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CASE STUDY

The application of real-time overall equipment efficiency indicator in a medium-sized company

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ABSTRACT

Goal: This research investigated the application of real-time Overall Equipment Efficiency (OEE) at three assembly work centers in a medium-sized company. The objective was to demonstrate the feasibility of integrating Industry 4.0 technologies, such as the Internet of Things, Big Data, and Cloud Computing, in manual work center environments. It aimed to underscore the potential improvements achievable through data-driven actions facilitated by Industry 4.0 technologies, while emphasizing the significance of acquiring real-time OEE data.

Design / Methodology / Approach: The research involved theoretical exploration, implementation, data collection (Nov 2022–May 2023), and analysis on assembly workstations in a medium-sized Brazilian eyewear manufacturer.

Results: Based on the captured data, the factory implemented a series of corrective actions, leading to a reduction in unplanned stops. The obtained results were significant, as the average efficiency of the studied work centers improved by 12.3% in 7 months, with an increase in performance and in availability.

Limitations of the investigation: The analysis faces challenges due time constraints, potentially limiting the full assessment of IoT impact. Seasonal variations in eyeglass production and style-specific demand complicate evaluating the true benefits of Industry 4.0 tools, making effective OEE improvement hard to determine.

Practical implications: The study demonstrates a method to gauge manual labor efficiency through Industry 4.0 technologies.

Originality / Value: This study shows how Industry 4.0 technologies (IoT, Big Data, Cloud Computing) can be integrated into manual workforces, enhancing efficiency and providing real-time OEE for workers to self-assess.

Keywords: OEE; IoT; Industry 4.0; Efficiency; Big Data.

1 INTRODUCTION

Industry 4.0, also known as the Fourth Industrial Revolution, is an emerging concept that first appeared in 2011 during an industrial fair held in Germany, focusing on the pursuit of efficiency (Santos and Lima, 2018). The central proposition of Industry 4.0 is the transformation of conventional production systems into collaborative systems through the incorporation of innovative technologies, such as synthetic biology, artificial intelligence, the IoT, additive manufacturing, Big Data, horizontal and vertical system integration, among others. While many companies are still not aligned with these changes, especially those with limited technology investments, there is a notable opportunity for quality improvement by implementing Industry 4.0 related technologies. Among these technologies, cyber-physical systems, modular automation, and the IoT stand out (Bruno, 2016).

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The failure rate in digital transformation challenges is estimated to range from 66% to 84%, with a significant portion of these difficulties arising from the introduction of entirely new skills into organizations characterized by deeply ingrained traditional cultures and well-established operational methods (Libert et al., 2016). A question that emerges is the feasibility of implementing Industry 4.0 in a work environment lacking robust infrastructure or, as discussed in this study, in a sector heavily reliant on manual labor.

In this project, the objective is to showcase the outcomes of employing the Key Performance Indicator OEE, coupled with technologies like IoT, Big Data, and Business Intelligence, within a sector relying solely on manual labor. The aim is to illustrate the enhancements in OEE achieved through the implementation of these technologies in selected work centers within the assembly sector of an eyewear factory.

2 LITERATURE REVIEW

This section will explore some essential concepts to understand the OEE in the digital era. Initially, a brief introduction to OEE will be provided, followed by a discussion on the IoT, a phenomenon that has transformed the way devices and objects interact with the virtual world. Next, the concept of Big Data, an area that deals with large volumes of data and seeks to extract valuable insights through advanced analytics, will be addressed. Additionally, Cloud Computing, which has revolutionized data storage and processing by providing scalability and flexibility for organizations will also be discussed. Lastly, the field of Business Intelligence, which involves the collection, analysis, and interpretation of data to assist in making strategic decisions, will be covered.

2.1 Overall Equipment Efficiency (OEE)

In the 1980s, Nakagima introduced a widely used method to this day called Total Productive Maintenance (TPM), which aims to maximize equipment efficiency and reliability. Based on the management and maintenance approaches adopted by this concept, an indicator known as OEE was created and extensively utilized in industries to measure the efficiency of machines and sectors (Sayuti et al., 2019). It is essential to highlight that TPM seeks to reduce costs related to productivity losses, using as its foundation the six major categories of losses in a production process (Nakagima, 1988):

1. Equipment failures (breakdowns);
2. Tool changes or adjustments;
3. Idling or micro stops;
4. Low production performance;
5. Defects or rework;
6. Time to stabilize production.

OEE is used as a metric system to measure these losses, which are calculated based on the relation between its three pillars, and plays a crucial role as a comparison parameter to evaluate the performance of a manufacturing operation (Li et al., 2022). In the Lean Manufacturing approach, the combination of this indicator with the six big losses is emphasized, providing a detailed description of the main causes of productivity loss. Categorized clearly, these losses help to identify different types of production inefficiencies and offer valuable guidance for implementing measures to avoid such waste (Lindegren et al., 2022). The use of OEE can lead to an increase in workforce efficiency; with the information provided by the indicator, operators have the ability to identify possible improvements in their performance and adjust their work practices. This results in empowering operators and can lead to an overall increase in productivity (Sayuti et al., 2019).

