A Literature Review on the Contribution of Industry 4.0 Technologies in OEE Improvement

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Abstract. Overall Equipment Effectiveness (OEE) has remained a valuable performance indicator over the decades. Yet, methods for improving equipment effectiveness have changed and advanced over time. This paper deals with the contribution of the Industry 4.0 in OEE improvement in the context of production systems monitoring and control through an analysis of the current literature. Industry 4.0 provides innovative technologies to enable new ways of tracking, taking decisions and acting upon production system health data. Internet of Things (IoT) when integrated into production systems, enables tracking of operational parameters remotely in real-time. Big Data and Artificial Intelligence enable analyzing historical and current operational data to using the results for predictive maintenance. Simulation and Digital Twins allow to test various production scenarios to measure their impact on production systems performance… This leads to better insights on production performance, identification and minimization of losses, and enhanced decision making in favor of increasing OEE values consistently. In this work, we give an overview of the Industry 4.0 technologies used in the literature. Then we identify and present different use cases that combine a number of these technologies to assure production monitoring and control.

Keywords: OEE · production system · monitoring · control · Industry 4.0

1 Introduction

The ultimate objective of production system monitoring and control is to optimize the production system's efficiency with its current resources capacity [1]. According to [2], to reach this objective, it is necessary to measure performance achieved by the controlled production system and comparing the results to previously set objectives. Then it is necessary to identify production losses, analyze their causes and develop solutions. The latter consist in applying corrective actions when the previously defined objectives are not reached or improvement actions when a potential source of progress has been detected.

One of the effective means to monitor and control production systems is the implementation of Key Performance Indicators (KPIs) and their follow-up. These indicators

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help provide a synthetic view of the use of production equipment and thus make it possible to identify performance degradation and search for their root causes [3].

OEE is a leading KPI widely used to manage production in the literature to measure and monitor the improvement of operational performance of production systems for decades [4]. OEE is a KPI that considers several types of production losses and encompasses 3 main rates affecting the performance of the production system: availability, quality and performance [5]. The analysis of this indicator and its components reveals sources of performance losses and indicates where improvement efforts are to be made. The methods of monitoring and controlling of production with the OEE vary and are changing with the evolution of new technologies to address the limitations of conventional methods. Over the last decade, the world is experiencing a fourth industrial revolution called Industry 4.0 based on large amounts of data, which offers promising potentials for monitoring and controlling production systems [6].

The main objective of this study is to explore the literature around the impact of Industry 4.0 on the monitoring and controlling of production systems based on OEE. For this purpose, in this article, we intend to provide a global view on the evolution of production systems management based on OEE in the context of Industry 4.0 and based on a review of the existing literature.

Then we will propose different use cases that combines Industry 4.0 technologies for production system monitoring and controlling.

2 Method

The methodology used in the study is a six-step process shown in Fig. 1. The process started by a specification of research purpose and research questions. The purpose of this paper is to discuss the contribution of Industry 4.0 technologies to the improvement of production systems monitoring and controlling using OEE.

According to the research motivations outlined in the purpose, this paper answers the following research questions: "How can industry 4.0 improve OEE for production systems?" and "What are the technologies used for this purpose?". These questions aimed to establish the scope of the review, leading to the search command with the keywords. A search for papers was performed using Science Direct and Google Scholar databases. Due to the target of our study, the keywords defined are "Industry 4.0", "OEE" and "Production systems". The authors have searched all publications that had the defined terms in the title, abstract or keywords. The inclusion and exclusion criteria were defined as follows: The only considered language was English. The publications considered are with an open access and describing applications using one or a combination of Industry 4.0 technologies to improve OEE. 140 papers were identified through databases searching. Once collected and the duplicate papers removed, the papers were filtered using defined inclusion and exclusion criteria, resulting in a corpus of 18 papers that are in the scope of our study.

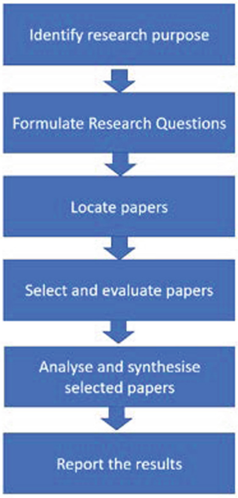

Fig. 1. Research methodology

3 Monitoring and Controlling of Production Systems Based on OEE

3.1 OEE as a KPI

OEE is a KPI that is initially introduced in the contribution of [5], to provide a methodology for estimating the inefficiency of industrial equipment. It has rapidly spread in the industrial and scientific context due to its ease of use and wide applicability. According to a recent study [4], there are more than 850 scientific publications related to OEE between 1996 and 2020. Most of the papers address the problem of improving this indicator using a variety of methods where initial values are compared to final values, thus quantifying the level of improvement achieved. Besides being a KPI to monitor production systems improvement, OEE is used to reveal production losses based on the analysis of its value and the value of its elements since the OEE rate is the result of the product of 3factors: Availability, performance, and quality [7]. Each factor is used to classify the major losses and is therefore used as a basis for defining actions to improve the performance of the equipment.

