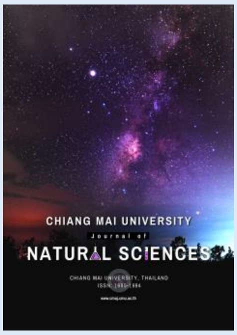

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Research article

Smart Mechanical Systems for Manufacturing in the Era of Industry 4.0: Condition-Based Predictive Maintenance and Dynamic System Modification for Small and Medium-Sized Enterprises

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Abstract We are in the era of the fourth industrial revolution. Which highlights adaptability, monitoring, digitisation and efficiency in manufacturing as a result of the design of new smart mechanical systems. A central role in Industry 4.0 is played by maintenance and, within this framework, we define and review condition-based predictive maintenance. Thereafter, we propose a new class of smart mechanical systems that self-optimise utilising both condition-based maintenance and dynamic system modification. Akin to smart structures, smart mechanical systems will recognise and predict faults or malfunctions and, subsequently, self-optimise to restore desirable system behaviour. Potential benefits include increased reliability and efficiency while reducing cost without the requirement of highly skilled technicians. Thus, small and medium-sized enterprises are a specific target of such technology due to their increasing level of automatisation within Industry 4.0.

Keywords: Condition-based predictive maintenance, Condition monitoring, Dynamic system modification, Small and medium-sized enterprises

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INTRODUCTION

The fourth industrial revolution - Industry 4.0 for short - is bringing forth a wide range of changes to manufacturing. This revolution results in new challenges and opportunities for small and medium-sized enterprises (SME) in the maintenance of manufacturing systems. Costs associated with maintenance comprise a significant part of manufacturing and new intelligent approaches promise to reduce these. Three main paradigms can be identified for maintenance management (Mobley, 2002):

• Run-to-failure: unscheduled repair is performed, and equipment operates until it fails;

• Preventive maintenance: a regular set of actions is performed to reduce the probability of machine or component failure;

• Predictive maintenance: operating condition of the mechanical system is used to properly schedule maintenance.

Run-to-failure is the most elementary approach to manage maintenance, but it is less effective as it is not known when the mechanical systems will fail or if this failure could result in catastrophic damage. The ever-growing importance of maintenance has led to a wide use of preventive approaches.

Periodic machine downtimes are scheduled for maintenance operations, e.g., in order to replace components at the end of their useful life. The effectiveness and efficiency of a preventive approach is directly correlated to the proper scheduling of the maintenance. Indeed, if the interval between maintenance is too large, an unforeseen failure could occur. Conversely, a maintenance interval that is too small leads to unnecessary maintenance costs.

The availability of inexpensive, smart sensors and real-time data has opened new horizons for increased reliability and diagnosability resulting in increased efficiency and decreased costs. The approach using smart sensors in maintenance is referred to as condition monitoring, which analyses the "health" of a mechanical system on the basis of sensor measurements. The data collected are then used directly or with correlating models. The sensors of such mechanical systems acquire vast amounts of data that result in accurate assessment of the operating conditions of the system. These include both direct and derived measures, including position, velocity, acceleration, vibration, temperature and pressure.

The use of sensors together with Industrial Internet of Things (IIoT), wireless communication and cloud infrastructure leads to condition-based predictive maintenance (CPM) that can lower machine downtime and, therefore, increase productivity (Jardine et al., 2006). With the availability of higher computational capacities, more data can be processed faster to facilitate the online networking of systems. These networks collect and store historical data of the system or of related systems in databases, which are readily accessed and compared with the current state of a system. Data sets include manufacturing quality, energy efficiency and system health. Health assessment monitors system behaviour for any change of the operating states that would imply a possible damage or subnormal behaviour; this can, in turn, lead to system failure or indicate a possible system failure. With this information, decisions can be made remotely to plan the timing of maintenance or interim provisions to avoid catastrophic failures. CPM is carried out by collecting and assessing real-time data. Based on this, this smart maintenance planner recommends maintenance based on the current condition of the system, the approximation when the machine will fail and which parts should be replaced to avoid failure (Alaswad and Xiang, 2017). Once a CPM system registers the need of future maintenance, the replacement of damaged parts is scheduled.

