# An Industry 4.0 approach toward Overall Equipment Effectiveness management and control

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**Abstract**: Today's manufacturing systems continually evolve as technological advances are developed in communication, data analysis and storage, and sensors fields. Indeed, the dramatic changes caused by artificial intelligence, the internet of things, cloud and edge computing, simulation, cyber-security, and virtual reality can potentially increase the industrial infrastructure's efficiency and flexibility. However, integrating these innovations with traditional approaches used until now in manufacturing management poses a challenge. In Operation Management, Overall Equipment Effectiveness (OEE) is the most common indicator used to measure and assess the efficiency of a manufacturing system. Therefore, in the present paper, a detailed framework is defined to guide the introduction of different technologies characterizing the industry 4.0 paradigm in the management and continuous control of OEE. Finally, new opportunities for optimization thus ensued are identified as well as limitations and possible drawbacks caused by this transformation.

**Keywords**: Overall Equipment Effectiveness, OEE, Operations management, Industry 4.0, I4.0 Design Principles.

## I. Introduction

In the past, as the manufacturing industry increasingly required more flexibility to achieve higher productivity, digitalization gradually consolidated into the production system. The main priority of the digitalization process is performance improvement through the provision of intelligence between devices and applications involved in the process. Industry 4.0 (I4.0) revolution has emerged as the perfect scenario for fostering this aspect in the manufacturing process control even more, thanks to the integration of innovative technologies. In this environment, the entire process can operate with near-zero human involvement, and real-time performance data can be analysed by algorithms and used for critical operational decisions. The main principle behind I4.0 is to create a smart manufacturing industry by interconnecting machines and devices that can control each other throughout the life cycle [1], providing sustainable environmental solutions.

Nevertheless, companies need to focus on the best strategy to attract more customers in a highly demanding market. Competitive advantage is inextricably linked to the capacity for technological innovation, and it depends on accurate performance monitoring and controlling based on a set of measures that focus on the main critical activities, called Key Performance Indicators (KPIs). Using KPIs, managers can control and guide the company towards improvement, making effective decisions. Overall Equipment Effectiveness (OEE) is a performance metric to assess manufacturing efficiency and identify its major impact factors [2]. OEE is also suitable for discrete, batch, and continuous production methodology [4] and influences strategic decisions for improvements. The OEE is computed by multiplying three sub-indicators: Availability (A), Performance (P), and Quality rate (Q). They are composed of the six major equipment losses: equipment failure, set up and adjustment, idling and minor stoppages, reduced speed, defects in the process, and reduced yield. This paper aims to establish a framework to guide the introduction of different technologies characterizing the I4.0 paradigm in the management and continuous control of OEE.

## II. Background

Over the years, several pieces of research have been published concerning the definition of OEE and its applications. A study [5] presented a framework emphasizing the 5S and the Total Productive Maintenance (TPM) as the critical success factors in OEE improvement. Another research [6] presented the application of the lean tools and six sigma approach to improving OEE, such as Single Minutes Exchange Die and Pareto Analysis. A macro framework [7] has been developed integrating the quality tool such as value stream mapping, failure mode effect analysis, and single minutes exchange die in OEE improvement, reducing nonvalue added process in operation and improving equipment utilization. Furthermore, several studies have been conducted on the relation between I4.0 and Lean Manufacturing (LM). A study [8] presented a continuous improvement framework that includes a wireless device system to support the real-time equipment performance measures through the integration of Information Technology (IT) and LM. A study in 2017 [9] proposed two indicators that aimed to assess the benefit of I4.0 technologies to LM tools, such as the TPM, confirming that their implementation can positively impact OEE. In this respect, another study [10] established an approach of structured guidelines and steps for OEE improvement implementation. A research work [11] proposes four Design Principles for the I4.0 Smart Factory component. Another study [12] presented a new operating paradigm in the pharmaceutical industry, including digitization, automation, and integrated online and real-time data. Despite expansive research activity aimed at defining OEE and its applications, the current scientific literature still lacks a proper and comprehensive analysis of the integration and the impact of I4.0 Enabling Technologies (ET) on manufacturing performance management and control. Therefore, the following section presents an integrated framework to analyse and optimize the introduction of I4.0 technologies in the assessment and optimization of OEE.

