

Hypotheses in Opportunistic Maintenance Modeling: A Critical and Systematic Literature Review

Lucas Equeter ^{1,*} , Phuc Do ² , Lorenzo Colantonio ¹ , Luca A. Tiberi ³ , Pierre Dehombreux ¹ 
and Benoît Iung ⁴ 

¹ Machine Design and Production Engineering Lab, Research Institute for the Science and Management of Risks, University of Mons, 7000 Mons, Belgium

² SyCoIA, IMT Mines Alès, 30100 Alès, France

³ Forensic Psychology Department, Research Institute for the Science and Management of Risks, University of Mons, 7000 Mons, Belgium

⁴ Centre de Recherche en Automatique de Nancy (CRAN), UMR CNRS 7039, Université de Lorraine, 54000 Nancy, France; benoit.iung@univ-lorraine.fr

* Correspondence: lucas.equeter@umons.ac.be

Abstract

Because they account for realistic effects in opportunistic maintenance modeling, dependency hypotheses are extremely diverse in the literature. Despite recent reviews, a clear view of the dependency hypotheses is currently missing in the literature, especially regarding component interactions, resource constraints and human factors. In this paper, we provide a conceptual background on dependence modeling and the notion of maintenance opportunity. Then, a critical systematic literature review, following the PRISMA guidelines, is carried out, focusing on the current hypotheses in opportunistic maintenance, including component interactions, workers' skills and resource constraints, economic dependence and optimization objectives. The different dependence types are identified and defined, and their presence in the literature is quantified. The included papers in this review ($n = 91$) were selected on the basis of relevance to the research questions from the Web of Science, Scopus and Google Scholar databases. Exclusion criteria were set, related to the year of publication (from 2000) and language (limited to French or English), and inclusion criteria required the paper to cover modeling, simulating or reviewing literature related to opportunistic maintenance with dependencies. The results show that economic dependence is mostly modeled by sharing downtime or set-up costs. The objective function for optimization is mostly found to be the economic cost of maintenance, with concerningly little consideration for environmental indicators. These results are finally discussed in light of advances in predictive analytics and current challenges in the sustainability of industrial processes. Further developments should consider including the social and environmental aspects of sustainability in the dependencies, but also look into the benefits that predictive analytics can bring to opportunistic maintenance. The variety of modeling assumptions and dependences presented in the literature does not always allow comparing the results of the models.

Keywords: opportunistic maintenance; dependence modeling; skills management; resource constraints



Received: 30 August 2025

Revised: 4 October 2025

Accepted: 11 October 2025

Published: 14 October 2025

Citation: Equeter, L.; Do, P.; Colantonio, L.; Tiberi, L.A.; Dehombreux, P.; Iung, B. Hypotheses in Opportunistic Maintenance Modeling: A Critical and Systematic Literature Review. *Machines* **2025**, *13*, 947. <https://doi.org/10.3390/machines13100947>

Copyright: © 2025 by the authors.

Licensee MDPI, Basel, Switzerland.

This article is an open access article distributed under the terms and conditions of the Creative Commons Attribution (CC BY) license

(<https://creativecommons.org/licenses/by/4.0/>).

1. Introduction

In manufacturing, maintenance involves technical and management tasks intended to sustain a component/system, or restore it to an operating state in which it can perform

designated functions [1]. Maintenance optimization aims at establishing an optimal maintenance planning that fulfills all requirements related to the maintained component/system and its logistical support, while minimizing overall maintenance costs [2]. Among various maintenance approaches, opportunistic maintenance has drawn a lot of attention from academic researchers and industrial practitioners [3]. Indeed, opportunistic maintenance arises from the existence of opportunities, defined as “other maintenance actions or other particular events” [4] that allow conducting otherwise unplanned maintenance actions. What constitutes such an opportunity is one of the questions that separate practices and authors [5]. The interpretation and assessment of these opportunities vary widely from author to author. The optimization of maintenance policies is usually performed with respect to economic criteria [5,6]. In particular, the opportunistic maintenance benefits are strongly linked with economic dependency [7]. This kind of dependency corresponds to cases when opportunistic maintenance induces an economic benefit, either thanks to performing the maintenance actions simultaneously or sharing parts of the maintenance costs. Further, opportunistic maintenance has an indisputable influence on other key performance indicators, such as the reliability of the overall system, its availability, etc. This is because maintenance actions are usually modeled as having a positive impact on reliability, hence improving the overall reliability of the system.

The earlier reviews covering maintenance policy hypotheses were not necessarily specific to opportunistic maintenance modeling but rather encompassed maintenance modeling in general. Dekker brought to light in his review that only a few case studies had been published before 1996, but also that the economic pressure would induce a rise in mathematical optimization of maintenance policies [8]. This trend was observed in the subsequent decades: this rise in research, and quick development of new models, led Van Horenbeek et al. to review models and criteria for maintenance optimization, highlighting the use of continuous and discrete optimizations, as well as deterministic and probabilistic methods [6]. They also identified that little attention was given to the choice of optimization criteria, mainly relying on costs, availability and reliability. In a later review, Van Horenbeek et al. investigated the joint optimization of maintenance and inventory management [9]. They identified the major characteristics of these joint optimizations, such as the quality of maintenance, the maintenance strategies and the objective functions (the cost remained the main criterion).

Ab-Samat and Kamaruddin reviewed similar questions but specifically addressed opportunistic maintenance [5]. Once again, they identified that costs were preponderant in the optimization criteria, and they highlighted how varying the definitions of opportunistic maintenance are throughout the literature. Most recently, a systematic review by Zeng et al. addressed the inclusion of dependent failures for estimating risk and reliability in recent studies, but without regard for resource constraints [10]. The identified past reviews do not seem to identify hypotheses on workers’ skills, nor resource constraints specifically in the case of opportunistic maintenance with dependencies. An overview of existing reviews and the limitation of their contribution with respect to the topic brought up in the present work is included in Table 1. Other reviews that do not address hypotheses or objective functions explicitly, but rather mention them marginally, e.g., because they focus on the maintenance policies or on optimization algorithms, are included in the results of the review and presented in the adequate sections below.

In this paper, a systematic literature review is conducted on current hypotheses on opportunistic maintenance. Three categories of hypotheses are considered: the influence of human factors in opportunistic maintenance modeling, the dependencies in opportunistic maintenance modeling and the resource constraints in opportunistic maintenance modeling.

Table 1. Summary of existing reviews on maintenance modeling and the limitation of their contribution with respect to the topic brought up in the present work.

Year	Paper	Topic	Limitations
1996	[8]	Maintenance optimization models	Does not cover resources or dependant failure modes
2008	[11]	Maintenance of multi-component systems	The human factor is not considered beyond economic dependency
2009	[12]	Multicomponent system maintenance	Does not cover resources or human factor
2010	[6]	Objective function of maintenance optimization	Does not cover resources or dependant failure modes
2013	[9]	Maintenance and inventory optimization	Does not cover resources different than inventory
2014	[5]	Opportunistic maintenance, objective function	Mentions but does not analyze the modeling of dependent failures or resource limitations
2015	[13]	Maintenance logistics for offshore wind farms	Limited to weather constraints and resource dependence
2016	[14]	Condition-based maintenance	Does not cover resources or human factor
2017	[15]	Condition-based maintenance	Limited to condition-based maintenance, limited analysis of dependencies
2017	[1]	Condition-based maintenance	Limited to condition-based maintenance, limited analysis of human factor
2020	[16]	Maintenance in the chemical industry	Does not cover dependent failure modes
2020	[2]	Maintenance optimization and assumption	Does not cover resources different than inventory
2021	[17]	Railway track maintenance	Limited to railway applications, found no article related to structural and stochastic dependencies
2022	[18]	Spare parts management for offshore wind farms	Specific scope, does not cover dependencies
2022	[19]	Sustainable maintenance strategies	No mention of the optimization objectives, limited analysis of dependencies
2023	[20]	Maintenance and spare-parts inventory	Does not cover dependent failure modes
2023	[10]	Dependent failures modeling	Limited to the risk and reliability points of view, does not cover resource limitations
2025	[21]	Performances of explainable artificial intelligence models in maintenance	Does not address opportunistic maintenance or hypotheses in maintenance modeling

Human factors play a crucial role in industrial processes. Knowledge management has been a growing interest in management studies [22,23]. As such, it should not be overlooked in maintenance modeling, as skills and knowledge are expected to have a considerable impact on maintenance performance [22].

In general, the concept of opportunistic maintenance is closely related to dependencies between system components, which create benefits from using opportunistic maintenance. Several such dependencies exist, and they are presented in more detail in Section 2.1.

Dependencies between components are not the only hypotheses considered in opportunistic maintenance. Other possible model variables include resource dependence [2], e.g., due to limited spare part ordering and production, or to workforce availability: either in staff population (“are technicians available?”) or in staff skills (“is the required skill available among the available technicians?”) [7].

However, this large number of possible hypotheses, along with the number of parameters associated with each and the complexity of implementation, lead to scattered uses of different hypotheses among the literature. Outside existing reviews, it is difficult to embrace the variety of hypotheses in opportunistic maintenance modeling. Further, existing reviews do not specifically explore the variety of hypotheses, including dependencies [5,8], or not specifically in opportunistic maintenance modeling [2,9,24]. Finally, the literature also presents contrasting inputs and outputs of maintenance models and various optimization objectives.

This systematic literature review is performed using the strategy proposed by Kitchenham et al. [25,26], and falls within the PRISMA 2020 framework [27]. The objective of using this protocol is to ensure the repeatability of the search and review process. The scope of this review is limited to the hypotheses in opportunistic maintenance modeling, regarding human aspects, dependencies and resource constraints. In the selected literature, the modeling of economic dependency and the optimization objectives were also investigated. The review is limited to results from Google Scholar, Scopus and Web of Science, and to literature written in the French and English languages.

First, an overview of the conceptual background is provided in Section 2. The methodology, as well as an overview of the results, are detailed in Section 3. In Section 4, we present the bibliometric results and the in-depth analysis of the literature. In Section 5, we critically discuss the results and the literature trends. Finally, in Section 6, we conclude and suggest future research opportunities.

2. Conceptual Background

In the context of maintenance optimization, it is often required to identify not only the types of actions to be implemented among those that are possible but also the intervention dates for each maintenance action. This must be done while respecting the requirements for the maintained/target system, such as availability and security. It must also respect those related to its support system, such as spare parts, tools, skills of repairers and cost. Generally speaking, the maintenance optimization process can be divided into three phases [28,29]:

- *Modeling and formulation of target system and logistic support.* This step is crucial for developing decision rules and/or optimizing maintenance planning. The quality of modeling and formulation can impact the optimality of an established maintenance schedule [28,30,31]. In the context of opportunistic maintenance, this phase requires explicitly modeling the dependencies between components and logistic resources to identify where potential maintenance opportunities may arise.
- *Development of appropriate maintenance strategies.* The objective is to construct decision rules for the selection of maintenance actions based on the level of dysfunction of the components/system while planning these actions per the specifications/constraints related to the maintained system and its support system. Here, opportunistic criteria such as component age, degradation level, remaining useful life or marginal cost savings are introduced to guide the decision of whether to extend a maintenance intervention to other components when an opportunity occurs.
- *Evaluation and optimization of the maintenance strategies developed* which aim firstly at evaluating the maintenance schedules provided by such a maintenance strategy defined according to one or more performance criteria (e.g., cost criterion, availability, security, etc.) then secondly, to determine an optimal maintenance planning according to one or more objective functions (e.g., minimize the total cost, maximize availability, etc.). In this phase, opportunistic criteria are assessed against the chosen objectives to determine the conditions under which opportunistic interventions provide the best trade-off between cost, reliability and availability.

In summary, opportunistic maintenance aspects are embedded throughout the optimization process: dependencies provide the structural basis for identifying opportunities, opportunistic criteria guide decision-making in strategy development and their effectiveness is validated during the evaluation and optimization phase. To detail these elements, Section 2.1 focuses on the modeling of dependencies as a foundation for opportunistic policies, Section 2.2 clarifies the notion and classification of maintenance opportunities and Section 2.3 distinguishes between maintenance grouping and opportunistic maintenance in practice.

2.1. Dependence Modeling and Integration in Maintenance-Optimization Process

There are currently real challenges regarding the modeling of interactions between different components and the way their modeling evolves [1,15]. This involves posing the problem of constructing a global evolution model for manufacturing systems composed of multiple components that interact and cannot be reduced to the simple superposition of different behaviors independent of each other [1,32,33]. There are several types of dependencies between components. They can be classified into six classes. Among these types of dependencies, the first two kinds of dependencies (stochastic and structural dependence) have a direct impact on the degradation and failure process of the maintained (target) system. The last two kinds (resource dependence and human errors) belong to the logistic support system and the remaining two types (economic and geographical dependence) have an impact on both the maintained system and the logistic support system. It should be noted that no canonical definition of these concepts exists, due to the various definitions or implementations in the relevant literature. This section provides a broad overview of the subject. The variations in the implementation (and, therefore, in the definitions) of each concept are discussed in Section 4.

1. **Stochastic dependencies** mean that the state of one component can impact the failure process of other components. Stochastic dependencies are classically classified into several subclasses as follows [1,32–34]:
 - Failure dependency where the failure of one component causes the failure of other components [35–37];
 - Load sharing with which the failure of one component accelerates the rate of degradation of other components [38];
 - Common-cause dependence exists when the processes of several components are simultaneously impacted by the same cause. For example, a common-cause dependence model was introduced in [39] where the external impact (shock/operating condition) simultaneously affects the processes of two components;
 - State interaction or degradation was recently introduced in [40–44]. Degradation interaction means that the degradation process of a component depends not only on its state (degradation level) but also on the degradation level of other components;
2. **Structural dependencies:** This type of dependency exists when different components physically form a part and the execution of maintenance on one component (i) physically implies an intervention on other components [11,32,45]; (ii) positively or negatively impacts the degradation process of other components [38,46]. Recently, another type of structural dependency was introduced in [47,48]: the failure or maintenance execution of one component implies a shutdown of other components. This type of dependency can be identified in series-parallel structures.
3. **Economic dependence** which represents the sharing of preparation tasks (machine opening, spare part transportation, etc.) and/or system downtime between different maintenance activities. In that way, the cost of joint execution of several maintenance actions is either cheaper (positive dependence) or more expensive (negative dependence) than when they are separately performed [49].
4. **Geographical dependence** exists when the maintained system is composed of several production sites located far apart from each other, and maintenance teams are not located at production sites [1]. Therefore, to perform maintenance actions of a given production site, a maintenance team needs to travel to the production site. As a consequence, the total distance/time of the joint maintenance group of several

components in different sites may be smaller than the total distance/time of each individual component.