3.2 Limitations of the Conventional Methods

The accuracy of OEE depends on several aspects such as the data collection accuracy and the measurement frequency. The level of difficulty of data collection is related to the level of the production system complexity and to the data collection method whether it is realized manually or automatically. For manual data collection, some data can be forgotten due to human error such as the difficulty of observing production stoppages in real-time and the time required to gather certain information. It can even lead some manufacturers to abandon the use of this approach considering that the operator will waste time collecting data or that the collected data is unreliable [7]. For the automated data collection, even though it facilitates the acquisition of large amounts of detailed data, the degree to which the resulting OEE rate actually reflects that the production system is performing well depends directly on how well companies are able to interpret and define the underlying factors of OEE [8].

In this context, the promising technologies of Industry 4.0 have enabled favorable conditions to obtain and analyze data in real-time with much less risk of error [9].

4 OEE in the Era of Industry 4.0

4.1 Industry 4.0

Industry 4.0 refers to the new stage in the organization and control of the industrial value chain by the integration and the interaction between the physical and virtual spaces. Its main goal is to enable having flexible manufacturing processes, monitor assets and processes in real time and improve autonomous decision-making processes [10]. The Industry 4.0 concept is proposed to achieve a better level of operational efficiency, productivity, and automation of production systems [11]. This new industrial step has been possible due to the recent evolution and the affordability of a set of technologies. According to [12], these technologies include IoT, Cloud Computing, Cyber-Physical Systems, Big Data and Data Analytics, Additive Manufacturing, Artificial Intelligence, simulation, and Digital Twins. In this paper, we focus on monitoring and controlling production systems related technologies used by the literature to improve OEE.

4.2 Monitoring and Controlling of Production Systems in the Era of Industry 4.0

Combining a powerful indicator as OEE with disruptive technological advances is changing the current production systems monitoring and controlling practice to meet the requirements of a data-driven, real-time, and digitalized context.

Several research works have been conducted to evaluate the impact of Industry 4.0 technologies on the OEE improvement for production systems. The objective of this part is to present, through a representative bibliography, the various technologies used for the measurement and for this purpose.

Simulation is considered as one of the key technologies for implementing Industry 4.0 [13]. It is an important technology for developing planning and exploration models that improve the understanding of how a production system operates under varying conditions and assess the impacts on operational performance. It helps to optimize decision making and operation of complex and intelligent production systems [14]. In [15], authors test different scenarios and evaluate the impact of the implementation of different Industry 4.0 technologies in the production line using OEE. Both [16] and [17] apply gathered data from production system by means of IoT sensors to validate the simulation model that is used later on to test improvement scenarios and make decisions based on the results. Combining IoT wearable sensors and simulation flow model, [18] investigates human working performance. For [19], the study is based on functioning signals as data input to a flow simulation to investigate future system evolution in near time and obtain calculated OEE values. Another study [20] proposes a data-driven approach for increasing OEE by utilizing discrete event simulation with Data Analytics tools (Power BI). While simulation tests different production configurations, Data Analytics tools support data analysis, translating and extracting meaningful information from Big Data stored to improve decision making performance [21].

Other research works adopted integrating Big Data with Artificial Intelligence solutions. This combination is considered in [22] to assure automatic quality prediction and have better quality outcomes. Furthermore, Artificial Intelligence plays an important role in predictive maintenance. Depending on historical production performance data and real time data, [23] investigates using Deep Learning algorithms to predict future values of OEE. Artificial Intelligence is used as well in the detection of future breakdowns like [24] who uses a decision tree model to predict the happening of incoming machine failure. In the works of [25] and [26], classification machine learning algorithms have been utilized in order to automatically detect changeovers in a shopfloor environment impacting to the availability of the assets.