Wear, friction, manufacturing errors and misalignment are all factors that negatively affect the useful life of mechanical systems. However, they do not necessarily result in system failure, but, rather, lead to changes in the system properties (e.g., geometric or inertial properties), resulting in suboptimal performance. When such change in system parameters is detected, instead of more traditional maintenance of part replacement, which requires a system shutdown, this paper suggests the possibility to modify or tune the system. The modification of the mechanical system requires a redesign of the system itself to change its dynamic behaviour. Such a strategy is known as (structural) dynamic modification, DM, (Avitable, 2003). DM is a model-based methodology that assigns the desired dynamics of the system by means of passive or active modifications. The choice of parameters to be changed and their values are determined by design optimisation, typical of the design of the "original" system (e.g., Baier et al., 1994; Rao, 2000; Wehrle et al., 2017). The desired dynamic behaviour is usually expressed through the natural frequencies and their corresponding mode shapes. Passive DM methods modify the system behaviour by means of a proper placement of mass, damping and stiffness (Belotti et al., 2015; 2017; Tsai et al., 2018). Conversely, active DM techniques use smart sensors (e.g., Bragg fibres) and smart actuators (e.g., piezoelectric and magnetostrictive actuators) (Ouyang, 2011). The sensors measure the state of the system, which is then used to properly control the smart actuators, whose control forces behave as active masses, springs and dampers. Recent studies have also investigated the possibility of modifying the system dynamics by means of a concurrent approach that exploits both the active and the passive modifications (Belotti et al., 2018b). This hybrid approach enlarges the capability of assigning the desired dynamic behaviour, ensuring a much closer fulfilment of the desired system modification.

Therefore, DM tunes system parameters in response to a change in the state conditions resulting from wear, damage or unforeseen usage. Using design optimisation methods considering the changed states, system parameters are redesigned optimally (Wehrle et al., 2019). This allows the running of the machine and its re-tuning for the postponement or, in the most successful cases, avoidance of the maintenance.

In the following, CPM is defined and quantitatively and qualitatively reviewed. We then propose and discuss a future class of smart mechanical systems in which CPM is coupled with DM. This will enable manufacturers - in particular SMEs - to reduce costs and increase performance.

MATERIALS AND METHODS

To assess the research activity in CPM, a quantitative bibliometric evaluation of the published papers has been done. This analysis was carried out including the keywords predictive maintenance and condition-based maintenance in title, abstract and keywords using the scientific database Scopus. Papers published between 2000 and 2020 were considered. The following searches were carried out:

- "predictive maintenance"
- "condition-based maintenance"
- "predictive maintenance" AND "condition-based",
- "predictive maintenance" AND "Industry 4.0",
- "condition-based maintenance" AND "Industry 4.0",
- "predictive maintenance" AND "condition-based" AND "Industry 4.0".
- "predictive maintenance" AND "SME",
- "condition-based maintenance" AND "SME",
- "predictive maintenance" AND "condition-based" AND "SME".

Additionally, a qualitative analysis of the published papers on CPM has been carried out by classifying them on the basis of the occurrence of a fault condition and on the basis of the main techniques employed to process the data coming from the monitored systems.

RESULTS

Bibliometric results

The results of the quantitative bibliometric analysis are shown in Figure 1, where the length of each coloured bar corresponds to the number of papers per search. The reported numbers clearly show the steady increase in research records in "predictive" and "condition-based" maintenance over the past two decades. The former almost doubled in the last two considered years (i.e., from more than two to four hundred records) while the latter appears more than three hundred times since 2012. On the contrary, "condition-based" and "predictive maintenance" have been "rarely" used together even if their combined use has been increasing in the recent years. "Industry 4.0", being a term introduced in 2011 and in the German area, appeared recently in the literature, but its link with predictive and/or condition-based maintenance has been growing quickly. This shows how it could be considered a new and worthy of attention research topic (or application domain) for the Industry 4.0 technologies and concepts. Finally, although maintenance is very important for the competitiveness of the SME, in the literature there are only a few papers addressing such a very important topic directly tailored for SMEs.