5. **Resources dependence** means that executing the maintenance of several components requires the same maintenance resources (spare parts, maintenance tools, maintenance skills, etc.) [15];
6. **Human errors.** Some specific errors of maintenance technicians may have important impact on the quality of executed maintenance actions, leading to an increase in the degradation/reliability process of a reduction of performance of maintained components/systems [13]. The human error may depend on different factors such as the technician skill and state, the characteristics of maintained components/system, maintenance tools, workload, variations in the environment, etc.

The impact of interactions between components in maintenance modeling and optimization has been investigated in a large number of works in the literature that several advanced works have summarized [1,10,32]. In this work, we focus mainly on the impacts of dependence on opportunistic maintenance.

2.2. Definition and Classification of Maintenance Opportunities

A maintenance opportunity (MO) is usually defined as a specific period in which executing a preventive or corrective maintenance is technically and/or economically beneficial. There are two primary categories of maintenance opportunities: external and internal MOs [5]. The external MOs can be categorized into two classes: 1-Production-based OM (P-OM) whereby an MO is created by a stoppage of components or systems resulting from specific production demands (production systems) or the system configuration in a specific mission phase (multi-phase systems) [33]; 2-External factor-based OMs (E-OMs) are OMs whose occurrences are associated with various external factors such as new technologies/more efficient components, discounts of spare parts, lower labor cost periods, good weather conditions [3,50].

Existing works on external MOs usually consider mainly single component systems and concentrate on the definition and formulation of the maintenance opportunities by modeling MO arrival time and duration. Indeed, the arrival time of an external MO can be described by a homogeneous Poisson process as in [50,51] or a non-homogeneous Poisson process as in [52]. Truong Ba et al. investigated the stochastic duration of external MOs [53]. Recently, an external MO concept based on inactivity periods with random occurrences has been proposed in [33]. An efficient method and an adaptive decision rule are proposed to consider this kind of external MO in maintenance decision-making. Nevertheless, the developed methodology is exclusively relevant to the series systems.

Internal MOs, whereby maintenance opportunity is created when maintenance action is needed, usually exist in multi-component systems, especially when components are interdependent since corrective or preventive maintenance of given components provide cost-effective opportunities to perform preventive maintenance on other dependent components (with reduced maintenance cost). Although the dependencies between components allow the opportunistic maintenance application to surpass internal MOs, they pose numerous challenges in both maintenance modeling and optimization [47,54]. Among different kinds of dependencies discussed in the previous section, the economic and structural dependencies have received considerable attention in the literature [55]. Regarding the nature of executed maintenance actions (preventive or corrective), the internal MOs can be categorized into two classes: preventive maintenance (PM)-based MO and corrective maintenance (CM)-based MO [7,56–58]. PM-based MO is triggered by PM of components, which may be planned in advance; the associated logistic support for PM-based MO can be carried out proactively. CM-based MO is activated by CM action of failed components; the

associated logistic support for the CM-based MO is more complex to organize [59,60]. A classification of MO is given in Figure 1.

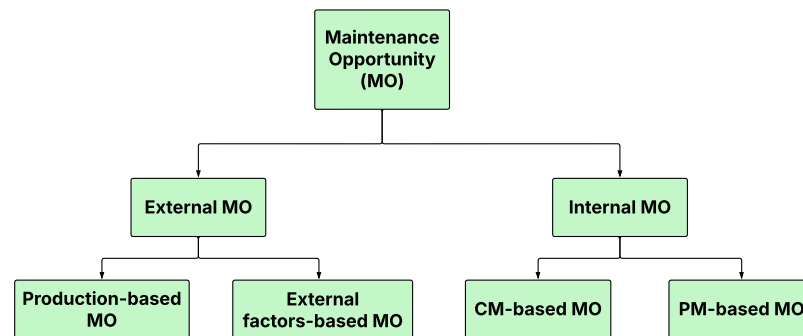


Figure 1. Classification of maintenance opportunities.

2.3. Maintenance Grouping vs. Opportunistic Maintenance

For specific industrial systems, the system components are assembled in groups that do not vary over time, i.e., the group members will always be maintained together [61]. In that way, maintenance groupings can be preestablished and be invariant over time. Indirect grouping can also stem from each component having its individual preventive maintenance periodicity: in that case, the groupings stem from the occurrence of the scheduled actions [61]. Dynamic grouping uses a rolling horizon over which long-term characteristics of the maintenance plans are adapted to match the short-term discrepancies caused by unscheduled events [33]. Other groupings are occasionally suggested, e.g., grouping by similarity of the action to be taken [62].

Another way to see maintenance grouping is to evaluate the state of components at the instant of a maintenance opportunity. This state can then be described through opportunistic criteria. The opportunistic criteria should not be confused with the optimization objective of the policy. The opportunistic criteria are a series of variables that describe how the decision process for opportunistic maintenance is modeled, i.e., what the logical comparison that induces the decision of opportunistic maintenance on the spot is. In turn, these criteria can then be optimized with respect to the objective function (discussed in Section 4.5) in order to identify the optimal values of the opportunistic criteria. These criteria can be of any nature, but usual modeling options include the components' cost of maintenance, reliability at the time of the opportunity, age, degradation level (measured or estimated), remaining time before the next scheduled maintenance, etc.

3. Methodology of the Systematic Review and Overview of the Results

This review is based on the systematic literature review protocol proposed by Kitchenham [25,26] and follows the PRISMA 2020 protocol [27]. Overall, this research follows the steps:

1. Defining the research questions
2. Identifying the search process, including search phrases and databases
3. Establishing inclusion and exclusion criteria, a set of rules that allows selecting the literature entries that are included in the review
4. Determining quality assessment criteria to assess the relevance of the selected papers to answer the research questions
5. Collecting the data, including procuring the papers, reading and curating a database regarding their contents
6. Analyzing the data and providing an insightful and critical review of the literature entries.

3.1. Research Questions

The objective of setting research questions (RQs) is to ensure consistency and the frame of the subject of the critical analysis. By setting questions, search phrases can be established to find relevant papers.

The research questions are defined as:

RQ1. How are the current hypotheses regarding workers' skills, dependencies and resource constraints made in opportunistic maintenance research modeled?

RQ2. Among the papers identified to answer RQ1, how is economic dependence modeled?

RQ3. Among the papers identified to answer RQ1, what are the optimization objectives?

RQ1 is the core question, raised by the analysis of a need for reviewing as expressed in Section 1. However, it brings together three different concepts: workers' skills, dependencies and resource constraints and this would impede the clarity of the answer. In consequence, RQ1 is divided into three subquestions:

RQ1a. How are workers' skills and skill evolution taken into account in opportunistic maintenance research?

RQ1b. How are dependencies, other than economic, taken into account in opportunistic maintenance research?

RQ1c. How are resource constraints and spare parts taken into account in opportunistic maintenance research?

3.2. Search Process

The search was carried out on three prominent databases on 20 February 2024: Google Scholar, Scopus and Web of Science core collection (WoS). The search process was completed with the help of the Publish or Perish software [63] for the search made on Google Scholar, while the Web of Science and Scopus searches were an export of search results obtained by typing the search phrases manually.

The Search Phrases (SPs) were built on a semantic analysis of the contents of RQ1a, RQ1b and RQ1c. Specifically, the three subquestions of RQ1 were decomposed into blocks of elementary meaning. In general, each subquestion can be split into two parts: one that concerns opportunistic maintenance and another that addresses a specific type of hypothesis. Identified expressions for each semantic block are provided in Table 2. A particularity arises with the "dynamic grouping*" keyword: while it can be used for designating opportunistic maintenance, it is also used in other domains. In that case, the keyword "maintenance" should also be used in the search, in order to filter out irrelevant search results. This filter seemed to be efficient, although the contamination of search results from specific other fields could not be quantified. Using parentheses and the logical operators | ("OR") and + ("AND"), as well as quote marks to search for exact expressions, RQ1a, RQ1b and RQ1c are translated into, respectively, SP1a, SP1b, SP1c:

Table 2. Synonyms for each semantic block, using * as a wildcard character.

Opportunistic Maintenance	Workers' Skills	Dependencies	Resource Constraints
opportunist* maintenanc*	skill*	dependenc*	resource* constraint*
dynamic grouping*	expertise		spare part*
			inventory
			logistic support

SP1a. ("opportunist* maintenanc*" | ("dynamic grouping*" + maintenanc*)) + (skill* | expertise)

SP1b. ("opportunist* maintenanc*" | ("dynamic grouping*" + maintenanc*)) + dependenc*

SP1c. ("opportunistic* maintenanc*" | ("dynamic grouping*" + maintenanc*)) + ("resource* constraint*" | "spare part*" | "inventory" | "logistic support")

The papers are split between the two first authors of the present paper, for assessment with respect to the inclusion, exclusion and quality assessment. Undecisive cases are discussed until a joint decision is reached.

After selecting the papers, a bibliometric analysis allows identifying the most prolific journals in the search results. An in-depth read of each publication then provides hindsight on the respective contributions and in turn to answer the research questions.

3.3. Inclusion Criteria

The inclusion criteria are necessary (but not sufficient) criteria that must be met by papers to be included in the literature review. The sufficient criteria, on the other hand, derive from the consideration of both the inclusion and the exclusion criteria.

- The publication is written either in French or in English.
- The publication addresses opportunistic maintenance through modeling, simulating or reviewing publications that include modeling and simulating.
- The publication describes how the workers' skills, dependencies or resource constraints are taken into account in opportunistic maintenance modeling.

3.4. Exclusion Criteria

The major rationale for implementing opportunistic maintenance is economic dependency: including publications that only address economic dependency would be virtually equivalent to including all literature on opportunistic maintenance. Therefore, the first exclusion criterion aims to limit two effects: a volume of literature that would not be treatable and that goes beyond the objectives of this review and a domination of the economic-only results in the dependency analysis. Nevertheless, because the economic dependency is essential to the understanding of opportunistic maintenance, the choice was made to examine the economic dependencies in the selected literature, while acknowledging the bias in the literature selection (see RQ2).

- Publications that only respond to RQ1b should not be limited to economic dependency
- Publications should not have been published before year 2000.

3.5. Quality Assessment

The quality of publications that are not reviews was evaluated based on the following quality assessment (QA) questions:

QA1. Are all hypotheses used in the model or simulation clearly mentioned?

QA2. Are the outputs or optimization criteria clearly identified?

QA3. Is the model for the considered objective function explicitly detailed?

The scoring is scaled as follows (1 is best):

QA1: 1, most hypotheses are listed or clearly mentioned in the text; 2, some hypotheses are left missing but implicitly understandable; 3, the hypotheses cannot be readily inferred.

QA2: 1, the outputs or optimization criteria are clearly defined and mentioned; 2, the outputs or optimization criteria are unclear or not mentioned.

QA3: 1, the cost model is entirely defined (or provided as normalized values); 2, the cost model is unclear or not mentioned.

3.6. Research Process and Results

The number of papers identified per source is provided in Figure 2, as well as quantitative information on the selection process. Using the search phrases defined in Section 3.2 yielded the results provided a number of results in each source for each research query.

Intra-source duplicates were removed (i.e., identical papers obtained within one source in response to different queries), then inter-source duplicates (i.e., identical papers obtained across the sources). The relatively small number of papers removed at this stage confirms the strong separation of the semantics of each RQ and the fact that only a few papers address more than one RQ at once.

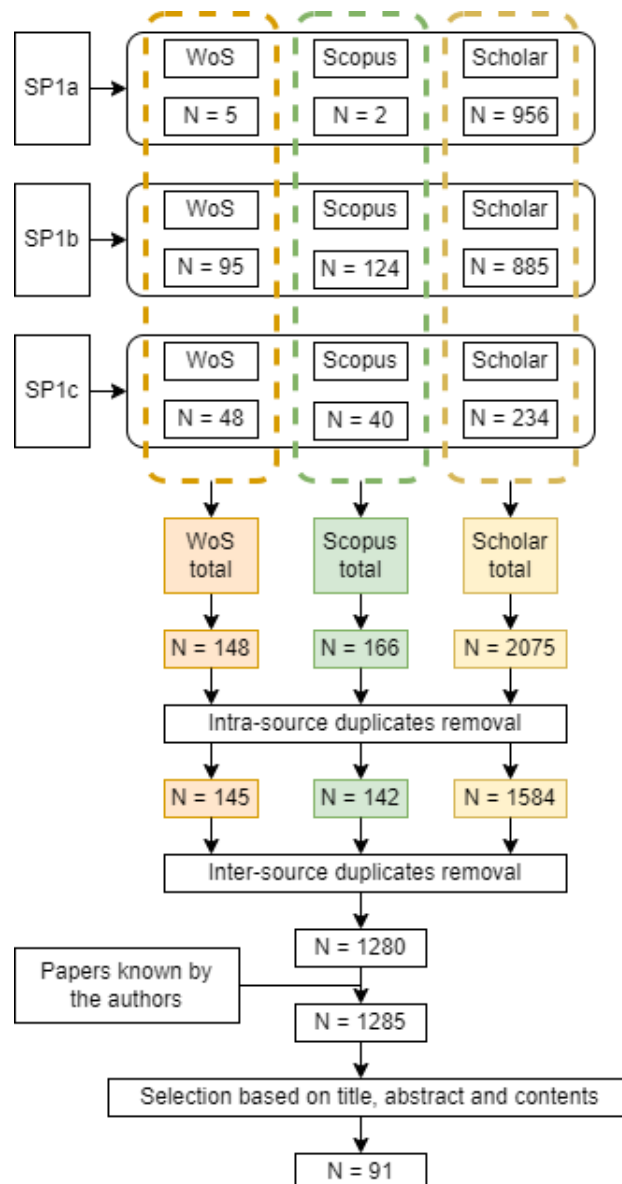


Figure 2. Number of papers identified in each source and initial analysis process.

It should be noticed that five papers ([1,2,15,64,65]) were added manually to the search results as they were known to exist by the authors but were not found within the search results in the databases. They are either recent remarkable reviews or recent research papers. The reason why these papers did not appear in the search results is either due to opportunistic maintenance not being the center subject of the paper, thus not appearing clearly in the search that is performed on keywords, titles and abstracts, or on less popular choices of terminology, e.g., “maintenance clustering”.

Afterward, all papers were carefully examined independently by the first two authors. On the basis of the title and abstract, a pre-selection of papers that could potentially answer the RQs was identified. This selection was further refined by reading each pre-selected

paper and identifying whether they answered the RQs. Table 3 recapitulates the found literature entries and specifies the type of each document.

Table 3. Identification of the 91 research results of the systematic literature-review process.