By definition, OEE is the product of three elements: performance rate, availability rate, and quality rate. This tool allows identifying potential losses and provides suggestions for actions to minimize them, making it applicable to both machines and people, resulting in an overall improvement in production performance (Sayuti et al., 2019).

$$OEE = AvailabilityxPerfor.xQuality \tag{1}$$

Availability indicates the machine's operating time, and its rate decreases whenever unplanned stops occur (Sant'Ana and Silva, 2020).

$$Availability = \frac{T_{programmed} - T_{Inactive}}{T_{programmed}} x100 \tag{2}$$

Performance decreases due to stoppage losses and interruptions for short periods (micro-stops) or losses due to reduced speed (Klimecka-Tatar and Ingaldi, 2022).

$$Perfor. = \frac{T_{IdealCycle} x Q_{produced}}{T_{programmed}} x100 \quad (3)$$

Quality losses are represented by defects and rework resulting from malfunctions of production equipment (Klimecka-Tatar and Ingaldi, 2022).

$$Quality = \frac{Q_{goodpieces}}{Q_{produced}} x100 \quad (4)$$

Despite this indicator having existed for some time, its implementation has always faced challenges, particularly when it comes to data collection, which represents a difficulty in obtaining accurate OEE. When data is gathered with the help of records made by production operators, there is a higher probability of errors occurring. These inaccuracies can lead to incorrect information and, consequently, to misguided decisions. It is in this context that the IoT technology has played a significant role in business models and the industrial sector. By enabling real-time data collection with minimal margin of error, the IoT allows organizations to promptly identify variations in the production process, resulting in precise and immediate measurement of OEE (Bakhsh and Raj, 2019).

2.2 Internet of Things (IoT)

The IoT represents a communication infrastructure that establishes connections between the physical and virtual worlds. This technology encompasses the inter-connectivity of various physical objects through sensors that capture real-world events and direct them to communication and interconnection platforms (Colombo and Filho, 2018).

With the advent of Industry 4.0, the incorporation of the IoT in companies allows machines to interact with each other, collecting and analyzing data that can be stored in the cloud. This approach makes it possible to identify and solve problems autonomously, dispensing with human intervention and allowing machines to make efficient decisions by themselves. With the IoT, it is possible to envision a future where all objects connect and communicate intelligently and seamlessly. In other words, the physical world is transformed into an extensive and intricate information system (Freitas, 2017).

The solution proposed by IoT is to combat problems such as delay in data collection, slow access to information, delay in receiving responses and late system updates (Teimoury et al., 2013). For the effective use of IoT, data visualization plays an extremely important role, as it allows a harmonious interaction between the user and the environment through gadgets such as tablets and smartphones (Ferreira, 2019).

2.3 Big Data

The concept of Big Data is intrinsically linked to the existence of large volumes of data that grow continuously. This data can be carefully managed in order to increase its reliability, by aggregating information from different sources, as well as being subjected to encryption to ensure security and privacy (Ferreira, 2019). Big Data encompasses seven essential characteristics that are worth highlighting:

- Volume refers to the abundance of data, whose exponential growth is remarkable;
- Speed is a crucial aspect, related to the efficiency in capturing, processing and agile use of this data;
- Variety highlights the diversity of available sources, enriching the spectrum of information;
- Veracity, in turn, guarantees the reliability of the data, making them capable of generating useful and reliable insights;
- The value of data, as its relevance lies in its ability to generate tangible benefits for organizations;
- Vulnerability, which ensures the security of information in the face of possible cyber attacks;
- Data visualization, which provides a more intuitive understanding through graphical representations and specialized software (Pita, 2023).

A fundamental element of every digital transformation strategy is centered on data. It acts as a facilitator for driving digital advancements; however, the continuous refreshment of data is crucial for its effective utilization (Correani et al., 2020). The goal of Big Data management is to ensure that these reliable data are readily accessible, easily managed, stored, and efficiently protected (Ferreira, 2019).

With the aim of streamlining Big Data analysis, auxiliary tools such as cloud computing can be employed, as will be expounded upon subsequently.

2.4 Cloud Computing

Cloud computing is a revolutionary technology that has transformed the way businesses address their demands and needs. Through this innovation, customers can run programs simply and intuitively using a cloud-based interface, resembling the experience of browsing the internet. Virtualization plays a vital role in this process, allowing the creation of virtual resources from physical ones, simplifying the establishment and management of cloud computing. The central idea involves virtualizing servers or parts of them to use these resources as needed. Cloud computing emerged as a response to the growing need to build complex infrastructures and handle tasks such as system configuration, updates, and installations. By opting to contract service providers, users can enjoy the benefits of IT infrastructure without the need for advanced technical knowledge. In summary, the proposal of cloud computing is to make software, platforms, and physical infrastructure available as services, all accessible via internet (Paula and Dian, 2021).

As one of the pillars of Industry 4.0, cloud computing is driving the digitization of production and enabling remote programming of production lines, as well as real-time adjustments. By utilizing cloud computing, users have access to virtually unlimited computing resources, leveraging services based on IoT. These services allow for the interconnection of industrial equipment and robots through sophisticated sensors, generating a vast amount of information every second. This information is stored and processed rapidly, providing unprecedented levels of efficiency, productivity, and quality (Paz and Loos, 2020).

According to Costa (2023), cloud computing is gaining increasing prominence in the industrial sector as it provides an efficient solution for data storage and processing, as well as enabling the outsourcing of hardware infrastructure, maintenance, and services that would typically require internal resources.