## III. Framework proposal

The focused knowledge of the adjustments required by the manufacturing process to get better results is the ideal method for determining an improvement framework. Therefore, the successful implementation of novel technology is dependent on the development of well-designed systems that consider how the intervention would optimize the process. The Design Principles (DP) presented in the aforementioned study [11] can aid in the selection of the I4.0 ET required for OEE improvement. These principles are as follows: real-time capability (the ability to collect and analyse data in real-time, allowing for immediate decision making); interoperability (the ability of objects, machines, and people to communicate, exchange data, and coordinate activities); virtualization (the ability to create a virtualized view of operations and evaluate change impact); and decentralization (the business logic contained in sub-systems or components rather than a central computer system, enabling autonomous decision making). Because the losses underlying each OEE component are often dependent on shared systems, starting the analysis from their definition may be misleading because it could be unable to notice the increase in each OEE component brought by the I4.0 ET implementation. A list of OEE calculation activities is then proposed to establish the actual and defined bounds of the process. The proposed framework is depicted by four steps, including a preliminary risk analysis phase that is typically undertaken prior to project implementation. The first step concerns the analysis of the relationship between I4.0 DP and the OEE operations, which are classified as measurement, calculation, and optimization. Proactive participation of the process expert is highly suggested to identify the appropriate set of process modifications. Similarly, the second step entails analysing the selected I4.0 ET and their characteristics in terms of I4.0 DP, including the advantages and criticality of each proposed I4.0 ET. The framework scheme and the first and the second steps are reported in Appendix A. It is noteworthy that users might choose from a wider range of I4.0 ET based on the industry in which the process operates, giving the framework more flexibility. The third step is to investigate the intercorrelation between OEE activities and the I4.0 ET. Furthermore, an indicator $I_{j,k,z}$ is calculated to assess the influence of each ET group on OEE activities:

$$I_{j,k,z} = \frac{\sum_j \left( \sum_k DPS_{j,k} \cdot \sum_z DPT_{j,z} \right)}{NT_k}$$

where $j$, $k$, $z$, are discrete indexes respectively referring to the DP, the OEE activities grouped by stage and the ET grouped by classification. The terms $DPS_{j,k}$ and $DPT_{j,z}$ represent the correlation between DP and OEE activities and ET respectively, assuming binary values between 0 and 1. The term $NT_k$ represents the total OEE activities per stage. In the last step, the calculated indicator values populate a table in which the I4.0 ET groups are sorted according to their impact on the OEE improvement (Fig.1).

| **I4.0 Enabling Technologies** | **OEE Activities** | | |
|---|---|---|---|
| | *Measurement* | *Processing* | *Control* |
| *Data Capturing and Processing Technologies* | 11 | 6.75 | 8.71 |
| *Network and Communication Technologies* | 11 | 5.25 | 7 |
| *Physical/Digital Interface Technologies* | 1.75 | 1.25 | 1.86 |

Fig. 1. Impact of I4.0 Enabling Technologies on OEE Activities

## IV. Discussion

This section aims to propose the analysis of the selected I4.0 ET, performed in the second step, useful to describe the advantages and critical factors to be considered in a preliminary analysis risk phase before the efficient introduction into the process. As results of the framework application, data capturing, processing, network and communication technologies highly impact the OEE calculation activities, while physical and digital interface technologies depend on the process and industry in which improvement are applied and could positively impact the OEE indicator.