Publication Type	Number Reviewed	Refs.
Original research: Journal papers	64	[3,7,35,47,49,54,55,64–120]
Original research: Conference papers	9	[62,121–128]
Book chapter	2	[129,130]
Review papers	12	[1,2,11–20]
Theses	4	[131–134]
Total	91	-

In terms of response to subquestions of RQ1: 10 publications were found to respond to RQ1a, 61 were found to respond to RQ1b and 39 were found to respond to RQ1c. Some publications respond to more than one of the subquestions of RQ1.

Figure 3 shows the yearly number of publications responding to RQ1 in total. The scientific production on the topic clearly grows over time. It shows that dependencies (RQ1b) are historically the earlier research subject (early 2000s), followed by resource constraints (RQ1c, late 2000s) and then only by human aspects (RQ1a, mid 2010s). In proportion, it also shows that dependencies remain the most important topic in the identified corpus. It also shows a sudden increase of publication in all domains covered by the RQs in the mid 2010s, which allows the present work to provide an overview of the last two decades of research, of which the last decade proved most proficient in research. In Figure 3, papers that respond to different subquestions of RQ1 are counted as many times as the number of questions they answer (e.g., if a 2017 paper answers both RQ1a and RQ1b, the same paper is counted twice in the 2017 column, once for RQ1a and once for RQ1b).

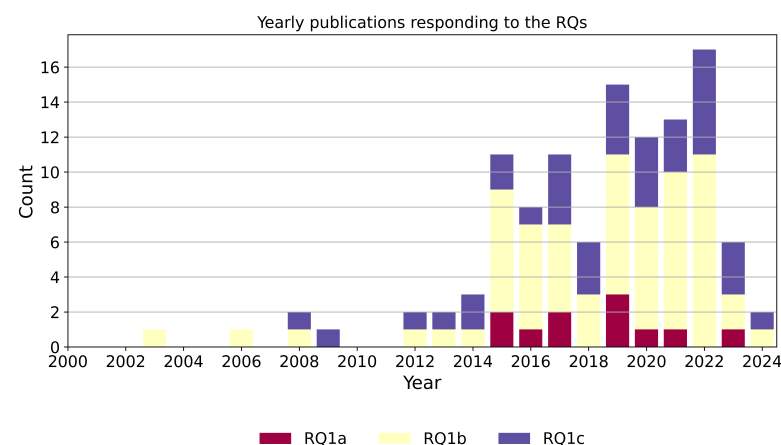


Figure 3. Timeline of publications responding to RQ1a, RQ1b and RQ1c. Papers that respond to more than one RQ are counted as many times as the number of RQs they answer.

It should also be noted that none of the selected literature entries present any experimental data collection. All papers that present numerical examples either rely on previously published data, on estimated values or simply do not provide information on data acquisition. However, this fact is not, in itself, problematic, because the central contribution of the selected papers never resides in data collection, which is used marginally to illustrate a concept or a method.

4. In-Depth Analysis for Maintenance Modeling

This section is divided on the basis of the RQs identified in Section 3. In the case of RQ1, for each subquestion, a timeline of identified publications responding to the subquestion

is given. Then, a description of the ways the identified publications respond to these questions is provided.

4.1. Human Factors in Opportunistic Maintenance Modeling

Human factors are a class of hypotheses related to the human performance in maintenance models. We observed the modeling hypotheses which can be divided into three main categories:

1. Skill type hypotheses, where different failure modes require specific skill sets for maintenance;
2. Human error hypotheses, describing situations where the maintenance is affected by human errors that are defined by their impact and probability of occurrence;
3. Skill level hypotheses, under which the workers' proficiency in their skills needs to exceed a given level in order for them to accomplish their maintenance tasks.

In general, these hypotheses add realistic constraints (skill or skill level) or consequential effects of the imperfect maintenance accomplished by real workers (human error).

Figure 4 shows the evolution of topics related to human factors over time. The topic remains rarely addressed (only $n = 11$ out of the 91 references that address this topic) and no clear time trend appears.

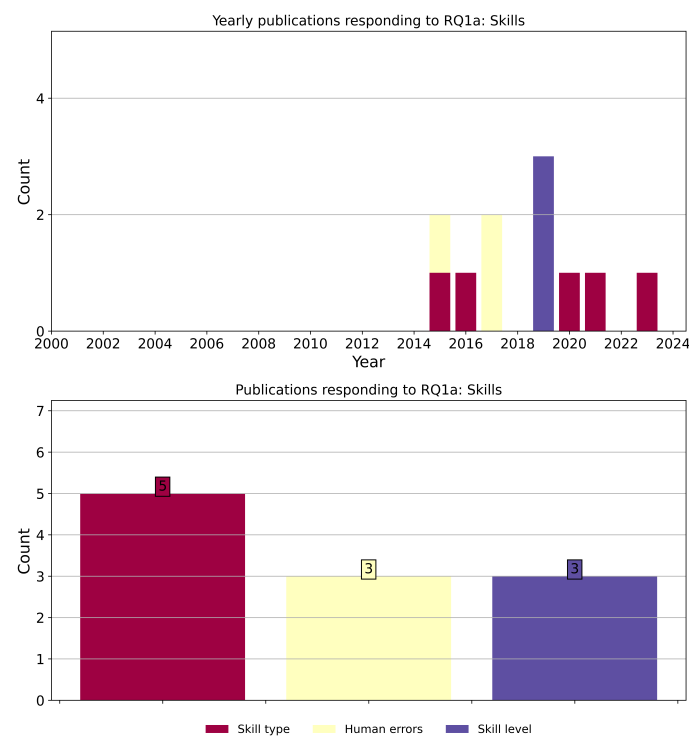


Figure 4. Timeline and count of publications responding to RQ1a (human factors).

Skill types were mentioned in a 2015 review by Shafiee [13]. In general, they are typically modeled in opportunistic maintenance by associating a given skill with a maintenance operation. The skill requirement then becomes a variable that is taken into account at the time of action grouping: an action can only be started if a worker who possesses the required skill is available [62,117]. The skill requirement can additionally be combined with other hypotheses, such as structural dependencies [3,7].

In the framework of human reliability, human error can be modeled as a dependency, where an error in doing a task affects the probability of error in another task. This definition can then play a role in defining maintenance action groups [66]. In that framework, the probability of error depends on the workload fluctuation, the variability in maintenance and

the human error dependency between maintenance tasks. Other factors of influence, such as issues with the maintenance procedures, fatigue and inadequate knowledge or experience are also identified. In that scenario, fatigue can be included during a planning phase by considering whether the maintenance action is pursued during the day or at night [73,91].

Skill levels are even more rarely mentioned in the literature of opportunistic maintenance. It can be used in assessing the customer's satisfaction of the maintenance provider [67]. At a deeper level of modeling, it can be used to create a skill level threshold under which workers are unable to perform a given action. In that case, in return, the skill level can also be linked with labor cost [110,132].

4.2. Dependencies in Opportunistic Maintenance Modeling

Except economic, human- and resource-related dependencies (which are treated in separate sections), dependencies of three major types have been identified in the literature review: stochastic dependencies (sto); structural dependencies (str); and geographical dependencies (geo). Several of these types often overlap in the literature (papers often use several of these hypotheses simultaneously).

Figure 5 shows the evolution of topics related to the dependencies other than human, resources or economic, over time and the distribution of dependency subtypes they address. The subtypes of dependencies identified in Figure 5 are the subject of the remainder of the current section. The time chart shows that some subtypes of dependencies seem to have been taken into account more recently than others in the opportunistic maintenance literature, such as weather dependencies.

4.2.1. Stochastic Dependencies

Stochastic dependencies can be further divided into types. In 2008, a review by Nicolai and Dekker identified two types and numbers them I and II [11]. In a 2016 thesis, Li identifies three numbered types [131], by subdividing Nicolai and Dekker's type II into two variants: II and III. Both rely on an identical reference for the theory of these types of dependences [135]. To provide a more detailed view, we elect to present the subdivided version:

- Type I: the failure of a component instantaneously induces a probability p of failure of the dependent component.
- Type II: the failure of component A induces a probability of instantaneous failure p on component B, whereas the failure of component B induces a shock on component A, modifying its failure rate, instead of inducing a probability of instantaneous failure.
- Type III: The failure of either component induces a shock on the other component, modifying its failure rate.

In addition to these three numbered types, our review also yielded another assumption commonly called stochastic dependence and is more general than the three types identified above. This additional type is identified as type IV:

- Type IV: The current state of degradation (typically modeled through stochastic processes) of a component influences the degradation process, or the failure rate of another component.

In summary, Types I–III are dependencies in which a failure must occur to invoke the dependency in the model, whereas Type IV occurs through the lives of the concerned equipment. Further, Types I and II are unidirectional relationships defined for directional pairs of components, whereas Types III and IV describe bidirectional relationships.

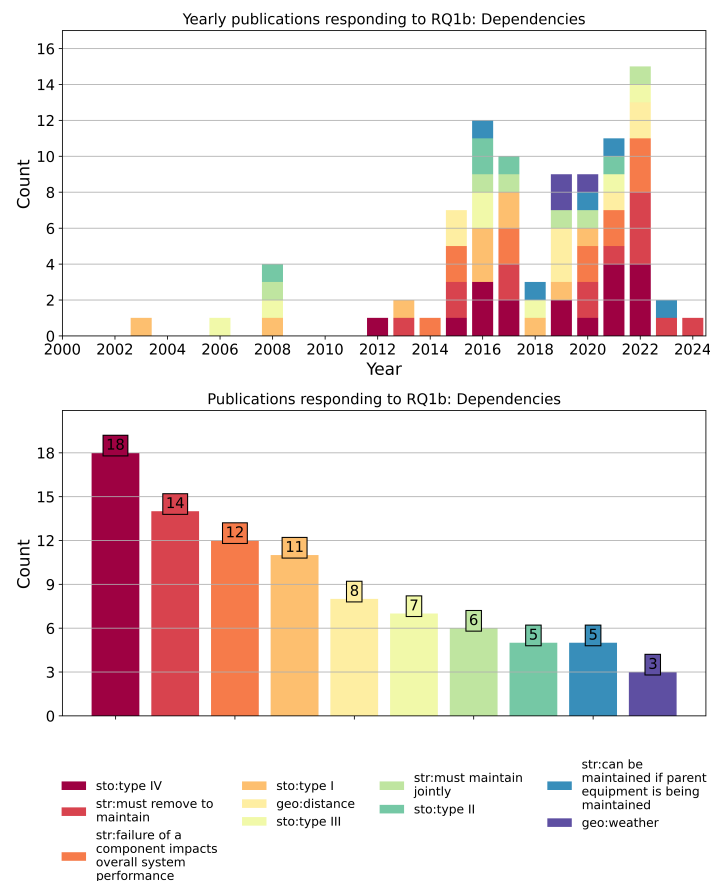


Figure 5. Timeline and count of publications responding to RQ1b (dependencies), by subtypes.

An alternative classification is proposed by Olde Keizer et al. (2017). This classification relies more on the reason for stochastic dependence rather than the way it is mathematically modeled. In particular, they identify failure-induced damage (as explained in types I to III), load sharing (in which the variation of load on one component increases or decreases the load on the other component, hence a variation in degradation—type IV) and finally common-mode degradation (in which the components sharing a similar environment are under similar stresses and share common influences in the way they deteriorate) [1].

Alternative monikers for stochastic dependence found in the literature include “random correlation” (e.g., in [77]) and “random dependence” (e.g., in [19]).

Types I through III are implemented in models as consequences to events, and offer fewer variations in the modeling than type IV, which is furthermore more present in the literature.

Type I is well represented in reviews [1,11,14–16,129]. This hypothesis can be found in papers comparing maintenance strategies one to another, contributing to the complexity of the models evaluated [104,127]. The identified original research using this type of stochastic dependence has applications such as bus clutches [35] or more general numerical examples [104,127]. Finally, two theses were found to make use of this type of stochastic dependence [131,133].

Type II stochastic dependence is an asymmetrical relationship and necessitates defining the members of the relationship as well as its direction. They are usually presented as matrices. Type II is mainly mentioned in previously discussed reviews [1,11]. In original research, both articles identified make use of this hypothesis to update the RUL estimate of the system, knowing the failure history of each component. One of them uses Bayesian networks to update the joint reliability distribution, and provides an example applied to

the diesel engine of a power plant [74]. The other uses Bayesian probability to update the RUL of the components and applies this approach to an abstract numerical example [78]. Finally, a thesis was found to use this hypothesis [131].

Type III is presented in two reviews [11,19]. Like in the case of type II, it is possible to use the hypothesis to update an RUL prediction, but also to use it asymmetrically, in the same way that type II is used, as well as using both types simultaneously, as in [78]. The existence, intensity and direction of a link are usually presented in matrices providing a value for each possible relationship in the system, as was shown using a tramway example in [121]. This type of stochastic dependency was also used in developing a multi-component cumulative damage model in the context of opportunistic maintenance [105]. Finally, one thesis was found to use this hypothesis [131].

Contrary to the three first types, type IV considers stochastic dependency as a permanent, mutual influence between the components, whereas types I through III assume that the influence of one component on the other occurs only upon failures. Alternative monikers for type IV stochastic dependency include “degradation interaction” [79] and “state dependence” [123]. Type IV stochastic dependency was presented in several reviews or book chapters [1,2,14,130]. It can be used in the context of failure trees, in which the evolution of the degradation of a component influences the performance of the others [68]. Alternatively, in reliability-centered approaches, it can be modeled as incrementing a component’s failure rate by a linear combination of the other components’ failure rates, as in [77]. Under a load-sharing mechanism, it can also be considered that the workload of non-functional components is shared among other components, thus lengthening the work-day duration for the other components [112]. In stochastic models, the current degradation state of a component can affect the next degradation jump of another component [79,80,123]. Using Lévy copulas, nested Clayton–Lévy copulas or Frank copulas, the stochastic dependence can also be modeled with similar intent [54,89,119]. Using gamma processes, it is also possible to implement variations in the process parameters that create a correlation between the degradation of components [92]. It can also be modeled through a dynamic Bayesian network combined with the result of a HAZOP analysis [106]. Finally, one thesis was found to use this hypothesis [131].

4.2.2. Structural Dependencies

Structural dependencies can also be further divided into types, albeit never being formally sorted into categories in the literature. Based on this observation, this division is an originality of the present review. An overview of this division is as follows:

- Type A: Must maintain jointly: two components must always be maintained simultaneously.
- Type B: Must remove to maintain: the structural dependence comes from topological considerations in the machine that is maintained, which requires disassembling one or more components to access other components.
- Type C: Can only be maintained if parent component is being maintained: a component can only be maintained in the eventuality a given other component is maintained as well.
- Type D: The failure of a component impacts the overall system performance such as a production flow restriction.

