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Maintenance optimization in industry 4.0

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ABSTRACT

This work reviews maintenance optimization from different and complementary points of view. Specifically, we systematically analyze the knowledge, information and data that can be exploited for maintenance optimization within the Industry 4.0 paradigm. Then, the possible objectives of the optimization are critically discussed, together with the maintenance features to be optimized, such as maintenance periods and degradation thresholds. The main challenges and trends of maintenance optimization are, then, highlighted and the need is identified for methods that do not require a-priori selection of a predefined maintenance strategy, are able to deal with large amounts of heterogeneous data collected from different sources, can properly treat all the uncertainties affecting the behavior of the systems and the environment, and can jointly consider multiple optimization objectives, including the emerging ones related to sustainability and resilience.

1. Introduction

Modern society relies on highly technological and mechanized industries and services to produce and distribute commodities. The industrial assets are inevitably affected by aging and degradation of their components, which strongly impact on production availability and product quality. To counteract this, Operation and Maintenance (O&M) activities are carefully planned and carried out, at a significant fraction of the total business cost. For example, in food-related industries, average maintenance costs represent about 15% of the production cost [1], in wind farms the O&M cost can reach 20%-25% of the life cycle cost [2], in mining industry the maintenance costs often account for over 30% of the total production cost [3] and in nuclear power plants and heavy industries, the O&M cost is about 60%-70% of the total cost of production [4].

The perception of maintenance and of maintenance management has substantially changed through the years. Traditionally, it has been seen as “a necessary evil”, i.e., a set of expensive activities to perform only if unavoidable, because required or even mandatory, and that cannot enhance profitability [5]. With the acquired field experience of the negative impacts of failures and accidents, the role of maintenance has emerged as a strategic one, for anticipating components failures and system degradation of performance, and nowadays production managers invest significant resources in the development and implementation of maintenance strategies for improving asset reliability, productivity, efficiency and sustainability [6]. On the other hand, planning maintenance in practice is far from being a trivial task, as it requires to consider the components health state, future profiles of system operation and aspects such as spare parts inventory and future production demand, with all associated uncertainties [7].

The increase interest in academia and demand in practice for maintenance optimization is demonstrated by the published works on the topic, both theoretical and applied. Fig. 1 shows the evolution, in the time period between 2000 and 2020, of the number of published works on maintenance optimization. The data have been obtained considering the publications indexed in the Scopus database and containing in the title, in the abstract or in the keywords, the terms “maintenance optimization” and at least one among the following terms: “scheduled”, “opportunistic”, “condition-based”, “predictive” and “prescriptive”. The increase of the ratio between the number of works related to maintenance optimization and the total number of works indexed by Scopus (rescaled in the picture by dividing by 1000) confirms the increasing interest in maintenance optimization [8–10].

Fig. 2 shows the repartition of the number of works on maintenance optimization in the various industrial fields reviewed in this work. It is evident that maintenance optimization is pervasive in almost all industries, with manufacturing and energy (wind power, oil & gas, power generation and distribution) sectors accounting for more than 50% of the total number of works considered.

Since the initial stages of the research on maintenance optimization, which date to the 1960s, several issues had been identified as

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Acronyms and symbols

AHP	Analytic Hierarchy Process
AI	Artificial Intelligence
ANP	Analytic Network Process
BA	Bayesian Approach
BCM	Business Centered Maintenance
CNN	Convolutional Neural Network
CPS	Cyber Physical System
DMG	Decision Making Grid
DP	Dynamic Programming
DSS	Decision Support System
DT	Decision Tree
ELECTRE	Elimination Et Choice Translating Reality
FL	Fuzzy Logic
GA	Genetic Algorithm
IoT	Internet of Things
KID	Knowledge, Information and Data
MA	Mathematical Approach
MCDM	Multiple Criteria Decision Making
MIP	Mixed Integer Programming
ML	Machine Learning
MOGA	Multi-Objective Genetic Algorithm
MOM	Maintenance Organization Model
MSA	Metaheuristic Search Algorithm
NLP	Natural Language Processing
O&M	Operation & Maintenance
RCM	Reliability Centered Maintenance
RL	Reinforcement Learning
RNN	Recurrent Neural Network
RUL	Remaining Useful Life
SM	Simulation Model
SP	Stochastic Programming
TOPSIS	Technique for Order Preference by Similarity to Ideal Solution
$\boldsymbol{K}$	Knowledge, information and data
$\boldsymbol{F}$	Objective function
$\boldsymbol{f}$	Vector of the optimization criteria
$\boldsymbol{x}$	Vector of the features to be optimized
$\boldsymbol{h}$	Constraint function
$\boldsymbol{b}$	Constraint function bound

challenging:

a the difficulty in retrieving data, information and knowledge for the development and validation of maintenance optimization models and approaches for practical applications. This issue especially affects newly designed and safety-critical systems, for which scarce information is available related to the degradation and failure processes of their components [7,10,11];

b the difficulty of dealing with the complexity of industrial systems, in terms of number of components and dependencies among them. Multi-unit systems had not been considered in the first surveys on maintenance optimization in the 1960s [12,13], and the lack of effective methods to treat them emerged in the 1970s [14]. Actually, even recent surveys have underlined that, although a lot of efforts had been devoted to the development of maintenance optimization models for multi-unit systems [7,15,16], the problem is still not fully solved. One key challenge is the proper identification and account of functional dependencies of different nature, e.g., economic, stochastic, structural or logic, among system components, which are extremely difficult to handle when they co-exist [7]. Also, the different units of a multi-unit system most likely require different maintenance strategies, which remarkably increases the complexity of the optimization problem;

c the difficulty of implementing the developed maintenance optimization approaches in real-world applications, which generates a gap between theory and practice. According to [11], this is mainly due to: *i*) the difficulty of explaining to maintenance planners the maintenance optimization models, which are often seen as black-boxes providing unintelligible maintenance recommendations, *ii*) the cost of developing maintenance optimization methods, which is not a-priori guaranteed to be balanced by the benefit of implementing the optimized maintenance policies.

Nowadays, maintenance practice can benefit from the technological developments driving the so called Industry 4.0 revolution. It was firstly introduced in Germany in 2011 as a part of the country's high-tech strategy [17] and the topic was quickly adopted globally to lead the development and improvement of 21st century industry. In the Industry 4.0 concept, production systems are built as smart systems in the form of Cyber Physical Systems (CPS), which enable real-time communication and cooperation between humans and machines [18], and more efficient and flexible production to meet more challenging performance and

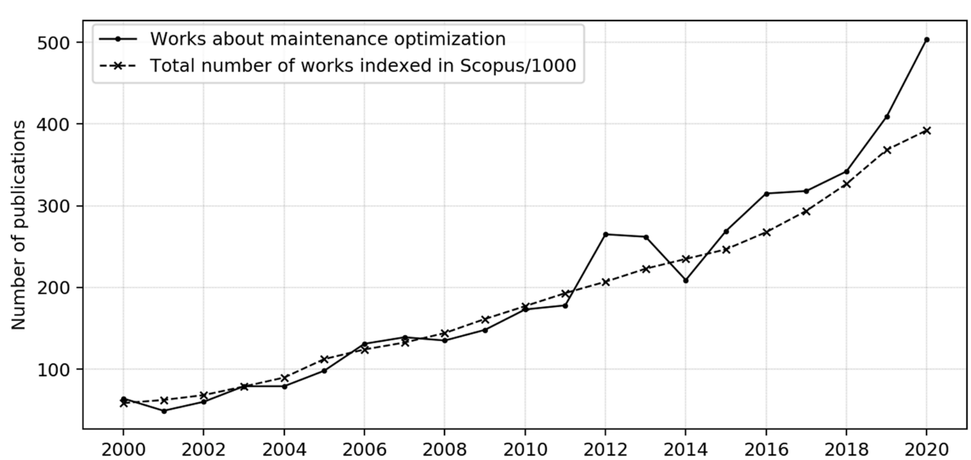

Fig. 1. Number of publications about maintenance optimization and total number of publications (divided by 1000) indexed in the Scopus database from 2000 to 2020.

safety goals. Industry 4.0 is based on the retrieval of large amount of data from the systems and the exploitation of the advancements in sensors, robotics and new technologies such as Artificial Intelligence (AI), Machine Learning (ML), augmented reality, big data analytics, and Internet of Things (IoT) [19].

With respect to issue *a*) above, new sources of information on complex multi-unit systems have been made available, e.g., real-time data and images related to the operation and to the health state of the components. The effective use of this information for maintenance optimization allows reducing the dependence on the subjective information from experts' knowledge. Indeed, AI algorithms are able to effectively exploit such information for detecting anomalies, diagnosing their causes and predicting failure times, operating conditions and demands [20]. The outcomes of the AI algorithms can be used to adapt maintenance plans to the actual and predicted conditions of the components and systems. With respect to issue *b*) above, deep learning algorithms can effectively deal with the big data collected from the complex systems [21–23], from which they can identify the functional dependencies among their components [24]. Finally, with respect to issue *c*) above, methods have been developed to interpret the outcomes of AI and ML algorithms [25,26], and offer ways to visualize the maintenance strategy for understanding and explaining the maintenance strategies identified by the optimization method [27].

