Taking Complexity into Account: A Structured Literature Review on Multi-component Systems in the Context of Predictive Maintenance

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Abstract. One of the most prominent use cases of a digitized industry is predictive maintenance. Advances in sensor and data technology enable continuous condition monitoring, thus, extending the opportunities for predictive maintenance. However, so far, most approaches stick to a simplistic paradigm viewing industrial systems as a single-component system (SCS), assuming independence or partially neglecting interdependencies between components. However, in practice, multiple components are coupled which interact with each other; thus, leading to a multi-component system (MCS) view. Implementing the MCS is challenging, but promises many advantages for predictive maintenance. We conduct a structured literature review to investigate the current state of research about MCS and how this can be transferred to data-driven predictive maintenance. We investigate the characteristics of MCS, the promises in contrast to SCS, the challenges of its implementation, and current application areas. Finally, we discuss future work on MCS in the context of predictive maintenance.

Keywords: Predictive maintenance · Multi-component systems · RUL · Stochastic dependence

1 Introduction

One of the most prominent use cases discussed in the context of digitization of industry or Industry 4.0 is predictive maintenance [20]. Various data-driven approaches for predictive maintenance in different industrial application settings can be found [32, 35, 40, 41]. This increasing interest from practice and science has three major reasons. First, maintenance is always a relevant topic and has huge influence on the production costs, quality, and reliability [6]. Second, the information basis increased due to the growing availability of cheap and powerful sensor technology [35, 44]. And finally, huge advances in data processing capabilities and the new rise of artificial intelligence (AI) offer new opportunities to build predictive models [45].

As a result, predictive maintenance was promoted in many industry sectors [29]. Despite the advancements in this field, current approaches predominantly rely on

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the paradigm of a SCS for their predictive maintenance models, rather than MCS [12–14, 19]. The most important reason to stick to SCS is the complexity of the system level maintenance modeling and limited algorithmic and computational power in the past [12–14]. Thus, SCS models and approaches are applied to complex systems composed of multiple subsystems ignoring their interdependencies. So far, the results are acceptable, but in practice, these assumptions are not reasonable as more precise results could not be achieved [13, 14].

AI based models realize good results for stable production processes for which good experience-based data sets are available. This is however changing as a result of mass customization, more complex production processes, and shorter product life cycles in digitized manufacturing [42]. Consequently, the production lines and their configuration change more frequently, or many different variants of one machine can be found in practice. Hence, data sets for one of those variants is small in most cases and not enough for training traditional models (small data challenge) [46]. Additionally, shorter product life cycles demand faster learning and a switch from experienced based models to data driven models. All these challenges and limitations lead to the need for new approaches which handle all these aspects properly. MCS seem promising in this regard.

MCS models and approaches are rarely used in predictive maintenance, but generally used in other research fields, such as corrective maintenance and preventive maintenance. However, the complexity of manufacturing systems, requires reliable condition monitoring, thus, various sensors are embedded within these systems for providing condition monitoring. This data can be used to predict the system health encouraging the need for state-of-the-art predictive maintenance approaches. Hence, this sounds promising to analyze the literature in these fields and to transfer the insights to data driven predictive maintenance for MCS.

The aim of this paper is to investigate the state of research on how MCS models and approaches can be used in the context of predictive maintenance. The goal is to identify promising solutions and their characteristics, advances in contrast to SCS, application areas and lastly, the challenges for their implementation. The next section provides an overview of the background with regard to MCS. In Sect. 3, the methodology used to conduct a literature review is introduced. Section 4 describes the results. Finally, conclusions are made defining the outlines for possible future work.