Types A to C stem from practical considerations related to the maintenance action itself. In contrast, type D is a much more dynamic consideration that applies to parallel or redundant systems and relates to load balancing between parallel systems. This distinction between technical dependence and performance dependence is also highlighted by Olde Keizer et al. [1].

Type A, or the case of components that must be maintained jointly, is presented in four previous reviews or book chapters [1,11,19,129]. In these, it is argued that both replaced components may make up a single part that must be replaced jointly [129] or that it is one possible situation [1,11,19]. Yet, in the selected literature entries, only one original research article specifically made use of this case. In this case which is applied on maritime fuel injector data, it is modeled through a reduction in maintenance time since both components are replaced at once and not sequentially [122].

Type B, or the necessity of disassembly to access components, is a recurring hypothesis that is presented in reviews and book chapters [1,2,19,130]. In particular, Do et al. suggested an implementation similar to the previous case, with a potential decrease in maintenance duration, thanks to several components of a group being maintained simultaneously [130]. However, in original research, it is identified on the contrary that it can also lead to an increase in maintenance duration due to the time necessary for disassembly [118]. The situation can also be more complex, with a potential duration increase. However, components that are on different disassembly paths must only be counted once per maintenance action, which mitigates this effect [118]. In original research, this type of structural dependency is represented by a directed graph presenting a hierarchical order in which low-level components (final ends of the tree) must be disassembled to access top-level components (the root of the tree) [64,76,81,107]. This graph can also be represented as a disassembly matrix [64,76,118]. This matrix representation of the dependency can also include information on the change in maintenance duration when disassembling a given component to access another one [77]. In general, this dependency can be modeled as affecting the maintenance duration, hence the costs [75,77,81,104,118], or as an event inducing a shock on disassembled components, hence degradation jumps [64,76], or both [114]. Finally, it is also one of the fundamental hypotheses used in a thesis [134].

Type C, or the possibility of maintenance only if a designated parent component is being maintained as well, is less represented in the literature. It was not explicitly mentioned in a review. It constitutes a moderate version of type A in that joint replacement is not bijectively mandatory but rather injectively (the replacement of component 1 does not always induce the replacement of component 2, but 2 always induces 1). This dependency can be implemented by identifying what components are non-operating after a failure and allowing opportunistic actions to be taken only on those matching that criterion [55]. Another way to implement this is to limit the list of potential opportunistic replacements to the components that must be disassembled to access the failed component [7,102,117]. This case then requires, just as type B, a disassembly graph or matrix. Finally, it is mentioned as a possible hypothesis in a thesis [134].

Type D, or the consideration of the impact of a component's failure on the system's performance, is a recurring subject in reviews [2]. In particular, Olde Keizer et al. provide an in-depth review of this dependency, with or without economic dependency in the context of condition-based maintenance [1]. It is also widely used in original research. A first possibility in modeling this dependency is the concept of load sharing. Under this hypothesis, several components are assumed to share the load: as one component fails, others must compensate for the capacity loss, increasing their load, hence deteriorating faster [65,112]. In other cases, in particular in parallel systems, the other components cannot share the load, and stopping components leads to a reduction of production flow in the system [93]. Another way to model this dependency is made necessary by complex series-parallel systems, in which the overall system state is dependent on the combination of components' failures. In that case, it can also be modeled through the use of Birnbaum's structural importance that derives from the notion of structure function, and that describes the proportion of cases in which a component's failure may induce the system's failure [100]. The structure

function provides the system state given the components' state [47]. This, in turn, can be used to optimize maintenance action groupings [3,49,101]. In these systems, it is also possible to model the probability of failure of the entire system as a function of the probabilities of failure of individual components [97]. Finally, some authors include the impact of maintenance on the total system downtime as part of structural dependencies [111].

4.2.3. Geographical Dependencies

Geographical dependencies can be separated into two categories: weather-related and distance-related. They are usually treated separately, as they represent distinct issues. These categories can be summed up as follows:

- Weather geographical dependencies: the maintenance actions are weather-dependent and are subject to seasonal and punctual schedule variations.
- Distance geographical dependencies: the assets that need maintenance are geographically distributed and require time and resources to be addressed.

Weather is a factor external to the studied system, i.e., governed by random events. On the other hand, the distance dependencies are internal factors, i.e., part of the system description.

Weather geographical dependencies are most frequently represented in the wind turbine-maintenance literature, among the results of the present review. No current review presenting this type of dependency in the context of opportunistic maintenance modeling is known to the authors. The original research that considers this dependency is consistently related to wind farms and wind turbines. Wind speed is the principal factor, with both positive and negative effects. Low wind speed, below a given criterion (called cut-in speed), is insufficient for production and hence provides a maintenance opportunity [94,98]. However, wind above another given speed does not allow maintenance operations at all [98]. Further, above yet another wind speed (cut-off speed), the wind turbine cannot produce safely and is turned off [94]. Specific models exist for generating wind speed data, and their output can be compared to actual data [86].

Distance geographical dependencies are mentioned in a previous review [13]. In original research, this dependence can be modeled by defining distances between the assets and assigning a traveling cost and velocity, hence delays [95,110,113,125]. In their opening review, Camci provides an overview of the variants of the traveling salesman problem that are specific to the maintenance context [108]. In particular, three different problems are identified, with varying hypotheses [108]:

- Travelling Repairman Problem (TRP), in which the assets to be visited have all failed.
- Vehicle Routing Problem, which is a variant of the TRP with several travelling agents.
- Travelling Maintainer Problem, in which the visited assets have not yet failed.

Finally, geographical dependence is a hypothesis used in a thesis [132].

4.3. Resource Constraints in Opportunistic Maintenance Modeling

In the literature identified in this review, we observed the modeling of resource constraints to be divided by the type of resource discussed: spare parts, crew, time, tools, budget, transport, production-related resources and other hypotheses that lead to the impossibility of simultaneous operations.

Figure 6 shows the evolution of topics related to resource constraints over time. The problem of spare parts is the backbone of the subject. The topics of crew and time issues are also rising over time in the identified literature. Overall, these types of constraints induce the inability to perform certain simultaneous maintenance actions (typically required by opportunistic maintenance policies). This inability may be due to insufficient resources

being available at the required time. The unavailability of resources usually necessitates outsourcing jobs or requires express deliveries, resulting in higher costs. These constraints are sometimes grouped under the term “maintenance logistic support” [3].

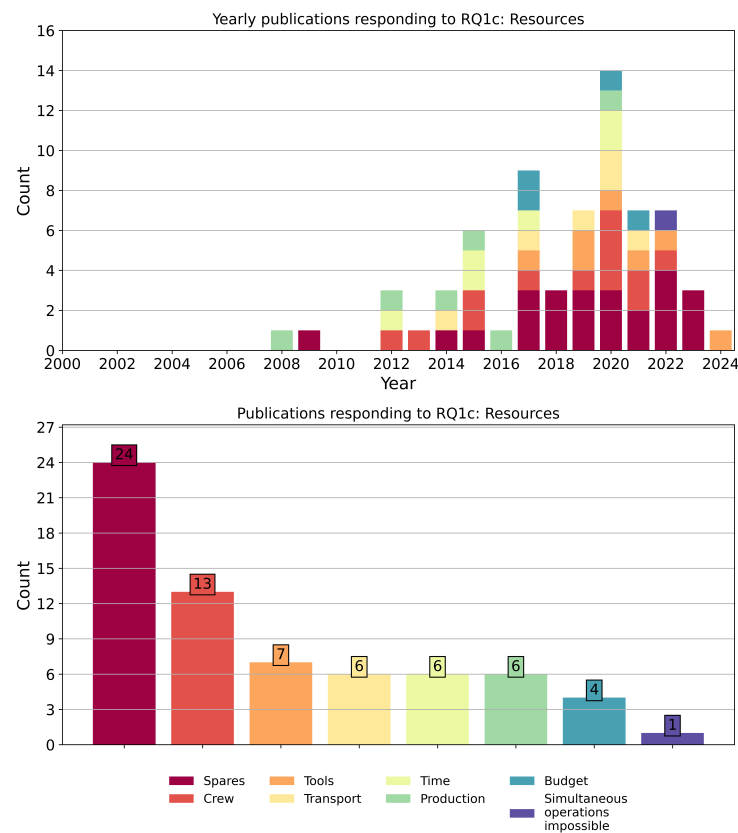


Figure 6. Timeline and count of publications responding to RQ1c (Resources).

The question of **spare parts** has been extensively covered in existing reviews. No less than eight reviews mentioning the hypothesis were found [1,12,13,16–20]. In original research, the resource constraint on spare parts can be implemented through a limited stock of spare parts of different types. Realistic additional hypotheses include delays when spare parts are unavailable (hence downtime costs) [86,98,103], or different machines using the same parts [82,115]. The optimization can then simultaneously address the maintenance policy itself as well as scheduling spare parts orders, which constitutes a major topic in the current literature [83–86,100,115,116,124,128]. This particular topic is extensively discussed in the recent review by Scarf et al. [20]. Furthermore, the cost of spare parts or the availability of discounts on their prices can create opportunities for maintenance to be seized through an appropriate maintenance policy [3]. Then, facing the issue of spare parts shortages, an emergency supply of spare parts can sometimes be used at a higher cost [82]. Because the lack of spare parts can be easily circumvented numerically by increasing the stock capacities, stocks can be modeled as inducing costs of inventory holding, which are proportional to the stock capacities [97]. Finally, this hypothesis is also mentioned in two theses [132,133].

The **crew**-related constraints have been mentioned in five previous reviews [1,2,13,16,17]. In original research, it can be modeled through the requirement of workers for a given maintenance job, these workers being possibly unavailable at the time of request [69,90,93,126]. These requirements can further specify the skill type of the required workers (see Section 4.1 on this topic) [69]. Then, only actions for which the required workers are available can be considered for grouping: the sizing of maintenance teams becomes part of the optimization.

Further, additional hypotheses can combine this constraint with geographical dependences (travel time [70], weather [98]) or include the use of contractors, which induces a delay [87].

The constraint stemming from the unavailability of **tools** was mentioned in two previous reviews [1,19]. In original research, it is modeled in a similar fashion to crew availability, postponing maintenance actions that cannot be undertaken within the required time [103,120]. Likewise, external resources (e.g., rental of specific maintenance tools) can be considered, usually at a higher cost, and can be further refined to several modes depending on the level of emergency [3]. It was also one of the hypotheses discussed in a thesis [132].

The **transport** constraints are akin to distance geographical dependencies, albeit seen from the perspective of the client of the vehicle fleet rather than its manager. In the standpoint of the transport constraint, there is no attempt to optimize the system with respect to the geographical dependencies, but rather the passive observation of the available transporting fleet. Therefore, the constraint can induce longer response times [103,124]. The level of emergency maintenance can also necessitate the use of different means of transportation, resulting in various delays and costs [3]. These constraints were also mentioned in previous reviews [1,16,17].

The **time** constraint was mentioned in three previous reviews [2,13,16]. In original research, it corresponds to cases when there is a limited amount of time to carry on the maintenance operation, which cannot be exceeded [81]. The actions grouping must then be optimized under the time constraint. The same constraint can also be formulated as a minimal availability to reach [90]. The timeline can then be broken down into missions, with different constraint values [90,126].

The constraint linked with **production** was not explicitly mentioned by a previous review. It is, however, mentioned in original research under several representations. It can be represented as a production lot size that limits the opportunities for system inspection (which are only possible between lots) [109]. Moreover, the maintenance opportunities can depend on the production inventory, the system stopping at full inventory and starting production when the inventory is depleted [109]. A variation of this last possibility is the case of building a larger inventory (called buffer inventory) intended to minimize production loss during downtime [99]. Finally, unexpected changes to production planning can shift scheduled maintenance times, thereby inducing the need for a dynamic grouping of actions [3,90,101,126].

The **budget** constraint was mentioned in three previous reviews [1,16,17]. In original research, a possible implementation is realized by breaking the timeline into missions and assigning a budget to each mission, which cannot be exceeded [81].

Finally, it is also possible to disturb the scheduled opportunistic maintenance by sporadically forbidding **simultaneous maintenance** actions without linking this phenomenon to specific constraints or events [71].

4.4. Modeling Economic Dependencies

Economic dependencies are the rationale for implementing opportunistic maintenance in cases when the cost is the objective function. However, the identified papers employ different methods to implement economic dependencies. The timeline of these options in the literature is shown in Figure 7. Some papers fail to clearly identify how their cost model is affected by the economic dependence (represented as “undefined” in Figure 7). Because providing an exhaustive analysis of the selected literature would be repetitive, this section provides a limited number of examples for each identified modeling way. It should also be noted that many ($n = 40$) of the identified papers combine more than one way to model economic dependencies.

On the other hand, the definition of economic dependency also strongly relies on each paper's cost model. There is no standardized cost model, which leads to papers implementing economic dependence through the available way in their cost model. This variety in the implementation of cost models and economic dependencies induces difficulties in comparing models, hence complexity in benchmarking proposed policies.

In the identified literature, four ways to model economic dependencies were found: sharing downtime costs; sharing set-up costs; sharing logistic (travel) costs; sharing a predetermined fraction of the costs.

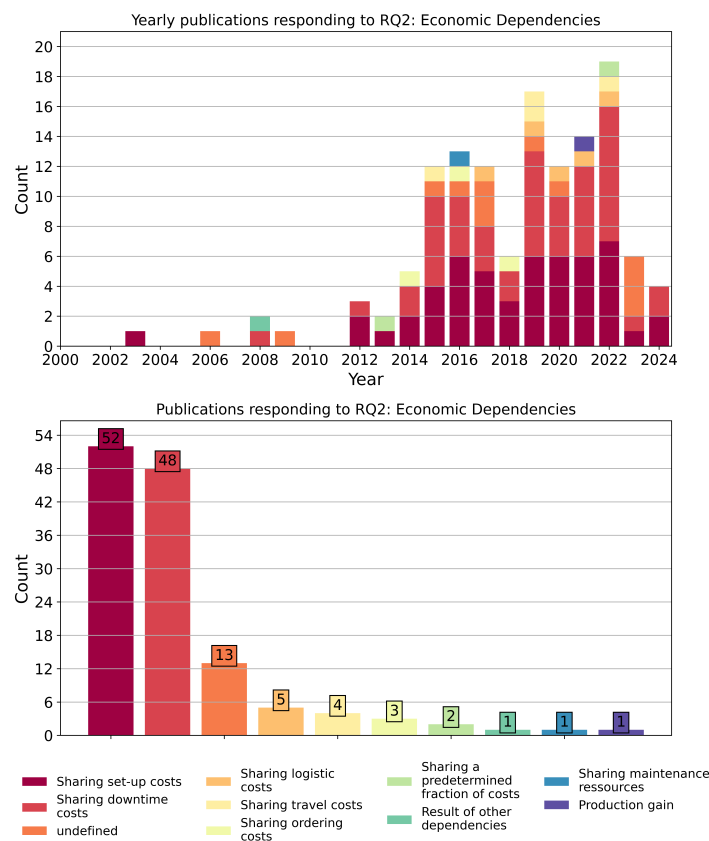


Figure 7. Timeline and count of publications responding to RQ3 (economic dependence), by subtype.