Another technology that we will focus on in this paper is the Internet of Things that consists in extending network connectivity and computing capability to devices to generate, exchange and consume data with minimal human intervention [27]. This allows these objects to have their own existence in the digital world. From a manufacturing perspective, the IoT is a way to digitize production processes. Industrial IoT uses a network of sensors to collect production data and uses various software to transform this data into valuable operational performance information [28]. It is used to solve the problem for complex and heterogeneous plants due to different types of machines and different generations of controllers and communication protocols. For this, [29] proposes a unified OEE data collection method by implementing IoT sensors to detect machine stoppage and capture the stoppage reasons. Besides, production systems like stamping machines necessitates providing a secured data collection for operators. For this reason, [30] focuses on designing and realizing a performance monitoring system for a stamping machine based on IoT to increase the effectiveness of the machine. IoT sensors allow also increasing the frequency of data collection and thus to have an instant and detailed insight of what is actually happening in the production system [31]. [32] underlines that automatic root cause identification in a production system can greatly improve decision-making efficiency. In this study, the authors use IoT and regression algorithms to define the root cause of OEE degradation indicating the measured values that may negatively affect production performance by eliciting historical data. Considered as the next wave in modelling and simulation [33], Digital Twins are used by the literature to monitor and control production systems. A Digital Twin is defined by [34] as "a set of adaptive models that emulate the behavior of a physical system in a virtual system getting real time data to update itself along its life cycle. The Digital Twin replicates the physical system to predict failures and opportunities for changing, to prescribe real time actions for optimizing and/or mitigating unexpected events observing and evaluating the operating profile system". Therefore, Digital Twins are useful for production optimization and operational control [35]. Digital Twins also offer advantages to OEE improvement. [36] provides a decision support system framework based on Digital Twin and IoT to monitor a conventional machine and enable the operator to perceive the machine status, production time, OEE and order scheduling in real-time. [37] focuses on improving production quality by proposing a framework of a Digital Twin that is based on anomaly detection. [38] develops a Digital Twin as a decision support system for a dynamic maintenance task prioritization using simulation-based optimization and genetic programming.

The Table 1 presents a summary of the different Industry 4.0 technologies used in the literature. It also shows that in most cases, several technologies are used together.

Table 1. Industry 4.0 technologies used by the literature to monitor and control production systems

References	Industry 4.0 technologies				
	Simulation	Digital Twin	IoT	Big Data/Data Analytics	Artificial Intelligence
[15, 19]	X				
[20]	X			X	
[16, 18]	X		X		
[17]	X		X	X	
[29, 30, 32]			X		
[31]			X	X	
[22]			X	X	X
[23]			X		X
[24–26]					X
[36]		X	X		
[37, 38]		X			X

4.3 Use Cases of Production Systems Monitoring and Controlling Using OEE

The second aim of this paper is to identify and present different use cases that combine a number of Industry 4.0 technologies to assure production systems monitoring and control. Then we classify the applications into those use cases according to their purpose in relation to the OEE.

We identify three general use cases: evaluation of current state, prediction of future state and decision making.

The first use case concerns the assessment of the current state of the production system and thus the current value of OEE. It includes data collection, identification and classification of performance losses, visualization, and analysis of what happened in the past or what is currently happening in the production. All these elements are complementary and have a common target which is to assess the current state of the production system. The first step to calculate accurate OEE rates is to collect reliable operational data which is not an easy task for certain cases. For instance, [29] focuses on this point by implementing IoT sensors for legacy machines that originally do not provide an interface for data collection. The authors use sensors to detect the machine stoppage in the first place and send an alert to allow operator to define stoppage reason on a Human Machine Interface which provide data for OEE calculations. Also, [30] proposes to set up IoT sensors on stamping machines to overcome security issues and have access to all the data collected displayed on a user interface. Another important point in this use case is the identification and classification of performance degradation causes. In this context, in [25] and in an extended research [26], the same research group is interested in automatically distinguishing the changeover phase operations from the production phase by an Artificial Intelligence trained model. This contributes to cover the aspect of maintaining production system availability and particularly to improve identification of heterogenous changeover processes that depends on different workers who perform different procedures to changeover a machine. They start by implementing different sensors on a CNC milling machine with very low data accessibility to have a big amount of data that they use later to train the classification machine learning algorithm. In terms of anomaly detection related to production quality, [37] implements a production twin that replicates the current pressing process which laid the foundation for an anomaly detection algorithm to detect defective pressing processes. The algorithm uses Gaussian process models for the detection of anomalies in the pressure curves of the system. This puts the light on the quality component of OEE and how Industry 4.0 technologies can be used to gain insight into quality issues causes and thus to adjust before production quality degradation. The developed solution enables to detect faulty products and too-high pressures at the machine. An additional topic covered by the literature that uses Industry 4.0 technologies having an overview of real-time condition of the production system. This aspect is covered by [31] and [36] by providing a dashboard that displays data visually. The first one [31] by developing an OEE SCADA system that provides a comprehensive view of the manufacturing production line regarding performance, quality, and availability, the second one [36] by implementing a data-driven Digital Twin for a conventional machine facilitating an interconnected system that can monitor a machine's conditions in real-time.