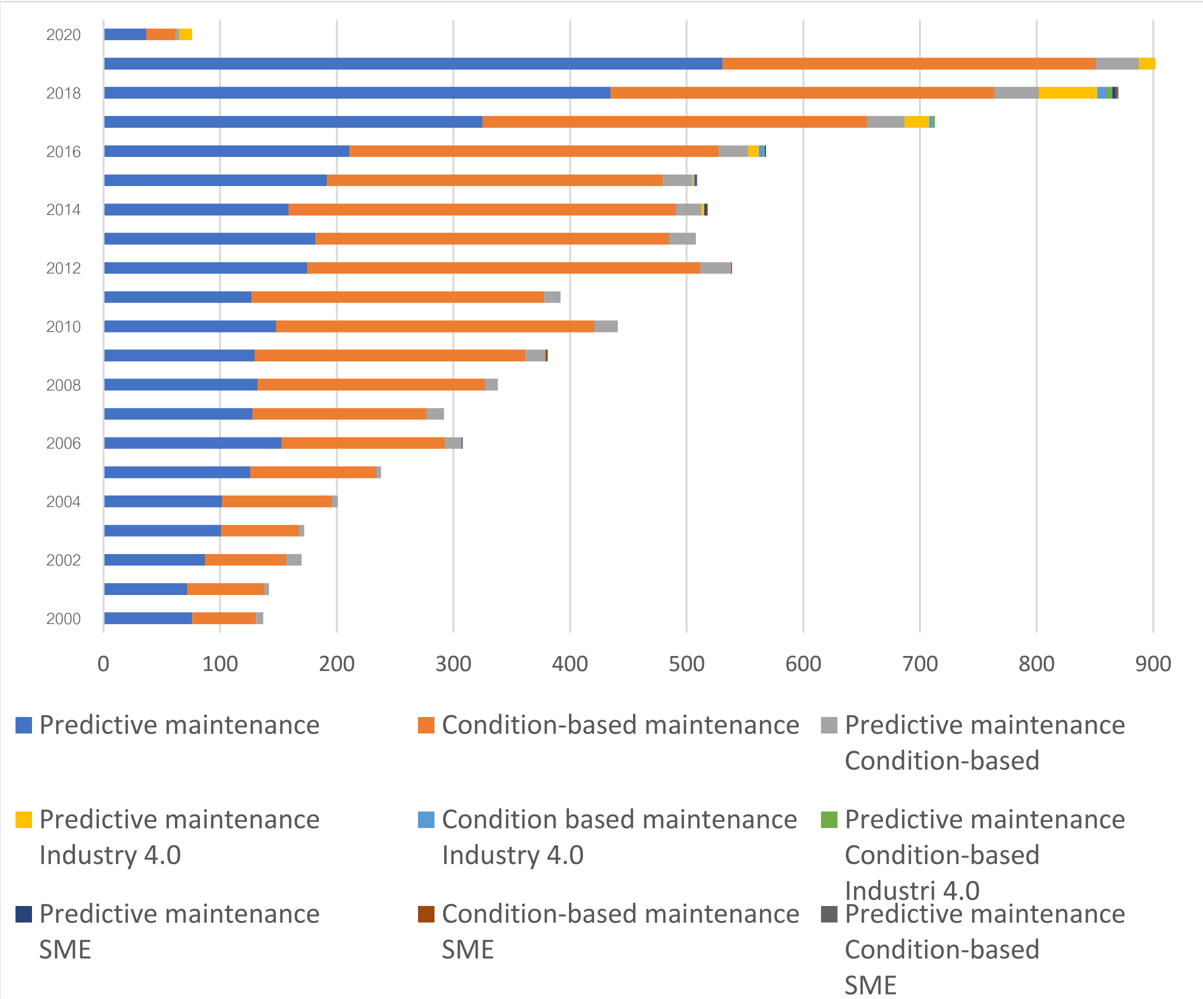

Figure 1. Results of bibliometric analysis of published papers by search string and year.

Condition-based predictive maintenance strategies: literature review

The basic idea of CPM is to plan maintenance based on certain observed system conditions and not on regular intervals, as is the industry standard. To implement such a strategy, the system is continuously monitored to extract information on the current process status. Such information is then compared with the fault-free state, i.e., normal operation. If there is a mismatch in data, the type, size and location of the fault are recognised and an alarm is triggered for the corresponding maintenance. A schematic representation of the CPM approach flow is provided in Figure 2. Despite the idea underlying CPM being very intuitive, its applicability and implementation pose several challenges. As demonstrated by the publication numbers shown in the previous section, this methodology has received great and growing attention in the past two decades. Reviews of the early studies can be found in Jardine et al. (2006), Kothamasu et al. (2006) and Peng et al. (2010).