Supportive information can be extracted utilizing Big Data Analytics, and preventive actions can be ensured from improved predictive maintenance thanks to the high amount of available real-time data, such as machine vibration, energy consumption, electric currents, and temperatures. Maintenance engineers can properly schedule interventions based on these data to avoid any unexpected machine downtime. Furthermore, I4.0 network technologies offer a large set of robust solutions to increase the Quality of Service (QoS) and avoid hacking of IT infrastructures. Radio Frequency Identification (RFID) technologies are the major components for real-time data management in traceability and reaction to system changes. Defect losses can be managed with an increased amount of stable real-time data. When properly elaborated, alerts on defective parts should be sent immediately to operators. Connected Collaborative Robots (Cobots), Cloud Systems, and Artificial Intelligence (AI) plays an essential role in the adaptation to changing requirements to satisfy system stability and agility [11]. Interoperability of communicative components could be satisfied using Cyber-Physical System (CPS) and Industrial Internet of Things (IIoT) adaptation such as Networking technologies. Moreover, simulation modeling and virtualization techniques such as Augmented Reality (AR) and Virtual Reality (VR) can be provided by monitoring the changes in the existing system.

### *A. Data capturing and processing technologies*

Continuous process improvement often requires collecting detailed information on the entire manufacturing cycle. The high amount of data collected from sources needs to be analysed and controlled to extract interesting and feasible information. Data analysis techniques have been developed in the last years, including Data Mining, Machine Learning (ML), and AI. Big Data Analytics techniques are used to recognize and eliminate non-essential data to maximize predictability, explore new possibilities, improve production efficiency, and help reduce overhead costs [13]. One of the foremost challenges concerning Big Data is identifying the valuable insights gained from it and their linkage with the value chain. Since innovative communications protocols like 5G and 6G will increase the amount of available information, the issues related to their physical storing in data centres and the database management complexity. Streaming and status data needs different management strategy. Streaming data is transmitted in large volumes and requires front-end pre-processing to send only valuable information to the back-end system. Status data can flow continuously due to their small volume, including simple information like on/off, failure/steady-state, or run status. Data capturing and processing technologies can improve the performance of this information flow.

Nevertheless, continuous uptime cannot be guaranteed in production lines without reliable redundancy and safety protocols in the communications network. The high availability of Big Data and the increase in computation power opens new possibilities for human-machine interfaces based on AI applications, enabling, for example, surveillance robots and running improved methods such as neural networks faster and more cost-effectively. AI also involves the integration of digital data and computational analysis to make decisions usually made by humans, involving reasoning, problem-solving, learning, and decision-making, among others [14].

As reported in the study [12], the application of AI in pharmaceutical manufacturing has already begun, including the use of machine vision technology to replace human visual inspection of packaging, caps, and vials. New predictive equipment maintenance to reduce disturbances, risks, production downtime, and automated quality control enables seamless analytical testing scheduling, continuous process quality assurance, and enhanced data integrity. Within the field of AI, ML and Artificial Neural Networks (ANN) have emerged as two of the more advanced methods for prediction and risk management. The supervised learning approaches ANN have seen steady progress in advanced manufacturing applications for prediction and control in pharmaceutical industry development, control schemes, and fault detection for complex dynamic processes. As AI is increasingly used in widely available products and services, the question of its damage potential has been raised. The research [15] suggests analysing and judging potential risks related to the level of criticality starting from the assessment of two aspects: a possible occurrence of damage caused by human beings and algorithm-terminated systems and its extent in terms of the right to privacy, the fundamental right to life and physical integrity and non-discrimination, as well as potential damage for the economy of societies and countries in terms of heavy dependence on a single AI solution or provider.

