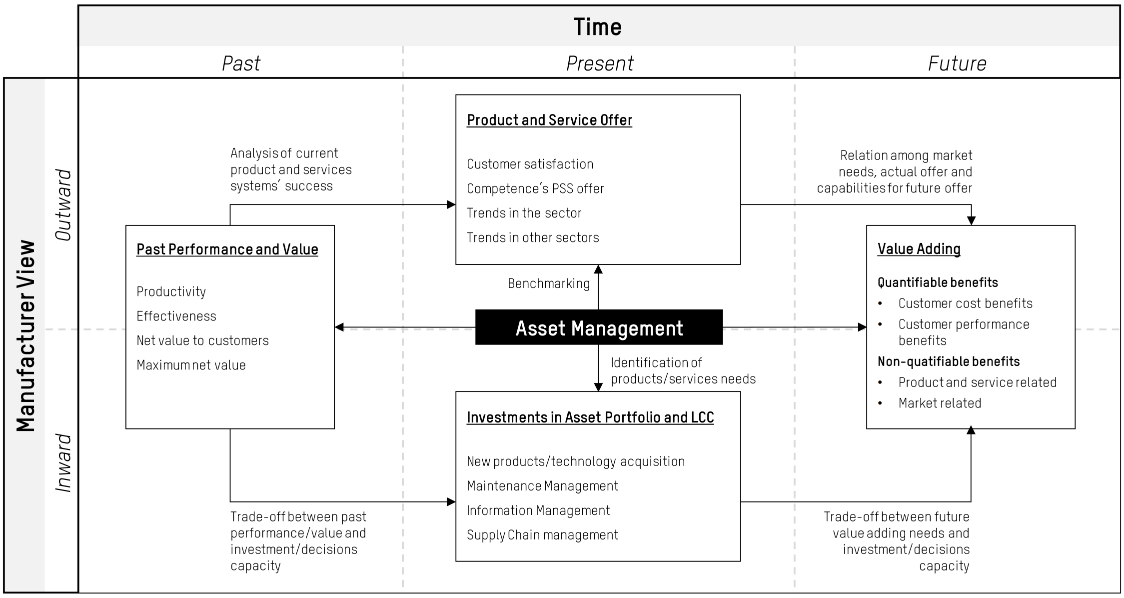


Figure 2: Asset management perspectives for Original Equipment Manufacturers

In general terms, past view identifies what value has been provided by the products in order to guide present decisions and ensure their efficient and effective management; thus leading to an increase of customers' future value perception [33]. Likewise, inward and outward views help ensure a balance between organisations' capabilities and market trends when making decisions. Therefore, in order to optimize organisations' AM decision making process, it is critical not to consider the stated views independently, but as an interconnected system (see the interactions in Figure 2).

For facilitating such decision processes, physical AM emphasizes on developing technical capabilities in the following domains to enhance assets' value (see [15, 32, 34, 35]):

AM1. Life-cycle management, to find a trade-off between initial investment and the value added by the asset, considering the whole life-cycle of the asset.

AM2. Risk-based management, to evaluate the decisions not only from a technical perspective but in a risk-based approach, addressing how uncertainty sources might jeopardize organizational objectives.

AM3. Alignment between organisational and asset management objectives, to ensure that decisions made over the assets are directed towards enhancing organisations' objectives.

AM4. Maintenance management, to operate and maintain assets within acceptable performance indicators such as, reliability, safety or cost.

AM5. Logistics support and procurement, to ensure that resources needs for asset management and operation are available.

2.3. PSS-AM relation and literature gap

Considering the strategic role that AM may play in service-oriented business models, manufacturers could benefit of such capabilities in order to face some of the main technical challenges (TC) that actually hinder their servitization process:

TC1. Definition of PSS life cycle cost and service level in uncertain scenarios [23].

TC2. Transparent breakdown of the actual price of a PSS offer [24].

TC3. Identification of the impact of operational decisions over the assets on the PSS [14].

TC4. Continuous review of the alignment among stakeholders' interests, PSS offer and AM strategy [17].

TC5. Characterization of the relationships with the stakeholders [36].

TC6. Translation of sustainability objectives into actions embedded in PSS offers [27].

Figure 3 provides a deeper insight into the relation between AM capabilities and PSS. The information included in the figure is the result of the research conducted to address the literature gap that connects servitization barriers with AM features -classified as "strong", "medium" or "none"-. By addressing this gap with specific models and tools, the work here presented intends to solve the technical challenges of PSS business models, which have as well been related in the figure to each AM feature and barrier for the PSS adoption.

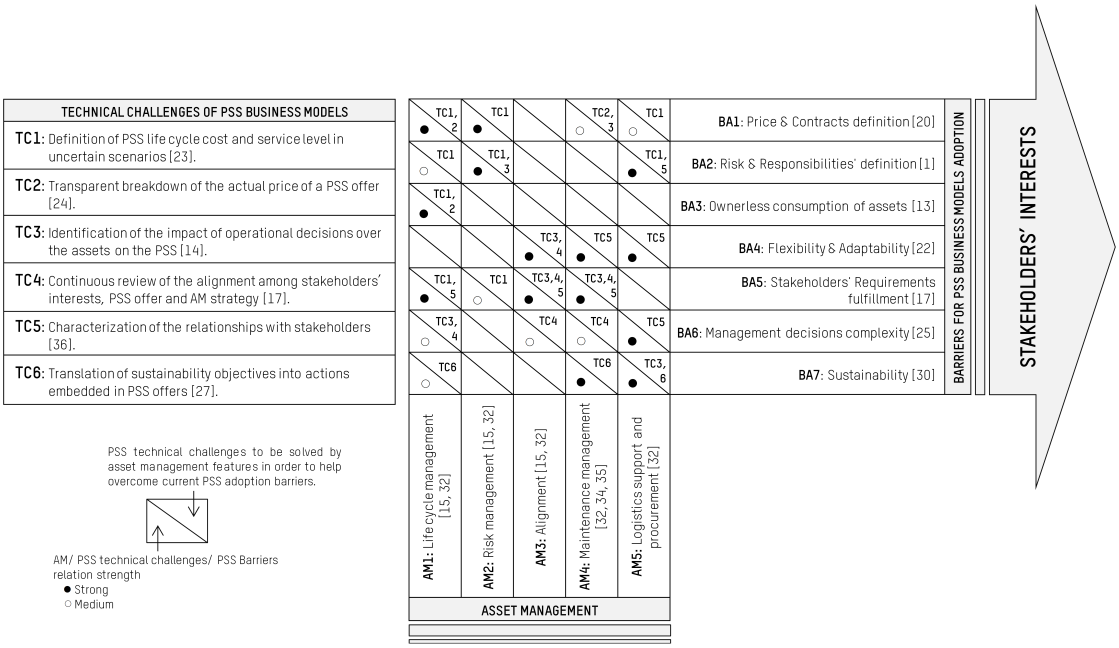


Figure 3: Matching key features of Asset Management and servitization barriers

3. Management Framework for Product-Service System design and management

As the reader may notice, the potential PSS business scenarios that manufacturers may face are almost infinite, as a result of combining products' and services' characteristics with the specific customers' demands. Furthermore, these scenarios are rather unknown for manufacturers, since their PSS portfolios are still under development [37]. In this context there is a clear need of models, methods and tools that can systematically help to design and manage the PSS offering [12, 32, 33, 37], which has led to the development of a management framework inspired in IDEF methodology [38] (see Figure 4).