Set-up costs are related to the costs of mobilizing crew, making safety provisions, transportation, tools disassembling the machines, etc. [106]. The assumption that these costs can be reduced by synchronizing maintenance actions, thus sharing these costs, is the most represented in the literature ($n = 52$).

In general, the downtime costs constitute a major part of the maintenance costs [2]. They typically may include loss of production and penalties due to late delivery, despite explicit cost breakdowns being rare. Consequently, the simultaneity of maintenance operations has a positive impact on the overall downtime cost. This assumes that the components to be repaired are necessarily shut down simultaneously, i.e., the components are not placed in parallel, or the entire system is shut down on the maintenance opportunity. This way of modeling economic dependence is extremely common ($n = 48$).

Logistic costs can, in some cases, be part of the set-up costs. However, in specific problems such as distributed equipment to be maintained, they can represent a specific cost type that can then be partially shared or reduced through an optimization akin to the traveling salesman problem [108]. In other cases, the spare parts fluxes can represent a cost of their own, either through inventory holding costs or ordering costs, which can be shared or reduced by combining maintenance operations and optimizing the logistic flux [100].

In a limited ($n = 2$) proportion of the literature, the simultaneity of maintenance actions simply reduces the sum of maintenance costs by a fraction [87].

The literature entries that combine more than one type of economic dependency ($n = 40$) most often combine sharing downtime costs with set-up costs ($n = 29$). Other combinations can include up to three types of economic dependencies, although the triple combinations are not favored by the literature ($n = 3$).

A clear limitation of the results regarding economic dependency modeling should be noted: as stated in RQ2, only the papers responding to RQ1 are examined to answer RQ2. Therefore, these results should not be construed as an analysis of how economic dependencies are modeled in general, but rather in the case where other dependencies are modeled too.

4.5. Optimization Objectives

The objective function is an essential feature of the maintenance policy optimization. In an overwhelming majority of the cases, the maintenance policies are optimized with respect to the costs ($n = 73$, see Figure 8). The maintenance duration or the downtime constitutes a possible alternative, which is a complement to the system availability. More rare optimization objectives include a client-satisfaction measure, the system reliability over the next mission, the production flow, the production quality and the carbon emission (see the lower graph in Figure 8 for the count of publications matching each optimization objective).

A limited number ($n = 9$) of entries use more than one optimization objective, always combining the costs with other variables such as maintenance duration ($n = 4$).

Similar to the limitations regarding the analysis of economic dependencies, as stated in RQ3, only the papers responding to RQ1 are examined to answer RQ3. Therefore, these results should not be construed as an analysis of the optimization objectives in opportunistic maintenance modeling in general, but rather in the case where dependencies are modeled beyond economic dependencies.

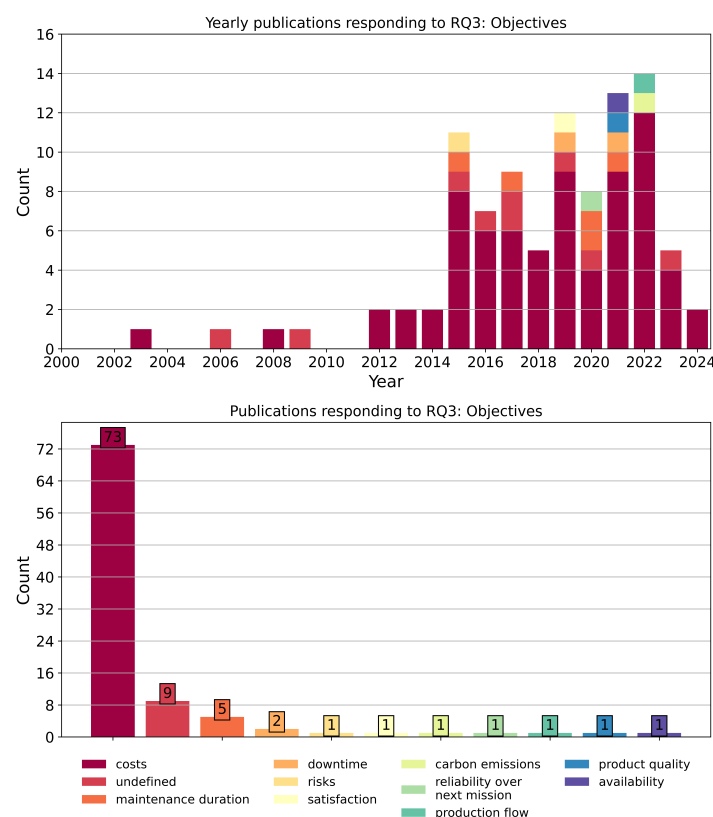


Figure 8. Timeline of publications responding to RQ4 (objective function), by subtypes.

5. Discussion and Future Research Directions

Section 4 shows the complexity of the definitions of dependencies in opportunistic maintenance modeling. In particular, the number of possible combinations of hypotheses makes holistic modeling (i.e., producing models that cover most of the possible dependencies) improbable.

Beyond the combination of dependencies, some specific choices are particularly lacking in the identified literature. Despite industrial progress in using advanced statistical methods for predicting upcoming failures and updating remaining useful life estimates (predictive maintenance), no entry of the present review uses such methods. Likewise, despite the existential need for sustainability inclusion in industrial decisions, the economic cost remains the most used objective function in optimizing maintenance policies among our results (see Section 4.5).

In this section, we mainly discuss the use of predictive analytics in modeling opportunistic maintenance and the inclusion of sustainability in assessing maintenance performance. These two challenging issues are strongly linked with the maintenance revolution faced to technological development (industry 4.0) and societal requirement (sustainable paradigm).

5.1. Human Factors in Opportunistic Maintenance

In general, few literature entries consider human factors in the literature related to dependencies in maintenance among our results (see Section 4.1). Entries that do include human-related considerations are focused on crew constraints [2,13,16].

However, it has long been established that human factors influence the performance of industrial systems, e.g., by considering the training and learning of workers in production [136]. Similar efforts could be pursued toward taking into account the evolution of skill levels of workers, for example, by modeling its influence on maintenance, either in imperfect maintenance models, or by investigating cases where the Mean Time To Repair would be affected by workers' training.

Likewise, human-centered questions can arise in relation to other frameworks. For example, the circular economy framework suggests a triple bottom line including a social component [137]. Evaluations regarding the wellbeing of maintenance workers on opportunistic maintenance jobs could be a future research direction, given the less predictable nature of opportunistic maintenance, and the potential pressure of actions grouping.

Finally, the benefits of newer technologies that belong to the Industry 5.0 framework, either for improving workers' training (e.g., augmented reality, virtual reality, etc.) and recent human-centric additions to the workspace (e.g., natural language interaction with models and documents, including Large Language Models, etc.) could also be studied to better assess their social benefits (among others) to the maintenance activities.

5.2. Predictive Analytics for Opportunistic Maintenance

Predictive analytics (PA) is a branch of advanced analytics that makes predictions about future outcomes using historical data combined with statistical algorithms, data-mining techniques and machine learning [138]. The application of PA in opportunistic maintenance can efficiently enhance failure prediction, optimize resource allocation and improve maintenance decision-making and inventory management. However, there has not yet been a significant adoption of PA for opportunistic maintenance in industrial applications [139].

For instance, Zhang et al. formulated OM for load-sharing multi-component systems as an infinite-horizon Markov Decision Process (MDP), where component hazard rates are influenced by shared loads and imperfect maintenance. They proposed a modified proximal

policy optimization (PPO) approach with parameterized action spaces to address mixed discrete–continuous decisions, demonstrating robust performance on both simulated and real-world systems such as nuclear power plant heaters [140]. Kuhnle et al. investigated OM for a parallel production system, showing that Reinforcement Learning (RL) agents can implicitly learn to anticipate breakdowns and schedule maintenance at moments of minimal opportunity cost, thereby outperforming reactive and time-based strategies [141]. RL-based OM policies have proven effective in balancing reliability with productivity by considering both system degradation and production load. The experimental results confirm that such approaches reduce breakdowns, lower maintenance costs and increase throughput compared to traditional benchmarks, highlighting RL as a promising tool for intelligent, context-aware maintenance optimization. Valet et al. presented a Deep Q-learning approach for opportunistic maintenance in a semiconductor front-end wafer production [142]. To maximize order dispatching and maintenance scheduling while taking maintenance human resources into account, they designed a single decision support system. When the machine is idle, there is no dispatch order, and at least one maintenance worker is available, a window of opportunity opens up. The agent monitors various aspects of the machines, products, buffers and maintenance workers. The maintenance decisions for the agent are dispatch, wait and preventive maintenance. Minimizing machine downtime is the goal. The reward function was created with a set reward: a positive reward for permitted actions and a negative reward for non-permitted actions.

Regardless of the advantages, there are several challenges associated with the application of PA for opportunistic maintenance:

- **Data quality and availability:** PA models often require high-quality, relevant data to make accurate predictions [143]. However, industrial data may be noisy, incomplete or not completely representative of all failure modes, which can limit the effectiveness of PA models [144]. Further, drifts may exist in the industrial data, which requires specific methodologies for adaptation of PA models [145]. Likewise, the sensors themselves evolve, are replaced or their number is increased over time, with the inherent complexity in PA model development [146]. The strong dependence of PA models on data could therefore be seen as creating potential resource constraints on data. In this case, the lack of data, data contamination, unexpected drifts and other phenomena could hinder the accuracy of PA models.
- **Complexity of opportunistic maintenance scheduling:** opportunistic maintenance scheduling is a complex task because it involves balancing multiple factors, such as the cost of downtime, and the availability of maintenance tools, resources and the criticality of different components in industrial systems [5]. Therefore, developing PA models that can handle this complexity requires careful design and significant computational power;
- **Real-time decision making:** In some specific industrial applications, opportunistic maintenance decisions need to be made in real time, especially in dynamic environments like manufacturing or transportation. This requires PA models to be fast and reliable, and to align correctly with existing maintenance-management systems [143]. For example, a major difficulty in this context is the necessary tradeoff between the latency of the prediction, energy consumption and prediction accuracy, leading the recent literature to either oppose or merge the concepts of cloud computing and edge computing in search of balanced performances with respect to these indicators [147].

5.3. Sustainability in Opportunistic Maintenance

The United Nations' Sustainable Development Goals (SDGs) constitute a common landmark for sustainability [148]. Maintenance and the SDGs are a rare association in

the literature ($n = 40$ in 2020 [149]), but the existing literature has been reviewed by Franciosi et al. Specifically in opportunistic maintenance modeling, examples of environmental considerations are extremely rare: in the present review, only one occurrence was found [77]. This specific occurrence offers insight into the influence of maintenance parameters on the total environmental impact of the policy.

Yet, sustainability is linked to the achievement of performance on three dimensions: environmental, economic and social [150]. In this framework, all three aspects are to be evaluated. As the current results show (see Section 4.5), the objective functions of opportunistic maintenance-optimization papers systematically favor economic or operational factors (downtime, quality, reliability). The environmental ($n = 1$) and especially the social impacts ($n = 0$) of the maintenance models are not modeled or discussed despite existing suggestions on research goals to achieve these results [150]. Hands-on evaluation of all three dimensions was already suggested [151], but never applied in opportunistic maintenance modeling to the authors' knowledge, which is a clear limitation of the current literature in opportunistic maintenance modeling.

Some authors have already started taking into account sustainability dimensions in their models, albeit not passing the inclusion criteria of the present review. In particular, Hennequin and Ramirez Restrepo provided a compound objective function, including all three dimensions for optimizing a preventive maintenance policy [152]. Saihi et al. covered in an in-depth review the existing efforts to implement all three dimensions of sustainability in maintenance [153]. A clear perspective in opportunistic maintenance modeling under dependencies should include replicating this type of model under the hypotheses presented in this review.

Further, the depth of the hypotheses used in sustainable maintenance models can also be questioned. As mentioned by Saihi et al., the environmental issues are often limited in their integration to equivalent CO₂ emissions. That assessment would not be explicitly based on Life Cycle Assessments (LCAs), and thus would not necessarily encompass planetary boundaries beyond climate change. Likewise, the social impact assessments are often overlooked or limited, and seldom validated through the use of real data or experiments [153].

The upcoming challenges associated with the inclusion of sustainability dimensions in the objective functions, therefore, include the numerical estimate and validation of the social impact of maintenance policies, as well as accurate and usable environmental impact-assessment policies.

6. Conclusions

This article presents a bibliographic review on dependence hypotheses in opportunistic maintenance modeling. To achieve this, a conceptual background was first presented (Section 2) that provided an overview about opportunistic maintenance and various dependencies that may have significant impacts in opportunistic maintenance. A methodology was then developed that guided the steps to be executed. A bibliometric analysis was carried out using the keywords from the articles, the year of publication and the most cited articles and journals. An in-depth analysis was conducted to address several key research questions related to the consideration of various dependencies between components and the optimization objectives in opportunistic maintenance.

Overall, the research questions are answered as follows:

- The current hypotheses regarding workers' skills, dependencies and resource constraints have been identified:

- Human factors are seldom represented in the identified literature, and mainly by dividing the workforce by skill types. Human errors and the separation of skill levels are also mentioned.
- Dependencies (other than economic) to be split into three large families—stochastic, structural and geographic—each of them being categorized into subtypes, all in relation to real effects.
- Resource constraints to be mainly concerned with spare parts, but also to cover multiple other hypotheses more sporadically invoked in the literature.
- In papers modeling other dependencies, the economic dependency is mostly represented as a sharing of set-up costs or downtime costs between maintenance operations. Other marginal models have been identified.
- In papers modeling dependencies that are not limited to the economic, the optimization objectives are almost exclusively costs and marginally maintenance duration. Other objectives are anecdotal, including the environmental impact of maintenance.

However, limitations influence the results of this review: the choice of databases (Google Scholar, Scopus, Web of Science), the inclusion criteria regarding the paper language and overall the variations in the modeling hypotheses from one paper to another that never allow direct comparison of results.

The discussion brings to light the opportunities for using predictive analytics in opportunistic maintenance-optimization methods. This sheds light on a clear perspective: the development of such methods, which would require the availability of quality data and the development of adequate predictive analytic models.