The identification, location detection, and condition monitoring of objects and resources can be supported by RFID technologies, which enable the aggregation and processing of the real-time data gathered from production processes. As a relatively new technology to widespread, large-scale manufacturing applications, RFID technology has potential issues that need to be considered, including the high expense since RFID implementations include the tags themselves in addition to readers, critical back-end systems, specialized personnel, issues related to security and privacy of the tagged object [16]. The interconnected sensor-cloud systems based on the IIoT can deal with a faster and more considerable amount of real-time data from the high potentiality of the fast network. The original Internet of Things is adapted to utilize specific industrial applications ranging from optimization of production lines to monitoring in-process environment and real-time data analysis [17]. IIoT also provides surveillance, hazard monitoring, and smart grid applications, essential for preventive measures and safety. However, IIoT can bring some associated risks related to privacy, security, and loss of data integrity [18]. Simulation is a valuable technology for developing models for assessing risks and barriers to implementing process adjustments by analysing their effect on performance within a specific scenario, including dynamic scheduling and planning due to the high-demanding and customized market [19]. According to this technology, the CPS consists of an embedded computer and networks that monitor and control the physical processes, assisted by several IIoT devices connected by high-speed networks. The development of IIoT has improved the integration of the sensor-cloud system with intelligent communication methods, like control systems and equipment. As CPS is an integration of physical and cyber components, industries have begun creating socio-cyber physical work systems [20], which aim to improve the security and industrial output and improve the collaboration of workers with the systems [21]. The simulation enables predictive and cost-effective manufacturing technologies like the Digital Twin (DT). While simulation depends on mathematical models, the DT is a digital replica of a physical process, such as an operation, machine, or activity, and depends on actual data from physical parts of the process. DT can be based on real-time data integrated with simulations to provide high-resolution models and verify process performance. The real-time mapping of the physical object, through IIoT devices, allows to analyze, monitor the digital version, and prevent the problems before they occur in the real world. The continuous involvement and interaction of the DT can increase productivity, ensure stability, accuracy, and quality [22], and positively impact the OEE indicator. The IIoT implementation has allowed the DT to spread out in the industry because of its cost-effective, dependable, and accessible technology [4]. The rapid advancement of AI, ML, and Big Data Analytics has enabled DT to reduce maintenance costs and improve overall performance [23]. However, in industrial practice, the development of Big Data analytics is usually conducted by data scientists with data engineering expertise in statistics and machine learning, which need to effectively work with maintenance technicians, complementing each other with their expertise [24].

### *B. Network and communication technologies*

The 5G network paradigm implementation has enabled the deployment of local mobile networks, eliminating the requirement of dedicated and vendor-specific hardware equipment [25]. Hence, the Private Mobile Network has been deployed to deliver localized and use case-specific network services so as Local 5G Operators can be used in I4.0 applications, even though regulation and management should be studied further for cost-efficient implementation [26]. Furthermore, the upcoming 6G network paradigm will offer significantly more value-added services to cover more extensive bandwidth requirements, making it possible to deliver ultra-high data rates, ultra-low latency, ultra-high reliability, high energy efficiency, traffic capacity, and support high-quality services [27]. Moreover, improved communication such as Machine-to-Machine/Man and Device-to-Device can give high reliability to the total process control [28] and aid the large-scale interconnection of several machines, reducing network levels. Nevertheless, many factors in terms of safety and availability of the communication lines need to be considered during risk assessment and the occurrence of redundant lines to guarantee a high QoS. Network Slicing enables multiple virtualized networks on top of a single physical network infrastructure, setting an interface between the virtualized world and heterogeneous networks in a self-organized, flexible, and optimal way. However, technical aspects need to be investigated for the practical IIoT realization via NS by improving network scalability, dynamicity, security, privacy, and QoS [29].

Edge Computing (EC) has been introduced to overcome this limitation and help reduce the network's load and latency, speeding up services and response times compared to a primary or cloud-based processing method. EC brings the computation and data storage capabilities closer to the client location and improves response time, bandwidth, and network capabilities. This technology can also increase security by eliminating the sharing of specific data over a network, also performing valuable operations such as data processing, cache coherency, computing offloading, transferring, and delivering requests [30]. The evolution of EC is Fog Computing, a decentralized computing infrastructure in which data, computing, storage, and applications are located between the data source and the cloud, reducing latency between the industrial network and the components. All these technologies have in common the need to ensure the safety of the data. Cyber Security is the application of technologies, processes, and controls to protect systems, networks, programs, devices, and data from cyber-attacks. It aims to reduce cyber-attack risk and protect against unauthorized exploitation of systems, networks, and technologies. A research [31] proposed six layers of Cyber Security, considered as the barriers through which hackers may gain access to an Industrial Control System, where the first line of defense is the Network Firewall against hackers, viruses, and malware.