Defined by functions and ICOMs interfaces (Inputs, Controls, Outputs and Mechanisms), and with a particular focus of enhancing aforementioned AM capabilities, the management framework allows modelling manufacturers' decisions and actions in a servitization context. To this aim, the management framework translates PSS and AM related data (I) into specific decisions regarding what PSSs should be offered and how should they be defined, what AM strategies are more suitable for enabling such PSSs, and what maintenance decisions should be made in order to fulfil customers' expectations (O). Such decisions will be optimized by means of analytical and simulation models (M), which will consider the specific context of manufacturers in a servitization context, as well as their customers' interests and the requisites of the mechanisms (C).

Given the complexity of the problem under consideration, the management framework has been divided in three modules (see Figure 5). These modules, further described in the next Subsections, are as follows:

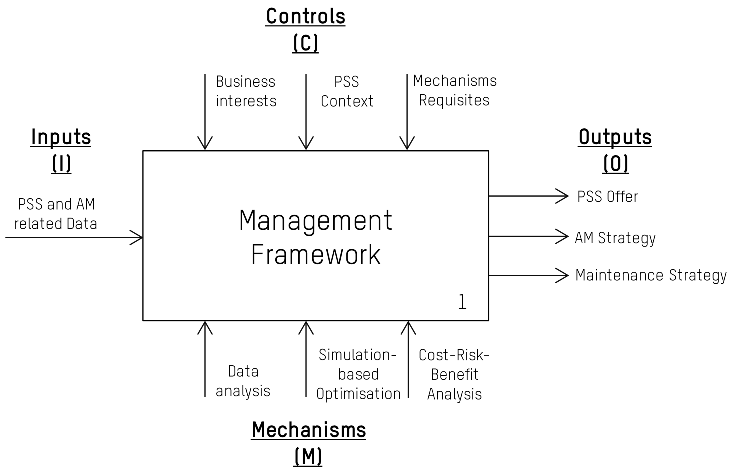


Figure 4: Overview of Management Framework for Product-Service System design and management

- **Data analysis module**, aiming at analyzing the operational data of already deployed products in order to assess the past performance of AM and to lay the foundations for enhancing manufacturers' AM decisions and PSS design.
- **Simulation-based optimization module**, aiming at optimizing the long-term performance of manufacturers' PSS and the AM strategies; considering AM inward and future views. The reader may notice that this module emphasizes in AM1, AM4 and AM5 capabilities.
- **Analysis and decision support module**, aiming at facilitating manufacturers' final decision-making process, finding a compromise among adopted risks, costs and stakeholders' benefits; it addresses AM outward and future views. The reader may notice that this module emphasizes in AM2 and AM3 capabilities.

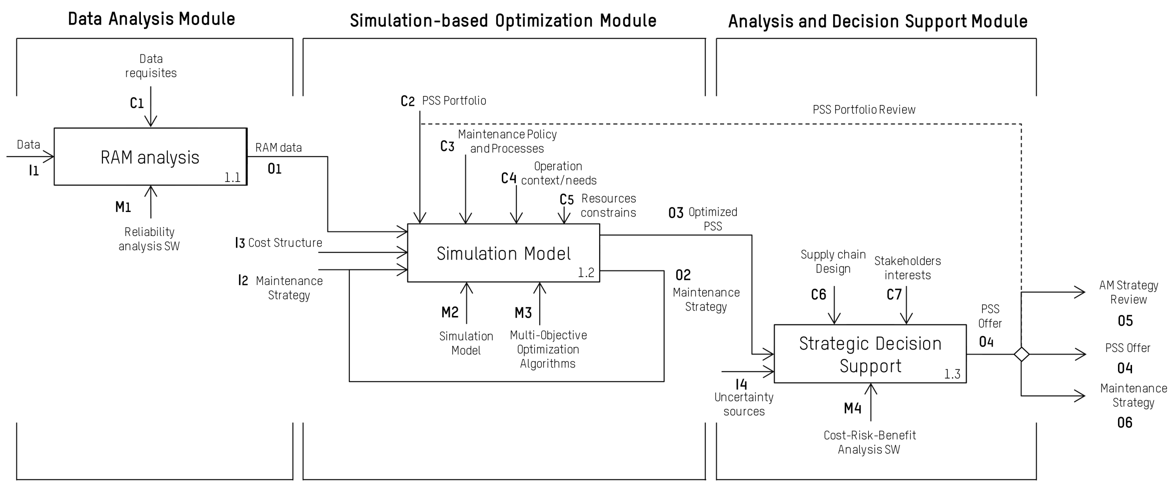


Figure 5: Management Framework for Product-Service System design and management

3.1. Data analysis module

Currently manufactured original equipments, especially in the context of the Industry 4.0, enable gathering a large amount of data [39]. These data, however, should be translated into useful information regarding assets' past performance in order to supports manufacturers' decisions related to the servitization process, being this the purpose of the *data analysis module*.

As described in Section 2, decisions made in AM domains have a positive impact on PSSs; decisions that usually regard to [34]: inspections, maintenance, retrofitting, new products development, new technology inclusion, etc. Accordingly, in order to facilitate such decisions it is especially relevant to analyze past performance of sold products according to their reliability, availability and maintainability [40, 41], i.e. a RAM analysis of the products that in service-oriented business models have to be managed as assets by manufacturers.

In particular, much of the current literature on RAM analysis pays attention to the modelling and accurate estimation of reliability [42]. This attention is motivated by the importance of such analysis when making decisions to improve operational safety and economical efficiency of the assets in a risk-based approach. In fact, being a wide research area, reliability models that regard either to operational or strategic decision-making process have been presented [42–44].

For the framework implementation (see case studies of Section 4), the authors have performed the necessary statistical analyses to determine the reliability of the failure modes of the products to be servitized. In order to avoid the usual and rather unrealistic assumption of identically and independently distributed (iid), which may lead to sub-optimal or even wrong results [44], the general renewal process (GRP) has been implemented [45]. The GRP considers that repair activities may return the systems to an operation condition worse than the new one but better than just before the maintenance task is performed, i.e. imperfect maintenance [45], based on two main concepts:

1. Virtual Age (VA). The calculated age of the system immediately after repair process.
2. Rejuvenation parameter (q). The effect of the repair process in the virtual age of the systems.