The present survey reports and analyzes maintenance optimization within the Industry 4.0 paradigm. We firstly review systematically: *i*) the knowledge, information and data available for maintenance optimization, *ii*) the optimization criteria typically considered, and *iii*) the outcomes of the optimization. The objective of the survey is to illustrate the advancements already achieved in maintenance optimization and those that can be potentially obtained, the challenges to be addressed and the most promising trends of methods development. The review considers also the recently developed approaches based on Reinforcement Learning (RL) and the prescriptive maintenance strategy paradigm that, at the best of the authors' knowledge, have not been considered in previous surveys. This work is expected to be useful for maintenance management professionals and researchers working on maintenance optimization.

Since the focus is on maintenance optimization, we purposely do not consider:

a the logical processes, such as Reliability-Centered Maintenance (RCM) and Business-Centered Maintenance (BCM) [28,29], which aim at identifying which components in a system should be maintained on a regular schedule basis, monitored and/or are suitable for a run-to-failure strategy by means of the analysis of the failure modes and consequences [30], and according to the company objectives [31];

b the approaches used to support the optimization procedure but not directly aimed at the optimization of the maintenance strategy, such as Bayesian Approaches (BAs) [10], which are widely applied to identify the value of the unknown parameters of failure time distributions given some empirical data [32] and to estimate the failure probabilities [33,34], Simulation Models (SMs) relying on Petri net [35,36], Markov chain [37] or Monte Carlo simulation [38], which are used to model the system behavior and to evaluate the goodness of different maintenance strategies;

c the frameworks employed to define an effective maintenance strategy, such as Decision Support Systems (DSS), i.e., model-based sets of procedures for processing data and judgments to support and improve the decision-making [39], and Maintenance Organization Models (MOMs), i.e., schemes to be followed during the organization of maintenance, which combine administrative, managerial and technical activities involved in maintenance strategy planning [40, 41].

The remainder of this review work is organized as follows: maintenance strategies are presented in Section 2; Section 3 analyses the maintenance optimization problem in terms of the knowledge, information and data available, optimization criteria and optimization outcomes; Section 4 discusses the optimization approaches; in Section 5, the main challenges related to maintenance optimization and the emerging trends are presented. Finally, Section 6 concludes the work.

2. Maintenance strategies

The concept of asset maintenance includes all actions aimed at monitoring, restoring or enhancing the functionality of an asset, or at preventing the asset to lose all or part of its functionality [42]. A maintenance strategy is the set of rules according to which the different maintenance actions are performed on the asset. It includes rules on the type of maintenance actions, on the maintenance instances, on the components or sub-systems priorities, on the spare parts flow on the maintenance technical crew to involve [31,43]. Accordingly, maintenance strategies are grouped into [44]:

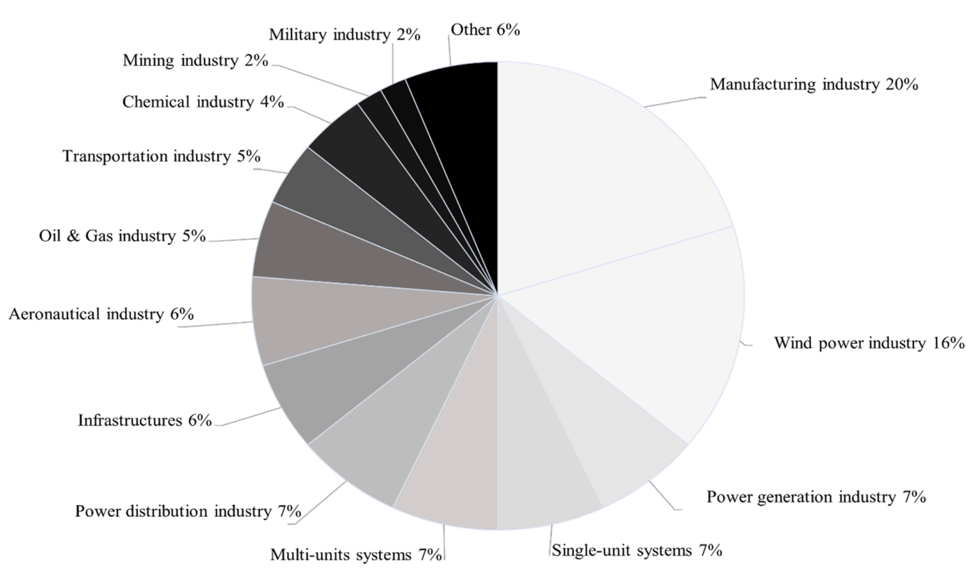

Fig. 2. Repartition of maintenance optimization into the different industrial fields of application, in the considered papers.

- *Corrective maintenance*. It restores the functionality of an asset after its failure. It involves only repairment or replacement procedures. It is suitable for non-safety critical systems for which the maintenance interventions can be performed quickly and at low costs, and whose failures do not induce severe consequences [45,46].
- *Preventive maintenance*. It aims at preventing the asset to lose its functionality, by performing maintenance actions before failure occurs. Five main types of preventive maintenance strategies are typically identified:
  - i *Scheduled maintenance*. It aims at preventing the asset to lose its functionality through maintenance actions that are performed at scheduled instances, both irregular or periodic. Typically, statistical data collected from assets, e.g., failure times and maintenance durations [47], are used to define the maintenance plan [42]. The schedule optimization task is difficult since degradation mechanisms are complex and characterized by large uncertainty [48]. Scheduled maintenance is suitable for high-risk systems, e.g., systems whose failure may lead to severe safety consequences, can cause large production losses or whose maintenance planning can provide economic advantages, e.g., because of not easily available spare parts, which should be ordered in advance.
  - ii *Opportunistic maintenance*. It aims at performing maintenance on more asset elements or sub-systems at the same time. This is done, for example, by combining the maintenance activities of components characterized by similar failure rates and operation conditions, or by exploiting a planned shutdown or an undesired breakdown as an opportunity to maintain several different components [49]. This maintenance strategy is suitable for systems characterized by similar components or undergoing long, planned shutdowns, e.g., nuclear power plants for refueling, and for systems whose maintenance activities require the rental of expensive equipment, e.g., a crane or a ship.
  - iii *Condition-based maintenance*. Similarly to scheduled maintenance, it aims at preventing the asset to lose its functionality, but the planning of the maintenance interventions is based on the elaboration of data collected from the asset itself to evaluate its conditions. The application of condition-based maintenance requires the availability of a monitoring system to collect data of physical quantities related to degradation of the asset [50]. Then, by applying fault detection and diagnostic techniques [51], abnormal conditions are detected and diagnosed, calling for specific maintenance actions to be performed [52]. Condition-based maintenance is suitable for systems in which the advantages of avoiding unplanned shutdowns caused by failures overcome the costs of the monitoring system and of the development of the detection and diagnostic tools [53].
  - iv *Predictive maintenance*. As an extension of condition-based maintenance, it processes further the monitoring data for prognostics [54,55], i.e., to estimate the failure time, thus allowing planning the maintenance activities in advance [56]. It requires the development of the monitoring system and the prognostic tools. The variable and uncertain conditions under which the components are operating can strongly influence the degradation processes and failure mechanisms, thus requiring the proper treatment of data characterized by several sources of uncertainty. Predictive maintenance is suitable for systems which can benefit from the same advantages of condition-based maintenance, but can also further benefit from planning in advance, e.g., due to not easily available spare parts which need to be ordered.
  - v *Prescriptive maintenance.* It goes beyond estimating the components failure time by exploring hypothetical scenarios generated by the O&M management. In fact, starting from the monitoring data collected from the asset, prescriptive maintenance provides a recommendation of the actions to be taken by anticipating the potential scenarios generated by such actions and evaluating their effects on the system. In other words, prescriptive maintenance exploits failure projections to optimize the operational implications of maintenance tasks [57]. The recommended actions can be maintenance actions or operational actions: for example, the repair of a pump or its running at a lower than nominal flow rate can be prescribed to slow down its degradation process for allowing the timely delivery of a new piece of equipment. Prescriptive maintenance requires the availability of historical and operational data collected in a wide variety of operating conditions [58], and advanced models of the considered system, e.g. digital mirrors and twins [59–62].