In Industry 4.0, the advantages of cloud computing are manifold. Apart from obviating the need for acquiring computational infrastructures, it also eliminates the necessity for software installation and management. This tool possesses the capability to seamlessly integrate the entire production chain by connecting equipment, thereby rendering processes significantly faster, more efficient, and reliable. Through the utilization of cloud computing and the Internet of Things (IoT), the analysis of Big Data is facilitated, as it allows for data processing using tools available in the cloud, streamlining the identification of patterns and correlations that contribute to insights and benefits within the industry (Albertin and Pontes, 2021).

2.5 Business Intelligence

The integration of information systems in Industry 4.0 allows industries to feed their operational data through the implementation of Business Intelligence technologies, which provide reports and dashboards to support decision-making. These technologies facilitate the collection, analysis, and delivery of information, including the transformation and cleansing of data through the Extraction, Transformation, Loading (ETL) process, resulting in processed data ready to support business decisions. The connection between Business Intelligence and the IoT is fundamental in this context (Neto and Campos, 2021).

2.6 OEE and the Industry 4.0

It is possible to find studies that demonstrate the influence of Industry 4.0 technologies on Key Performance Indicators (KPIs), such as OEE. However, these studies often focus on how to use these tools to calculate machine efficiency, but not manual processes.

Silva (2020) and Ammar et al. (2021) emphasize that utilizing IoT and big data technologies to obtain OEE brings a range of benefits, including real-time analytics, advanced reports and dashboards, intelligent real-time alerts, increased transparency in management, secure data transfer, improved production efficiency, and reduced losses.

IoT plays a crucial role in improving OEE design as the integration of these two tools provides the ability to automatically measure availability, performance, and quality, resulting in real-time OEE. This allows to accurately identify production losses. Furthermore, the use of IoT makes it possible to monitor the real state of machines, enabling an extension of intervals between maintenance when the equipment is in good working order. Moreover, OEE measured through IoT typically provides much more accurate data than manually recorded data (Hwang et al., 2017).

According to Herrero (2020), estimating OEE in real-time using IoT allows managers to identify areas that need to be studied with the purpose of enhancing the efficiency of the production process.

Some studies highlight efficiency gains when adopting these technologies. In a study conducted by Cañizares (2018), a company in the metal-mechanical sector experienced significant improvements upon implementing IoT. In this case, there was a 61.8% increase in the automation of subprocesses, and the factory's production capacity expanded by approximately 25% due to a reduction in workload resulting from improved process management. The control implemented in the production process led to a 15% reduction in the production time for each product. Another positive outcome observed was a 15% increase in the company's OEE. These results demonstrate how implementing IoT can bring substantial benefits to the industry, enhancing both efficiency and productivity.

In the study carried out by Bakhsh and Raj (2019), a pilot test was carried out on an industrial assembly line. During this experiment, work center operators underwent training related to the implemented system. Over a period of 7 months, a significant increase of 20% in the Overall Efficiency Index (OEE) was observed. These results highlight the effectiveness of using OEE in conjunction with the Internet of Things (IoT), highlighting its positive impact on several sectors.

2.7 General considerations

OEE is a crucial metric for assessing machine performance and identifying opportunities for production improvement. With the implementation of sensors and connected devices, IoT allows the real-time collection of data from different assets and industrial processes, providing a comprehensive view of performance and enabling immediate corrective actions.

The massive collection of data from IoT, combined with the power of Big Data, opens the door to advanced analytics, allowing you to identify patterns and trends in data, providing a more complete understanding of industrial processes. Cloud computing and Business Intelligence play a key role in providing a flexible and scalable platform for storing, processing, and analyzing data. By moving operations and analytics to the cloud, companies can access real-time information, collaborate more effectively, and make decisions based on up-to-date data from anywhere at any time.

3 METHOD

In this section, various aspects related to the research in question will be addressed. Firstly, the fundamental stages of the research will be discussed, followed by an exploration of the main characteristics of this study. In addition, relevant information about the company under analysis and the sector in which the study was conducted will be presented, providing a broader context to understand the results obtained. A section will be dedicated to discussing the software used during the research, emphasizing its functionalities and its contribution to data collection and analysis. Finally, the execution of the project will be outlined, including a flowchart detailing the installation process, the execution of training, and the operational workflow.

3.1 Research Steps

The undertaken research commenced with an initial theoretical survey into the pertinent subject matter, succeeded by an implementation and training phase. Following this, the data collection transpired, utilizing information acquired from the company over the timeframe spanning November 2022 to May 2023, with a specific focus on data pertaining to the OEE of individual workstations. Ultimately, a comprehensive analysis was undertaken to examine the alterations that manifested throughout the course of the process and their consequential impact on the operational efficacy of each production line.

3.2 Characteristics of the Research

There are several ways to classify a research study, taking into consideration its approach, nature, objectives, and procedures. Regarding the approach, this study is classified as quantitative since it seeks to use mathematical language to analyze and describe the causes of a phenomenon, establishing relationships between its variables by utilizing indicators and representative data (Mussi et al., 2019).

The nature of the presented research is applied, as it aims to generate knowledge with the purpose of practical application (Silveira and Córdova, 2009). The objective of this research is classified as explanatory since it aims to provide explanations about the conditions that determine the occurrence of related facts and phenomena through statements (Leonel and Motta, 2022).

As for the procedure, this study is considered to be a case study, which involves the analysis of a specific entity, such as an institution, a person, or a program. The purpose of this procedure is to investigate the reasons behind a certain phenomenon, seeking to discover its essential and peculiar characteristics (Fonseca, 2002).