In contrast, the outermost layer is Business Continuity and Disaster Recovery, which necessitates spotting potential and preparing a continuity and recovery plan. Between the layers is developed the Data Encryption, which uses passwords or digital locks to secure the systems and data. Longer and more complex passwords ensure more robust encryption and a lesser chance of hackers breaking into the systems. In this layer, Blockchain technology is used to record data in a digital form using cryptographic methods to make them less susceptible to hacks, leaks, or precarious access [32]. The potential of Blockchain in IIoT is quite promising but also faces technological, security, and privacy-based challenges that need to be developed [33].

### *C. Physical/digital interface technologies*

A vital contribution also comes from technologies directly involved in the real world as an interface for the digital one. Augmented Virtual Reality (VR/AR) is a promising technology characterized as a facet that enriches the real world with virtual objects generated on a computer. These objects look like they exist in a similar location to the real world and are effectively used for robotics, repair and maintenance, and manufacturing applications [34]. VR/AR content creation may require infrastructure redesign and unique knowledge of domains such as interface design, modelling in 3D, fiducial marker, spatial tracking, and programming [35]. VR/AR ensures higher levels of awareness on the shop floor and speedy symmetrical information distribution due to enhanced technologies for communication like the 5G networks [36]. To enhance the abilities to recognize safety risks accurately and promptly, AR has been studied and applied in the construction process of inspection, and supervision, as reported in the study [37], identifying five trends of future development related to safety issues and ergonomics which could make an optimal combination to improve the future safety management in the construction industry. Another emerging technology is eXtended Reality (XR), which improves human-machine interactions by combining virtual and physical worlds [38]. XR is a term that encapsulates Augmented Reality, Virtual Reality, and Mixed Reality (MR) [39]. While AR integrates virtual and real objects in a real-time display, VR allows users to control and navigate their movements in a stimulated real or imagined world. XR has been used in related applications such as remote assistance, assembly-line monitoring, and maintenance. A study [40] reports that consumers' decisions regarding XR adoption hinge on the technology and other factors. Indeed, the impact of immersion and presence on XR adoption is not straightforward since their relationships are mediated by other variables, such as perceived usefulness, enjoyment, flow, and embodiment. Future research should therefore disentangle these underlying dimensions and deepen the analysis of their influence.

The Collaborative Robots (Cobots) are another disruptive technology in physical/digital interfacing. They are robots acting in collaboration through one or more integrated software programs and are often used for increasing the production output and efficiency of processes. Repetitive and monotonous tasks will be assigned to the robots and the humans' critical and cognitive thinking tasks. A research [41] was conducted using marker-based and marker-less AR technologies to develop an intuitive method for robotic manipulator teaching. In another research [42], AR for human-robot collaborative manufacturing was introduced to enable an AR-centred instruction system, planning and re-planning of the task sequence, monitoring of workers, and industrial robot control integrating technologies like IIoT and Cloud-based systems. [43]. Nevertheless, the ability of Cobots to share activities with humans still presents several limitations in guaranteeing safety. A virtual or physical safety cage can be introduced to allow the operator to interact naturally and intuitively with either Industrial or Cobots [44]. Specific issues concerning the co-working of humans and robots must still be considered. For instance, the fear of losing jobs among humans must be dealt with and eventually compensated, as well as the ethical problems associated with ergonomics, regulatory issues, and psychological concerns to make humans adopt a new way of working. Furthermore, robot programming is a time-consuming and detailed task that requires highly skilled personnel and control schemes to develop faster programming techniques and safer ecosystems for I4.0 [45].

## V. CONCLUSION

A highly efficient process will result from the targeted deployment of I4.0 ET, speeding up the entire process and improving quality control. By applying predictive solutions based on supervised algorithms, I4.0 ET may assist in boosting equipment availability and image processing can have an influence on quality through deep and machine learning. Cutting setup and cycle times might result in a considerable improvement in performance metrics. However, technical integration problems and a lack of industry precedent are the key barriers to the deployment of I4.0 ET. Manufacturers and regulators will need to make cultural changes and innovate in order to handle all the inherent risks and knowledge gaps for the successful transition to a Smart Factory. In this respect, the proposed conceptual approach provides a basic method for successfully adopting I4.0 ET in the industrial sector, highlighting the real benefits brought to the business by increasing OEE value. Future pilot projects will test the proposed approach, and the impact on OEE improvement will be evaluated.