Fig. 3 shows the evolution of the number of publications relative to the different maintenance strategies mentioned above. Notice that the interest in scheduled maintenance has been decreasing, whereas the interest in condition-based and predictive maintenance has been increasing, coherently with the development of the enabling technology. Some works about prescriptive maintenance have been recently published [63]. This trend is confirmed by the results of the survey in [64], according to which 79% of the interviewed professionals (mainly from energy, transportation and manufacturing sectors) believe that predictive and prescriptive maintenance of equipment will play a fundamental role in their companies in the future. Nevertheless, the scheduled maintenance strategy is still popular among systems managers and researchers, with several works related to its optimization being still published in recent years. Also, mixed maintenance strategies have been adopted in some industrial applications. For example, a mixed maintenance strategy combining corrective, scheduled and opportunistic maintenance has been developed to minimize the life cycle cost of rolling bearings in [65]. Corrective, condition-based and predictive maintenance strategies are mixed to minimize the maintenance cost and maximize the reliability of nuclear power plant feeding pipes in [66]. To counterbalance the fact that preventive maintenance interventions can be imperfect, i.e., they are not able to restore equipment in as-good-as-new condition, a mixed maintenance strategy composed of preventive actions, e.g., lubrication, cleaning, and adjustment, and corrective actions, e.g., replacement, is proposed and optimized in [67]. When condition-based or predictive maintenance strategies are adopted, it can be useful to perform scheduled inspections to check the asset health state during system shutdowns.

In practice, there is not an automatic way to select the most appropriate maintenance strategy for a specific system: each maintenance strategy has its own particular characteristics and the maintenance engineer should take into account several aspects, e.g., company objectives, type of system, failure consequences, maintenance costs, availability of spare parts, etc.

3. Maintenance optimization

In general, an optimization problem involves a vector of features of the system to be optimized, $\boldsymbol{x} = [x_1, \ldots, x_n]$, an objective function to be minimized (maximized), $F(\boldsymbol{x}) : \mathbb{R}^n \rightarrow \mathbb{R}$, which may involve q different criteria, $\boldsymbol{f}(\boldsymbol{x}) = [f_1(\boldsymbol{x}), \ldots, f_q(\boldsymbol{x})]$, and possibly m constraint functions, $h_i(\boldsymbol{x}) : \mathbb{R}^n \rightarrow \mathbb{R}$, $i = 1, \ldots, m$, with associated bounds, b_i, which limit the choices on $\boldsymbol{x}$ because of physical, economic, environmental or other reasons. Then, the optimization problem can be mathematically framed in terms of the identification of the vector $\boldsymbol{x}$ which satisfies [68]:

$$\begin{aligned} &argmin_x(argmax_x)\ F(\boldsymbol{x}) \\ &subject\ to\ h_i(\boldsymbol{x}) \leq b_i,\ \ i = 1, \ldots, m \end{aligned} \tag{1}$$

Specifically, in maintenance optimization, the features in the vector, $\boldsymbol{x}$, to be optimized relate to aspects of the maintenance planning, such as the interval between consecutive instances of maintenance intervention, the degradation threshold for detection, the type of maintenance actions to be performed, etc. The objective function, $F(\boldsymbol{x})$, quantitatively describes objectives such as profit, reliability, safety and sustainability. The constraint functions, $h_i(\boldsymbol{x})$, and associated bounds, b_i, are set

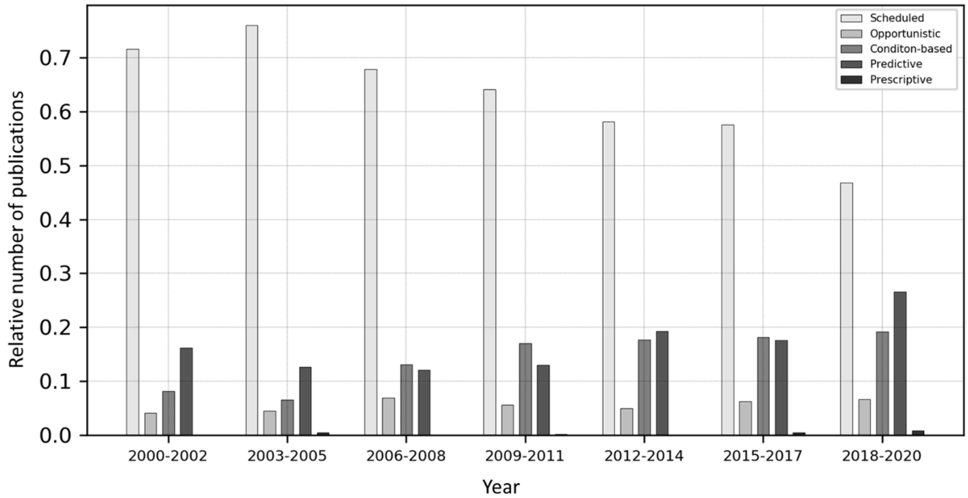

Fig. 3. Relative number of publications related to the optimization of different maintenance strategies from 2000 to 2020 [www.scopus.com].

according to specific physical limits of design and operation, e.g., the maximum power that can be produced by a system, and regulations, such as the maximum allowed interval of time between two consecutive instances of inspection, or the minimum reliability accepted or maximum cost allowed.

In practice, the definition of $\boldsymbol{x},\ F(\boldsymbol{x}),\ h_i(\boldsymbol{x}),\ b_i$ depends on the available knowledge, information and data, K, about the behavior of the system and its environment.

The remaining part of this section will discuss the elements of the optimization problem defined above, that are: *i*) knowledge, information and data available, K, (Section 3.1), *ii*) optimization criteria, $\boldsymbol{f}(\boldsymbol{x})$, (Section 0), *iii*) optimization features, $\boldsymbol{x}$, (Section 3.3).

3.1. Knowledge, information and data

In practice, different sources of Knowledge, Information and Data (KID) [69], $\boldsymbol{K}$, concur to the definition of the optimization problem in Eq. (1), depending on availability and on the input required by the specific optimization method employed. They can be organized with respect to: i) the type of KID, which is here classified as "expert knowledge", "mathematical models" and "data", where the latter can be in the form of numbers, texts and images, and ii) the topic, i.e., what the KID represent. With respect to the latter, the KID typically involved in maintenance optimization represent characteristics of the maintenance intervention, of the system and components reliability, availability and safety, of the degradation processes and health states of the system and components, e.g., the normal/abnormal condition outcome of an anomaly detection module, the classification of the type of abnormal condition, i.e., the outcome of a fault diagnostic module, and the prediction of the component Remaining Useful Life (RUL), i.e., the outcome of a fault prognostic module, of the system operating conditions and other information needed for the definition of the objective function.

Table 1 reports the classification of some works about maintenance optimization in terms of type and topic of $\boldsymbol{K}$. Expert knowledge is fundamental when new technologies, for which limited data are available, are considered. It is mainly used for the definition of the objective function [44], the set of feasible maintenance strategies [70] and the setting of the values of model parameters and constraints [71]. It has been used in different sectors, such as in chemical [72], manufacturing [70] and oil & gas [73] industries. Mathematical models are typically used for describing component degradation processes [74,75] and the effects of maintenance activities [76], and for monitoring the system health state [77]. Stochastic models are typically exploited to deal with the uncertainty inherent in stochastic processes such as degradation or the evolution of operating and environmental conditions. They have been used in the context of maintenance optimization to model components degradation in nuclear [74] and manufacturing industries [78], availability and revenues in wind power industry [79] and maintenance costs in nuclear industry [80]. Numerical data, such as failure times and maintenance costs, are typically used to set the model parameters [48], to properly represent uncertainty [81,82] and the system health state [83]. In the context of Industry 4.0, signal measurements input to models for fault detection, diagnostics and prognostics, in support to condition-based, predictive and prescriptive maintenance approaches. For example, the potential of using data for maintenance optimization was shown in a manufacturing plant [84], in a wind farm [85], in aeronautical systems [86] and in infrastructures [87]. Table 2 reports the classification of the considered works in terms of type of KID and industrial field of application. It can be seen that independently from the industrial field, models and data are the main sources of KID.

Fig. 4 represents the maintenance strategies considering the KID typically used for their identification and development. It shows that each maintenance strategy requires different sources of KID to be properly developed. Reliability and availability models are used for developing scheduled [88] and opportunistic [89] maintenance strategies. Degradation models and real time data about components health states are fundamental for the development of condition-based [83] and predictive [90] maintenance strategies. Data and models of the operating conditions are employed to develop prescriptive maintenance strategies, which require considering their influence on components degradation and failure [85].

Even if some works have considered textual data for the development of reliability, availability and maintainability models [91], and images have been used for the development of diagnostics models [92], these two types of data have not yet been used for maintenance optimization purposes. This is because text and image processing typically relies on ML methodologies, such as Natural Language Processing (NLP) techniques and Convolutional Neural Networks (CNN), which are difficult to integrate within an optimization problem and whose functioning and results are difficult to understand and interpret by maintenance planners. We expect that with the advancement of concepts of Industry 4.0 and Internet of Things (IoT) [93], the capability of ML methodologies in dealing with large amounts of heterogeneous data and the development of techniques for the interpretation of AI algorithm outcomes, textual data and images, will become more and more relevant to the field of maintenance optimization.