2 Background

2.1 Multi Component Systems

MCS are more complex than SCS as they consider a higher degree of complexity and dynamic behavior of the environment. MCS models represent a variety of components, regarding both life span and purpose, and also represent interactions between subcomponents. An MCS is defined as a system which consists of multiple components, and these components strongly interact with each other [4, 8, 15, 17]. Therefore, dependencies among system components are assumed and can be modelled. Moreover, an MCS is often described as a complex system [15] which consist of multiple interacting sub-components [7]. Also, a complex system is defined as a system, which consist of multiple components and the reliability dependency between system and components' may not be completely known [35]. Furthermore, the term MCS is mostly used as interchangeably to refer to both the system, which consists of multiple assets or engineering assets consisting of multiple components [5]. Figure 1 shows an example of an MCS – a welding device which is composed of several components such as cooling unit or hosepack. In the MCS now, interdependencies between these sub- components can be modeled and considered for analytical tasks. In the related work focusing on MCS, the interdependencies are classified into three key categories: stochastic, economic, and structural interdependencies [2, 6].

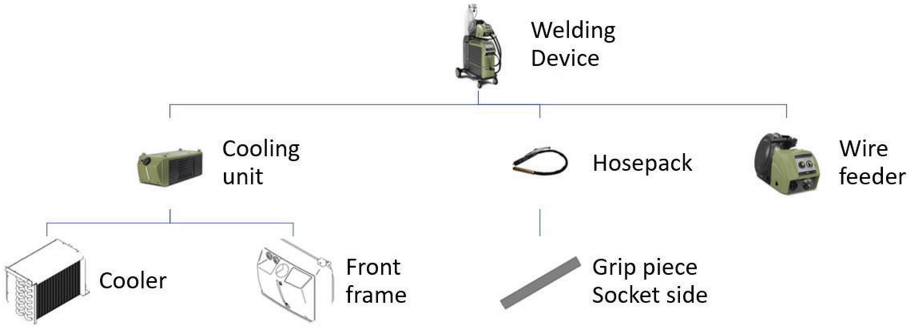

Fig. 1. Multi-layer MCS structure based on hierarchical structure.

Stochastic interdependencies between multiple components are present within the system; when the deterioration process of one or multiple component is affected from the deterioration state of other components [2, 8, 11, 19]. Moreover, the deterioration process of a component depends not only on the current state of the system and on the operation conditions of the system but also on the current state of other components which it is interacting with. For example, an old worn out component which interacts with new components, will potentially accelerate the wear rate of a new one, which in turn might have the same effect on the already worn up component [17].

Economic dependencies represent the cost relationships between components. The assumption is that the maintenance of a group of components at once lead to different costs than applying separate maintenance for each component [2, 11, 19]. In literature, two types of economic dependencies exist. The first type is noted as positive economic dependence, which provide that the joint maintenance costs for a group of components lead to cheaper costs, compared to performed maintenance on components separately. The second type is known as negative economic dependence, which in contrast provides that the joint maintenance costs of a group of components leads to higher costs than performing maintenance individually [2, 6].

Structural dependencies mean that multiple components within a system are structurally dependent [2, 3, 11, 19]. In other words, the components structurally form a part within the MCS. Whereby a failure implies actions, such as disassembly, on the other components too. For example, while replacing a component, it indirectly forces other components to be dismantled or replaced as well.

However, in the latest trend, the possibility of the fourth type of interdependencies, i.e., the resource dependence has been considered. Resource interdependence is focused on describing or modeling the dependency between a component or group of components and spare parts or even a limited number of maintenance workers [19].

2.2 Predictive Maintenance

Maintenance in industrial setting or manufacturing equipment is essential to guarantee higher quality, productivity, sustainability, and safe working environment [20]. Traditional approaches, e.g. time-based maintenance or condition-based maintenance usually perform maintenance based on the current state of devices. Time-based maintenance ensures that maintenance is performed at regular basis based on predefined time-interval [2, 6]. Condition-based maintenance uses the data gathered through multiple sensors, which are assembled within the equipment for providing condition monitoring [6].

