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# How is technology changing the position of the maintenance operator as part of Industry 4.0?

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**Abstract:** New skills are required of maintenance operators due to the implementation of Industry 4.0 technology, such as the ability to communicate with Cyber-Physical Systems and robots. In this paper, we examine the state-of-the-art Industry 4.0 innovations that are transforming operations and production management. Then, we explore how maintenance operators' roles are changing in such a digitalized world. We discovered that in addition to the ability to communicate with computers, digital databases, and robots, Maintenance Operator 4.0 should locate relevant information and forecast events through the correct use of Big Data analytics. Finally, the ability to quickly adapt his abilities to new technologies is highly valued.

**Keywords: Industry 4.0 · maintenance · maintenance operator 4.0 · smart factory**

## I. INTRODUCTION:

The so-called ”nine pillars” of advanced technologies can transform a traditional factory into a smart factory [1–3], mainly through implementing the most representative technologies, Cyber-Physical Systems (CPS) and Internet of Things technology [4, 5], which are supporting the fourth industrial revolution.The pairing of manufacturing processes defines the creation of smart factories capable of meeting new management goals [6–8] in a more versatile manner with information and communications technology (ICT) [9] in such a digitalized period. As a result of the improvements in human resource management and tasks [2, 10] brought on by Industry 4.0, it is now possible to recognize new skills required by operators, or ”Operator 4.0,” as it is often referred to. On the other hand, a digitalized world has created new challenges in terms of process and product dynamics and how operators must handle and use new technology [11]. Romero [12] discussed the idea of the Operator 4.0 in the sense of human-CPS interaction, resulting in ”human-automation symbiosis work systems for a socially productive manufacturing workforce.” The same authors have identified four major stagesin the evolution of the Operator:

- Operator 1.0, ”known as humans performing manual and dextrous work’ with specific mechanical and manually operated machine tools,”
- Operator 2.0, which ”represents a human being doing ’assisted work’ with the assistance of machine tools,”
- Operator 3.0, which ”embodies a human being engaged in ”cooperative work” with robots, other computers, and computer tools, also known as ”human-robot collaboration,”
- Operator 4.0, which represents ”the ’future operator,’ a smart and skilled operator who conducts ’work assisted’ by machines as and when necessary.”

This study aims to identify improvements for Maintenance Operator 4.0 in a ”smart factory,” and to do so; we needed to conduct a preliminary literature review of recent publications [13–15]. According to recent scientific reports, a thorough literature review allows for identifying knowledge gaps and creating theoretical foundations for the proposed analysis.

## II. STATE-OF-THE-ART IN INDUSTRY 4.0 TECHNOLOGY:

Industry 4.0 is focused on implementing the ”nine pillars” of technologies, as previously stated. 1) Industrial Internet of Things (IIoT); 2) Big Data; 3) Horizontal and vertical device integration; 4)

Simulations; 5) Clouds; 6) Augmented Reality; 7) Autonomous Robots; 8) 3D printing, and 9) Cyber Security are some of the pillars. All Cyber-Physical Systems (CPS) used in smart factories are the Industrial Internet of Things (IIoT). Such systems are linked through the internet, allowing for creating a communication network capable of exchanging real-time data without the need for human interaction [16, 17]. Big Data, according to Kaisler [18], is "the sum of data that technology can't store, handle, or process efficiently." CPSs account for a significant portion of the total digital data in an intelligent plant. In a highly dynamic structure [19], horizontal and vertical system integration enables complete connectivity of all parts of the entire supply chain. Simulations can be thought of as a digital tool for designing manufacturing processes, and they can also extract real-time data from CPSs [20].

Cloud technology refers to cloud computing and digital storage solutions [3] that allow "on-demand" digital data sharing between CPSs and other smart devices [21, 22]. Augmented Reality (AR) overlays digital data on the physical world, enabling humans and CPSs to interact [23]. Within a smart factory, robotic applications can serve a variety of purposes. They usually assist operators in their tasks and can also communicate with other cobots [24]. During their operations, robots are just another method for acquiring and sharing data. The 3D printing of physical structures is referred to as additive manufacturing. They may also use 3D CAD digital prototypes as a digital source [25]. The ninth pill is Cyber Security, which helps to prevent cyber-attacks on digital data and smart devices [26].