Furthermore, the discussion also highlights the alarming lack of sustainable indicators ($n = 1$) as objective functions in the opportunistic maintenance literature, as well as the complexity of identifying such indicators that can encompass all three dimensions of sustainability.

Future research could focus on utilizing predictive analytics in opportunistic maintenance modeling. It could also incorporate sustainability indicators (particularly environmental and social), e.g., through the use of compound objective functions. This would also influence the modeling and dependency choices, potentially leading to deeper exploration of currently overlooked dependencies, such as human factors. The inclusion of scarce or contaminated data as a resource constraint could also prepare the widespread adoption of PA models in industrial practice.

Author Contributions: Conceptualization, L.E. and P.D. (Phuc Do); Methodology, L.E., P.D. (Phuc Do) and L.A.T.; Software, L.E.; Validation, L.E., P.D. (Phuc Do) and L.A.T.; Formal analysis, L.E., L.C. and L.A.T.; Investigation, L.E. and P.D. (Phuc Do); Data curation, L.E., P.D. (Phuc Do) and L.C.; Writing—original draft, L.E. and P.D. (Phuc Do); Writing—review & editing, L.E., P.D. (Phuc Do), L.C., L.A.T., P.D. (Pierre Dehombreux) and B.I.; Visualization, L.C.; Supervision, P.D. (Pierre Dehombreux) and B.I.; Project administration, P.D. (Pierre Dehombreux) and B.I.; Funding acquisition, L.E. All authors have read and agreed to the published version of the manuscript.

Funding: This research was partially funded by the Belgian Fund for Scientific Research (FRS-FNRS) through mobility grant #40015776.

Data Availability Statement: The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest: The authors declare no conflicts of interest

References

1. Olde Keizer, M.C.; Flapper, S.D.P.; Teunter, R.H. Condition-Based Maintenance Policies for Systems with Multiple Dependent Components: A Review. *Eur. J. Oper. Res.* **2017**, *261*, 405–420. [\[CrossRef\]](#)
2. de Jonge, B.; Scarf, P. A Review on Maintenance Optimization. *Eur. J. Oper. Res.* **2020**, *285*, 805–824. [\[CrossRef\]](#)
3. Vu, H.C.; Do, P.; Fouladirad, M.; Grall, A. Dynamic Opportunistic Maintenance Planning for Multi-Component Redundant Systems with Various Types of Opportunities. *Reliab. Eng. Syst. Saf.* **2020**, *198*, 106854. [\[CrossRef\]](#)
4. EN 13306:2017; Maintenance—Maintenance Terminology. CEN: Bruxelles, Belgium, 2017.
5. Ab-Samat, H.; Kamaruddin, S. Opportunistic Maintenance (OM) as a New Advancement in Maintenance Approaches: A Review. *J. Qual. Maint. Eng.* **2014**, *20*, 98–121. [\[CrossRef\]](#)
6. Van Horenbeek, A.; Pintelon, L.; Muchiri, P. Maintenance Optimization Models and Criteria. *Int. J. Syst. Assur. Eng. Manag.* **2010**, *1*, 189–200. [\[CrossRef\]](#)
7. Iung, B.; Do, P.; Levrat, E.; Voisin, A. Opportunistic Maintenance Based on Multi-Dependent Components of Manufacturing System. *CIRP Ann.* **2016**, *65*, 401–404. [\[CrossRef\]](#)
8. Dekker, R. Applications of Maintenance Optimization Models: A Review and Analysis. *Reliab. Eng. Syst. Saf.* **1996**, *51*, 229–240. [\[CrossRef\]](#)
9. Van Horenbeek, A.; Buré, J.; Cattrysse, D.; Pintelon, L.; Vansteenwegen, P. Joint Maintenance and Inventory Optimization Systems: A Review. *Int. J. Prod. Econ.* **2013**, *143*, 499–508. [\[CrossRef\]](#)
10. Zeng, Z.; Barros, A.; Coit, D. Dependent Failure Behavior Modeling for Risk and Reliability: A Systematic and Critical Literature Review. *Reliab. Eng. Syst. Saf.* **2023**, *239*, 109515. [\[CrossRef\]](#)
11. Nicolai, R.P.; Dekker, R. Optimal Maintenance of Multi-component Systems: A Review. In *Complex System Maintenance Handbook*; Springer: London, UK, 2008; pp. 263–286. [\[CrossRef\]](#)
12. Nowakowski, T.; Werbińska-Wojciechowska, S. On Problems of Multicomponent System Maintenance Modeling. *Int. J. Autom. Comput.* **2009**, *6*, 364–378. [\[CrossRef\]](#)
13. Shafiee, M. Maintenance Logistics Organization for Offshore Wind Energy: Current Progress and Future Perspectives. *Renew. Energy* **2015**, *77*, 182–193. [\[CrossRef\]](#)
14. Wang, R.; Chen, N. A Survey of Condition-Based Maintenance Modeling of Multi-Component Systems. In Proceedings of the 2016 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Bali, Indonesia, 4–7 December 2016; pp. 1664–1668. [\[CrossRef\]](#)
15. Alaswad, S.; Xiang, Y. A Review on Condition-Based Maintenance Optimization Models for Stochastically Deteriorating System. *Reliab. Eng. Syst. Saf.* **2017**, *157*, 54–63. [\[CrossRef\]](#)
16. Chin, H.H.; Varbanov, P.S.; Klemesš, J.J.; Benjamin, M.F.D.; Tan, R.R. Asset Maintenance Optimisation Approaches in the Chemical and Process Industries—A Review. *Chem. Eng. Res. Des.* **2020**, *164*, 162–194. [\[CrossRef\]](#)
17. Sedghi, M.; Kauppila, O.; Bergquist, B.; Vanhatalo, E.; Kulahci, M. A Taxonomy of Railway Track Maintenance Planning and Scheduling: A Review and Research Trends. *Reliab. Eng. Syst. Saf.* **2021**, *215*, 107827. [\[CrossRef\]](#)
18. Tusar, M.I.H.; Sarker, B.R. Spare Parts Control Strategies for Offshore Wind Farms: A Critical Review and Comparative Study. *Wind Eng.* **2022**, *46*, 1629–1656. [\[CrossRef\]](#)
19. Zhao, J.; Gao, C.; Tang, T. A Review of Sustainable Maintenance Strategies for Single Component and Multicomponent Equipment. *Sustainability* **2022**, *14*, 2992. [\[CrossRef\]](#)
20. Scarf, P.; Syntetos, A.; Teunter, R. Joint Maintenance and Spare-Parts Inventory Models: A Review and Discussion of Practical Stock-Keeping Rules. *IMA J. Manag. Math.* **2023**, *35*, 83–109. [\[CrossRef\]](#)
21. Shadi, M.R.; Mirshekali, H.; Shaker, H.R. Explainable Artificial Intelligence for Energy Systems Maintenance: A Review on Concepts, Current Techniques, Challenges, and Prospects. *Renew. Sustain. Energy Rev.* **2025**, *216*, 115668. [\[CrossRef\]](#)
22. Abbas, Y.; Martinetti, A. Design for an Integrated Knowledge Management Policy for Railway Maintenance: An Industrial Synopsis. *Procedia CIRP* **2023**, *119*, 521–526. [\[CrossRef\]](#)
23. Cárcel-Carrasco, J.; Gómez-Gómez, C. Qualitative Analysis of the Perception of Company Managers in Knowledge Management in the Maintenance Activity in the Era of Industry 4.0. *Processes* **2021**, *9*, 121. [\[CrossRef\]](#)
24. Wang, H. A Survey of Maintenance Policies of Deteriorating Systems. *Eur. J. Oper. Res.* **2002**, *139*, 469–489. [\[CrossRef\]](#)
25. Kitchenham, B. *Procedures for Performing a Systematic Reviews*; Technical Report; Keele University: Keele, Staffs, UK, 2004.
26. Kitchenham, B.; Pearl Brereton, O.; Budgen, D.; Turner, M.; Bailey, J.; Linkman, S. Systematic Literature Reviews in Software Engineering—A Systematic Literature Review. *Inf. Softw. Technol.* **2009**, *51*, 7–15. [\[CrossRef\]](#)
27. Page, M.J.; McKenzie, J.E.; Bossuyt, P.M.; Boutron, I.; Hoffmann, T.C.; Mulrow, C.D.; Shamseer, L.; Tetzlaff, J.M.; Akl, E.A.; Brennan, S.E.; et al. The PRISMA 2020 Statement: An Updated Guideline for Reporting Systematic Reviews. *BMJ* **2021**, *372*, n71. [\[CrossRef\]](#) [\[PubMed\]](#)
28. Ahmad, R.; Kamaruddin, S. An Overview of Time-Based and Condition-Based Maintenance in Industrial Application. *Comput. Ind. Eng.* **2012**, *63*, 135–149. [\[CrossRef\]](#)

29. Do, P. *Contribution au Développement de Modèles d'aide à La Décision en Maintenance Pour des Systèmes à Dépendances Multiples: Vers une Maintenance Prescriptive*; Habilitation to Supervise Research; Université de Lorraine: Nancy, France, 2019.
30. Friederich, J.; Lazarova-Molnar, S. Reliability Assessment of Manufacturing Systems: A Comprehensive Overview, Challenges and Opportunities. *J. Manuf. Syst.* **2024**, *72*, 38–58. [\[CrossRef\]](#)
31. Mo, R.; Zhou, H.; Yin, H.; Si, X. A Survey on Few-Shot Learning for Remaining Useful Life Prediction. *Reliab. Eng. Syst. Saf.* **2025**, *257*, 110850. [\[CrossRef\]](#)
32. Dekker, R.; Wildeman, R.E.; Van Der Duyn Schouten, F.A. A Review of Multi-Component Maintenance Models with Economic Dependence. *Math. Methods Oper. Res.* **1997**, *45*, 411–435. [\[CrossRef\]](#)
33. Do, P.; Barros, A.; Berenguer, C.; Bouvard, K.; Brissaud, F. Dynamic Grouping Maintenance with Time Limited Opportunities. *Reliab. Eng. Syst. Saf.* **2013**, *120*, 51–59. [\[CrossRef\]](#)
34. Hong, H.; Zhou, W.; Zhang, S.; Ye, W. Optimal Condition-Based Maintenance Decisions for Systems with Dependent Stochastic Degradation of Components. *Reliab. Eng. Syst. Saf.* **2014**, *121*, 276–288. [\[CrossRef\]](#)
35. Scarf, P.; Dears, M. Block Replacement Policies for a Two-Component System with Failure Dependence. *Nav. Res. Logist.* **2003**, *50*, 70–87. [\[CrossRef\]](#)
36. Golmakani, H.R.; Moakedi, H. Periodic Inspection Optimization Model for a Two-Component Repairable System with Failure Interaction. *Comput. Ind. Eng.* **2012**, *63*, 540–545. [\[CrossRef\]](#)
37. Zhang, N.; Fouladirad, M.; Barros, A. Warranty Analysis of a Two-Component System with Type I Stochastic Dependence. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.* **2018**, *232*, 274–283. [\[CrossRef\]](#)
38. Marseguerra, M.; Zio, E.; Podofillini, L. Condition-Based Maintenance Optimization by Means of Genetic Algorithms and Monte Carlo Simulation. *Reliab. Eng. Syst. Saf.* **2002**, *77*, 151–165. [\[CrossRef\]](#)
39. Mercier, S.; Pham, H.H. A Random Shock Model with Mixed Effect, Including Competing Soft and Sudden Failures, and Dependence. *Methodol. Comput. Appl. Probab.* **2016**, *18*, 377–400. [\[CrossRef\]](#)
40. Assaf, R.; Do, P.; Nefti-Meziani, S.; Scarf, P. Wear Rate–State Interactions within a Multi-Component System: A Study of a Gearbox-Accelerated Life Testing Platform. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.* **2018**, *232*, 425–434. [\[CrossRef\]](#)
41. Bian, L.; Gebraeel, N. Stochastic Framework for Partially Degradation Systems with Continuous Component Degradation-rate-interactions. *Nav. Res. Logist. (NRL)* **2014**, *61*, 286–303. [\[CrossRef\]](#)
42. Bian, L.; Gebraeel, N. Stochastic Modeling and Real-Time Prognostics for Multi-Component Systems with Degradation Rate Interactions. *IIE Trans.* **2014**, *46*, 470–482. [\[CrossRef\]](#)
43. Rasmekomen, N.; Parlikad, A.K. Condition-Based Maintenance of Multi-Component Systems with Degradation State-Rate Interactions. *Reliab. Eng. Syst. Saf.* **2016**, *148*, 1–10. [\[CrossRef\]](#)
44. Zhang, N.; Fouladirad, M.; Barros, A.; Zhang, J. Condition-Based Maintenance for a K-out-of-N Deteriorating System under Periodic Inspection with Failure Dependence. *Eur. J. Oper. Res.* **2020**, *287*, 159–167. [\[CrossRef\]](#)
45. Thomas, L. A Survey of Maintenance and Replacement Models for Maintainability and Reliability of Multi-Item Systems. *Reliab. Eng.* **1986**, *16*, 297–309. [\[CrossRef\]](#)
46. Do, P.; Barros, A.; Berenguer, C. Importance Measure on Finite Time Horizon and Application to Markovian Multistate Production Systems. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.* **2008**, *222*, 449–461. [\[CrossRef\]](#)
47. Nguyen, K.A.; Do, P.; Grall, A. Multi-Level Predictive Maintenance for Multi-Component Systems. *Reliab. Eng. Syst. Saf.* **2015**, *144*, 83–94. [\[CrossRef\]](#)
48. Camci, F. System Maintenance Scheduling with Prognostics Information Using Genetic Algorithm. *IEEE Trans. Reliab.* **2009**, *58*, 539–552. [\[CrossRef\]](#)
49. Vu, H.C.; Do, P.; Barros, A.; Berenguer, C. Maintenance Planning and Dynamic Grouping for Multi-Component Systems with Positive and Negative Economic Dependencies. *IMA J. Manag. Math.* **2015**, *26*, 145–170. [\[CrossRef\]](#)
50. Yang, L.; Zhao, Y.; Peng, R.; Ma, X. Opportunistic Maintenance of Production Systems Subject to Random Wait Time and Multiple Control Limits. *J. Manuf. Syst.* **2018**, *47*, 12–34. [\[CrossRef\]](#)
51. Cavalcante, C.; Lopes, R.; Scarf, P. A General Inspection and Opportunistic Replacement Policy for One-Component Systems of Variable Quality. *Eur. J. Oper. Res.* **2018**, *266*, 911–919. [\[CrossRef\]](#)
52. Yang, L.; Zhao, Y.; Peng, R.; Ma, X. Hybrid Preventive Maintenance of Competing Failures under Random Environment. *Reliab. Eng. Syst. Saf.* **2018**, *174*, 130–140. [\[CrossRef\]](#)
53. Truong Ba, H.; Cholette, M.; Borghesani, P.; Zhou, Y.; Ma, L. Opportunistic Maintenance Considering Non-Homogenous Opportunity Arrivals and Stochastic Opportunity Durations. *Reliab. Eng. Syst. Saf.* **2017**, *160*, 151–161. [\[CrossRef\]](#)
54. Li, H.; Deloux, E.; Dieulle, L. A Condition-Based Maintenance Policy for Multi-Component Systems with Lévy Copulas Dependence. *Reliab. Eng. Syst. Saf.* **2016**, *149*, 44–55. [\[CrossRef\]](#)
55. Ait Mokhtar, E.H.; Chateauneuf, A.; Laggoune, R. Condition Based Opportunistic Preventive Maintenance Policy for Utility Systems with Both Economic and Structural Dependencies—Application to a Gas Supply Network. *Int. J. Press. Vessel. Pip.* **2018**, *165*, 214–223. [\[CrossRef\]](#)