Predictive maintenance is gaining a lot of attention in the last decade, due to the availability of condition monitoring data [35]. The aim of predictive maintenance is to identify the optimal time for maintenance and thus also in a proactive way. Implementing effective prediction offers a variety of benefits including increase of system reliability, machine availability, production performance, sustainability, system safety, maintenance effectiveness and decrease maintenance costs, number of accidents, and downtime machinery. Predictive maintenance is also defined as condition-based maintenance followed by a prediction, which uses the knowledge derived from the analysis of crucial parameters regarding the degradation of the device [20]. In most cases, the aim of prediction is to estimate Remaining Useful Life (RUL) and its confidence intervals [20].

Existing approaches rely on the SCS metaphor so far. Statistical or AI approaches are applied without considering the interdependencies of the subcomponents explicitly. However, the complexity of current manufacturing processes is increasing tremendously. On the one hand the number of components and the interactions between these components are increasing. Also, cheap sensors, powerful algorithms, increased bandwidth and ever-growing storage capacity increase the available data basis significantly. As a result of digitization and mass customization, the variability with regard to the components is increasing sharply. Usually, the number of similar product variants is large, but the data set for one specific variant is small [3]. Hence, the challenge is to transfer the insights and models from one variant to another. Traditional approaches considering only the SCS which conveniently lack to handle this particular challenge and the general requirements resulting from digitization of industry. Therefore, predictive maintenance for MCS is gaining more attention in the last years, aiming for more realistic solutions, which are applicable in real complex use cases [35].

3 Methodology

We conducted our structured literature review about MCS in the context of predictive maintenance based on Webster and Watson [31]. The literature review is conducted focusing on the period 2008 to 2019 as shown in Table 1. In order to perform the forward and backward search, Google scholar is used. Within this process 19 relevant keyword combinations suitable for the review were identified and applied to 11 Journals and 1 Conference. These journals and the conference are selected, since the MCS topic is a key focus and they have great impact factor. The search is performed with restriction to title, abstract and author-specified keywords.

Table 1. Review Matrix for data-driven solution for MCS. In the x-axis relevant keywords are listed. On the top of the table each journal/conference is represented as distinct column.

Keywords combinations / Journals and Conferences	Computers in Industry	International Journal of Advanced Manufacturing Technology	Computers & Industrial Engineering	Reliability engineering & systems safety	Journal of Intelligent Manufacturing	Journal of Manufacturing Systems	Industrial Management and Data Systems	Expert Systems with Applications	Mechanical Systems and Signal Processing	IEEE Transactions on Reliability	European Journal of Operational Research	Prognostics and Health Management, PHM, International Conference on	SUM
multi-compont + diagnosis	0	0	0	0	0	0	0	0	0	0	0	3	3
MCS + imperfect	0	2	2	3	0	1	1	0	0	0	0	0	9
MCS + failure	1	6	5	16	1	1	0	0	0	6	6	0	42
MCS + prognostics	1	0	0	4	0	1	0	0	0	0	0	0	6
MCS + diagnostic	0	0	0	0	1	1	1	0	0	0	0	0	3
MCS + information	0	0	0	7	2	0	0	0	0	0	1	0	10
MCS + data uncertainty	0	0	0	1	0	0	0	0	0	0	0	0	1
MCS + Condition Monitoring	0	0	1	2	0	0	0	0	0	0	1	0	4
MCS + predictive maintenance	0	0	0	3	0	0	0	0	0	1	0	0	4
MCS + conditions	0	4	2	1	0	0	0	1	0	0	0	0	8
MCS + degradation	0	2	2	9	1	1	0	0	0	3	1	0	19
MCS + deterioration	0	0	2	4	0	0	0	1	0	0	1	0	8
MCS + Stochastic	0	1	2	9	0	2	1	0	0	0	2	0	17
MCS + CBM	1	0	3	8	1	1	0	0	0	1	3	0	18
Multi unit system + condition monitoring	0	1	0	1	0	0	0	0	0	1	0	0	3
CBM + Stochastic dependence	0	0	1	3	0	1	0	0	0	0	0	0	5
Multi components + complex system	0	1	2	7	0	0	0	1	0	0	3	0	14
Complex systems + prediction	1	6	2	11	1	0	0	17	5	1	1	0	45
Complex systems + degradation	2	3	2	11	0	0	1	6	4	5	0	0	34
Keywords: 19 / SUM:	6	26	26	100	7	9	4	26	9	18	19	3	253
UNIQUES	4	18	11	46	4	2	2	21	6	10	6	3	133