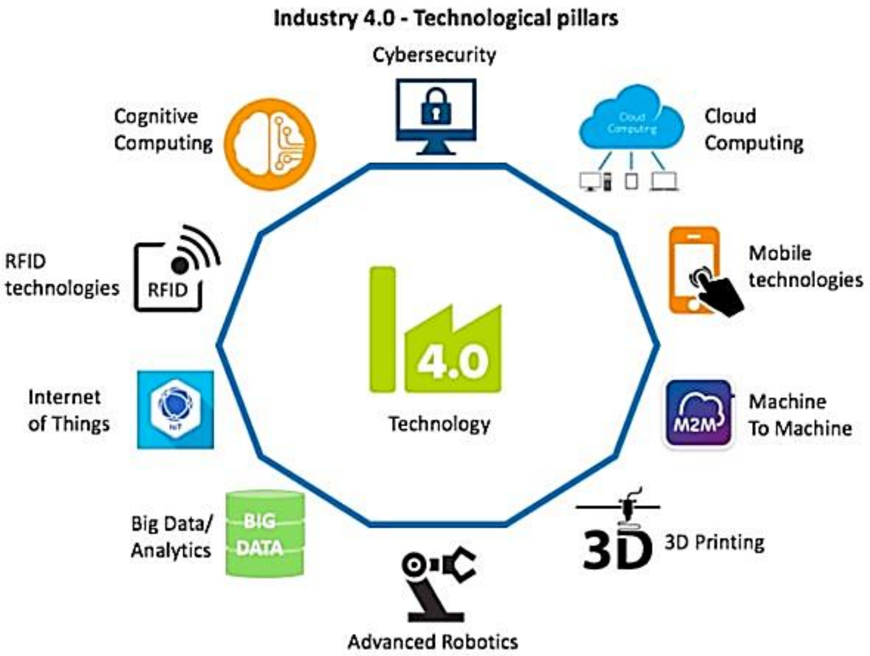


Fig. 1: Technologies for industry 4.0

## III. THE MAINTENANCE OPERATOR 4.0

Industry 4.0 has increased the complexity and complexities of operations and manufacturing processes and modified protocols and human tasks [11], as mentioned in the introduction section. According to Zolotova [3], the transition from operator to Operator 4.0 is possible by enhancing physical, sensing, and cognitive capacities and then being able to help key maintenance processes. The primary function of Operator 4.0, according to Wittenberg [10], is to supervise automated development using enhanced monitoring systems. Because of the increased amount of accessible digital data, the same author also addresses how traditional interfaces for handling information are now unsuitable. Ansari [27] lays out how to achieve proper coordination between operators and CPSs for maintenance activities, while Fantini [28] lays out a protocol for dealing with circumstances in which operators must communicate with CPSs.

According to Manyika [29], even though Big Data Analysis plays a critical role in economic innovation, there has been a general shortage of operators capable of extracting insights from Big Data, resulting in a slowdown in technology adoption. Using virtual reality technologies and analyzing digital data obtained in conjunction with robots, operator 4.0 can enhance his or her real-world understanding, which leads to better control and execution of maintenance tasks [30]. Virtual reality is an effective tool for training and assisting operators in making decisions on new maintenance procedures [3]. AR tablets, on the other hand, are often used for repair. On the other hand, tablets have significant drawbacks, such as the need for battery power and the fact that they are not hands-free devices [30, 31]. Wearable augmented reality (AR), or headmounted displays (HMD) are becoming increasingly common as a result [32]. According to a 2016 study, most maintenance operators consider smart devices to be beneficial in reducing uncertainty during activities [10]. Maintenance is needed. Operator 4.0 is a smart operator with improved physical, sensory, and cognitive capabilities thanks to the convergence of Industry 4.0 technologies. Table 2 summarizes the primary and critical aspects of the maintenance Operator 4.0. Finally, Fantini [28] emphasizes the importance of proper workplace design in easing the human-automation symbiosis, while Koch [33] discusses appropriate interfaces for an efficient relationship between operators and robots, including necessary skills.