The reader should notice that a value of $q = 1$ leads to a perfect maintenance ($VA = 0$, failed component returns to as good as new condition), whereas $0 < q < 1$ leads to an imperfect maintenance (Eq.1). In this context, before making any decision regarding the servitized asset, failure probability conditioned to the survival of the new virtual age has to be estimated (Eq.2). Due to the widespread application of Weibull distribution in the industry, the conditioned failure probability has been particularized to such distribution in Eq.3. The interested reader may address Yañez et al. [45] for further details on the GRP modelling and fitting.

$$VA_i^{new} = VA_i^{old}(1 - q_i) \tag{1}$$

$$F\left(t|VA_i^{new}\right) \quad = \quad P\left[T_i \leq t|T_i > VA_i^{new}\right] = \frac{F\left(t\right) - F\left(VA_i^{new}\right)}{1 - F\left(VA_i^{new}\right)} \tag{2}$$

$$F\left(t|VA_i^{new}\right) = exp\left[\left(\frac{VA_i^{new}}{\alpha_i}\right)^{\beta_i} - \left(\frac{t}{\alpha_i}\right)^{\beta_i}\right] \tag{3}$$

This reliability analysis, along with the less complex maintainability and availability statistical analyses, lays the foundations for analysing assets' past performance and tackling the convoluted problem of making AM and servitization decisions in a risk-based approach. Therefore, as shown in Figure 5, the IDEF0 formalization of the data analysis module has been defined as follows: input data related to failures (I); RAM analysis mechanisms (M1), which based on aforementioned algorithms, are able to translate assets' operational data into useful RAM information (O1) for facilitating subsequent AM and PSS decision-making processes; and controls (C1), understood as the traditional requisites for performing the different statistical analyses, such as data sample or quality (see Figure 5).

3.2. Simulation-based optimization module

As reviewed in Section 2.1, the adoption of PSSs entails making decisions on several and diverse tactics, having often to consider stochastic processes and changing environments within the decision making process, such as: unexpected failures or maintenance actions, changes in customers' expectations and requisites, new competitors, etc. In this complex context, simulation modelling becomes a powerful tool in order to analyze the long-term impact of decisions to be made through life-cycle analyses [13, 46, 47], thus reducing assumed risks by OEMs adopting PSS business models.

Simulation tools, which have already been successfully utilized to solve engineering problems [48], allow modelling *as is* scenarios and then analyze how different decisions would affect those situations (*what if* scenarios). Therefore, aiming at systematically identifying optimal PSS decisions, this *simulation-based optimization module* is constituted both by a simulation model (M2) that evaluates AM (inward view) and PSS performance, in terms of operational expenditure and service-level [41], and by an optimization algorithm (M3) that enables to iteratively analyze selected *what if* scenarios following the logic underlying behind the algorithm [47].

In the particular context of PSS business models, there are several stakeholders involved which usually present conflicting interests, e.g. PSS service level and cost. Thus, decisions should achieve a compromise among the different objectives to be optimized. To this respect, multi-objective optimization search techniques, able to provide a set of non-dominated set of solutions, should be implemented, such as Newtonians methods or multi-objectives meta-heuristics [14, 47, 49]. For the presented management framework implementation the evolutionary Non-Sorted Genetic Algorithm II (NSGA II) has been selected [50], adopting the optimization process presented in Figure 6 (note that the population is represented by the decision variables of the asset management and service related decisions to be optimized).

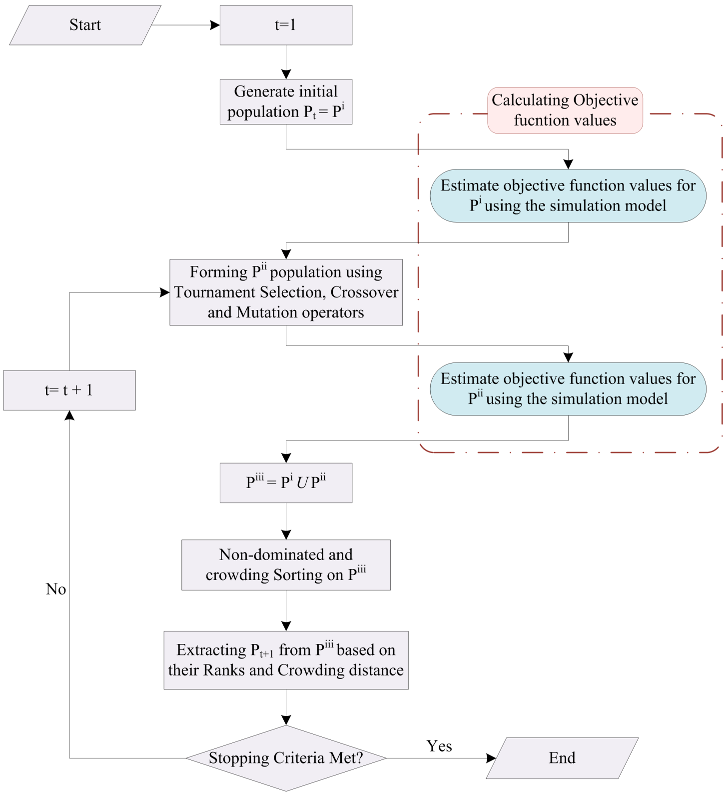


Figure 6: Simulation-based Optimization Mechanism for NSGA II (adapted from Attar et al. [47])

In order to illustrate the suitability and potential of the simulation-based optimization mechanism for facilitating decisions, and given the key role that maintenance management plays both in asset management and servitization context [34, 51], a maintenance optimization problem has been derived and implemented. Accordingly, based on the described RAM information from the previous module and the maintenance cost structure (I3), the simulation-based optimization mechanism will focus on optimizing the maintenance strategy until the stopping criteria are met (I2 and O2, iteratively, see Figure 5). The mathematical formulation is summarized as follows:

1. **Objective functions.** Operational expenditure (OPEX) and service-level disruptions along the time period under study (T) are calculated (see Eq. 4 and 5). They are directly determined by the maintenance strategy adopted, and they depend on the number of preventive and corrective

Table 1: Variables utilised in the maintenance mathematical model

Decision variables	***Intermediate binary variables***
$MRT_{ik} = Minimum\, Reliability\, Threshold\, of\, FM\; k\; of\; system\; i$	$y_{likjt} = \begin{cases} 1 & if\; PM\; j\; is\; performed\; in\; FM\; k\; of\; system\; i \\ & in\; period\; t \\ 0 & otherwise \end{cases}$
$PRT_{ik} = Perfect\, Reliability\, Threshold\, of\, FM\; k\; of\; system\; i$	
$IRT_{ik} = Imperfect\, Reliability\, Threshold\, of\, FM\; k\; of\; system\; i$	$z_{likt} = \begin{cases} 1 & if\; FM\; k\; of\; system\; i\; happens\; in\; period\; t \\ 0 & otherwise \end{cases}$

maintenance activities carried out, the maintenance resources cost and the penalizations for not meeting the established objectives.