To identify the most relevant papers, an abstract and conclusion scan is performed to the 133 distinct papers identified before. All papers that focus on providing data driven approaches to maintenance, such as preventive maintenance, time-based maintenance, condition-based maintenance, or predictive maintenance for MCS, or complex system are considered as relevant. Finally, 30 papers are selected as relevant.

Thus, 14 additional papers are identified in a backward and forward search according to Webster and Watson. Consequently, 44 papers are chosen and analyzed in detail, providing a good overview about the current research state with regard to data driven solution for MCS. In the last step, the identified papers are scrutinized in detail using the qualitative content analysis [43]. Here, some works are dropped after careful analysis, because the focus of these papers did not exactly fit the goal of this literature review, and as a result, the analysis of 31 papers is provided in the next section.

4 Results

4.1 Characteristics of MCS

MCS models provide the option to describe a system in much more detail, thus, providing a more detailed but also more complex description of reality. In the following we will present these core characteristics of MCS models we found in our structured literature review.

In the literature, dependencies between components within an MCS model are well described. These dependencies can be classified into four groups: stochastic, structural, economic, and resource-based dependence [19].

The ***stochastic dependence*** describes the effect of the health-state of one specific component towards all other related components [2, 8, 11, 30]. The main advantage of considering stochastic dependencies is a higher accuracy while estimating or predicting RUL and reliability of the system, sub-system or components. Moreover, this will provide a valuable basis to reduce overall costs, while performing cost optimization approaches. The challenge is to collect sufficient data to detect and then model stochastic dependencies.

The ***structural dependence*** focuses on the structural dependence between coupled components within a system. In this case, replacement of a component requires dismantling or replacement of other components. In literature, structure dependencies are clustered into two groups: technical dependence, where technical point of view is considered, and performance dependence where performance point of view is investigated. Modeling structural dependence, accordingly, strongly improves maintenance cost [2].

Managing maintenance actions is not a pure technical approach, economic aspects like costs or benefits are crucial as well and they are represented in the ***economic dependence***. Economic dependence shows the impact on the costs, while considering maintenance to related components instead of applying maintenance only to the failed/worn out components. Combining maintenance on multiple components, could either increase costs, heading to negative economic dependence, or decrease them, leading to positive economic dependence. The key advantage of modeling economic dependence is obviously the improvement on maintenance costs [2, 6].

Lastly, the ***resource dependence*** is focused on the relationship between components and needed resources (e.g., spare parts, human resources) to perform maintenance [1]. Typically, the following resource categories have been investigated in literature: maintenance workers, tool parts, spare parts, transport, and budget. Maintenance scheduling can be properly achieved, granted that the needed resources are available. First and foremost, organizing the needed resources accordingly, helps to improve sustainability and overall maintenance costs. In general, dependencies between components for SCS are ignored (as shown in Table 2), thus, reducing the complexity while modeling the systems, but missing important aspects which are present in practice.

Table 2. MCS characteristics in comparison with SCS.