3.3 The Company and the Sector

The research took place in a medium-sized company specializing in the manufacturing and sale of sunglasses and frames, situated in the southern region of Brazil and employing approximately 130 personnel. The facility encompasses five distinct departments, comprising plastic injection, painting, ornament assembly, lens cutting, and dispatch.

Figure 1 - Sectors of the Studied Factory
Source: The authors.

The study was conducted in three work centers within the ornament assembly sector. Each work center is responsible for transforming painted parts, received from the previous sector, into assembled frames with ornaments. The implementation of this study needed the installation of an IoT device in conjunction with a push-button switch at each of these workstations. The push-button switch serves as a pivotal means of communication between the workstations and the IoT device. Moreover, a tablet was integrated into each workstation, serving the dual purpose of reporting the ongoing efficiency status and serves as a tool to inform the system of production order, reject reporting, or indicate a reason for any stoppage.

The selected IoT devices were chosen due to their internal memory buffer, which allows data to be stored in case of an internet connection failure. As a result, the equipment continues to collect and store data in its memory until the situation is normalized or the memory becomes full.

The installed push-button switches have the function of notifying the IoT device whenever an assembly is completed. Therefore, the operator activates the push-button switch each time an assembly is finished, sending a signal to the IoT device to record this information.

Figure 2 - Assembly Workstation and Push-button
Source: The authors.

3.4 The Software

To handle the collected data, a software functions as a production control platform, performing data collection and processing, along with offering various other functionalities accessible from any device through the cloud. It provides historical and analytical reports on the production of the work centers, presenting information on overall equipment efficiency, availability, quality, and performance. It also offers insights into production, downtime, scrap, rework, cycle times, losses, and personnel data. Also, the software includes a real-time dashboard displaying the OEE of each work center, allowing users to identify which factors are causing efficiency losses.

The software is acquired using the Software as a Service (SaaS) model, with monthly charges per work center. To use the software correctly, the time required to complete each product (cycle time) is registered. Additionally, reasons for product defects (rejects) or rework, as well as the causes for stoppages, and the duration a work center should remain inactive to register a stoppage (stoppages are triggered in the software by absence of counting), are all entered into the system.

For seamless operation, the software has been integrated with the Enterprise Resource Planning (ERP) system used by the company. Training sessions were conducted with each work center operator to explain how to monitor OEE, record scrap, and change production orders.

3.5 Installation and Data Collection Start

To clarify the project execution, a flowchart was developed, as depicted in Figure 3. In this illustration, a lateral line on the left side signifies the division of the project into four distinct phases: Installation, Data Collection Start, Training, and Operation.