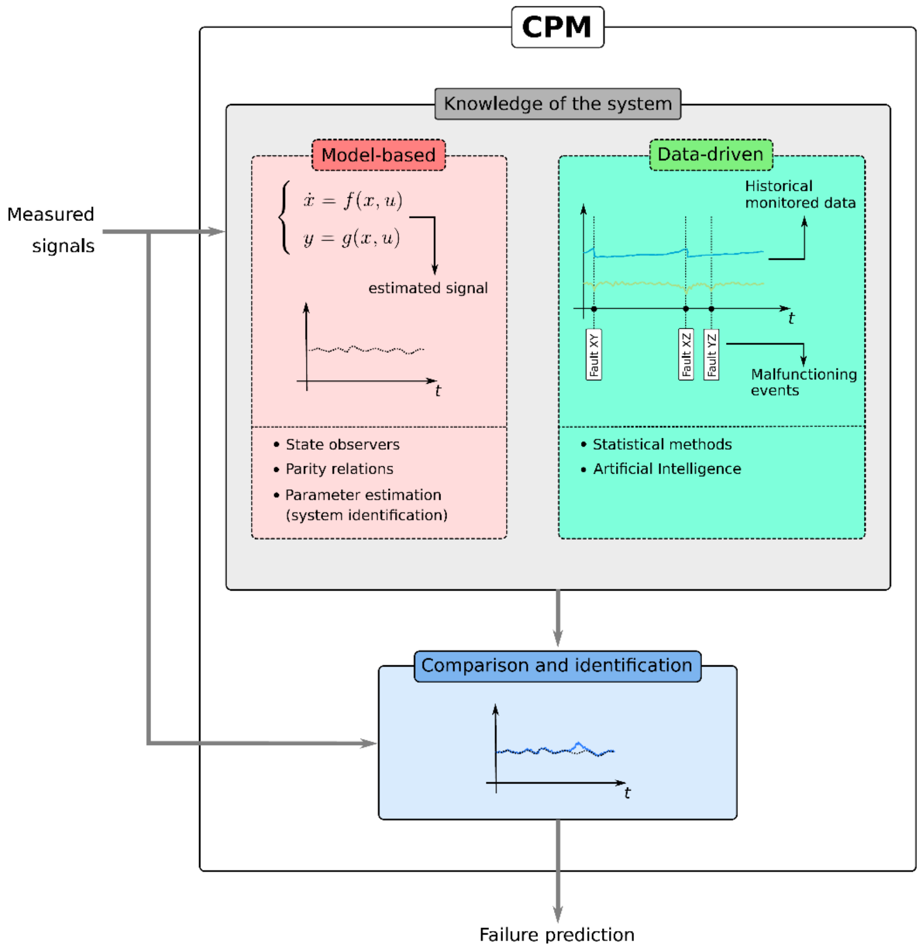

Figure 2. General flow of CPM approaches.

Following a widespread classification of the CPM techniques, there are two main ways to verify the occurrence of a fault condition in a system and, hence, to implement CPM (Jardine et al., 2006):

- Model-based predictive maintenance: utilising mathematical models
- Data-driven predictive maintenance: via signal processing.

The model-based CPM approach includes physical models, state observers and parameter estimation, while the data-driven CPM approaches include wavelet analysis, principal component analysis, spectral analysis, Bayesian networks and artificial neural networks. The model-based approach is generally more effective than an approach based only on data (Peng et al., 2010). However, this is the case only if an accurate model is available. As modelling of complex systems is in some cases not feasible, the data-driven approach is also a valuable method for CPM.

Model-based CPM

The model-based approach identifies faults by comparing measured signals of the monitored system with the outputs of a physics-based mathematical model. The outcomes of this consistency check are called residuals and are indicative of fault presence in the machine. Residuals under a certain threshold are registered as normal behaviour such as noise and/or modelling errors. Those residuals that exceed the threshold are identified as system malfunctions and damage. Several model-based approaches have been applied to fault detection of a variety of mechanical systems, for example, gearboxes (Zhan et al., 2006; Concli et al., 2018), bearings (Saha et al., 2014; Lei et al., 2016), vehicle suspensions (Börner et al., 2002), tires (Umeno et al., 2001), and motors (Kim et al., 1998; Moseler and Isermann, 2000; Saha et al., 2014). The model-based approaches can be divided into three main categories, according to the way used for residual generation:

- State observers (Isermann, 1984; Patton and Chen, 1997): These methods compute the residual as the difference between the sensed outputs from the system and those estimated through, for example, Kalman filters or Luenberger observers.
- Parameter estimation or system identification (Isermann, 1984): Faults are recognised by means of changes in measured model parameters, which are estimated through model-based parameter estimation strategies.
- Parity relations (Patton and Chen, 1994; Hafaifa et al., 2015): These are based on input-output or state-space models of the system, which check for consistency of the inputs and outputs.