Characteristics	SCS	MCS	Advantages
Economic dependence	No	Yes	Cost optimization
Structural dependence	No	Yes	Cost optimization
Stochastic dependence	No	Yes	Reliability, Accuracy, Cost optimization
Resource dependence	No	Yes	Availability, Sustainability
Interaction with human beings and environment	No	Yes	Reliability, Accuracy
Variability of components	Yes	Yes	Reliability, Accuracy
Stochastic reliability structure	Yes (only deterministic structure)	Yes	Reliability, Accuracy

Moreover, interaction of components with humans and their environments increases the complexity further [16]. Considering these interactions, could possibly help to improve system reliability, and fault or wear out prediction/detection accuracy. This aspect is difficult to model, because of the unpredictable nature of human behavior and the complex application context. Therefore, this aspect was not considered regarding both SCS and MCS as shown in Table 2.

Another important characteristic of MCS, is the variability between components. Usually, a system consists of a number of components, which are different regarding key characteristics, such as life span. These characteristics are important when estimating the RUL, since the prediction accuracy within this aspect is essential. Moreover, modeling this aspect properly, could also help to improve system reliability.

In the reviewed papers, the reliability structure of an SCS is often assumed to be deterministic, rather than stochastic [33, 35]. Further, the stochastic reliability structure (shown in Table 2) is another important characteristic of MCSs. However, in practice, complex MCS meets high uncertainty in the system reliability structure. Furthermore, a capability to recognize and model this characteristic can be a big advantage, when handling use cases in industrial practice.

4.2 Decision Support for Maintenance of MCS

Predicting the RUL for a system requires understanding of how the degradation process of system evolves over time and accurate estimation of the deterioration state. Modelling the degradation process for MCS requires modeling of MCS characteristics, such as interdependencies to provide reasonable estimation and prediction. Therefore, in the last decade, this topic has gained more research interest [38].

Predicting the RUL consist of two key parts, known as diagnostics and prognostics (see Table 3). On the one hand, diagnostics aims to identify the need for modeling the interactions between components. On the other hand, prognostics focus more on modelling the interactions, while predicting the RUL of components, or the whole system. In the following, we will discuss the results of various works with focus in both diagnostics and prognostics for MCS. In particular, the deterioration relationship between components and the advantages of interdependencies between components, the application area, and the methods used to model interdependencies are discussed.

In literature, researchers stated the need for monitoring and modelling interactions between MCS components in fault identification and maintenance support. Assaf et al. [17, 36] introduced approaches on fault detection with a focus on the stochastic interdependencies between components. Moreover, all these works focus on 1-1 mutual deterioration relationship between components within an MCS. Results are evaluated using both a Gearbox testing platform and a numerical example. For this purpose, methods such as Short Time Fourier Transform (SFTF) for time frequency domain analysis was introduced [17, 36]. The main advantage of using this method is that, it can denoise signals, which contain data from different components (mixed nature of the signal), thus, providing high accuracy on extracting components health indicators. Assaf et al. [36] shows that using unsupervised methods such as Gaussian Mixture Models, the health indicators can be extracted automatically and in an accurate way.

In the analyzed literature, the focus has not been only on diagnostics, but also on RUL estimation for MCS. In this case, Xu et al. [39], proposes a state discretization technique based on change point detection algorithm to model state-rate stochastic interdependences between components. The main advantage of this method is that it can handle multiple change point problems for multivariate time series with different levels of dependences. The evaluation is performed using a simple Gearbox platform which consists of two components. Furthermore, only a 1-1 mutual deterioration relationship between components is considered.

Bian et al. [33] proposes an approach in which stochastic interdependences between components are modeled as continuous-time stochastic, and the degradation interactions as change points in signals using a change point algorithm based on Schwarz's criterion [34]. This enables the option to deal with linear degradation data, and discrete type degradation rate interaction. This approach considers only 1-1 and 1-M ($M > 1$ and represents number of components) interactions between components.

Lee et al. [35], introduced a predictive maintenance framework for MCS based on discrete time Markov chain models for modeling deterioration processes of components and BN used to model the reliability structure of the system. The key advantage of using this approach is that it can properly handle the uncertainties and component reliability. The author did not provide explicitly the information regarding the deterioration relationship within this work. Yet, using BN to model and predict the reliability structure of the system provides enough evidence, that only 1-1 and 1-M deterioration interdependencies between components are considered.