2. **Maintenance strategy adopted.** Based on the reliability analysis implemented in the data analysis module, a multi-level opportunistic maintenance strategy driven by reliability thresholds has been defined. These reliability thresholds, which are associated to the different failure modes, conform the decision variables to be optimized (see Table 1), and each of them triggers a specific maintenance decision (see Eq. 6):
   (a) MRT_{ik}, perfect preventive maintenance ($j = 2$) is compulsory performed in failure mode k of system i ($y_{ik2t} = 1$).
   (b) PRT_{ik}, perfect preventive maintenance ($j = 2$) is performed in failure mode k of system i ($y_{ik2t} = 1$) if corrective ($z_{ikt} = 1$) or preventive maintenance ($y_{ikjt} = 1$) has to be performed in the same system.
   (c) IRT_{ik}, imperfect preventive maintenance ($j = 1$) is performed in failure mode k of system i ($y_{ik1t} = 1$) if corrective ($z_{ikt} = 1$) or preventive maintenance ($y_{ikjt} = 1$) has to be performed in the same system.
3. **Capacity constraints.** They allow modelling some of the controls (C) to be considered within the simulation-based optimization module, such as resources constraints. As an example, Eq. 7 limits the maintenance tasks according to their maintainabiliy $\left(m^{c}_{ik}, m^{p}_{ikj}\right)$ and the available resources, which depend on the number of maintenance workers (NT) and their working time (T^{wt}).
4. **Maintenance restrictions.** Only one maintenance activity per FM and period of time can be performed (Eq. 8); considered as controls as well.

$$Minimize\ OPEX\left(MRT_{ik}, PRT_{ik}, IRT_{ik}\right) \quad (4)$$
$$Minimize\ Service\,level\,disruptions\left(MRT_{ik}, PRT_{ik}, IRT_{ik}\right) \quad (5)$$

$S.T.$
$$0 \leq MRT_{ik} \leq PRT_{ik} \leq IRT_{ik} \leq 1 \quad \forall i \epsilon I, \forall k \epsilon K \quad (6)$$
$$\sum_{i}\sum_{k}\sum_{j} m^{pr}_{ikj} \cdot y_{ikjt} + \sum_{i}\sum_{k} m^{c}_{ik} \cdot z_{ikt} \leq NT \cdot T^{wt} \quad \forall t \epsilon T \quad (7)$$
$$\sum_{j} y_{ikjt} + z_{ikt} \leq 1 \quad \forall i \epsilon I, \forall k \epsilon K, \forall t \epsilon T \quad (8)$$
$$z_{ikt}, y_{ikjt} \epsilon \{0,1\} \ \forall i \epsilon I, \forall k \epsilon K, \forall j = \{1,2\}, \forall t \epsilon T$$

The reader should notice that whereas the simulation-based optimization mechanism allows enhancing some of the decisions to be made in the context of servitization, such as mentioned maintenance management, there are some business decisions to be made which are out of the scope of the optimization tools. These decisions usually refer to specific PSS restrictions or customer requirements, and thus, they have to considered as controls (C) within the IDEF0 definition of the module. It is the case, for instance, of the PSS business model to be adopted (C2), the specific maintenance processes (C4) and context of PSS (C4) or the resources to be deployed (C5) in terms of logistics and procurement (see Figure 5).

Certainly, these controls define the specific PSS adopted and will act as boundaries of the optimal decisions provided by the simulation-based optimization mechanism, conforming the so called optimized PSS (O3) (see Figure 5). As a consequence, if decision-makers wanted to address strategic decisions regarding the modification of the controls, they should address them using the simulation-based optimization mechanism to identify and compare different optimized PSS scenarios. Such decisions are specifically addressed in the analysis and decision support module.

3.3. Analysis and decision support module

In order to facilitate the final decision-making process and to help manufacturers overcome previously presented barriers for PSSs adoption, this last module focuses on analyzing the information gathered in the preceding modules. Based on this analysis, decision-makers will not only be aware of the feasibility of the designed PSSs, but also of what AM strategies, including maintenance strategies, should be adopted to satisfy their stakeholders' interests.

Within this module, along with the stakeholders' interests to be fulfilled and the limitations related to the supply chain design (C6, C7), it is critical to consider a risk-based decision approach that assesses how the different uncertainty sources might condition the organisational objectives [52]. Accordingly, it has to be quantified how the uncertainty propagates from the model input variables (e.g. RAM data), through the system model (e.g. simulation model), to the quantities of interest (e.g. objective functions) [53]. As illustrated in Figure 7, where the optimal Pareto Front to be obtained from the previous module is shown, the uncertainty will imply a variability in the quantities of interest of the PSS solutions, which should be considered in order to design a less risky yet appealing PSS offer.

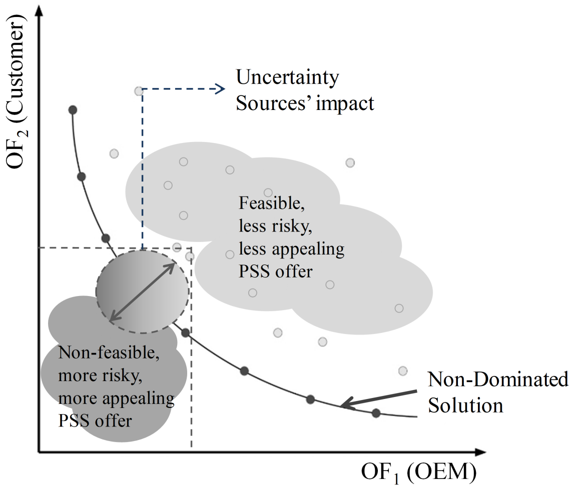


Figure 7: Uncertainty impact in PSS offer [54]

In order to facilitate such risk-based decision process, the *strategic decision support* function has been provided with a cost-risk-benefit mechanism (M4). This mechanism iteratively evaluates the optimized PSS solutions (O3) under different uncertainty sources' influence (I4), which will let analyze the variability of the outcome of the Optimized PSS; thus enabling to design a feasible PSS offer (O4) with its associated maintenance strategy (O6), that meets stakeholders' interests at an admissible risk adoption (see Figure 7).

The cost-risk-benefit mechanism implements numeric expressions, which based on the foundations of probability, estimate the likelihood of uncertain events [55]. These statistical analyses will provide manfacturers with confidence intervals [56, 57], letting them define specific rules that will restrain adopted risks, e.g. a maximum variability on an specific objective Z $\left(\sigma^2(z) < Variability\,Threshold\right)$ or a minimum value of such objective with a probability $(P\left[Z > z_s\right] \geq Probability\,Threshold)$ [53]. The interested reader is addressed to authors' paper [54] for further details on this mechanism implementation and application.

Once the outcome of the decisions is assessed within the *strategic decision support* function, in case of non-feasible PSS requirements or a non-appealing offer (see Figure 7), decision-makers will be able to review (in an iterative process) their AM strategy (O5) or/and the controls that characterize the PSS (O4→C2) in order to find new and enhanced PSS scenarios (see feedback loop in Figure 5 and case study II). This *analysis and decision support module* represents the final step on the designing of the PSS.