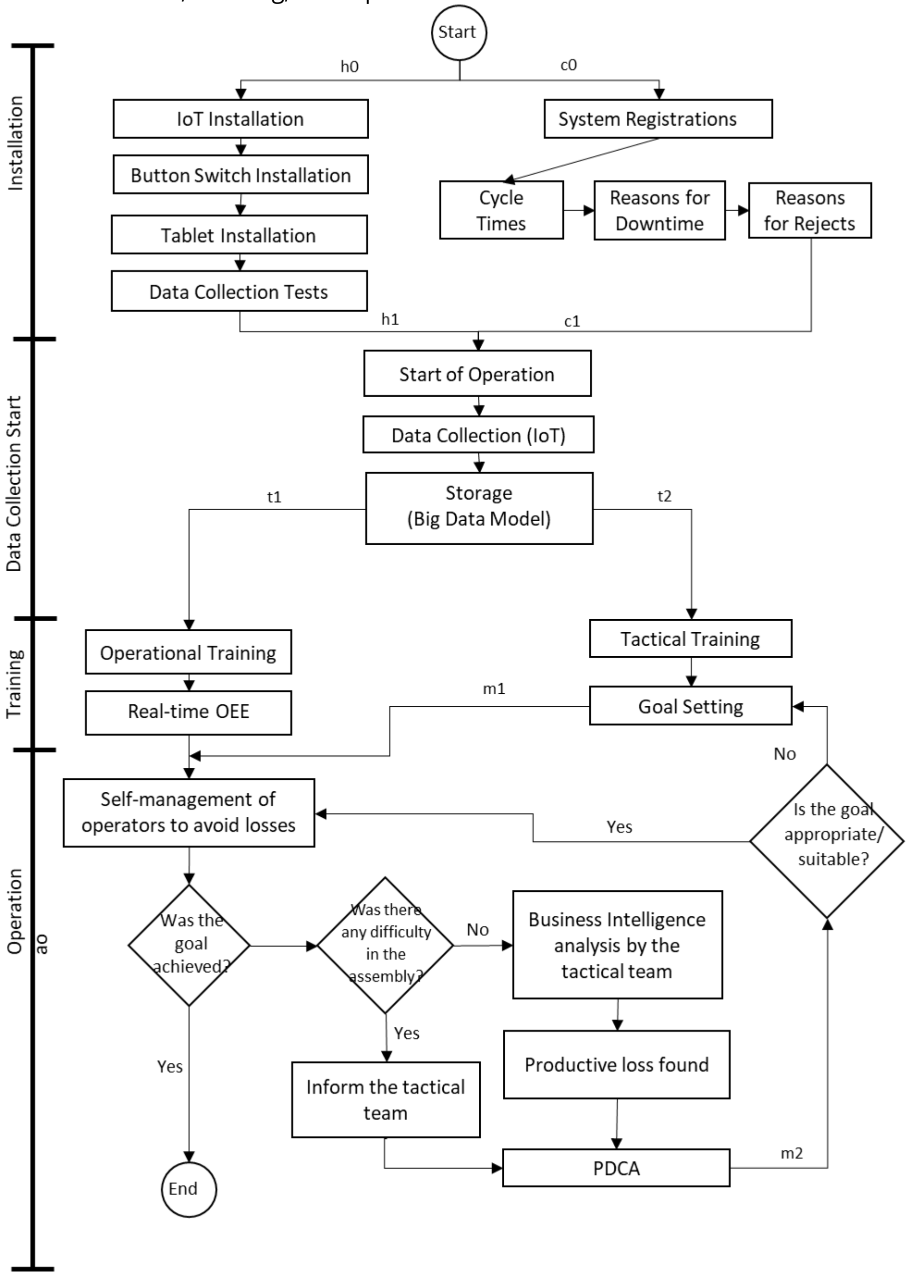

Figure 3 – Execution Flowchart
Source: The authors.

The installation phase can be subdivided into two components: the installation of hardware and software configurations. In order to expedite the project, the relationships denoted as h0 and c0 in Figure 3 can be concurrently addressed, considering that different teams can manage these relationships simultaneously. In the context of the investigated company, the h0 aspect was overseen by the maintenance team, encompassing hardware installations such as the setup of IoT devices and their connection to the push-button switches located at the work centers. Concurrently, c0 was undertaken by the process engineering team.

The c0 pathway entails the establishment of registrations within the software, encompassing the input of cycle times for each product, all conceivable factors that could halt a work center, and all potential reasons leading to the production of defective items. Both of these pathways necessitate completion before commencing production, thus prompting the merging of h1 and c1 relationships prior to reaching the "Start of Operation."

Upon the initiation of operation, operators receive instructions to assemble the glasses individually, clicking on the push-button switch upon completing each assembled frame. Simultaneously, IoT devices commence data collection, and Big Data becomes instrumental in data storage and processing. Following the initiation of data collection, the training phase can be initiated.

3.6 Training

After the installation and the start of data collection, training sessions were conducted for all involved parties. Through the t2 relationship, the department leader and engineers underwent comprehensive training with the objective of mastering the entire software. They learned about the functioning of registrations, including stops and product registrations. Additionally, they were taught how to change production orders, record stoppages and scrap, as well as conduct complex analyses in the program's Business Intelligence. These analyses included OEE, stoppages, cycle times, scrap, and other options.

On the other hand, the t1 relationship represents the training for production operators. The training focused on the data entry screens, production order changes, and understanding the control panel. The control panel provides real-time information on the OEE, as well as indicating losses related to performance, availability, quality, and cycle time. Figure 4 shows the screens used by the operators.

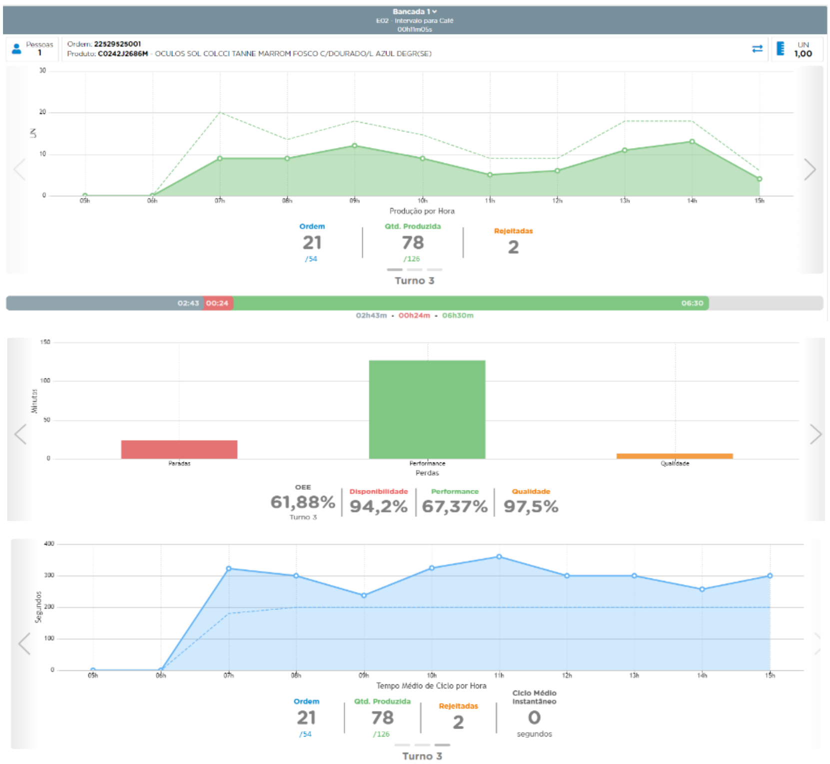

Figure 4 - Screens used by the operators.
Source: The authors.

3.7 Operation

Operation begins with the operator's self-management activity. In this activity, the operator aims to prevent losses by monitoring their real-time OEE. Simultaneously, they refer to the operation training screens to understand which OEE rates are causing the indicator to decrease. If the goal is not achieved due to difficulties with tools, raw materials, or even variations in production from other sectors, the workstation must inform the tactical team. In case the goal not being achieved, but the issue is not related to any of the mentioned factors, the tactical team, through Business Intelligence, must analyze the losses and devise an action plan to resolve the problem.