The literature focused on RUL estimation for MCS in real use cases, such as Turbofan Engines and Civil Aerospace turbine [37, 38], stochastic interdependencies are modeled using Bayesian hierarchical models. The key advantage behind this approach is that it can handle both high uncertainty and non-linear degradation data. By definition, the introduction of Bayesian-based models shows that the 1-M relationship is handled accordingly.

Table 3. Result's overview of the research works with focus on modeling RUL.

Paper	Method	Deterioration relationship	Application area	Advantages	Focus of the approach
[17]	STFT	1-1 mutual interaction	Gearbox testing platform/numerical example	Mixed nature of the signals, high accuracy on extracting component health Indicators	Diagnostics
[36]	STFT and Gaussian Mixture Models			Automatically and accurately extract components health indicators	
[39]	State discretization technique based on change point detection algorithm		Gearbox	Multiple change point problems for multivariate time series with different levels of dependences	Prognostics
[33]	Change point detection and Bavesian framework	1-1 and 1-M	Simulation study	Linear degradation data and discrete type degradation rate interaction	
[35]	Markov chains and Bavesian network (BN)			Uncertainties and component reliability	
[37]	Bayesian hierarchical Model		Civil aerospace gas turbine	High uncertainty and non-linear degradation data	
[38]	Ratio has ed change point detection and hierarchical Bayesian model				
[5]	Multiple linear regression and Gaussian Process Regression		Industrial cold bos in a petrochemical plant	Multivariate time series data and relationship between variables, which is not explicitly defined	

Rasmekomen et al. [5], models state-rate degradation between components using a regression-based approach and is evaluated using a two-component real use case of industrial cold box in a petrochemical plant. The approach followed within this work, consisting of two key steps. In the first step, the deterioration behavior of each component explicitly is modeled using a multivariate linear regression model. Next, the Gaussian process regression is used to model the interdependencies between components. Within this work, 1-1 and 1-M deterioration relationship was studied.

In general, the focus in this research area is more into use cases of simple MCS (two components system), or simulation studies, rather than on real use cases of complex MCS, which consist of multiple components, and various complex interdependencies are present.

4.3 Improve Decision Quality

Reliability and cost optimization in the context of predictive maintenance for industrial settings are of central interest. Therefore, the key focus in our selected papers was primarily on improving maintenance quality, but also on precise and accurate prediction of fault events or RUL. In the considered papers, on the one hand, the focus is primary on finding the optimal time for decision support. On the other hand, various papers focus not only on improving the maintenance timing [3, 6, 8], but also on the required type of maintenance [2, 21, 22]. Hence, in this section, we will introduce several works and their application highlighting these aspects.

In our review we found solutions with a focus on improving decision quality by only estimating the optimal time to perform maintenance. These solutions take the advantages by modeling only economic dependencies, or together with structural or stochastic dependencies. Laggoune et al. [3], proposes an opportunistic replacement policy for MCS over hydrogen compressor in an oil refinery is introduced. The introduced opportunistic policy considers the economic dependence between components. Moreover, in this work, the small data challenge was successfully handled by considering the bootstrap and Weibull technique.

Niu et al. [8], introduces an approach, which estimates the optimal maintenance time for components within a braking system of rail vehicles was proposed. The non-parametric modeling was applied on the component level, and later this model is used to find the global optimization on the system level. Nguyen et al. [6], introduces a decision-making process considering multi-level details for MCS. This approach provides high quality decision regarding the optimal time for maintenance by considering stochastic, structural, and economic dependencies. Do et al. [12], introduces a model for a Gearbox system which aims for optimal maintenance time for a two-component system considering stochastic and economic dependencies. In this case, it has been shown that the state dependence between components is important and it has a significant impact of 29.3% on the cost. Kammoun et al. [10], introduced a new approach based on data mining to optimize selective maintenance for MCS. This approach aims to find the optimal maintenance time by considering economic dependencies. This solution is suitable, if only maintenance data are available and sensor data are missing. Van Horenbeek er al. [27] introduced a new approach, which considers stochastic, structural, and economic dependencies to provide optimal maintenance time by considering short-term information, such as component degradation, into maintenance planning. We found several papers, which consider only economic, or altogether with stochastic, or structural dependence between the components and aim to improve decision quality by taking into account only optimal maintenance time [9, 11, 13, 14, 18, 24–26, 28, 32].