4. Framework application and discussion

The present section seeks to exemplify and validate, through a multi-sectorial case study based on real field data, the usefulness of the described management framework to exploit AM capabilities and face servitization challenges. These case studies assess different decisions to be made in service-oriented business models based on the application of the presented framework and developed technical solutions (see case studies description in Tables 2-4). In particular, data available has been provided by wind turbines and railway rolling stock manufacturers, whose customers are now demanding for services along with the products they acquire.

The result analysis is mainly supported by the Pareto Front provided by the implemented NSGA II optimization algorithm. As described in Subsection 3.2, each of the solutions that conform the Pareto Front corresponds to a specific optimal maintenance strategy (defined by the reliability thresholds) within the defined control boundaries of the PSS. Finally, the reader should notice that as follows presented case studies regard to the operational expenditures, according to derived simulation-based optimization problem, and to specific critical components for which failure and cost data were available.

Case study I: Designing result-oriented PSS

Case study description	Design of result-oriented business model, where assets' outcome (service-level) is sold rather than the assets themselves.	
Faced challenge	Life-cycle cost and service level estimation (TC1), operational decisions (maintenance) impact identification (TC3), and alignment between PSS and AM strategy (TC4).	
Barriers to be overcome	Price and contracts definition (BA1), flexibility and adaptability (BA4), and stakeholders' requirements fulfillment (BA5).	
Framework objective	To identify the optimal maintenance strategies for sold products, as well as the expected PSS operational expenditure and service-level outcomes. To provide manufacturers' with insights to define the contracts according to their business objectives.	
Framework ICOMs	*I*	Failure and cost data of a fleet of 21 light-rails, 4 systems (brake, traction, heating and ventilation air conditioning and gates) with 2-3 failure modes each.
	C	Specific maintenance process and constraints considered. Result oriented PSS design. Reliability analysis and optimization constraints' consideration.
	M	Weibull reliability analysis per failure mode (α, β), Imperfect reliability-based opportunistic maintenance strategy optimization, agent-based simulation model in Anylogic®, NSGA II multi-objective optimization algorithm implemented.
	O	Optimized result-oriented PSS for rolling stock, with a portfolio of maintenance strategies (defined by reliability thresholds).
Authors' related work	[58]	

Table 2: Case study I characterization

If rolling stock manufacturers were to offer a profitable and successful result-oriented PSS, they should not only be able to estimate their products' performance during the life-cycle, but to identify how their decisions affect such performance as well (TC1, TC3). To this respect, as illustrated in Figure 8, the *simulation-based optimization module* of the management framework provides valuable insights, identifying the operational expenditure and service level to which the optimal maintenance strategies lead within the boundaries of the designed PSS (see case study characterization in Table 2).

Once manufacturers have this information, they will be able to balance, through the definition of the contract terms and the AM decisions they make, the profitability and appeal of the PSS offered according to their customers' requisites and interests (TC4). Thus, as well as facing some of their main technical challenges and related barriers (BA4, BA5), they will convert contracts' definition from a barrier (BA1) into a business competitive advantage. As illustrated in Figure 8 for the "PSS requisites 2" (in blue), manufacturers may choose different PSS scenarios:

- *Appealing PSS for the customer*, since within the cost limits established by customers, a better service level may be provided (e.g. 5% improvement).
- *Profitable PSS for the manufacturer*, since within the service level limits established by customers, costs may be minimized and thus manufacturers' profits enhanced (e.g. 6.4% of the OPEX is improved).
- *Intermediate win-win scenarios*, where both customers' expectations and manufacturers' profits may be enhanced in a balanced way.

Case study II: Making decisions on PSS improvements

Besides the maintenance-related decision-making process, the management framework proposed allows facilitating other AM decisions to enhance the PSS performance, facing TC1 and TC4. Such enhancements in the PSS, which are analyzed in the *decision support module* based on the optimized PSS, might have diverse sources: changes in assets' portfolio and/or technology, new terms in relationships with providers, modifications in supply chain processes, etc. In order to analyze their suitability, the inputs and controls defined in the management framework of Figure 5 should be updated, and subsequently evaluate and compare the different PSS alternatives according to stakeholders' interests (see BA5, BA6).

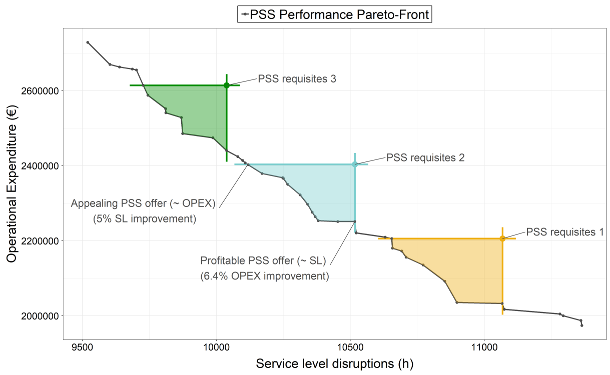


Figure 8: Representation of feasible PSS boundary

Case study description	Making decisions on PSS improvements in oder to identify how changes in the PSS inputs and controls may affect its outcomes, further analyzing investments' suitability.	
Faced challenge	Life-cycle cost and service level estimation (TC1), and alignment between PSS and AM strategy (TC4).	
Barriers to be overcome	Stakeholders' requirements fulfillment (BA5), and management decisions complexity (BA6).	
Framework objective	To facilitate strategic decisions regarding PSS potential improvements by comparing and analyzing different scenarios.	
Framework ICOMs	*I*	Current and enhanced failure and cost data of a fleet of 21 light-rails (reliability and maintainability of two failure modes enhanced), 4 systems (brake, traction, heating and ventilation air conditioning and gates) with 2-3 failure modes each.
	C	Idem to Case Study I (see Table 2)
	M	Idem to Case Study I (see Table 2)
	O	Comparison between current and enhanced optimized result-oriented PSS for rolling stock.
Authors' related work	[58]	

Table 3: Case study II characterization

As an example (see case study characterization in Table 3), the impact of respectively enhancing the reliability and maintainability of two critical failure modes has been analyzed ($\simeq$35% of improvement respectively). As shown in Figure 9, the new PSS pareto optimal would outperform the current one both in terms of operational expenditure and service level. Nonetheless, since these improvements will usually come at an investment cost, decision-makers should consider such cost in order to identify their real profitability.

To this respect, the improvement area of the new PSS, which has been highlighted in Figure 9, determines as well the maximum profitable investment per expected PSS sale (in present value). For instance, for a service-level disruption of 9600 hours, the OPEX of the PSS would be improved by a 18,13% ($\simeq$ 484000€), while for a 10500 hours service-level disruption, the OPEX of the PSS would be improved by a 14.86% ($\simeq$ 335000€). Therefore, from an economical point of view (to be afterwards complemented by qualitative managerial insights), if the same service-level was to be offered to the customers of the PSS in each of the cases, the investment cost per PSS should not exceed 484000€ and 335000€ respectively.