56. Lu, B.; Zhou, X. Opportunistic Preventive Maintenance Scheduling for Serial-Parallel Multistage Manufacturing Systems with Multiple Streams of Deterioration. *Reliab. Eng. Syst. Saf.* **2017**, *168*, 116–127. [\[CrossRef\]](#)
57. Zhou, X.; Shi, K. Capacity Failure Rate Based Opportunistic Maintenance Modeling for Series-Parallel Multi-Station Manufacturing Systems. *Reliab. Eng. Syst. Saf.* **2019**, *181*, 46–53. [\[CrossRef\]](#)
58. Huynh, K.T.; Barros, A.; Christophe Berenguer. A Reliability-Based Opportunistic Predictive Maintenance Model for k-out-of-n Deteriorating Systems. *Chem. Eng. Trans.* **2013**, *33*, 493–498. [\[CrossRef\]](#)
59. Radner, R.; Jorgenson, D.W. Opportunistic Replacement of a Single Part in the Presence of Several Monitored Parts. *Manag. Sci.* **1963**, *10*, 70–84. [\[CrossRef\]](#)
60. Sarker, B.R.; Faiz, T.I. Minimizing Maintenance Cost for Offshore Wind Turbines Following Multi-Level Opportunistic Preventive Strategy. *Renew. Energy* **2016**, *85*, 104–113. [\[CrossRef\]](#)
61. Wildeman, R.E.; Dekker, R. Dynamic Influences in Multi-Component Maintenance. *Qual. Reliab. Eng. Int.* **1997**, *13*, 199–207. [\[CrossRef\]](#)
62. Agergaard, J.K.; Sigsgaard, K.V.; Mortensen, N.H.; Ge, J.; Hansen, K.B.; Khalid, W. Standardising Maintenance Jobs to Improve Grouping Decision Making. In Proceedings of the Design Society, Gothenburg, Sweden, 16–20 August 2021; Volume 1, pp. 2701–2710. [\[CrossRef\]](#)
63. Harzing, A.W. Publish or Perish. 2007. Available online: <https://harzing.com/resources/publish-or-perish> (accessed on 8 August 2025).
64. Dinh, D.H.; Do, P.; Iung, B. Degradation Modeling and Reliability Assessment for a Multi-Component System with Structural Dependence. *Comput. Ind. Eng.* **2020**, *144*, 106443. [\[CrossRef\]](#)
65. Oakley, J.L.; Wilson, K.J.; Philipson, P. A Condition-Based Maintenance Policy for Continuously Monitored Multi-Component Systems with Economic and Stochastic Dependence. *Reliab. Eng. Syst. Saf.* **2022**, *222*, 108321. [\[CrossRef\]](#)
66. Okoh, P. Maintenance Grouping Optimization for the Management of Risk in Offshore Riser System. *Process Saf. Environ. Prot.* **2015**, *98*, 33–39. [\[CrossRef\]](#)
67. Chang, F.; Zhou, G.; Cheng, W.; Zhang, C.; Tian, C. A Service-Oriented Multi-Player Maintenance Grouping Strategy for Complex Multi-Component System Based on Game Theory. *Adv. Eng. Inform.* **2019**, *42*, 100970. [\[CrossRef\]](#)
68. Aizpurua, J.; Catterson, V.; Papadopoulos, Y.; Chiacchio, F.; D'Urso, D. Supporting Group Maintenance through Prognostics-Enhanced Dynamic Dependability Prediction. *Reliab. Eng. Syst. Saf.* **2017**, *168*, 171–188. [\[CrossRef\]](#)
69. Viveros, P.; Mena, R.; Zio, E.; Miqueles, L.; Kristjanpoller, F. Integrated Planning Framework for Preventive Maintenance Grouping: A Case Study for a Conveyor System in the Chilean Mining Industry. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.* **2021**, *237*, 1011–1028. [\[CrossRef\]](#)
70. Si, G.; Xia, T.; Zhu, Y.; Du, S.; Xi, L. Triple-Level Opportunistic Maintenance Policy for Leasehold Service Network of Multi-Location Production Lines. *Reliab. Eng. Syst. Saf.* **2019**, *190*, 106519. [\[CrossRef\]](#)
71. Liu, G.; Chen, S.; Ho, T.; Ran, X.; Mao, B.; Lan, Z. Optimum Opportunistic Maintenance Schedule over Variable Horizons Considering Multi-Stage Degradation and Dynamic Strategy. *Reliab. Eng. Syst. Saf.* **2022**, *225*, 108572. [\[CrossRef\]](#)
72. Shen, J.; Zhang, Y.; Ma, Y.; Lin, C. A Novel Opportunistic Maintenance Strategy for Systems with Dependent Main and Auxiliary Components. *IMA J. Manag. Math.* **2021**, *32*, 69–90. [\[CrossRef\]](#)
73. Sheikhalishahi, M.; Azadeh, A.; Pintelon, L. Dynamic Maintenance Planning Approach by Considering Grouping Strategy and Human Factors. *Process Saf. Environ. Prot.* **2017**, *107*, 289–298. [\[CrossRef\]](#)
74. Vijayan, V.; Chaturvedi, S.K. Multi-Component Maintenance Grouping Optimization Based on Stochastic Dependency. *Proc. Inst. Mech. Eng. Part O J. Risk Reliab.* **2021**, *235*, 293–305. [\[CrossRef\]](#)
75. Geng, J.; Azarian, M.; Pecht, M. Opportunistic Maintenance for Multi-Component Systems Considering Structural Dependence and Economic Dependence. *J. Syst. Eng. Electron.* **2015**, *26*, 493–501. [\[CrossRef\]](#)
76. Dinh, D.H.; Do, P.; Iung, B. Multi-Level Opportunistic Predictive Maintenance for Multi-Component Systems with Economic Dependence and Assembly/Disassembly Impacts. *Reliab. Eng. Syst. Saf.* **2022**, *217*, 108055. [\[CrossRef\]](#)
77. Liu, Q.; Li, Z.; Xia, T.; Hsieh, M.; Li, J. Integrated Structural Dependence and Stochastic Dependence for Opportunistic Maintenance of Wind Turbines by Considering Carbon Emissions. *Energies* **2022**, *15*, 625. [\[CrossRef\]](#)
78. Shi, H.; Zeng, J.C. Real-Time Prediction of Remaining Useful Life and Preventive Opportunistic Maintenance Strategy for Multi-Component Systems Considering Stochastic Dependence. *Comput. Ind. Eng.* **2016**, *93*, 192–204. [\[CrossRef\]](#)
79. Wang, Y.; Li, X.; Chen, J.; Liu, Y. A Condition-Based Maintenance Policy for Multi-Component Systems Subject to Stochastic and Economic Dependencies. *Reliab. Eng. Syst. Saf.* **2022**, *219*, 108174. [\[CrossRef\]](#)
80. Do, P.; Assaf, R.; Scarf, P.; Iung, B. Modeling and Application of Condition-Based Maintenance for a Two-Component System with Stochastic and Economic Dependencies. *Reliab. Eng. Syst. Saf.* **2019**, *182*, 86–97. [\[CrossRef\]](#)
81. Dao, C.D.; Zuo, M.J. Selective Maintenance of Multi-State Systems with Structural Dependence. *Reliab. Eng. Syst. Saf.* **2017**, *159*, 184–195. [\[CrossRef\]](#)

82. Zhu, M.; Zhou, X. Hypergraph-Based Joint Optimization of Spare Part Provision and Maintenance Scheduling for Serial-Parallel Multi-Station Manufacturing Systems. *Reliab. Eng. Syst. Saf.* **2022**, *225*, 108619. [\[CrossRef\]](#)
83. Zhang, X.H.; Zeng, J.C. Joint Optimization of Condition-Based Opportunistic Maintenance and Spare Parts Provisioning Policy in Multiunit Systems. *Eur. J. Oper. Res.* **2017**, *262*, 479–498. [\[CrossRef\]](#)
84. Zhang, X.H.; Zeng, J.C.; Gan, J. Joint Optimization of Condition-Based Maintenance and Spare Part Inventory for Two-Component System. *J. Ind. Prod. Eng.* **2018**, *35*, 394–420. [\[CrossRef\]](#)
85. Zhang, X.H.; Liao, H.; Zeng, J.C.; Shi, G.; Zhao, B. Optimal Condition-based Opportunistic Maintenance and Spare Parts Provisioning for a Two-unit System Using a State Space Partitioning Approach. *Reliab. Eng. Syst. Saf.* **2021**, *209*, 107451. [\[CrossRef\]](#)
86. Zhang, C.; Gao, W.; Yang, T.; Guo, S. Opportunistic Maintenance Strategy for Wind Turbines Considering Weather Conditions and Spare Parts Inventory Management. *Renew. Energy* **2019**, *133*, 703–711. [\[CrossRef\]](#)
87. Koochaki, J.; Bokhorst, J.A.; Wortmann, H.; Klingenberg, W. The Influence of Condition-Based Maintenance on Workforce Planning and Maintenance Scheduling. *Int. J. Prod. Res.* **2013**, *51*, 2339–2351. [\[CrossRef\]](#)
88. Xu, J.; Liang, Z.; Li, Y.F.; Wang, K. Generalized Condition-Based Maintenance Optimization for Multi-Component Systems Considering Stochastic Dependency and Imperfect Maintenance. *Reliab. Eng. Syst. Saf.* **2021**, *211*, 107592. [\[CrossRef\]](#)
89. Li, H.; Zhu, W.; Dieulle, L.; Deloux, E. Condition-Based Maintenance Strategies for Stochastically Dependent Systems Using Nested Lévy Copulas. *Reliab. Eng. Syst. Saf.* **2022**, *217*, 108038. [\[CrossRef\]](#)
90. Do, P.; Vu, H.C.; Barros, A.; Berenguer, C. Maintenance Grouping for Multi-Component Systems with Availability Constraints and Limited Maintenance Teams. *Reliab. Eng. Syst. Saf.* **2015**, *142*, 56–67. [\[CrossRef\]](#)
91. Sheikhalishahi, M.; Pintelon, L.; Azadeh, A. An Integrated Approach for Maintenance Planning by Considering Human Factors: Application to a Petrochemical Plant. *Process Saf. Environ. Prot.* **2017**, *109*, 400–409. [\[CrossRef\]](#)
92. Liu, B.; Pandey, M.D.; Wang, X.; Zhao, X. A Finite-Horizon Condition-Based Maintenance Policy for a Two-Unit System with Dependent Degradation Processes. *Eur. J. Oper. Res.* **2021**, *295*, 705–717. [\[CrossRef\]](#)
93. Urbani, M.; Brunelli, M.; Punkka, A. An Approach for Bi-Objective Maintenance Scheduling on a Networked System with Limited Resources. *Eur. J. Oper. Res.* **2023**, *305*, 101–113. [\[CrossRef\]](#)
94. Zhu, W.; Castanier, B.; Bettayeb, B. A Dynamic Programming-Based Maintenance Model of Offshore Wind Turbine Considering Logistic Delay and Weather Condition. *Reliab. Eng. Syst. Saf.* **2019**, *190*, 106512. [\[CrossRef\]](#)
95. Si, G.; Xia, T.; Pan, E.; Xi, L. Service-Oriented Global Optimization Integrating Maintenance Grouping and Technician Routing for Multi-Location Multi-Unit Production Systems. *IIE Trans.* **2022**, *54*, 894–907. [\[CrossRef\]](#)
96. Yang, L.; Zhao, Y.; Ma, X. Group Maintenance Scheduling for Two-Component Systems with Failure Interaction. *Appl. Math. Model.* **2019**, *71*, 118–137. [\[CrossRef\]](#)
97. Zhang, J.; Zhao, X.; Song, Y.; Qiu, Q. Joint Optimization of Condition-Based Maintenance and Spares Inventory for a Series-Parallel System with Two Failure Modes. *Comput. Ind. Eng.* **2022**, *168*, 108094. [\[CrossRef\]](#)
98. Yang, L.; Peng, R.; Li, G.; Lee, C.G. Operations Management of Wind Farms Integrating Multiple Impacts of Wind Conditions and Resource Constraints. *Energy Convers. Manag.* **2020**, *205*, 112162. [\[CrossRef\]](#)
99. Zequeira, R.I.; Valdes, J.E.; Berenguer, C. Optimal Buffer Inventory and Opportunistic Preventive Maintenance under Random Production Capacity Availability. *Int. J. Prod. Econ.* **2008**, *111*, 686–696. [\[CrossRef\]](#)
100. Nguyen, K.A.; Do, P.; Grall, A. Joint Predictive Maintenance and Inventory Strategy for Multi-Component Systems Using Birnbaum's Structural Importance. *Reliab. Eng. Syst. Saf.* **2017**, *168*, 249–261. [\[CrossRef\]](#)
101. Vu, H.C.; Do, P.; Barros, A.; Berenguer, C. Maintenance Grouping Strategy for Multi-Component Systems with Dynamic Contexts. *Reliab. Eng. Syst. Saf.* **2014**, *132*, 233–249. [\[CrossRef\]](#)
102. Dinh, D.H.; Do, P.; Iung, B. Maintenance Optimisation for Multi-Component System with Structural Dependence: Application to Machine Tool Sub-System. *CIRP Ann.* **2020**, *69*, 417–420. [\[CrossRef\]](#)
103. Chang, F.; Zhou, G.; Zhang, C.; Xiao, Z.; Wang, C. A Service-Oriented Dynamic Multi-Level Maintenance Grouping Strategy Based on Prediction Information of Multi-Component Systems. *J. Manuf. Syst.* **2019**, *53*, 49–61. [\[CrossRef\]](#)
104. Van Horenbeek, A.; Pintelon, L. A Dynamic Predictive Maintenance Policy for Complex Multi-Component Systems. *Reliab. Eng. Syst. Saf.* **2013**, *120*, 39–50. [\[CrossRef\]](#)
105. Cui, L.; Li, H. Opportunistic Maintenance for Multi-component Shock Models. *Math. Methods Oper. Res.* **2006**, *63*, 493–511. [\[CrossRef\]](#)
106. Hu, J.; Zhang, L.; Liang, W. Opportunistic Predictive Maintenance for Complex Multi-Component Systems Based on DBN-HAZOP Model. *Process Saf. Environ. Prot.* **2012**, *90*, 376–388. [\[CrossRef\]](#)
107. Zhou, X.; Huang, K.; Xi, L.; Lee, J. Preventive Maintenance Modeling for Multi-Component Systems with Considering Stochastic Failures and Disassembly Sequence. *Reliab. Eng. Syst. Saf.* **2015**, *142*, 231–237. [\[CrossRef\]](#)
108. Camci, F. Maintenance Scheduling of Geographically Distributed Assets with Prognostics Information. *Eur. J. Oper. Res.* **2015**, *245*, 506–516. [\[CrossRef\]](#)