The second use case concerns the prediction of the possible evolution of the production system. It involves prediction of the future value of OEE based on historical data or by the prediction of incoming failures. For the part of predicting the possible evolution of production performance, the literature treats the problem in different ways using different Industry 4.0 technologies namely simulation for the case of [19] to investigate preventively or in near-real-time the evolution of production performance when variabilities are considered for some parameters. Another method purely based on historical production performance data is proposed by [23] that lean on Artificial Intelligence algorithms to predict OEE value with a daily frequency. The authors point to the relevance of this approach to apply on fresh product packaging production system where unexpected downtime can easily lead to product waste. Concerning the failure prediction in the context of improving OEE, different authors base their methods on IoT gathered historical production data to explore the happening of incoming failure but in a variety of ways. [24] applies an Artificial Intelligence algorithm to this data to predict failure in near real-time which contributes to reducing the undesired production breakdowns and thus increase equipment availability. On the other hand, [32] develops, for a given KPI, an analysis algorithm that exploits the KPI and follows its dependencies until the root measures for the performance degradation has been identified. Finally, that measure is presented to the user as the source that will negatively affect the performance of production in the near future.

The last use case is about using the current or predicted OEE rate to make decisions and control production systems. This includes testing possible changes in production to evaluate the best improvement scenario, anticipating an action to avoid a failure or acting in real-time to restore a breakdown. In a logic of using OEE as an indicator of enhancing production systems performance and making improvement decisions, many research works depended on simulation. This is whether to test the effect of changing some parameters of the production system [16, 17], or to assess the impact of Industry 4.0 technologies implementation of the production system [15]. The benefit of using simulation in these situations is having a testing space without the need to interrupt the real system. Others [38] combine simulation-based optimization tool and genetic programming in a Digital Twin-based decision support system to conduct short-term corrective maintenance task prioritization. The authors propose this approach to address the problem of pre-defined prioritizations in a dynamically changing production environment. With the proposed use cases, we managed to gather reviewed papers considering their common purpose in relation to OEE which is summarized in Table 2.

Table 2. Reviewed papers according to their common purpose in relation to OEE

Use Case	Element of the Use Case	References
Evaluation of current state	Data collection	[18, 29–31]
	Identification and classification of performance losses	[25, 26]
	Visualization, and analysis of what happened in the past or what is currently happening in the production system	[18, 30, 31, 36, 37]
Estimation of future State	Prediction of the future value of OEE based on historical data	[19, 23]
	Prediction of incoming failures	[22, 24, 32]
Decision making	Testing possible changes in production to evaluate the best improvement scenario	[15–17, 20]
	Anticipating an action to avoid a failure or acting in real-time to restore a breakdown	[38]

5 Conclusion

In this paper, we review the state of the research about the integration of Industry 4.0 by one or multiple technologies into monitoring and controlling production systems through the OEE indicator. This study finds that Industry 4.0 technologies can be applied on different complementary perspectives in relation to improving OEE to overcome traditional methods limitations. Real-time gathering data by IoT replaces periodic and manual data collection and enables better, continuous, and remote monitoring of operational parameters of production systems. These connected devices provide better quality, more detailed, real-time and more accurate data which improves OEE calculations. Besides, the analysis with Data Analytics or Artificial Intelligence algorithms allows predictive maintenance and makes OEE improvement more proactive instead of being reactive. Moreover, these advanced technologies with the provided current state of production systems, allow to take a condition-based approach to maintenance. This approach prolongs the time between planned maintenance when production system is in good condition. This increases productive hours and minimizes unplanned downtimes. In addition, simulations and Digital Twins can offer an insight over quality issues and a better guidance for diagnostics by reproducing production system's behavior as well as testing its possible evolution to predict production future performance.

A second contribution of this work is the classification of the studied literature into three use cases according to their purpose in relation to the OEE indicator. The first use case gathers papers that tend to evaluate the current state of production system. The second use case consists in predicting the evolution of production performance whether through predicting directly future values of OEE or through predicting incoming failures. The last use case concerns papers that use OEE values in decision-making. This classification showed that in every use case, researchers can use the same technologies to treat different OEE related problems and can use different technologies to achieve the same target and this depends on the production system studied.

The research has identified that Industry 4.0 technologies provide a lot of benefits to improving OEE. The exploitation of this potential didn't reach its limits yet and still have a lot more to offer. There are combinations that are able to cover the purpose of all the use cases such as the Digital Twin and Artificial Intelligence. As future work, we intend to explore this duo in all the use cases.

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