3.2. Optimization criteria

The objective function $F(\boldsymbol{x})$, which drives the maintenance strategy

Table 1
Classification of the knowledge, information and data involved in maintenance optimization, with respect to type and topic.

KID topic KID type		Maintenance	Reliability, availability and safety	Degradation process	Health state Detection	Diagnostics	Prognostics	Operating conditions	Objective function
Expert knowledge		• Set of possible maintenance alternative strategies [94]; • Set of possible O&M actions [95].	• Parameter values, e.g., failure rate [96] and reliability threshold [71].	Parameter values, e.g., degradation and failure thresholds [97].				Parameters of the models for simulating the operating conditions [85].	• Weights to be associated to the different maintenance criteria [44]; • Fitness of alternatives with respect to the criteria [98].
Models		Models of the duration [99], effect [76] and cost [81] of the maintenance interventions.	• Models of system reliability, availability and safety, e.g., Bayesian networks [100], Markov models [101], Petri nets [36], Monte Carlo simulation models [83].	• Models of system degradation [74].	Models for the detection of system abnormal conditions, based on data-driven statistics and AI approaches [102].	Models for fault diagnostics of the system components based on data-driven AI approaches [77].	Models for the prediction of the Remaining Useful Life (RUL) of the system components, based on model-based and data-driven approaches [77].	Models for the predictions of the operating environment based on present and past time measurements, e.g., wind speed, energy demand [89].	
Data	Numerical	• Maintenance cost [103]; • Information about previous inspections, e.g., time since last maintenance [104] or type of maintenance intervention.	• Failure times; • Databases of component failure rates, e.g., OREDA [105]; • Availability and Reliability of the components [106]; • Transition probabilities/ rates in Markov models of system reliability and availability.	• Simulation parameters, e.g., transition probabilities among degradation states [107]; • Parameters of the degradation models [48]; • Information related to measurement uncertainty, e.g., measurement noise [81].	• Result of inspections, e.g., non-destructive test and degradation indicator values [108]; • Real time signal values [83].	• Results of inspections, e.g., non-destructive test and degradation indicators [108]; • Real time signal values [83].	• Real time signal values [109]; • Remaining Useful Life estimations [81].	• Information related to system quantities, e.g., production level [110], buffer or spare parts inventory levels [111]; • Meteorological data [89].	
	Textual	Maintenance reports and work orders.	• Maintenance reports and work orders; • Accident investigation reports.	Maintenance reports and work orders.					
	Images				• Televisual inspections; • Thermal images; • X-rays images.	• Televisual inspections; • Thermal images; • X-rays images.	• Televisual inspections; • Thermal images; • X-rays images.		

optimization, is often defined considering several different optimization criteria, $f(x)$, [182]. In this respect, it is possible to distinguish between approaches that consider a single criterion and approaches that consider multiple criteria.

The works which optimize a single criterion employ performance metrics related to:

1 the economic benefit provided by the maintenance strategy, e.g., maintenance cost [71,103], life-cycle cost [157], profit [81,83,121], production loss and unmet demand [110,144];
2 system safety and reliability, considering failure occurrences and mitigation of failure consequences; availability [183], reliability [88, 109], safety / risk [150,184] and resilience [154] are typical quantitative metrics used.

The works which optimize multiple criteria jointly consider metrics quantifying:

1 the effectiveness of personnel management and logistics; for example, the quality of the shift schedule for the workers [185,186] and of the management of the spare parts inventory [111,129] have been considered;

Table 2
Classification of the considered works in terms of type of KID and industrial field of application.

KID type Industrial field	Expert knowledge	Mathematical models	Data
Manufacturing industry	[70,110, 112–120]	[78,84,110,111, 114–118,120–128]	[78,84,110–114, 116–120, 123–129]
Wind power industry	[81,85,100, 130–133]	[79,81,85,89,100, 131–144]	[79,81,85,89,100, 131–144]
Power production industry	[145–148]	[74,145–151]	[74,145–151]
Power distribution industry	[152,153]	[101,107,152–156]	[101,107, 152–156]
Infrastructures	[87]	[87,96,104, 157–160]	[87,96,104, 157–160]
Aeronautical industry	[86,161,162]	[86,90,163–165]	[86,90,162–165]
Oil & Gas industry	[44,73, 166–168]	[73,168,169]	[44,73,167–169]
Transportation industry	[170–173]	[171–174]	[171–174]
Chemical industry	[72,175]	[108,176]	[72,108,175,176]
Automation systems		[177]	[177]
Semiconductor industry	[178]		
Mining industry		[88,179]	[88,179]
Military industry	[94]	[180]	[180]
Water distribution industry	[181]		[181]
Data storage systems	[71]	[71]	[71]

2 the effects of maintenance on the asset performance from the point of view of sustainability, environmental impact [158,174,187] and production quality [44,166];
3 the time loss, e.g., the effects of time delays caused by maintenance on other activities [96] and on the total maintenance time [128];
4 the feasibility of performing the maintenance interventions [70,98] and the accessibility of the components [167].

Table 3 reports the classification of the considered works in terms of optimization criteria and industrial field of application. Regardless of the field of application, the most used criteria are economic and safety-related [182], with the economic criteria mostly used in non-safety critical applications. Differently from what was pointed out in [182], it can be noticed that the trend is shifting towards multi-objective optimization problems, in which several application-related criteria are jointly considered. This is due to the increasing complexity of industrial systems, which are expected to simultaneously satisfy multiple objectives. For example, in production plants, it is desirable to minimize the maintenance cost while maximizing the machines availability and the production output [120]. Furthermore, in recent years, maintenance has become a key factor for sustainable operation and production, leading to an increase in the number of research papers on sustainable maintenance management. The objectives are typically related to the efficient management of resources and energy, the reduction of wastes produced by maintenance and of storage material [188], the reduction of the maintenance environmental impact, including hazardous emissions caused by system malfunctioning [189], and the increase of workers and public safety [190]. However, it has been pointed out that research in maintenance optimization is still limited and mainly focused on conventional performance criteria [191]. Another criterion that has recently emerged for critical systems and infrastructures is resilience, which is defined as the ability of a system to withstand potentially high-impact disruptions, by mitigating impacts and quickly recovering normal conditions [192]. Resilience is considered to be fundamental in the context of Industry 4.0, since nowadays systems can be affected by several potential disruptive events, such as natural events, pandemics, cyber-attacks [193], and their ability to quickly recover their functionalities is of utmost importance. Then, it is reasonable to think that in the next years more and more researchers and practitioners will consider environmental impact, sustainability and resilience as criteria of maintenance optimization.

3.3. Optimization outcomes

Maintenance optimization concerns different types of features (x in Eq. (1)) and considers them in different ways. They include the following, in relation to the optimization outcome:

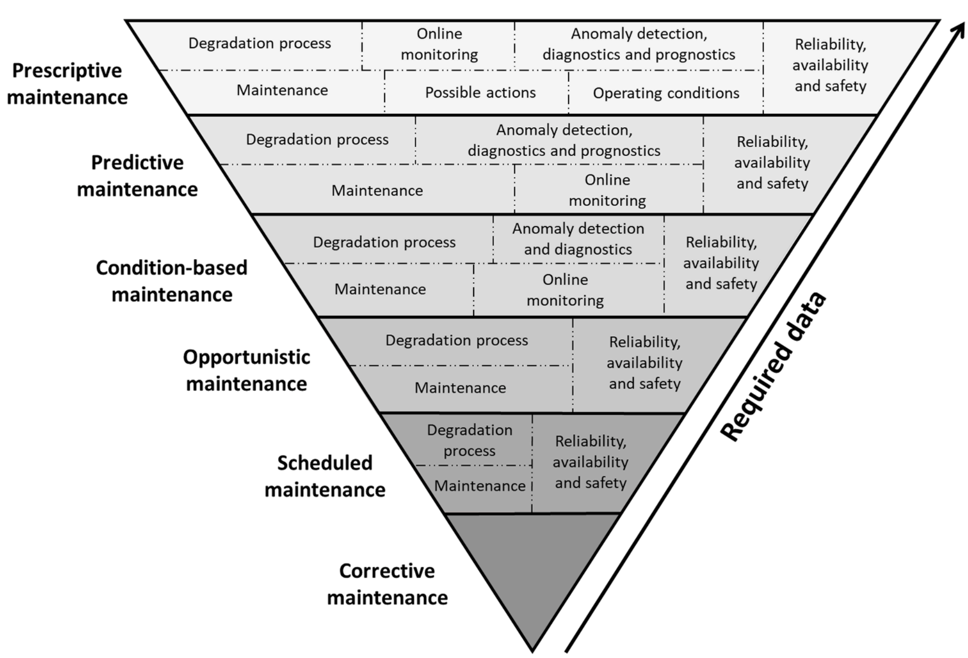

Fig. 4. Representation of the maintenance strategies in relation to the type of required information.