The main advantage of model-based CPM approaches is the ability to incorporate the underlying physics of the system via the model into monitoring. This increases the understanding of the system degradation phenomena and, therefore, the "intelligence" of the diagnostic system. However, the effectiveness of model-based approaches relies on the model used. Therefore, to improve the reliability of the system models and of the predictive maintenance techniques, model updating methodologies are employed in a preliminary stage (Sehgal and Kumar, 2016; Belotti et al., 2018a). Additionally, these models should accurately simulate the response of the system for given input signals (Jardine et al., 2006) and be of sufficiently low computational effort to allow for real-time computation. Tailored model-reduction techniques can be employed to further reduce computational effort of the models (Palomba et al., 2014; 2015).

Data-driven CPM

Data-driven methods are derived purely from monitoring data from the system in operation. They use past data to detect malfunctioning points and to predict the time before the machine failure, which is referred to as the remaining useful life (RUL). Statistical or learning techniques are applied to predict the health of a system as well as to approximate the RUL (Luo et al., 2003). Statistical methods divide the machine life in two intervals, which are separated by the occurrence of a malfunctioning event. Before the point of malfunction, the machine works properly and the condition-monitoring data are varying randomly about an average value within a safe range. After a malfunction, the machine no longer performs the function for which it was originally intended and the condition-monitoring data start to deviate significantly (Jardine et al., 2006). They include a wide range of techniques (Peng et al. 2010):

- Conventional statistical process control: originally developed in quality control;
- Multivariate statistical methods: e.g., static and dynamic principal component analysis, multivariate statistical process control, linear discriminant analysis, quadratic discriminant analysis, partial least squares, canonical variety analysis, learning vector quantisation;

• State space models: e.g., Bayesian networks, dynamic Bayesian network, hidden Markov models and hidden semi-Markov models;

• Regression models: e.g., proportional hazard model, proportional intensity model, logistic regression model.

Statistical process control techniques evaluate the deviation of machine condition from a reference health state (Goode et al., 2000; Deloux et al., 2009; Vassilakis and Besseris, 2010). Goode et al. (2000) go further, presenting also a method to estimate the total time to failure, representing the two machine intervals with Weibull distributions, which parameters have been derived from an analysis of the machine's historical failures. Multivariate statistical methods are popular tools in a data-driven monitoring method used to reduce the dimensionality of data, while retaining most of the information. This allows to identify patterns in data and express them in such a way as to display those similarities and differences (Banerjee et al., 2007; Amruthnath and Gupta, 2018; Long et al., 2018). Bayesian networks and dynamic Bayesian networks are powerful tools that synthesise probability and graph theory (Peng et al. 2010) and are suitable for modelling of causal processes with uncertainty (Gebraeel et al., 2005; Sheppard and Kaufman, 2005). Statistical regression models are widely used in survival analysis and are useful tools for RUL estimation (Feigl and Zelen, 1965; Chinnam and Baruah, 2003; Kwan et al., 2003; Vlok et al., 2004; Dong and He., 2007).

The second main category of data-driven approach uses artificial intelligence (AI) methods. These are also called "black-box techniques", since they do not provide an explicit analytical model of the processing (Banerjee et al., 2007), but, despite this, they can even show improved performance over conventional approaches in terms of process speed and complexity (Jardine et al., 2006). AI methods for CPM are essentially based on efficient surrogate models (Xu et al., 2013) or an artificial neural network (ANN) that mimics the human brain structure thanks to a series of layers (Peng et al., 2010). ANNs include an input layer, one or more hidden layers and an output layer. These contain a number of simple nodes interconnected through weighted connections: weights are adjusted during the learning procedure by observations of input and output. The system learns to perform tasks by considering examples (Peng et al., 2010). The learning procedure can be supervised or unsupervised. In the first case, a set of experimental data with known faults is used. Conversely, in the unsupervised learning procedure the AI learns by using new information available (Jardine et al., 2006). There are several types of ANN, such as polynomial neural networks, dynamic wavelet neural networks, self-organising feature maps, or multilayer perception neural networks. ANN are generally used in CPM applications to predict the fault propagation process, estimate the RUL (Zhang and Ganesan, 1997; Wang and Vachtsevanos, 2001) and to predict the machine condition (Yam et al., 2001; Dong et al., 2004).