Case study III. Designing complex and customizable PSS

PSS terms are often complex to define and they might entail a conflict of interest between manufacturers and customers, which usually brings customers' mistrust and avoids the actual PSS implementation (see BA1 and BA3). In this context, the customized and transparent design of the PSSs' terms by manufacturers and customers plays a key role on the final PSS implementation and success.

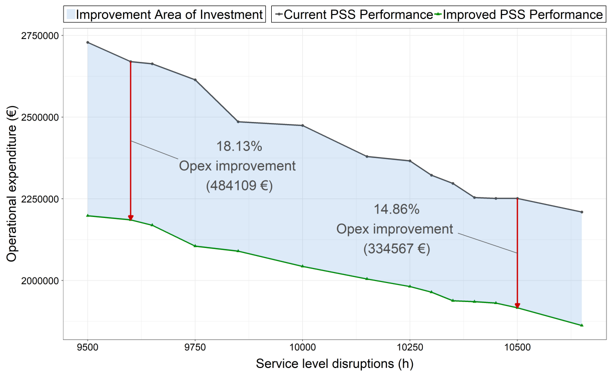


Figure 9: Representation of investments' impact on PSS performance

Case study description	Transparent design of complex and customized PSS profitable and appeal for both customers and manufacturers.	
Faced challenge	Life-cycle cost and service level estimation (TC1), and transparent breakdown of complex PSS price (TC2)	
Barriers to be overcome	Price and contracts definition (BA1), ownerless consumption of assets (BA3), stakeholders' requirements fulfillment (BA5), and management decisions complexity (BA6).	
Framework objective	To provide manufacturers with insights for transparently designing complex PSS along with customers in order to overcome the mistrust caused by the conflict of interests.	
Framework ICOMs	*I*	Fleet of 70 wind turbines, 4 systems (gearbox, blades, pitch and yaw system) with 2 failure modes each.
	C	Specific maintenance process and constraints considered. Result oriented PSS design. Reliability analysis and optimization constraints' consideration.
	M	Weibull reliability analysis per failure mode (α, β), Imperfect reliability-based opportunistic maintenance strategy optimization, agent-based simulation model in Anylogic®, NSGA II multi-objective optimization algorithm implemented.
	O	Optimized result-oriented PSS for wind turbines operating 7 and 20 years, with a portfolio of maintenance strategies (defined by reliability thresholds).
Authors' related work	[54, 59]	

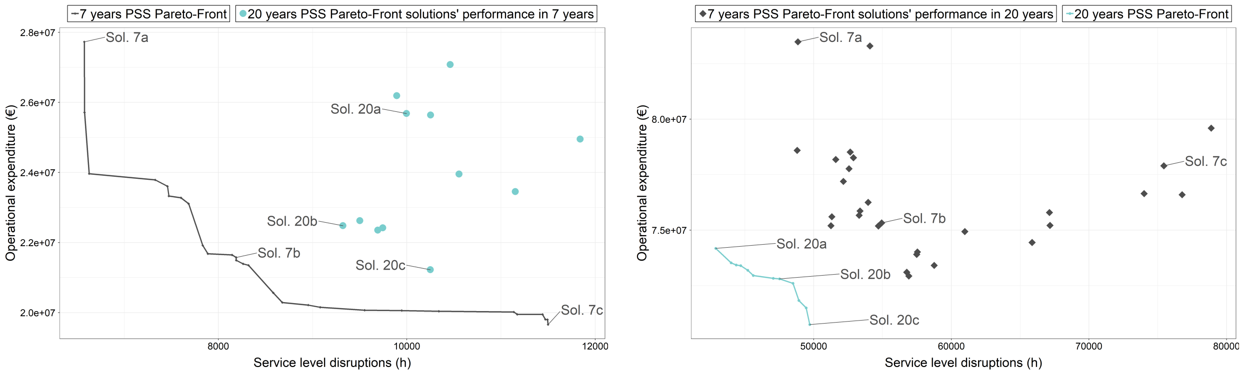
Table 4: Case study III characterization

For instance, in the wind energy sector, manufacturers have traditionally base their business model on the wind turbines' sale and a further 3-5 years-period warranty, i.e. product-oriented PSS. However, once the established warranty period is over, wind farms are managed by the operators, who struggle on this management process due to a lack of product knowledge. In this context, the management framework presented may help transparently design a customized PSS attractive for both manufacturers and operators (facing TC1 and TC2).

In order to demonstrate the usefulness of the framework, the following complex PSS scenario where both manufacturers are operators could enhance their profits, is designed as an example (see Table 4 for case study characterization):

1. Initial 7 years of result-oriented PSS, where manufacturers' incomes can be increased compared to the previous 3-5 years warranty period.
2. Spare parts' supply product-oriented PSS after the 7th year until the estimated end of life-cycle at year 20, where wind farms will be proactively managed by operators according to manufacturers' instructions.

The study of the wind farm performance for 7 and 20 years through the management framework leads to Figure 10. It specifically shows that optimal maintenance solutions considering a 20-year-period (plotted in blue) are not optimal for a 7-year-period, where the optimal Pareto-front is defined by the solutions plotted in gray. Likewise, Figure 10b shows that optimal solutions for a 7-year-period (gray), are not optimal for a 20-year-period (blue). In fact, a more detailed analysis shows that solution 7a, which is the best solution in terms of service level for a 7-years period, is rather inefficient in a 20 year period either in terms of OPEX or service level, dominated for instance by 20a and 20b (see Figure 10b).



(a) Performance of PSS offer for 7 years

(b) Performance of PSS for 20 years

Figure 10: Performance comparison between 7 and 20 years PSS offers

Therefore, Figure 10 exemplifies the conflict of interest between manufacturers and operators and justifies the mistrust that may arise at operators' side, i.e. manufacturers could adopt the optimal maintenance solutions of 7-year-period, which according to the aforementioned PSS clauses would enhance their results in the initial 7 years of result-oriented PSS (better service level at lower OPEX) and also from year 7 to 20 (since more spare parts would be needed while worse OPEX and service level are achieved). In this context, transparently designing a customized PSS based on the management framework outputs and selecting the 20-year-period solutions (see Figure 10b), would give customers the confidence that the PSS protects their long-term interests; further ensuring win-win PSS implementation.

5. Concluding remarks

The present research addresses how the development of asset management capabilities can enhance the design and integration of services within the strategic and operative management of organisations, respectively facing and overcoming some of the main technical challenges and barriers that product-service systems' implementation require.

To this aim, a management framework, which draws the decisions and actions to be considered for the practical alignment and integration of asset management and product-service systems, is proposed. This framework has been provided with specifically developed technical solutions, such as reliability algorithms, maintenance optimization problems and simulation-based optimization mechanisms, which have proven to be useful and valuable in both the railway and wind energy case studies based on real-field data.

Within these case studies some of the main technical challenges to be faced in the context of product-service systems are analyzed and discussed based on the framework utilization. In particular, each of the three case studies addresses a specific decision to be made by manufacturers, where results obtained validate the usefulness of the developed framework.