The m2 relationship aims to demonstrate the continuous improvement involved in the operation, where the tactical team is always seeking to enhance processes and, when necessary, redefine the goal.

4 RESULTS

The research was conducted in three work centers within the ornament assembly sector, referred to as Workstation 01, Workstation 02, and Workstation 03. In November, when the study began, these workstations had an average OEE of 63.49% - availability was 86.36%, performance achieved 74.92%, and quality reached 98.11%. It is worth noting that, according to Li et al. (2022), OEE plays a fundamental role in categorizing and identifying significant losses in the manufacturing process, providing a comprehensive view of operational performance by considering availability, performance, and quality.

Upon individually analyzing each workstation, differences in their respective OEEs were evident. At the time, it was observed that Workstation 01 had a higher efficiency, mainly driven by better performance. Conversely, Workstation 02 was the least efficient due to low performance.

Table 1 – OEE and its Rates in November 2022

Work Center	OEE (%)	Availability (%)	Performance (%)	Quality (%)
Total	63,49	86,36	74,92	98,11
Workstation 01	70,26	86,45	83,58	97,24
Workstation 02	54,62	86,36	64,00	98,82
Workstation 03	64,75	86,32	76,11	98,56

Source: The authors.

In November, 12,686 pieces were produced, while the estimated production capacity for all three workstations was 19,981 pieces. This indicates that the OEE resulted in production significantly below the productive capacity. When analyzing the losses in hours, the OEE indicators are confirmed. In November, the highest waste occurred in the performance area, with 98.48 hours lost. Next, availability accounted for 61.94 hours of loss, and lastly, quality contributed to 5.55 hours of loss.

As stated by Klimecka-Tatar and Ingaldi (2022), performance losses occur when a piece is being produced more slowly than planned. During the month of November, due to the implementation of the IoT system, there were changes in the way each Work Center operated, which may justify the decrease in performance during an adaptation period. With the introduction of the system, each product had to be completed before starting a new one, which altered the previous workflow before IoT. Previously, a workstation could assemble an ornament on all products of the same model before starting to assemble the second ornament, which took more time to complete the assembly of the first frame. With the new system, the assembly process was redesigned so that the workstation finishes the first assembly before starting the second, even if they are of the same model. Therefore, the process became more structured. Other reasons for the performance loss may be related to inadequate working tools. An evaluation was carried out on products that showed performance below 60% to identify any issues that occurred during assembly.

According to Sayuti et al. (2019), OEE can help identify and reduce equipment downtime, and to improve it, it is necessary to decrease unplanned stoppages. When examining losses due to availability, it was observed that the main cause of stoppages during the month of November was also related to low performance. The workstation remained idle for a significant amount of time due to slow production speed, which triggered the system to record a stoppage. To justify this stoppage, a category called "Stoppage caused by low performance" was created. In this case, the OEE was reduced due to the availability indicator, even though the issue affecting performance was related to the performance itself. Table 2 displays all the stoppages and the time lost due to them in the month of November.

Table 2 – Unplanned Stoppages in November 2022

Reason Code	Time Lost
E06 – Stoppage caused by low performance	21:56
D03 – Setup	18:18
F02 – Rework-Reframing	07:15
E07 – Product Cycle Error	3:26
Pending Stoppage	03:23
E05 – Operator Absence	02:53
E04 – Water / Bathroom	01:51
E07 – Loss due to Cycle Error	01:25
F03 – Stoppage for Paint Review	01:19
Stoppage caused due to defects in the Acetate Tip	00:08
F01 – Waiting for Authorization	00:02

Source: The authors.

In addition to low performance, other inefficiencies described by Nakagima (1988) in his book were identified. Within the six major categories of losses, the "D03 – Model Change" stoppage is related to setup, the "F02 – Reframing Rework" stoppage is related to scrap or rework, while the "E07 – Product Cycle Error" is related to incorrect registered cycles, and pending stoppages are unexplained stoppages in the system. To reduce these losses, several actions were adopted, including a strategy for quick tool changes, conducting training sessions, and acquiring tablets for all workstations. These tablets allowed stoppages to be justified immediately and enabled Production Order changes to be performed by the operators themselves, avoiding unnecessary stoppages due to model changes. Additionally, the tablets also allowed operators to monitor the performance of their respective workstations, which, according to Sayuti et al. (2019), is one of the advantages of OEE – providing operators with the autonomy to identify improvements and adjust work practices to increase productivity.

With the acquisition of data on inefficiencies, actions were implemented to reduce these losses. Over time, improvements in the results were observed, as evidenced by the system. One example of this is the significant reduction in the largest unplanned stoppages at the workstations. For instance, the stoppage named E06 - "Stoppage caused by low performance," which totaled approximately 21 hours and 56 minutes in November, decreased to 8 hours and 19 minutes in May. This reduction was due to two factors:

1. Self-management: The operator sought to maintain a higher performance rate;
2. Tactical Management Support: The tactical team worked to improve processes, tools, and raw materials.

An example of the second factor: for frames that used MPA1179 screws, operators reported difficulties in maintaining good performance for some frames, and the tactical team identified that the screws were out of standard. Additionally, the stoppage related to model change was also significantly reduced. This reduction was partly due to the implementation of a strategy that created a production queue to enter the work center. This means that when a production order is completed, the parts for the next order, along with their adornments, are already placed together at a designated location on the workstation, expediting the start of production. This approach makes the model change process faster by reducing the setup time of the workstation. Individual tablets played a crucial role in reducing this stoppage. With the availability of tablets and the provided training, operators became responsible for performing the Production Order change, making the process faster and more efficient.