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## Appendix A. FIRST APPENDIX

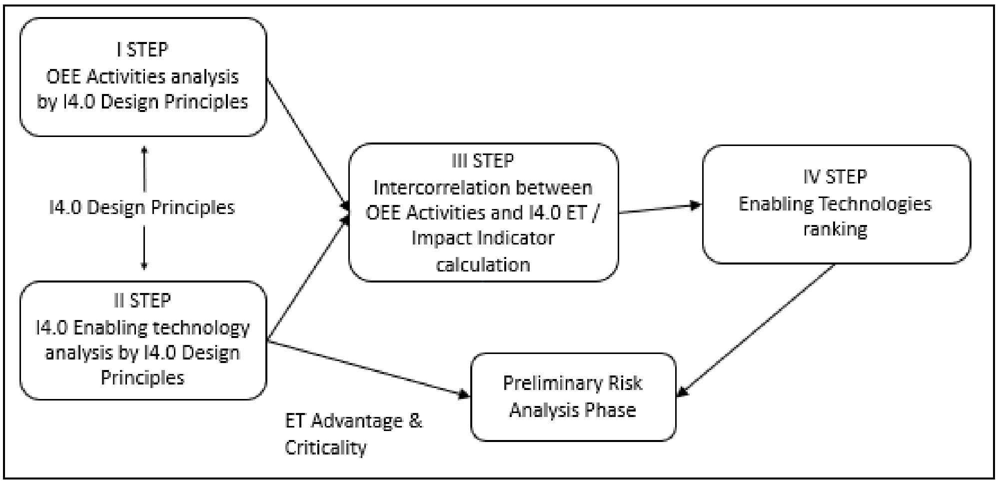


Fig. 2. Framework proposal for the OEE improvement

| **I4.0 Design Principles** | **OEE Calculation Activities** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Measurement* | | | | *Processing* | | | | *Control* | | | | | | |
| | *Real-time measurement* | *Back-end data transmission* | *Data-Filtering* | *Data storage* | *Aggregated calculation* | *Trends calculation* | *Root cause identification* | *Warning and Alarm processing* | *Shop floor dashboard* | *Data visualization* | *Bottleneck verification* | *Intervention verification* | *Task and procedures description* | *Change simulation* | *OEE optimization* |
| *Real-time capability* | X | X | X | | X | X | X | X | | | X | X | | | X |
| *Interoperability* | X | X | X | X | | | X | | X | X | | X | X | X | |
| *Virtualization* | | | | | | | X | X | | | | X | X | X | X |
| *Decentralization* | X | X | | X | | | | | X | X | | | X | | |

Fig. 3. Correlation between I4.0 Design Principles and OEE calculation activities

| **I4.0 Design Principles** | **I4.0 Enabling Technologies** | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | *Data capturing and processing* | | | | | | | *Network and communication* | | | | | *Physical/digital interface* | | |
| | *Big Data Analysis* | *Artificial Intelligence* | *RFID* | *Internet of Things* | *Simulation and modelling* | *Cyber-Physical System* | *Digital Twins* | *Network Slicing* | *Cloud Edge and Fog Computing* | *Cyber Security/Blockchain* | *Private Mobile Network* | *5G and 6G communication* | *Augmented Virtual Reality* | *Extended reality* | *Collaborative robots* |
| *Real-time data capability* | X | X | X | X | | | | X | X | | X | X | | | |
| *Interoperability* | | | X | X | X | X | X | X | X | X | X | X | | | X |
| *Virtualization* | | | | | X | X | X | | | | | | X | X | |
| *Decentralization* | X | X | X | X | | | | X | X | | X | X | | | X |

Fig. 4. Correlation between I4.0 Design Principles and I4.0 Enabling Technologies