Firstly, the definition of product-service systems' contracts and maintenance strategies is addressed, where results show that the framework ensures a profitable yet appealing offer both for manufacturers and customers. Secondly, the framework proves useful for assessing the suitability of investments when improving product service systems, it allows comparing between the current and the enhanced product-service systems and quantify their expected outcome. Finally, the design of complex product-service systems is studied, demonstrating that the framework provides valuable insights for meeting both manufacturers' and customers' interests while overcoming the conflicts of interests that may appear.

The presented research opens a new research line, where the role that asset management has in product-service systems has been drawn. If this novel proposal was to be fully exploited, further investigation specifically regarding each of the diverse topics mentioned in the paper should be addressed. Among others, there are still unanswered questions about the particular affection of supply chain management decisions to the product-service system or about the fulfillment of the expectations that each stakeholder might have in the different product-service system scenarios. Likewise, since the management framework allows designing rather complex product-service system scenarios, as the one exemplified in the third case study, further win-win scenarios for both manufacturers and customers should be explored.

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References

[1] T. Baines, H. Lightfoot, S. Evans, A. Neely, R. Greenough, J. Peppard, R. Roy, E. Shehab, A. Braganza, A. Tiwari, J. Alcock, J. Angus, M. Basti, A. Cousens, P. Irving, M. Johnson, J. Kingston, H. Lockett, V. Martinez, P. Michele, D. Tranfield, I. Walton, H. Wilson, State-of-the-art in product-service systems, Proceedings of the Institution of Mechanical Engineers, Part B: Journal of Engineering Manufacture 221 (10) (2007) 1543–1552. doi:10.1243/09544054JEM858.

[2] J. Banks, Discrete event simulation, in: Encyclopedia of Information Systems, Elsevier BV, 2003, pp. 663–671. doi:10.1016/b0-12-227240-4/00045-9.

[3] M. Wong, Implementation of innovative product service-systems in the consumer goods industry, Ph.D. thesis, Cambridge University (2004).

[4] M. J. Goedkoop, C. J. Van Halen, H. R. Te Riele, P. J. Rommens, et al., Product service systems, ecological and economic basics, Report for Dutch Ministries of environment (VROM) and economic affairs (EZ) 36 (1) (1999) 1–122.

[5] A. Tan, T. McAloone, D. Matzen, Service-oriented strategies for manufacturing firms, in: Introduction to Product/Service-System Design, Springer London, 2009, pp. 197–218. doi:10.1007/978-1-84882-909-1_10.

[6] O. Mont, Clarifying the concept of product–service system, Journal of Cleaner Production 10 (3) (2002) 237–245. doi:10.1016/s0959-6526(01)00039-7.

[7] M. B. Cook, T. Bhamra, M. Lemon, The transfer and application of product service systems: from academia to uk manufacturing firms, Journal of Cleaner Production 14 (17) (2006) 1455–1465.

[8] K. Öner, G. Kiesmüller, G. Van Houtum, optimization of component reliability in the design phase of capital goods, Quality control and applied statistics 56 (4) (2010) 397–399.

[9] M. Cohen, S. Whang, Competing in product and service: A product life-cycle model, Management Science 43 (4) (1997) 535–545.

[10] V. González-Prida, A. C. MÃ¡rquez, A framework for warranty management in industrial assets, Computers in Industry 63 (9) (2012) 960 – 971. doi:http://dx.doi.org/10.1016/j.compind.2012.09.001.

[11] C. Su, X. Wang, Modeling flexible two-dimensional warranty contracts for used products considering reliability improvement actions, Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 230 (2) (2016) 237–247. doi:10.1177/1748006X15627395.

[12] J. Aurich, C. Mannweiler, E. Schweitzer, How to design and offer services successfully, CIRP Journal of Manufacturing Science and Technology 2 (3) (2010) 136–143. doi:10.1016/j.cirpj.2010.03.002.

[13] F. H. Beuren, M. G. G. Ferreira, P. A. C. Miguel, Product-service systems: a literature review on integrated products and services, Journal of Cleaner Production 47 (2013) 222–231.

[14] E. L. S. Teixeira, B. Tjahjono, S. C. A. Alfaro, A novel framework to link prognostics and health management and product–service systems using online simulation, Computers in Industry 63 (7) (2012) 669–679. doi:10.1016/j.compind.2012.03.004.

[15] ISO, 55000:2014. asset management-overview, principles and terminology, Tech. rep., AENOR (2014).

[16] A. Tukker, Eight types of product–service system: eight ways to sustainability? experiences from SusProNet, Business Strategy and the Environment 13 (4) (2004) 246–260. doi:10.1002/bse.414.

[17] W. Song, Requirement management for product-service systems: Status review and future trends, Computers in Industry 85 (2017) 11–22. doi:10.1016/j.compind.2016.11.005.

[18] N. Maussang, P. Zwolinski, D. Brissaud, Product-service system design methodology: from the PSS architecture design to the products specifications, Journal of Engineering Design 20 (4) (2009) 349–366. doi:10.1080/09544820903149313.

[19] M.-J. Kang, R. Wimmer, Product service systems as systemic cures for obese consumption and production, Journal of Cleaner Production 16 (11) (2008) 1146–1152. doi:10.1016/j.jclepro.2007.08.009.

[20] W. Reim, V. Parida, D. Örtqvist, Product-service systems (PSS) business models and tactics - a systematic literature review, Journal of Cleaner Production 97 (2015) 61–75. doi:10.1016/j.jclepro.2014.07.003.

[21] R. Casadesus-Masanell, J. E. Ricart, From strategy to business models and onto tactics, Long Range Planning 43 (2-3) (2010) 195–215. doi:10.1016/j.lrp.2010.01.004.

[22] A. Azarenko, R. Roy, E. Shehab, A. Tiwari, Technical product-service systems: some implications for the machine tool industry, Journal of Manufacturing Technology Management 20 (5) (2009) 700–722. doi:10.1108/17410380910961064.

[23] A. Richter, T. Sadek, M. Steven, Flexibility in industrial product-service systems and use-oriented business models, CIRP Journal of Manufacturing Science and Technology 3 (2) (2010) 128–134. doi:10.1016/j.cirpj.2010.06.003.

[24] G. Schuh, W. Boos, S. Kozielski, Life cycle cost-orientated service models for tool and die companies, in: Proceedings of the 19th CIRP Design Conference–Competitive Design, Cranfield University Press, 2009.

[25] D. Kindström, Towards a service-based business model – key aspects for future competitive advantage, European Management Journal 28 (6) (2010) 479–490. doi:10.1016/j.emj.2010.07.002.

[26] E. Sundin, B. Bras, Making functional sales environmentally and economically beneficial through product remanufacturing, Journal of Cleaner Production 13 (9) (2005) 913–925. doi:10.1016/j.jclepro.2004.04.006.

[27] S. Evans, P. J. Partidário, J. Lambert, Industrialization as a key element of sustainable product-service solutions, International Journal of Production Research 45 (18-19) (2007) 4225–4246. doi:10.1080/00207540701449999.