109. Jafari, L.; Makis, V. Joint Optimization of Lot-Sizing and Maintenance Policy for a Partially Observable Two-Unit System. *Int. J. Adv. Manuf. Technol.* **2016**, *87*, 1621–1639. [\[CrossRef\]](#)
110. Nguyen, H.S.H.; Do, P.; Vu, H.C.; Iung, B. Dynamic Maintenance Grouping and Routing for Geographically Dispersed Production Systems. *Reliab. Eng. Syst. Saf.* **2019**, *185*, 392–404. [\[CrossRef\]](#)
111. Wakiru, J.M.; Pintelon, L.; Muchiri, P.; Chemweno, P. Integrated Maintenance Policies for Performance Improvement of a Multi-Unit Repairable, One Product Manufacturing System. *Prod. Plan. Control* **2021**, *32*, 347–367. [\[CrossRef\]](#)
112. Qiu, S.; Ming, X.; Sallak, M.; Lu, J. Joint Optimization of Production and Condition-Based Maintenance Scheduling for Make-to-Order Manufacturing Systems. *Comput. Ind. Eng.* **2021**, *162*, 107753. [\[CrossRef\]](#)
113. Manco, P.; Rinaldi, M.; Caterino, M.; Fera, M.; Macchiaroli, R. Maintenance Management for Geographically Distributed Assets: A Criticality-Based Approach. *Reliab. Eng. Syst. Saf.* **2022**, *218*, 108148. [\[CrossRef\]](#)
114. Dinh, D.H.; Do, P.; Iung, B.; Nguyen, P.T.N. Reliability Modeling and Opportunistic Maintenance Optimization for a Multicomponent System with Structural Dependence. *Reliab. Eng. Syst. Saf.* **2024**, *241*, 109708. [\[CrossRef\]](#)
115. Zhu, M.; Zhou, X. Hybrid Opportunistic Maintenance Policy for Serial-Parallel Multi-Station Manufacturing Systems with Spare Part Overlap. *Reliab. Eng. Syst. Saf.* **2023**, *236*, 109304. [\[CrossRef\]](#)
116. Zhu, M.; Zhou, X. Hierarchical-Clustering-Based Joint Optimization of Spare Part Provision and Maintenance Scheduling for Serial-Parallel Multi-Station Manufacturing Systems. *Int. J. Prod. Econ.* **2023**, *264*, 108971. [\[CrossRef\]](#)
117. Einabadi, B.; Mahmoodjanloo, M.; Baboli, A.; Rother, E. Dynamic Predictive and Preventive Maintenance Planning with Failure Risk and Opportunistic Grouping Considerations: A Case Study in the Automotive Industry. *J. Manuf. Syst.* **2023**, *69*, 292–310. [\[CrossRef\]](#)
118. Boujarif, A.; Coit, D.; Jouini, O.; Zeng, Z.; Heidsieck, R. Opportunistic Maintenance of Multi-Component Systems Under Structure and Economic Dependencies: A Healthcare System Case Study. In Proceedings of the 12th International Conference on Operations Research and Enterprise Systems, Lisbon, Portugal, 19–21 February 2023; pp. 158–166. [\[CrossRef\]](#)
119. Ma, W.N.; Li, H.; Yang, Z.Y.; Hu, Q.W. Maintenance Optimization for Two-Component Series Systems with Degradation Dependence. *IEEE Access* **2021**, *9*, 48174–48184. [\[CrossRef\]](#)
120. Zhou, X.; Mao, W. Maintenance Modeling for Hot Rolling Production Lines with Constraint of Auxiliary Resources. *Comput. Ind. Eng.* **2024**, *188*, 109938. [\[CrossRef\]](#)
121. Ghamlouch, H.; Grall, A. Opportunistic Maintenance Strategy for a Train Fleet under Safety Constraints and Inter-System Dependencies. In Proceedings of the Safety and Reliability—Safe Societies in a Changing World, Trondheim, Norway, 17–21 June 2018; pp. 579–586. [\[CrossRef\]](#)
122. Li, Z.; Chen, X.; Li, J.; Huang, X. Opportunistic Group Maintenance Optimization of Multi-unit System Considering Dependency. In Proceedings of the 2020 6th International Conference on Control, Automation and Robotics (ICCAR), Singapore, 20–23 April 2020; pp. 33–38. [\[CrossRef\]](#)
123. Do, P.; Scarf, P.; Iung, B. Condition-Based Maintenance for a Two-Component System with Dependencies. *IFAC-PapersOnLine* **2015**, *48*, 946–951. [\[CrossRef\]](#)
124. Nguyen, K.A.; Do, P.; Grall, A. A Joint Predictive Maintenance and Spare Parts Provisioning Policy for Multi-component Systems Using RUL Prediction and Importance Measure. In Proceedings of the European Conference of the Prognostics and Health Management Society 2014, Nantes, France, 8–10 July 2014; p. 12.
125. Si, G.; Xia, T.; Zhang, K.; Wang, D.; Pan, E.; Xi, L. Technician Collaboration and Routing Optimization in Global Maintenance Scheduling for Multi-Center Service Networks. *IEEE Trans. Autom. Sci. Eng.* **2022**, *19*, 1542–1554. [\[CrossRef\]](#)
126. Do, P.; Vu, H.C.; Barros, A.; Berenguer, C. Grouping Maintenance Strategy with Availability Constraint under Limited Repairmen. In Proceedings of the SAFEPROCESS 2012—8th IFAC Symposium on Fault Detection, Supervision and Safety for Technical Processes, Mexico City, Mexico, 16–18 April 2012; Volume 45, pp. 486–491. [\[CrossRef\]](#)
127. Wu, Q.; Lv, C.; Zhou, D.; Wang, Y.; Yu, D. Study on Multi-Event Opportunistic Maintenance Decision-Making Model Based on Condition. In Proceedings of the 2016 IEEE International Conference on Prognostics and Health Management (ICPHM), Ottawa, ON, Canada, 20–22 June 2016; pp. 1–5. [\[CrossRef\]](#)
128. Salari, N.; Makis, V.; Abbou, A. Joint Optimization of Maintenance and Spare Parts Provisioning for Multi-Unit Systems. In Proceedings of the 2018 Industrial and Systems Engineering Research Conference, Orlando, FL, USA, 19–22 May 2018; p. 7.
129. Werbińska-Wojciechowska, S. Preventive Maintenance Models for Technical Systems. In *Technical System Maintenance*; Springer International Publishing: Cham, Switzerland, 2019; pp. 21–100. [\[CrossRef\]](#)
130. Do, P.; Assaf, R.; Scarf, P. Opportunistic Maintenance Policies for Multi-Components Systems. In *Multicriteria and Optimization Models for Risk, Reliability, and Maintenance Decision Analysis*; de Almeida, A.T., Ekenberg, L., Scarf, P., Zio, E., Zuo, M.J., Eds.; Springer International Publishing: Cham, Switzerland, 2022; Volume 321, pp. 403–422. [\[CrossRef\]](#)
131. Li, H. Condition-Based Maintenance Policies for Multi-Component Systems Considering Stochastic Dependences. Ph.D. Thesis, Université de Technologie de Troyes, Troyes, France, 2016.

132. Nguyen, H.S.H. Développement d’une Stratégie de Regroupement Dynamique d’actions de Maintenance Pour Un Système de Production Géographiquement Dispersé. Ph.D. Thesis, Université de Lorraine, Nancy, France, 2019.
133. Alghanmi, S. Opportunistic Maintenance Optimization Based on Stochastic Dependence for Multi-Component System Exposed to Different Failure Modes. Ph.D. Thesis, University of Akron, Akron, OH, USA, 2018.
134. Dinh, D.H. Opportunistic Predictive Maintenance for Multi-Component Systems with Multiple Dependences. Ph.D. Thesis, Université de Lorraine, Nancy, France, 2021.
135. Murthy, D.N.P.; Nguyen, D.G. Study of Two-component System with Failure Interaction. *Nav. Res. Logist. Q.* **1985**, *32*, 239–247. [\[CrossRef\]](#)
136. Peña, C.; Romero, D.; Noguez, J. Workforce Learning Curves for Human-Based Assembly Operations: A State-of-the-Art Review. *Appl. Sci.* **2022**, *12*, 9608. [\[CrossRef\]](#)
137. Gimenez, C.; Sierra, V.; Rodon, J. Sustainable Operations: Their Impact on the Triple Bottom Line. *Int. J. Prod. Econ.* **2012**, *140*, 149–159. [\[CrossRef\]](#)
138. Achouch, M.; Dimitrova, M.; Ziane, K.; Sattarpanah Karganroudi, S.; Dhouib, R.; Ibrahim, H.; Adda, M. On Predictive Maintenance in Industry 4.0: Overview, Models, and Challenges. *Appl. Sci.* **2022**, *12*, 8081. [\[CrossRef\]](#)
139. Nunes, P.; Santos, J.; Rocha, E. Challenges in Predictive Maintenance—A Review. *CIRP J. Manuf. Sci. Technol.* **2023**, *40*, 53–67. [\[CrossRef\]](#)
140. Zhang, C.; Li, Y.F.; Coit, D.W. Deep Reinforcement Learning for Dynamic Opportunistic Maintenance of Multi-Component Systems with Load Sharing. *IEEE Trans. Reliab.* **2023**, *72*, 863–877. [\[CrossRef\]](#)
141. Kuhnle, A.; Jakubik, J.; Lanza, G. Reinforcement Learning for Opportunistic Maintenance Optimization. *Prod. Eng.* **2019**, *13*, 33–41. [\[CrossRef\]](#)
142. Valet, A.; Altenmüller, T.; Waschneck, B.; May, M.C.; Kuhnle, A.; Lanza, G. Opportunistic Maintenance Scheduling with Deep Reinforcement Learning. *J. Manuf. Syst.* **2022**, *64*, 518–534. [\[CrossRef\]](#)
143. Nassehi, A.; Zhong, R.Y.; Li, X.; Epureanu, B.I. Review of Machine Learning Technologies and Artificial Intelligence in Modern Manufacturing Systems. In *Design and Operation of Production Networks for Mass Personalization in the Era of Cloud Technology*; Elsevier: Amsterdam, The Netherlands, 2022; pp. 317–348. [\[CrossRef\]](#)
144. Deng, W.; Nguyen, K.T.; Gogu, C.; Medjaher, K.; Morio, J. Enhancing Prognostics for Sparse Labeled Data Using Advanced Contrastive Self-Supervised Learning with Downstream Integration. *Eng. Appl. Artif. Intell.* **2024**, *138*, 109268. [\[CrossRef\]](#)
145. Zhou, H.; Yin, H.; Zhao, D.; Cai, L. Incremental Learning and Conditional Drift Adaptation for Nonstationary Industrial Process Fault Diagnosis. *IEEE Trans. Ind. Inform.* **2023**, *19*, 5935–5944. [\[CrossRef\]](#)
146. Zhou, H.; Yin, H.; Qin, Y.; Yuen, C. Industrial Fault Diagnosis with Incremental Learning Capability Under Varying Sensory Data. *IEEE Trans. Syst. Man Cybern. Syst.* **2025**, *55*, 1322–1333. [\[CrossRef\]](#)
147. Sathupadi, K.; Achar, S.; Bhaskaran, S.V.; Faruqui, N.; Abdullah-Al-Wadud, M.; Uddin, J. Edge-Cloud Synergy for AI-Enhanced Sensor Network Data: A Real-Time Predictive Maintenance Framework. *Sensors* **2024**, *24*, 7918. [\[CrossRef\]](#) [\[PubMed\]](#)
148. Independent Group of Scientists appointed by the Secretary-General. Global Sustainable Development Report 2019: The Future Is Now—Science for Achieving Sustainable Development. Technical Report, United Nations, New York, 2019. Available online: https://pure.iiasa.ac.at/id/eprint/16067/1/24797GSDR_report_2019.pdf (accessed on 3 March 2025).
149. Franciosi, C.; Voisin, A.; Miranda, S.; Riemma, S.; Lung, B. Measuring Maintenance Impacts on Sustainability of Manufacturing Industries: From a Systematic Literature Review to a Framework Proposal. *J. Clean. Prod.* **2020**, *260*, 121065. [\[CrossRef\]](#)
150. Sénéchal, O. Research Directions for Integrating the Triple Bottom Line in Maintenance Dashboards. *J. Clean. Prod.* **2017**, *142*, 331–342. [\[CrossRef\]](#)
151. Sénéchal, O.; Trentesaux, D. A Framework to Help Decision Makers to Be Environmentally Aware during the Maintenance of Cyber Physical Systems. *Environ. Impact Assess. Rev.* **2019**, *77*, 11–22. [\[CrossRef\]](#)
152. Hennequin, S.; Ramirez Restrepo, L.M. Fuzzy Model of a Joint Maintenance and Production Control under Sustainability Constraints. *IFAC-PapersOnLine* **2016**, *49*, 1216–1221. [\[CrossRef\]](#)
153. Saihi, A.; Ben-Daya, M.; As’ad, R.A. Maintenance and Sustainability: A Systematic Review of Modeling-Based Literature. *J. Qual. Maint. Eng.* **2023**, *29*, 155–187. [\[CrossRef\]](#)

Disclaimer/Publisher’s Note: The statements, opinions and data contained in all publications are solely those of the individual author(s) and contributor(s) and not of MDPI and/or the editor(s). MDPI and/or the editor(s) disclaim responsibility for any injury to people or property resulting from any ideas, methods, instructions or products referred to in the content.