The introduction of stochastic dependencies while aiming for optimal timing of maintenance is complex. Rasmekomen et al. [5] introduced an optimization of condition-based maintenance policy for MCS considering state-rate interactions. This works shows that the decision quality could be improved by considering the stochastic interdependencies between components. Feng et al. [4] provides a novel approach based on stochastic dependencies in which one dominant/independent component and "n" statistically dependent components are used to optimize the maintenance timing.

In our selected papers, we found various works with focus on improving the quality of decision support, which do not restrict their focus only on optimal time, but also consider the required maintenance type, or the relevant sparse parts. For instance, Verbert et al. [21], proposed a new approach for railway network case, which represent a typical MCS. In this work, the economic and structural dependencies are investigated and modeled providing significant impact on decision quality. Furthermore, this approach provides decision support by considering both the optimal time, and the required type of maintenance. Another approach for improving the decision quality for high pressure in casting machine was introduced in [22]. Besides the optimal time for maintenance, also the required relevant maintenance action is provided. Nguyen et al. [2] proposes a joint optimization of optimal maintenance time and required spare parts using the advantage of prognostic information and economic dependency. Moreover, the structural importance together with predictive reliability is considered to improve the decision-making process. Duan et al. [23], introduces a new approach considering the economic dependencies for feed system of a machine tool. The aim was to improve the decision quality by introducing both the optimal time and maintenance type. This approach is suitable for MCS with multiple identical components.

Summarized, the focus of the papers on improving decision quality for MCS is more focused on estimation of optimal time. However, there are various papers, which alongside optimal time, also focus on other aspects, such as maintenance type, or the relevant spare parts. Furthermore, several solutions are either evaluated against simple MCS, usually consisting of two or three components, or the approaches are evaluated using simulation studies, rather than real life use cases.

5 Conclusion and Future Work

In this paper, we investigated the application of MCS models and approaches in the context of predictive maintenance. Our review identified different interdependencies and their application settings. Our review provides an overview of already existing approaches and can be used to select suitable approaches. The review also showed that MCS are superior to SCS in terms of prediction quality and decision quality. Additionally, MCS provide advanced decision perspectives which are useful in the context of predictive maintenance. To our best knowledge, the M-M relationship of stochastic interdependencies were not considered in the current works and is an aspect which requires more attention from the research community.

Our literature review also showed that research on MCS in the context of predictive maintenance is in an early stage. Most MCS presented in the investigated papers are simple, i.e., having 2–5 subcomponents and they are evaluated in simulation scenarios. Thus, the work on MCS in the context of predictive maintenance can be considered as mostly theoretical and more research on the implementation and application of MCS in practice is needed. This can be also considered as the promising direction for future research.

Second, researchers frequently mention that data collection and modelling of interdependencies between MCS components is a complex task. However, so far, no approaches helping deciders in this process can be found until now. Hence, studies, frameworks, guidelines supporting this modelling effort seem very useful and are considered as a further avenue for future research.

Third, most authors highlight the advanced decision support features of MCS models, but literature lacks work on representations or interfaces so far. However, to evaluate this in practice, suitable approaches are needed. This is especially true as maintenance workers also expect a certain level of explainability before they trust and accept MCS solutions. Hence, to push the acceptance of MCS in industrial practice more research on the presentation of MCS recommendations is needed.

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