[28] S. W. Lee, M. W. Seong, Y. J. Jeon, C. H. Chung, Ubiquitin e3 ligases controlling p53 stability, Animal Cells and Systems 16 (3) (2012) 173–182. doi:10.1080/19768354.2012.688769.

[29] N. Bocken, S. Short, P. Rana, S. Evans, A literature and practice review to develop sustainable business model archetypes, Journal of Cleaner Production 65 (2014) 42–56. doi:10.1016/j.jclepro.2013.11.039.
[30] T. C. Kuo, Simulation of purchase or rental decision-making based on product service system, The International Journal of Advanced Manufacturing Technology 52 (9-12) (2010) 1239–1249. doi:10.1007/s00170-010-2768-2.
[31] V. M. Story, C. Raddats, J. Burton, J. Zolkiewski, T. Baines, Capabilities for advanced services: A multi-actor perspective, Industrial Marketing Management 60 (2017) 54–68. doi:10.1016/j.indmarman.2016.04.015.
[32] N. A. Hastings, Physical asset management, Vol. 2, Springer, 2010.
[33] Z. Tao, F. Zophy, J. Wiegmann, Asset management model and systems integration approach, Transportation Research Record: Journal of the Transportation Research Board (1719) (2000) 191–199.
[34] EN, 16646:2014. maintenance within physical asset management, Tech. rep., AENOR (2014).
[35] Pas-55 asset management (2012).
[36] G. Schuh, W. Boos, M. Völker, Collaboration platforms to enable global service provision in the tooling industry, Production Engineering 5 (1) (2010) 9–16. doi:10.1007/s11740-010-0274-x.
[37] S. Cavalieri, G. Pezzotta, Product–service systems engineering: State of the art and research challenges, Computers in Industry 63 (4) (2012) 278–288. doi:10.1016/j.compind.2012.02.006.
[38] N. I. o. S. NIST, Integration definition for function modelling (idef0), Federal information processing standards publication 183.
[39] J. Lee, Y. Chen, H. A. Atat, M. AbuAli, E. Lapira, A systematic approach for predictive maintenance service design: methodology and applications, International Journal of Internet Manufacturing and Services 2 (1) (2009) 76. doi:10.1504/ijims.2009.031341.
[40] A. C. Márquez, The Maintenance Management Framework, Springer-Verlag GmbH, 2007.
[41] E. Settanni, L. B. Newnes, N. E. Thenent, G. Parry, Y. M. Goh, A through-life costing methodology for use in product–service-systems, International Journal of Production Economics 153 (2014) 161–177. doi:10.1016/j.ijpe.2014.02.016.
[42] E. Zio, Reliability engineering: Old problems and new challenges, Reliability Engineering & System Safety 94 (2) (2009) 125–141. doi:10.1016/j.ress.2008.06.002.
[43] I. A. Okaro, L. Tao, Reliability analysis and optimisation of subsea compression system facing operational covariate stresses, Reliability Engineering & System Safety 156 (2016) 159–174. doi:10.1016/j.ress.2016.07.018.
[44] D. Louit, R. Pascual, A. Jardine, A practical procedure for the selection of time-to-failure models based on the assessment of trends in maintenance data, Reliability Engineering & System Safety 94 (10) (2009) 1618–1628. doi:10.1016/j.ress.2009.04.001.
[45] M. Yañez, F. Joglar, M. Modarres, Generalized renewal process for analysis of repairable systems with limited failure experience, Reliability Engineering & System Safety 77 (2) (2002) 167–180. doi:10.1016/S0951-8320(02)00044-3.
[46] R. Laggoune, A. Chateauneuf, D. Aissani, Impact of few failure data on the opportunistic replacement policy for multi-component systems, Reliability Engineering & System Safety 95 (2) (2010) 108–119. doi:10.1016/j.ress.2009.08.007.
[47] A. Attar, S. Raissi, K. Khalili-Damghani, A simulation-based optimization approach for free distributed repairable multi-state availability-redundancy allocation problems, Reliability Engineering & System Safety 157 (2017) 177–191. doi:10.1016/j.ress.2016.09.006.
[48] M. Niazi, A. Hussain, Agent-based computing from multi-agent systems to agent-based models: a visual survey, Scientometrics 89 (2) (2011) 479–499. doi:10.1007/s11192-011-0468-9.
[49] H. Abdollahzadeh, K. Atashgar, Optimal design of a multi-state system with uncertainty in supplier selection, Computers & Industrial Engineering 105 (2017) 411–424. doi:10.1016/j.cie.2017.01.019.
[50] K. Deb, A. Pratap, S. Agarwal, T. Meyarivan, A fast and elitist multiobjective genetic algorithm: NSGA-II, IEEE Transactions on Evolutionary Computation 6 (2) (2002) 182–197. doi:10.1109/4235.996017.
[51] M. Garetti, P. Rosa, S. Terzi, Life cycle simulation for the design of product–service systems, Computers in Industry 63 (4) (2012) 361–369. doi:10.1016/j.compind.2012.02.007.
[52] 31000:2009 risk management - principles and guidelines.
[53] E. de Rocquigny, N. Devictor, S. Tarantola, Uncertainty in industrial practice: a guide to quantitative uncertainty management, John Wiley & Sons, 2008.
[54] A. Erguido, A. Crespo, E. Castellano, J. L. Flores, After-sales services optimisation through dynamic opportunistic maintenance: a wind energy case study, Proceedings of the Institution of Mechanical Engineers, Part O: Journal of Risk and Reliability 232 (4) (2018) 352–367. doi:10.1177/1748006x17753500.
[55] O. De Weck, C. Eckert, J. Clarkson, A classification of uncertainty for early product and system design, Vol. DS 42, 2007.
[56] J. Villanueva, A. Sanchez, S. Carlos, S. Martorell, Genetic algorithm-based optimization of testing and maintenance under uncertain unavailability and cost estimation: A survey of strategies for harmonizing evolution and accuracy, Reliability Engineering & System Safety 93 (12) (2008) 1830 – 1841, 17th European Safety and Reliability Conference. doi:10.1016/j.ress.2008.03.014.
[57] A. Sanchez, S. Carlos, S. Martorell, J. F. Villanueva, Addressing imperfect maintenance modelling uncertainty in unavailability and cost based optimization, Reliability Engineering & System Safety 94 (1) (2009) 22 – 32, maintenance Modeling and Application. doi:10.1016/j.ress.2007.03.022.
[58] A. Erguido, A. Crespo Márquez, E. Castellano, J. Flores, J. Gómez Fernández, Reliability-based advanced maintenance modelling to enhance rolling stock manufacturers' objectives, Submitted to Reliability Engineering and System Safety.
[59] A. Erguido, A. Crespo Márquez, E. Castellano, J. Gómez Fernández, A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms, Renewable Energy 114 (2017) 843–856. doi:10.1016/j.renene.2017.07.017.