Table 3
Classification of the considered works in terms of optimization criteria and industrial field of application.

Optimization criteria Industrial field	Economic Criteria	Safety criteria	Management criteria	Performance criteria	Temporal criteria	Practicality criteria
Manufacturing industry	[70,84,110,111,116–123,125,126,129]	[70,113–118,120,124,126,127]	[129]	[113,115,120]	[120]	[70]
Wind power industry	[79,81,85,89,100,130–132,134–144]	[130–132]	[130]	[130]		
Power production industry	[74,145–151]	[145,150,151]				
Power distribution industry	[101,107,152,153,155,156]	[107,154]				
Oil & Gas industry	[44,73,166–169]	[44,73,166–168]		[44,166]		[44,167]
Infrastructures	[87,96,157–160]	[104,159]		[158]	[96]	
Aeronautical industry	[86,161,164,165]	[90,109,162,164,165]	[86]			
Transportation industry	[171,172,174]	[170,172,173]	[172]	[174]	[172]	
Mining industry	[88,179]	[88]				
Military industry	[94]	[180]				
Automation systems	[177]					
Semiconductor industry		[178]		[178]		
Water distribution industry	[181]			[181]		
Chemical industry	[72,108,175,176]	[72,175]		[108]		
Data storage systems	[71]					

- optimal maintenance strategy among several a-priori predefined alternatives [44,108]; some works produce also a ranking of the alternatives with respect to the optimization criteria;
- optimized parameters values defining a single maintenance strategy selected a-priori [76,88], e.g., the maintenance period or age threshold for scheduled maintenance, the degradation threshold for condition-based maintenance, or the type of action performed, e.g., repairment, replacement;
- optimal maintenance action to be performed for given data, such as monitoring signals or operating conditions [104,133]; in this case, the a-priori selection of the maintenance strategy is not needed since the outcome is directly the action to be performed, e.g., repair, replace, order the spare parts, or decrease the production level to reduce the degradation rate;
- optimized grouping of components for opportunistic maintenance [194,195]; the outcome consists in the optimal set of components to be maintained at the same time, assuming an a-priori maintenance strategy, e.g., scheduled;
- optimized inventory management strategy [129,147]; the outcome consists in the optimized spare parts flow or the optimized spare parts or product inventory management strategy.

Table 4 reports the classification of the considered works with respect to the topic of the KID and the optimization outcome. Notice that the information provided by the anomaly detection, fault diagnostics and prognostics, is not considered in the majority of the works on maintenance optimization. This is mainly due to the fact that researchers have been mainly focused on the development of detection, diagnostics and prognostics methods for individual components of different types, and only recently the interest has shifted towards the exploitation of the outcomes of these methods for maintenance optimization. The challenge is that diagnostics and prognostics methods typically consider single components, whereas maintenance optimization requires to take

Table 4
Classification of the considered works in terms of required knowledge, information and data, topic and outcome.

Optimization outcome KID topic		Best maintenance strategy among several alternatives	Optimized parameters for the a-priori selected maintenance strategy	Optimal maintenance strategy	Optimal grouping of components for maintenance	Optimized inventory management strategy
Maintenance		[44,70,72,94,98,100,112–117,130,131,145,157,161,162,166,167,170,173,175,178,181]	[48,67,71,74,78–80,83,84,88–90,97,99,101,106–111,118,119,121–126,128,129,132,134–144,149,150,154–156,158–160,164,165,169,174,176,177,179,180,185,151,196–202]	[73,81,85–87,95,104,127,133,146–148,152,153,168,171,172,203]	[96,194,195]	[99,111,129,147]
System reliability, availability and safety		[72,113,157,167]	[67,71,74,76,78–80,83,84,88,89,99,101,106,107,109,119,124–126,132,134,136–141,143,149,150,154–156,165,169,177,185,197–200,202]	[87,95,146,148,171,172,203]	[80,194,195]	[99]
Degradation process		[113,157,178]	[48,67,74,78–80,83,88,89,97,101,106–110,118,119,122–126,137,140,141,143,149,156,164,165,169,174,176,177,179,180,185,151,196–201]	[73,81,85–87,95,104,127,133,146–148,152,153,168,171,172,203]	[80,194,195]	[111,147]
System health state	Detection	[100,157,178]	[80,83,118,125,134,140,149,198]	[87,171,172]	[80]	
	Diagnostics		[83,125,144,149,198]	[172]		
	Prognostics		[84,90,109,134,144,176,177]	[81,85,86,95,133,147,148]		[147]
Operating condition		[114,116]	[89,90,99,110,111,118,119,121–125,128,129,134,137–140,144,155,159,164,165,176,177,198–200]	[73,81,85,86,95,127,133,148,152,153,168,172]	[96,195]	[99,111,129]
Objective function		[44,70,72,94,98,112–114,130,161,166,167,170,173,175,181]			[194]	

decisions considering the whole system. Furthermore, it can be noticed that only few works, which try to achieve predictive or prescriptive maintenance, use input data and information from most of the categories listed above. This is due to the fact that, as already commented in Section 2, these maintenance strategies require a large amount of data to be properly implemented and deployed.

The most popular outcomes of maintenance optimization are *i) ranking of different maintenance alternatives* and *ii) optimized parameters values for the a-priori given maintenance strategy*: the two share the need of a-priori selecting the maintenance strategy. This way, the obtained maintenance strategy is optimal with respect to a limited set of options. Actually, in the context of Industry 4.0, it can be expected that prescriptive maintenance will become more and more popular [64] and, therefore, approaches are expected to be developed, which give as outcome the optimal maintenance action considering the present state of the system. They are expected to be advantageous since they do not require assuming a predetermined maintenance strategy.

4. Optimization approaches

The optimization approaches are here presented considering the features, $\boldsymbol{x}$, to be optimized. Section 4.1 will be dedicated to Multiple Criteria Decision Making, Decision Making Grid and Decision Tree, which have been mainly applied to the identification of the best among several alternatives of maintenance strategy. Section 4.2 will present Mathematical Approaches, Mixed Integer Programming, Dynamic Programming and Metaheuristic Search Algorithms, which have been mainly used for optimizing the parameters of a predefined maintenance strategy. Section 4.3 will introduce Reinforcement Learning to select the optimal maintenance actions to be performed. Table 5 reports the works in which the described optimization approaches have been applied to obtain the different outcomes.

4.1. Approaches for the identification of the best maintenance strategy among a predefined set of alternatives

The following algorithms have been mainly applied to select the best maintenance strategy among a predefined set of alternatives. They use experts' knowledge as one of the main sources of input, which allow considering both quantitative and qualitative aspects of maintenance:

- **Multiple Criteria Decision Making (MCDM)**: A commonly applied MCDM method for O&M optimization is the Analytic Hierarchy Process (AHP), which hierarchically structures the decision process into a series of pairwise comparisons and allows considering both qualitative and quantitative aspects [204]. It was applied to the optimization of the maintenance strategy of an oil refinery [44] and a wind farm [130]. The integration of MCDM with Fuzzy Logic (FL) was extensively studied to cope with the uncertainty and the subjectivity of the decision making process [112,166,205]. A generalized version of AHP, i.e., Analytic Network Process (ANP), has been applied to the selection of the best maintenance strategy for a chemical plant [175]. The main advantage of ANP is that the decision process is structured as a network instead of a hierarchy and this makes it suitable to deal with the interdependencies among the criteria [206]. Other popular MCDM algorithms are the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and the Elimination Et Choice Translating Reality (ELECTRE). TOPSIS is a decision-making algorithm in which the best solution among the possible alternatives is chosen by selecting the one which minimizes the Euclidean distance from the ideal optimal option and maximizes the Euclidean distance from the worst possible option [207]. It was applied to select the optimal maintenance plan for military equipment [94], manufacturing plants [70] and aeronautical systems [161]. In [113] and [72], a FL/TOPSIS-based approach was proposed to deal with the selection of the most suitable maintenance strategy. ELECTRE is based on the concept of outranking relations between alternatives [208]. It was used to select the best set of elements to be replaced at each scheduled maintenance in a multi-unit system [194] and it was applied to the selection of the optimal maintenance strategy of compressors in the chemical industry, and in water distribution networks [98,181]. The simplicity of these algorithms and the high interpretability of their outcomes contributed to their popularity for maintenance optimization, even if inter-dependence between alternatives and objectives can lead to inaccurate results [209].
- **Decision making grid (DMG)**: DMG is a graphical support tool used to help the decision makers in selecting the most effective maintenance strategy by considering multiple criteria, such as downtime, failure frequency and failure cost. The main drawback is that it strongly relies on the user's experience and can provide biased results. DMG was applied to automotive industry [170] and aeronautical systems [162]. A fuzzy logic DMG was also proposed to consider equipment reliability and criticality [114]. DMG are useful when the available KID, $\boldsymbol{K}$, is limited to expert knowledge.
- **Decision Tree (DT)**: DT is a decision-making support tool whose outcomes are easy to interpret and which allows comparing the performance of different alternatives in obtaining an established goal, while considering random events, possible decisions and their consequences [210]. DTs are generally not suitable to deal with complex problems and for long time-horizons [100]. DTs were structured to identify the optimal maintenance strategy of gas [145]

Table 5
Classification of the considered works in terms of optimization approach and outcome.