The "Reframing Rework" stoppage also showed a significant decrease. As shown in Figure 5, this stoppage decreased from 7.25 hours to 1.17 hours. This improvement was possible due to increased attention from the workstation regarding this issue. With the system providing a history of workstations that had passed defective pieces to the next department, it became possible to train those operators to avoid the mistakes made in the past. This increased awareness and monitoring contributed to reducing stoppages related to reframing rework, demonstrating an improvement in the quality of work carried out by the workstations.

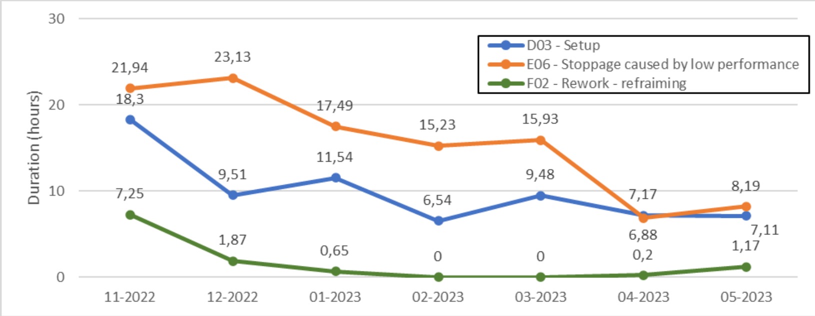

Figure 5 - History of the three largest stoppage reasons in November
Source: The authors.

The stoppage due to product cycle errors occurred because some products had incorrect times registered in the system. As the times were corrected by the engineering department, these stoppages gradually decreased. The correction of cycle times by the engineering department contributed to the reduction of stoppages related to this issue, improving the accuracy and efficiency of the production process.

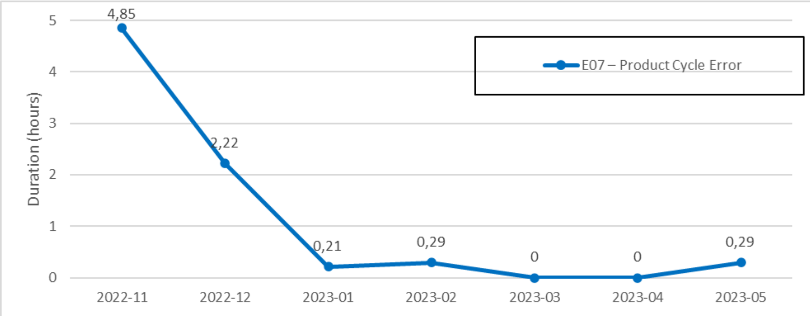

Figure 6 - "E07 – Product Cycle Error" Stoppage
Source: The authors.

With the tactical team working to reduce losses and a real-time system showing the numbers to the operators, enabling them to actively seek to avoid losses, it became possible to reduce unplanned stoppages from 61.94 hours to 40.64 hours.

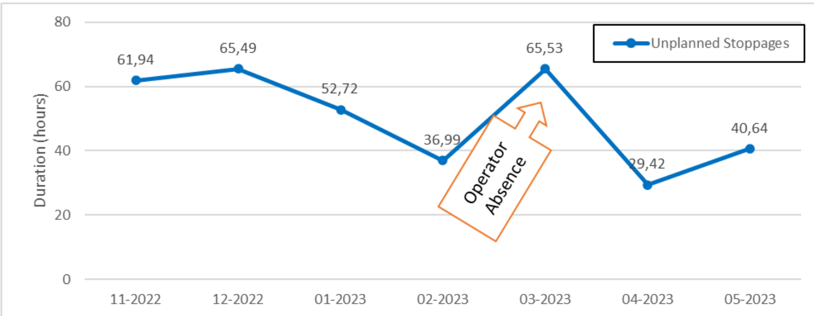

Figure 7 - Unplanned Stoppages
Source: The authors.

It's important to highlight that, despite this progress, there was an increase in unscheduled downtime in March due to the absence of a team member for a few days. These periods of absence can affect productivity and result in unplanned stops. However, even with this setback, the overall trend shows a reduction in unscheduled stops over time, demonstrating the effectiveness of real-time OEE along with the tactical team's action plans.

The evolution of OEE and its indicators throughout the analyzed period is presented in Figure 8. The results show an improvement in the overall efficiency of the workstations, which was achieved due to an increase in both availability and performance. The OEE increased by 12.3%, and availability also showed progress, rising from 86.4% to 91.0%. Similarly, performance saw significant growth, increasing from 63.5% to 75.8%. These findings demonstrate that real-time OEE, combined with implemented actions such as training, tablet adoption, production queue strategies, and improvements in raw materials, contributed to enhancing the efficiency and performance of the workstations. The progress in availability and performance directly influenced the increase in OEE, indicating a positive evolution in the overall performance of the operations.