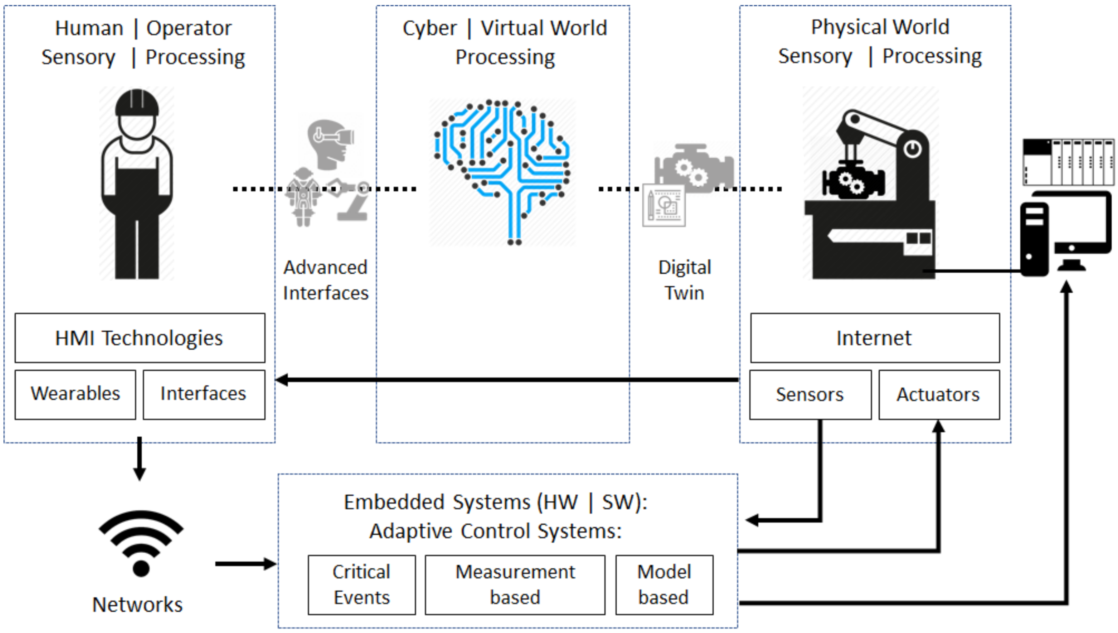


Fig. 2: The Maintenance Operator 4.0

## IV. VALUE MANAGEMENT:

Understanding the value that an asset provides is a crucial starting point for any asset management strategy. Tools are given in the IAMS to calculate and manage this value, using factors that enable value to be appropriately expressed. This quantification is done using so-called severity factors or value factors, which would allow Crespo [34] to realize the asset hierarchy within the IAMS framework. Criticality analysis is a technique for identifying and prioritizing an installation's assets based on the significance and implications of possible failure events for the company. The properties of a facility for which it is worthwhile to direct resources are identified through criticality analysis (human, economic, and technological) [35]. The components are divided into groups by the critical review, which can be handled in a more controlled and auditable manner. Nevertheless, we must first define the value factors that will be included in the study. These factors can differ based on the market climate, business goals, or different areas of the company, contracts, countries, and their regulations, etc. The following are the significance or severity variables suggested assessing the effects of a functional failure of each of the elements to be analyzed: i) Safety: This aspect assesses the effects of an element's functional failure in terms of harm to staff or other individuals. ii) Production Line Activity: This factor assesses the effect of a functional loss of an element on the production line's operation. iii) Finished Good Quality: This factor assesses the effect of an element's functional failure on the quality of finished goods. iv) Corrective Maintenance Cost: This factor assesses the effects of an element's functional failure in terms of the item's corrective maintenance costs. For each of these factors, a scale will be formed (for example, inadmissible, high, medium, and low), to which numerical values will be provided in such a way that the effect that said asset would have for each specified severity factor can be evaluated quantitatively. Similarly, each element will have a different effect on the company depending on the system's strategic goals, with greater or lesser weight. In this case, the weighting chosen for each factor appears in Table 1 below:

| Factor to measure the Consequences and their weighting | | | |
|---|---|---|---|
| Safety | Line Operation | Finished Good Quality | Corrective Maintenance Cost |
| 35% | 30% | 20% | 25% |

Table 1: Factor to measure the Consequences and their weighting

To define these principles, a business expert group must be established with detailed knowledge of how the installation works. The weights assigned to each severity factor are calculated based on previous experience. Following the definition of the weighting values, the asset valuation requirements must be defined. These can be valued manually by evaluating factors one by one for each asset or automatically by describing logical functions (AND/OR) based on the values of the intrinsic attributes specified for the asset, which have been established and loaded as additional data. While this automation of the factor valuation encourages and significantly speeds up the asset hierarchization process, it will not be feasible for all organizations because they either lack sufficient data or have external influences on the asset's valuation. The essential matrix obtained as a result of the hierarchy of assets is shown in Fig. 3, in which the failure frequencies (failures/year) are expressed on the y-axis versus the failure consequence on the x-axis.