Optimization outcome Optimization approach	Best maintenance strategy among several alternatives	Optimized parameters for the a-priori selected maintenance strategy	Optimal maintenance strategy	Optimal grouping of components for maintenance	Optimized inventory management strategy
MCDM	[44,70,72,94,98,112,113,130,161,166,167,175,181]			[194]	
DMG	[114,162]	[170]			
DT	[100,115,145,178]				
MA	[121]	[48,99,122,123,143,177,197]	[171]		[99]
MIP		[84,89,90,124,134–136,149,154,155,165,176,202]	[172]		
DP		[107,160,164,179,201]	[104]	[96]	[111]
MSA	[94,120,156,169–171]	[65,78–80,83,101,106,116–119,123,125,128,131,132,137–139,141,142,151,156–159,173,195,199,200,219,227]		[195,200]	
RL		[180,198]	[81,85–87,95,110,127,146,148,152,153,168,169,203]		[147]

and wind turbines [100], and in the semiconductor [178] and manufacturing [115] industries.

4.2. Approaches to optimize the parameters of an a-priori selected maintenance strategy

With respect to the setting of the optimal parameters of an a-priori predefined maintenance strategy, the following approaches have been used:

- **Mathematical Approaches (MAs)**: MAs comprise all the approaches in which the optimization problem is formulated by means of mathematical equations, which are then solved by means of differential calculus to identify the optimal parameters of the maintenance strategy. In [121], a MA was used for optimizing maintenance profitability. In [122], a MA based on the Riccati equation was used to identify a sub-optimal production and maintenance plan which maximizes the total profit of a manufacturing system. In [99], a MA was proposed to optimize the inventory management and the scheduled maintenance strategy of a single unit. In [44] and [127] a MA was used for scheduling maintenance considering uncertainty. In [143] a MA is developed to define the optimal imperfect preventive maintenance plan. Finally, a MA was used to optimize the prescriptive maintenance strategy of locomotive wheels in the railway industry [171]. The use of MAs for maintenance optimization is mainly limited to simple systems for which the optimization problem can be solved analytically or numerically, but it is unfeasible for complex systems unless simplifications of the system behavior are introduced.
- **Mixed integer programming (MIP)**: MIP is the area of optimization that addresses optimization problems with continuous and integer variables in the objective or in the constraints. The problems can be linear (MILP) or present non-linearities (MINLP) [211]. The application of MIP to maintenance optimization requires using integer variables to represent the possible maintenance optima. MIP was applied to the optimization of the maintenance schedule of a wind farm [89,134–136] and a power distribution system [154,155] and to the optimization of the condition-based maintenance strategy of a gas turbine considering the value of information [149]. The joint optimization of the flight and maintenance plans of aircrafts was performed using MIP in [90]. In [124], a practical integrated production and scheduled maintenance planning was addressed developing a MIP model, which considers the system's manufacturing capacity and its reliability. When some of the variables need to be modeled by means of random variables, to deal with uncertainty, Stochastic Programming (SP) is implemented [212]. SP was used to define the optimal maintenance schedule for a multi-unit system [165,202] and for the joint production and predictive maintenance optimization of a chemical plant [176]. Although its popularity, the main drawback of MIP is that the computation time tends to rapidly increase with the complexity of the systems [213].
- **Dynamic Programming (DP)**: DP is a method for solving multi-stage decision problems [214]. It is based on the concept of breaking down complex problems into simpler sub-problems. For example, for problems which involve long time horizons, DP constructs a sub-problem to be solved recursively, at each time step. DP was used to determine the optimal maintenance strategy of road networks considering budget constraints [96]. It was also applied to the optimization of the scheduled maintenance plans considering spare parts inventory management [111] and of the replacement strategy under uncertainty for assets in the mining industry [179]. In [164], a DP-based methodology for the optimization of the maintenance check schedules in the aeronautical industry was presented. DP was also proposed to determine the optimal maintenance strategy for power cables, considering the stochastic nature of cable failures [107], and used to deal with the optimization of lifetime-extending maintenance decisions for aging infrastructures [160] and equipment under parameters uncertainty [201]. The main issues with DP are the curse of dimensionality and the need of explicitly defining the transition probabilities among all the possible system states, which makes it unsuitable for complex systems [215].
- **Metaheuristic Search algorithms (MSAs)**: Metaheuristics are computational procedures used to approximate the solution of an optimization problem by iteratively improving the candidate solutions [216,217]. Genetic algorithms (GAs) are one of the most popular MSAs. They are based on the principles of genetics and natural selection [218]. GAs were applied to set the degradation threshold for condition-based maintenance [83], to choose the best maintenance plan for a network of infrastructure facilities [157], to schedule preventive maintenance interventions in the manufacturing and railway industries [106,173]. In [137,142], GAs were used to optimize the scheduled maintenance strategy of a wind farm considering the stochasticity of wind power production. GAs were applied to identify the opportunistic maintenance strategy for industrial components [195,200] and the condition-based maintenance strategy of degrading nozzles of gas turbines [151]. Also, GAs were used to optimize the scheduled maintenance strategy of a multi-unit system [199], the inspection and maintenance planning of pressure vessels [108], the opportunistic maintenance plan of an onshore wind farm considering the dependencies among the components [138] and the deterioration thresholds for condition-based maintenance [125]. Multi-Objective GAs (MOGAs) were adopted for the optimization of the preventive maintenance plan [120] and the inspection policy of a safety system [219], simultaneously considering several optimization criteria. Finally, in [118], a GA-based framework was developed to analyze the advantages of optimizing the scheduled maintenance plan starting from different initial guesses of the maintenance policy in manufacturing industry.

  Other MSAs used for maintenance optimization are: Grid search, Nelder-Mead algorithm [220], Harmony Search algorithm [221], Differential Evolution [222], Particle Swarm Optimization algorithm [223], Simulated Annealing [224], Artificial Colony Optimization algorithms, e.g., ant colony optimization [225] and artificial bee colony [226]. Grid search was used to set the optimal scheduled maintenance interval in the power distribution industry [101], to optimize the mixed maintenance strategy of battery packs [156], to compare several production, setup and maintenance policies of a manufacturing system [116], and in the wind power industry [131,141]. Nelder-Mead algorithm was used to develop a simulation and optimization platform to analyze the performance of several maintenance policies in manufacturing industry [117]. Harmony Search algorithm was used to find the best maintenance strategy for bridges infrastructures [158]. Particle Swarm Optimization algorithm was applied to optimize the predictive maintenance interval of a manufacturing system [119] and the opportunistic maintenance strategy for a wind farm [139]. Simulated Annealing [224] was applied to find the optimal scheduled maintenance plan of bridge networks [159] and of multi-unit systems [126]. Ant Colony Optimization was used to optimize the maintenance scheduling of multi-unit systems [128] and offshore wind turbines [132], whereas an Artificial Bee Colony was applied to the optimization of the opportunistic maintenance strategy of a wind farm [227]. MSAs are simple to understand and easily adaptable to different optimization problems. On the other hand, they are slow to converge and do not guarantee convergence towards the global optimum.