DISCUSSION

Future of smart mechanical systems for SME manufacturing

Building on the ideas of CPM and DM, the logical extension is their combination. This allows the ability to automatically modify mechanical systems and their operation to account for environmental changes, including wear and non-catastrophic damage, while remaining in service. As both system parameters and operational conditions may change during the life of a mechanical system, it may be required to adapt parameters to the operating condition to return performance to an optimum. To do this, the original design problem is reapplied with the change in conditions. An application of DM with passive modifications performed "in-operational", i.e., without stopping operation, is exemplified by Wehrle et al. (2019) with reference to a planetary gearbox modelled with an efficient lumped-parameter model (Wehrle et al., 2018; 2019). In this work, the authors added masses to move the eigenvalues of the gear housing out of new critical ranges that had shifted due to wear.

This methodology implies that the mechanical system does not need to be fully taken out of service for modification. This can be either done to postpone maintenance or to adapt to other environmental changes leading to new smart mechanical systems.

These are outfitted with an intelligent in-operation system modification based on CPM. Analogous to smart structures, which are defined by structures that sense and react to their environment, smart mechanical systems are dynamical systems that, with the help of sensors and CPM strategies, react to changes and give feedback or self-optimise in regard to their operation. Smart mechanical systems are networked to allow for self-optimisation based on the assessment of their current health and performance.

Examples of future applications are manufacturing systems and their components, e.g., robots and gear sets. We define here smart mechanical systems as mechanical systems capable of both condition-based maintenance and in-operation modification. The condition-based maintenance systems have already found application with high-performance and, therefore, high-cost systems such as wind turbines, spacecraft, manufacturing as well as petroleum extraction and transportation. The availability and reduction in cost of sensing systems and computing power now makes such systems available to small and medium-sized enterprises.

In this regard, the Industry 4.0 technologies and the digitalisation of manufacturing systems through, among others, cyber-physical systems, cloud computing, deep learning, are enabling the fast collection and analysis of large amounts of data (i.e., Big Data) that can be used in the context of smart mechanical systems to reduce costs and increase productivity. Optimal design of self-adaptive machines will, in fact, improve performance, product quality and reliability by lowering production and maintenance costs as well as manufacturing time. The achievement of these goals is made possible by the concurrent approach proposed, that integrates in the design of a machine all the features that will guarantee an in-operation modification on the basis of the CPM suggestions. The possibility of having structures and machines able to self-adapt according to the operating conditions enables systems to always work at their best.

Consequently, the study of smart structures with self-sensing and monitoring capabilities will have positive impacts on predictive maintenance of machines and structures, to increase safety, reliability and reduce maintenance costs. This perspective is even more interesting in the light of Big Data systems that will be able to handle the huge amount of information provided by smart sensors.

SMEs are defined by the European Union as having fewer than 250 employees and less than 50 million € in turnover. As SMEs involved with manufacturing increase their level of automation within the framework of Industry 4.0, the maintenance of such mechanical systems is critical for product quality and efficiency. Unexpected machine shutdown can be especially damaging to the bottom line of such smaller companies. Further, it is often not possible to have highly skilled teams of technicians and engineers dedicated to the maintenance. Smart mechanical systems will stand up to both these challenges, allowing for reduced (or even eliminated) downtime and machine self-optimisation

CONCLUSIONS

In the framework of the fourth industrial revolution, new horizons have been opened in manufacturing and mechanical design for SMEs. In this work, we focused on condition-based predictive maintenance and dynamic modification as well as their possible combined application for future smart machines and smart mechanical systems.

Starting from a quantitative analysis and qualitative review of the literature and research trends in the condition-based predictive maintenance, a discussion has been provided of the main methodologies and techniques. Further, we propose a combined approach, exploiting condition-based predictive maintenance and dynamic modification for the development of a new class of smart mechanical systems. This proposal highlights potential benefits and needs in its application, especially to SMEs.

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