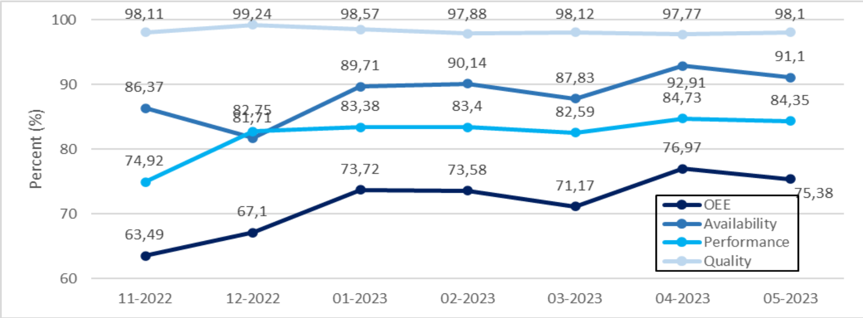

Figure 8 - Evolution of OEE and its components
Source: The authors.

Despite the increase in OEE, the production capacity did not show a significant increase. In November, the production capacity was 19,981 units, while in May, it decreased to 16,403 units. This is because the industry in question is influenced by seasonality, which affects the demand for the different models produced, each with distinct cycle times. The analysis of the average cycle time per month shows an increase, resulting in a lower production capacity. Thus, although the performance has improved, as the actual cycle time is closer to the nominal cycle time, the total production was affected by demand variation and longer cycle times. These pieces of information can be observed in Figure 9, which represents the comparison between the actual cycle time and the nominal cycle time over time, reflecting the improvement in workstation performance and the decrease in production capacity.

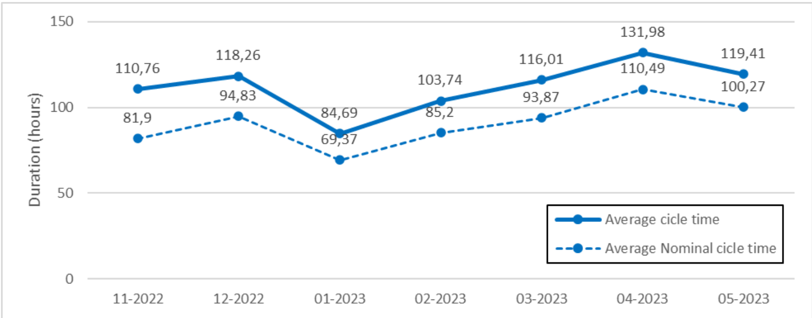

Figure 9 - Evolution of average monthly cycle time
Source: The authors.

Indeed, when individually comparing each workstation in November and in May, it can be observed that Workstation 03 had a 19.47% increase in its efficiency, demonstrating substantial progress compared to its previous performance. Workstation 01 showed an improvement of 5.66% in its efficiency, while Workstation 02 had an increase of 5.21%. These numbers reflect the positive impact of the implemented actions on their respective workstations. Additionally, all workstations showed progress in their performance.

The improvement in availability is also notable in Workstations 01 and 03. These results highlight the success of the measures taken to increase the availability of these workstations. Workstation 2 experienced approximately 11 hours of downtime due to the reason "E05 – Operator Absence" indicating that availability would have improved if this absence had not occurred.

In summary, the individual improvements in each workstation's performance and availability contributed to the overall enhancement of results and the OEE of the workstations.

Table 3 – OEE and its rates in May 2023

Work Center	OEE (%)	Availability (%)	Performance (%)	Quality (%)
Workstation 01	75,92	91,80	85,25	97,02
Workstation 02	59,83	86,19	70,06	99,09
Workstation 03	84,22	94,39	90,58	98,50

Source: The authors.

Analyzing the results in Table 3 for Workstation 2, the low OEE of this workstation was caused by both low performance and availability. Regarding performance, when examining the downtime related to performance losses on this workstation, we noticed that Workstation 2 assembled three exclusive products, which resulted in a total of 14.84 hours of lost time. The tactical team has already been analyzing the two products with the highest performance losses and developing an improvement plan in collaboration with the rod supplier for these products. However, since the material is imported, it will take some time to solve this issue (it may take a few months until the new product arrives).

As for availability, Workstation 2 had 9.14 hours more downtime than Workstation 3 (which has the best availability) due to the operator's absence for a few hours on two days. These issues in performance and availability are contributing to the low OEE for Workstation 2, and addressing them through the improvement plan and resolving the material supply problem will be essential to enhance the overall efficiency of this workstation.

5 CONCLUSION

This study has shown that it is possible to integrate Industry 4.0 tools with fully manual work centers, as is the case with assembly workbenches. Based on the collected data, the system has shown that there have been improvements in all three workstations. The newly implemented system, along with IoT data collection, played a fundamental role in obtaining valuable information to enhance the efficiency of each workstation.

The real-time OEE availability provided by the software enabled operators to monitor their individual performance. This allowed them to identify areas for improvement and work towards enhancing their performance, bringing their actual cycle times closer to the expected times. This self-assessment and self-regulation capability of the operators contributed to overall performance improvements.

Furthermore, the Business Intelligence capabilities of the software offered valuable insights to engineers and industry leaders. These professionals could analyze the collected data, identify patterns, trends, and specific issues in each workstation. Based on this information, they were able to develop a strategic action plan to address and resolve the identified problems, resulting in continuous and targeted improvements.

In summary, the combination of the new system with IoT data collection and the use of Business Intelligence software allowed for more precise monitoring and detailed analysis of operations. This data-driven approach empowered both operators and engineers to make informed decisions and implement effective strategies to optimize workstation performance. As a result, there was an average efficiency increase of 12.3% across all three workstations. However, despite this progress, the production capacity did not grow during this period due to an increase in the average cycle time, which can be attributed to seasonality.

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