4.3. Approaches for the selection of the optimal maintenance actions

The most applied approach for the direct selection of the optimal actions to be performed is reinforcement learning:

- **Reinforcement Learning (RL)**: RL is a branch of machine learning, based on DP, in which the learning agent learns the optimal set of actions to maximize a properly defined reward function by interacting, in a trial and error manner, with the environment [215]. Differently from DP, model-free RL does not require the definition of the transition probabilities among the system states, which makes it suitable for dealing with maintenance optimization of complex systems. When an artificial neural network is employed as learning agent, all the available sources of information, including predictions about the future evolution of components health state and operating conditions, can be exploited as input. This can help the development of condition-based and predictive maintenance strategies, which receive data from the systems in real time. Also, the output can be the best action to be performed at every time step, resulting in a prescriptive maintenance strategy, without the need of a-priori selecting a maintenance strategy [81,110]. RL was used to select the best time to perform maintenance, assuming a condition-based maintenance framework [198] and to optimize the time between consecutive maintenance interventions assuming a scheduled maintenance strategy [180]. In [147], gas turbine parts flow was optimized by means of RL, and tabular [152] and neural network-based [153] RL were applied to the O&M optimization of power grids. RL was applied to find the optimal maintenance strategy for a deteriorating pumping system equipped with health monitoring capabilities [95] and to optimize the opportunistic maintenance strategy for a manufacturing plant in [127]. Also, it was applied to the optimization of the maintenance strategy considering multi-state systems [73], a wind farm [81,85], aeronautical systems [86], a steel manufacturing line [110], infrastructures [87] and a generic multi-component system using ML. Finally, RL was applied to oil & gas pipeline networks [168] and to nuclear power plants prescriptive maintenance optimization [146,148]. Despite its advantages, RL applications are limited by the large computation cost and by the non-guaranteed convergence of the solution to the optimal one [215].
- Other approaches, already commented in Sections 4.1 and 4.2, have been applied for the selection of the optimal action to be performed. For example, MIP was applied to the optimization of the prescriptive maintenance strategy of railway infrastructures [172] and DP was used to determine the optimal maintenance strategy for bridge decks [104].

5. Findings

In this Section the challenges related to maintenance optimization in Industry 4.0 are analyzed (Section 5.1) and the emerging trends in the methods to address them are discussed (Section 5.2).

5.1. Challenges in maintenance optimization

The following practical challenges of maintenance optimization in Industry 4.0 emerge from the previous sections: (1) complexity of the industrial systems, (2) data acquisition and processing, (3) new optimization criteria and (4) prescriptive maintenance.

Challenge 1) calls for the development of methods able to deal with:
1.a) multipurpose systems for which multiple criteria should be jointly optimized;
1.b) the uncertainty of the complex system behavior and the stochasticity of the environment in which the system operates;
1.c) unknown dependences and inter-dependencies among components, subsystems, systems and even systems of systems [228,229].

These issues require to move away from static maintenance strategies, which are not suitable to deal with unexpected events, and develop dynamic maintenance strategies for adapting to the context changing in real-time [230]. Also, the extensive use of data-driven approaches in Industry 4.0 requires to properly represent and treat model and data uncertainty since its wrong quantification can lead to sub-optimal or even erroneous decisions [230].

With respect to challenge 2), Industry 4.0 makes data acquisition and processing technologies easily accessible. However, the tradeoff between the opportunities of exploiting new KID for maintenance optimization and the capital investments required to purchase the sensors and software necessary to perform ad hoc analyses and to properly train the operators to use the outcomes for their decisions on operation, control and maintenance [93], should be carefully evaluated [231]. For safety critical systems, e.g., nuclear power plants, aeronautical systems, or for systems in which maintenance cannot be easily performed, e.g., offshore wind farms, the advantages of using new sources of KID have been intensively studied [232] and several approaches have been proposed. Notice that the approaches should, on the one hand, properly manage the increasing KID becoming available during the system life cycle and, on the other hand, they should deal with the fact that the KID for new technologies and production processes may be, initially, not sufficient for the implementation of advanced maintenance strategies, such as predictive or prescriptive ones.

For what concerns challenge 3), Industry 4.0 comes in a historical time in which new challenges related to environment and modern society are receiving an ever-increasing attention. The concepts of sustainability and resilience are getting more and more critical and need to be considered by the companies, together with safety and economics-related objectives. Despite their importance, their consideration is not widespread among practitioners and it is typically limited to qualitative aspects due to the lack of formal metrics for their evaluation [191].

Finally, with respect to challenge 4), Industry 4.0 is changing the perception of maintenance: from monitoring the degradation state of the components and anticipating their failures to prescribing the most suitable action to optimally manage the whole system considering the dynamic production environment in which it is embedded [19]. This requires the development of an optimization framework suitable to process all sources of information available, with the associated uncertainties, and manage the large number of system states and possible maintenance actions.

5.2. Trends in maintenance optimization methods

In response to the challenges presented in the previous subsection, the emerging trends of maintenance optimization methods are here analyzed. Table 6 reports the main trends and their impacts on the definition of the optimization problem in terms of KID, $\boldsymbol{K}$, optimization criteria, $\boldsymbol{f}(\boldsymbol{x})$, and outcomes, $\boldsymbol{x}$.

5.2.1. Complexity of the industrial systems

With respect to the joint optimization of multiple criteria (challenge 1.*a*) in Section 5.1), MCDM and MSAs are expected to gain attention for application in the next years. The value of MCDM approaches lies in the fact that they are suitable to deal also with qualitative aspects, that they provide easily interpretable solutions and that they do not require any particular expertise in information technology. As pointed out in [233], MCDM approaches, especially AHP, have been applied to solve problems of maintenance strategy selection in which the best maintenance strategy among several alternatives is to be selected considering requirements at the organizational level and company goals. Given the subjectivity of the results, which is due to the qualitative nature of the criteria and the use of expert's knowledge for the evaluation, it is expected that the research in this area will move towards the combination of MCDM with methods to manage uncertainty, such as FL [234], and the use of big data to extract more objective information.

MSAs have been shown to provide optimal maintenance solutions for complex systems characterized by significant uncertainty in their behavior. They are adaptable to many different problem formulations

Table 6
Findings of the present review.

Trends in Industry	Consequences on the maintenance optimization problem K	f	x	Trends in optimization approaches
Complexity of the industrial systems: • Multipurpose systems; • Large uncertainty in the system behavior and stochasticity of the environment; • Unknown dependences and inter-dependencies among components and subsystems.	• Need to manage uncertainty in data and models; • Need to extract information about components dependencies from data.	Need to jointly optimize multiple criteria.		• Interest in multi-objective optimization, e.g., MCDM, MSAs; • Interest in AI and ML techniques to manage the inter-dependencies among the components, e.g., MSA, RL; • Interest in AI and ML techniques intrinsically able to treat uncertainty, e.g., MSA, RL; • Enhancement of MCDM with FL and use of SP
Advancements in sensors and sensor technology	Need to deal with: • Large amount of data; • Heterogeneous data (numerical signals, images and texts).			• AI and ML techniques to manage big data and extract information from them; • Reduced dependence on experts' knowledge.
Availability of AI algorithms for data mining	Possibility of exploiting: • Real time estimations of the present and future health states of system components; • Estimation of present and future operating conditions.			Integration of AI and ML techniques, e.g., NLP, CNN, within the optimization approach.
New and more challenging performance and safety goals		New criteria: • sustainability/environmental impact; • resilience.		• Multi-objective optimization; • Methods to consider quantitative and qualitative criteria, e.g., MCDM.
Operation and maintenance considered as two sides of the same coin (prescriptive maintenance)	Possibility of exploiting: • Detection, diagnostic and prognostics information; • Estimation of present and future operating conditions.		Need to identify optimal operation and maintenance actions to be performed.	Increasing interest in new optimization approaches, i.e., RL

and can be used also with non-differentiable objective functions. Despite their popularity, GAs require the empirical setting of some hyper-parameters, such as population size, crossover and mutation probabilities, whose setting can affect both the goodness of the solution and the convergence speed. In this context, Self-Organizing GAs, which automatically adapt the hyperparameters to the characteristics of the specific problem, are a promising research direction [235]. Limitations of MSAs are that they do not guarantee convergence to the global optimum and the computation of the fitness value of the candidate solutions can be very demanding. This latter problem can be tackled by developing fast surrogate AI-based models for the computation of the fitness.

With respect to the management of the uncertainty induced by the increased complexity of the systems in a stochastic environment (challenge 1.*b*) in Section 5.1), new ML approaches, such as RL, are expected to further rise in popularity. In RL, the learning agent learns how to deal with the stochasticity of the environment and the variability of the effects of the performed actions by directly interacting with the environment [236]. Another major advantage of RL is that it tackles the problem of maintenance management dynamically, i.e., considering the effects of the O&M actions on the future system behavior and degradation evolution, which allows identifying the actions to be performed at every decision time [54]. Despite these potentialities, the application of RL to maintenance optimization of complex systems is still limited by the following issues: *i*) the large computational effort, which is due to the low convergence speed of RL and *ii*) the difficulty of explaining the rationale behind the selection of the maintenance actions, which, in some cases, may appear counterintuitive and, therefore, obstacles its practical application. To overcome the latter limitation, studies are being devoted to the development of explainable RL [237], with the objective of justifying the actions suggested by the RL agent. Finally, the implementation of the most promising RL approaches, which are based on deep learning, require a great amount of data and the development of an accurate and realistic model of the environment the learning agent has to interact with. Indeed, despite the learning agent can discover the optimal maintenance policy by means of direct interactions with the real-world system, this turns out to be unfeasible for economic, safety and time issues [215]. Specifically, due to the trial-and-error nature of the learning process, the agent would need to perform several times the actions suggested by the algorithm to explore their outcomes, leading to economically inconvenient and unsafe system management in the early stages of the learning process, when the actions selected are not yet optimal. To improve this issue, the learning agent should be trained using a white-box model of the system representative of the real-world environment.