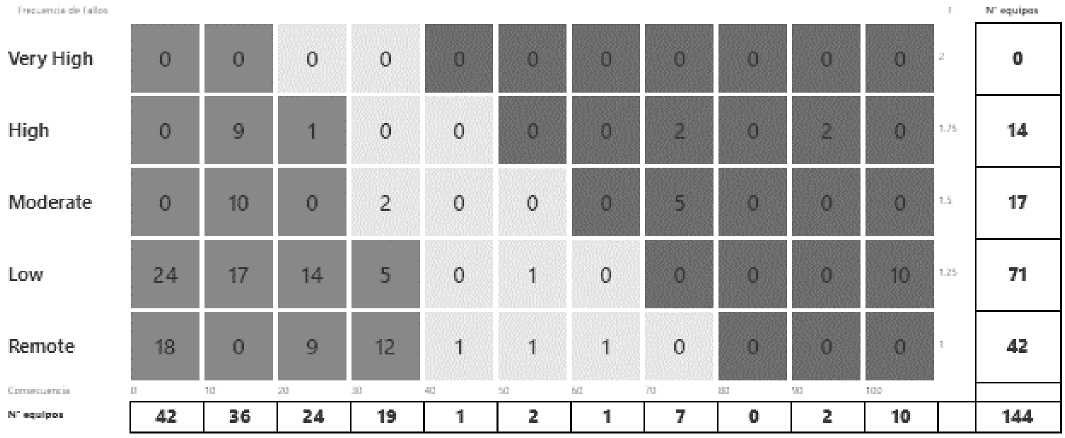


Fig. 3: Criticality matrix obtained

There are three zones in the matrix: critical (left), semi-critical (middle), and noncritical (right) (right). This makes it easier for the maintenance manager to make decisons about maintenance task preparation, with particular attention paid to assets located in the sensitive area due to the significant effect on the organization.

## V. Real time risk monitoring

The input variables are declared, and direct or derivative indicators calculated from these input variables are defined to perform the monitoring. Risk analysis is generated for each failure mode detected, using established and fed controlled variables, and based on experience. Using logical functions, the levels of risk in which the asset can be found are identified in real-time for the mode of associated failure, based on the indicators. The tool is backed up by another platform that displays the results obtained and tracking the current state of the studied system, with this platform serving as the management control panel.

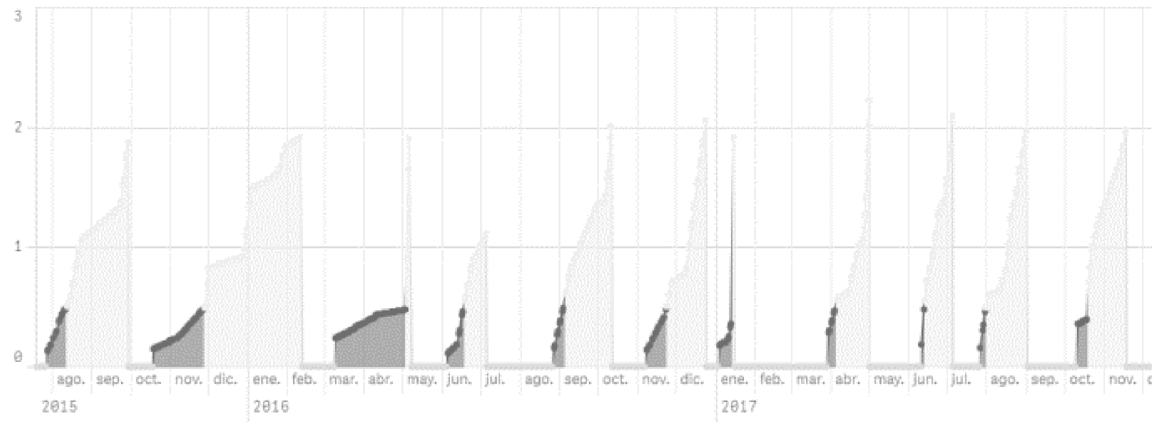


Fig. 4: Real time risk modelling at the scorecard

Figure 4 depicts an example of monitoring specified input variables and the evolution of those described in the scorecard so that the risk level rises before the asset is maintained. For example, when measuring vibrations, thresholds are identified. When the upper limit of the proposed threshold is exceeded, a corrective operation is performed, restoring the equipment to its proper operating state.

## VI. Discussion and conclusion

This project aimed to identify improvements for maintenance workers in a ”smart factory.” To do so, a preliminary literature review was conducted to determine state-ofthe-art Industry technology. By adopting the ”nine pillars” innovations, Industry 4.0 has made significant improvements to processes and production structures, and new skills are required of maintenance operators. Although the complexities and dynamics of manufacturing processes have increased in such a digitized setting, a maintenance operator can use technologies like AR and CPSs to get real-time feedback and better training. Hand-free technology, on the other hand, seems to be a requirement. In addition to the ability to communicate with computers, databases, and robots, Operator 4.0 should be able to locate relevant information and forecast events using Big Data analytics [24]. Over the last five years, the maintenance Operator 4.0 has undergone significant changes, including the need to be creative and communicate with CPSs, collaborate with robots and other smart technology, and perform various tasks in an improved physical, visual, and cognitive environment. Operator 4.0, according to Gilchrist and Perez [36, 37], must be able to quickly adapt his skills to a new environment where technologies are constantly implemented. Finally, repair technicians' skills and efficiency are expected to continue to develop in the near future. However, thanks to Industry 4.0 innovations like smart devices and virtual reality, the training process can be improved.

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