Other approaches, such as MCDM and MIP, have been shown to be suitable to deal with uncertainty when combined with FL and SP, respectively, whereas some other approaches, such as MSAs and DP, have already been successfully applied to maintenance optimization considering uncertainty [142,201,202,205].

With respect to the management of unknown dependencies and inter-dependencies among components and subsystems (challenge 1.*c*) in Section 5.1), AI and ML algorithms have been used to identify dependencies among components from the information collected from the system. For example, alarms signals have been used to identify dependencies in complex technical infrastructures, allowing the reduction of the computational burden of classical association rule mining approaches [238]. In the context of Industry 4.0, these approaches are expected to attract the interest of the researchers dealing with complex systems of systems, since they can discover previously unknown dependencies. Furthermore, being these methods able to identify dependencies among the components of different nature, they can be extremely useful when opportunistic maintenance is adopted, since they help grouping different components to be maintained during the same maintenance opportunity [239].

5.2.2. Data acquisition and processing

The second trend highlighted in Table 6 is related to the advancements of Industry 4.0 in sensors and sensor technology, which makes available a large amount of heterogenous data containing valuable information on the system state, the degradation of the components and the environment. Specifically, the use of historical data, such as signal values, images and maintenance reports, and of real time information collected from the system is expected to reduce the dependence of the maintenance optimization on the subjectivity of experts' knowledge and, therefore, contributing to reduce the uncertainty and leading to a more unbiased decision-making process. In this regard, one of the main challenges of maintenance optimization methods is to fully exploit all the available KID. To this aim, MAs and MCDM approaches are expected to be replaced by MIP, MSAs and RL, which have been shown to be able to manage large amounts of data in optimization problems [240]. In particular, RL can be trained including feedbacks from on-field operators, allowing the learning agent to learn how they would act in a specific situation [241].

The integration of new AI algorithms (third trend in Table 6) in maintenance optimization approaches is a necessary research direction to take into high consideration, especially considering the demand for predictive and prescriptive maintenance. Also, that data-driven approaches are capable of dealing with uncertainty [242]. Yet, although applications of autoencoders to detect anomalies [243,244], DNN to real-time estimate the present and future health states of components [245], Recurrent Neural Networks (RNN) to catch the dynamic evolution of the signals [246,247], CNN to classify images [248] and NLP to extract information from texts [249,250] have been proposed, the effective integration of these algorithms into the methods for maintenance optimization is still in its infancy. The challenge is to pass from the capability of performing fault detection, diagnostics and prognostics on a single component to optimize the maintenance of a complex system composed by interacting and dependent components using the information provided in real time by fault detection, diagnostics and prognostics algorithms [58].

5.2.3. New optimization criteria

Although Industry 4.0 includes some objectives in terms of energy efficiency and environmental impact [251], its original concept focuses on enhancing performance, efficiency and safety of industry by means of the possibilities provided by the technological advancements in AI, cyber-physical systems, internet of things and robotics. In the last few years, the interest of modern society has broadened to new challenges related to resilience and sustainability. Industry 5.0, which has been proposed as an extension of Industry 4.0, focuses on the role of research and innovation to support industry in a long-term service to humanity [251,252], taking into account the worldwide spread challenges that affect the society the most. Consequently, maintenance optimization will definitely evolve to consider new criteria together with those related to performance and safety. This requires the definition of measurable quantities to evaluate the performance of a specific maintenance strategy with respect of system resilience and sustainability. For example, a metric to quantify resilience has been defined in [253], whereas a new metric based on return on investment was introduced to consider at the same time safety, sustainability, reliability, and resilience [254]. It can be expected that many researchers will focus on defining new ad-hoc metrics to integrate new criteria of interest in existing maintenance optimization approaches.

5.2.4. Prescriptive maintenance

The last trend highlighted in Table 6 is prescriptive maintenance, which is rapidly gaining popularity among researchers, even if the literature works related to its optimization are still very limited [56,255]. This is due to the fact that it is common to think that complex maintenance strategies are always the best solutions and that corrective maintenance should always be avoided [93,256], which is not always true, given that the most suitable maintenance strategy should be selected according to the characteristics of each component, e.g., functionality, costs, criticality, environmental legislations, and the company objectives. Therefore, a dynamic and flexible maintenance strategy, adaptable to the specific conditions of the system and its environment should be preferred. For this reason, we expect the developments of methodologies that require maintenance engineers to list the possible operation and maintenance actions, without a-priori selecting a maintenance strategy for all components in all conditions. According to our analysis, MIP, DP and RL emerge as possible ways to tackle this issue, but it is expected that other approaches will be proposed to optimize prescriptive maintenance in the near future.

5.2.5. Further comments

Table 7 reports the classification of the considered papers according to the adopted optimization approaches and the industrial field considered. It can be noticed that most of Industry 4.0 applications focus on the use of MIP, MSAs and RL in manufacturing, energy and aeronautical industries. Also, few works consider real-world case studies, whereas many works focus on generic multi-unit systems. This highlights that the gap between maintenance theory and practice is still present and needs to be narrowed by means of capital investments by the companies and more realistic case studies by the researchers. Also, noticed that, although many industrial fields were not explored, the developed methods are general and can be easily transferred to other field where the same sources of KID are available.

Finally, as already pointed out in several surveys on maintenance optimization, it is important to mention the lack of benchmarks for the evaluation of maintenance strategies on well-defined case studies. In [257], a benchmark has been proposed to compare the performance of different algorithms for the optimization of scheduled maintenance in a power plant. Although it limits the problem to the optimization of the maintenance schedule, it can be considered a starting point for benchmarking in maintenance optimization.

6. Conclusions

In this work we have presented a survey on maintenance optimization. The analysis has been focused on the identification of the knowledge, information and data available in the context of Industry 4.0, the optimization criteria of interest and the possible outcomes of the optimization. Maintenance management professionals and researchers working on maintenance optimization can find in the present review reference case studies and a guideline to select the maintenance optimization approach given the characteristics of the industrial system and the objectives. It emerges that the complexity of the modern systems calls for the development of maintenance optimization methods able to jointly optimize several objectives and to properly treat the large uncertainty affecting the system behaviors and the environment in which they operate. Also, the advancements in sensors and sensor technology and the availability of new AI and ML algorithms offer the possibility to mine very useful information on the present and future health states of system components, which need to be properly considered for maintenance optimization at the system level. The analysis of the optimization criteria has shown that several industrial sectors are demanding to consider new metrics related to the concepts of sustainability and resilience within maintenance optimization. Also, there is an increasing interest towards prescriptive maintenance, which considers operation and maintenance as two sides of the same coin, and overcomes the need of a-priori selecting a maintenance strategy to be applied to the system during the time horizon of the optimization.

The capability of the different optimization methods to deal with the identified challenges has been reviewed. Although at the present state of the art there is not a single approach able to satisfactory tackle all the open issues, the analysis performed in this work allows concluding that multi-objective MSAs and RL-based approaches are among the most

Table 7
Classification of the considered works in terms of industrial field of application and optimization approach.

Optimization approach Industrial field	MCDM	DMG	DT	MA	MIP	DP	MSA	RL
Manufacturing industry	[70,113]	[114]	[115]	[121–123]	[84,124]	[111]	[78,116–120,125,126,128,129]	[110,127]
Wind power industry	[130]		[100]	[143]	[89,134–136,144]		[79,131,132,137–142]	[81,85]
Power production industry			[145]		[149]		[74,150,151]	[146–148]
Power distribution industry					[154,155]	[107]	[101,156]	[152,153]
Infrastructures			[157–159]			[96,104,160]		[87]
Aeronautical industry	[161]	[162]			[90,109]	[164,165]		[86]
Oil & Gas industry	[44,166,167]						[169]	[73,168]
Transportation industry		[170]		[171]	[172]		[173,174]	
Chemical industry	[72,175]				[176]		[108]	
Mining industry						[179]	[88]	
Military industry	[94]							[180]
Automation system				[177]				
Semiconductor industry			[178]					
Water distribution industry	[181]							
Data storage system					[71]			

promising maintenance optimization approaches, given their capability of dealing with the joint optimization of several criteria and with the uncertainty of the system behavior and of the environment.

CRediT authorship contribution statement

Luca Pinciroli: Conceptualization, Methodology, Validation, Visualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing. **Piero Baraldi:** Conceptualization, Methodology, Validation, Visualization, Formal analysis, Investigation, Writing – original draft, Writing – review & editing, Supervision. **Enrico Zio:** Conceptualization, Methodology, Formal analysis, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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