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CHARACTERIZATION STUDY OF THE PRODUCTIVE EFFICIENCY IN THE ELECTRONICS ASSEMBLY INDUSTRIES OF THE MANAUS INDUSTRIAL POLE THROUGH THE CALCULATION OF THE OEE - AUTOMATION CASE STUDY

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ABSTRACT
This study presents the implementation of enabling technologies of Industry 4.0, with emphasis on the use of Digital Twins and the automation of the calculation of OEE (Overall Equipment Effectiveness), applied to an assembly line of electrical and electronic boards in the Industrial Pole of Manaus (PIM). The objective was to develop a solution capable of identifying, in real time, the times and reasons for production stoppages, aiming at optimizing industrial processes and reducing operating costs. The data was collected through IoT sensors installed on the production lines, integrated with a digital platform that virtually replicated the manufacturing plant in a Digital Twin system. OEE was automatically calculated from the three main indicators: Availability, Performance and Quality. Simulations in the virtual environment identified production bottlenecks and allowed predictive actions to avoid failures and optimize machine performance. The results, obtained over 80 days of monitoring, showed evolution in production efficiency indicators, with a reduction in unscheduled downtime, dynamic adjustment of production parameters

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and improvement in product quality, positively impacting industrial sustainability and energy efficiency. The study also discussed challenges faced, such as integration with legacy systems, quality of the data collected, and technical training of the team, which was essential for the success of the digital transformation. It is concluded that the combination of Digital Twins, automated OEE and Industry 4.0 technologies constitutes a viable path to operational excellence, contributing to the competitiveness and sustainability of the PIM industries.

Keywords: Industry 4.0. Digital Twins. OEE. Industrial Sustainability. Iot.

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INTRODUCTION

Industrialization is the transformative process of the most significant economic centers in the world, as it expands the generation of employment for its populations, demands its continuous training and specialization, adds innovative technologies for process efficiency and increases the reliability of quality in the production of consumer goods, as is the case of the electrical and electronic devices that characterize the Industry of the Manaus Free Trade Zone, AGUIAR (2022).

The structuring policies of the Western Amazon have as their most important initiative the Manaus Free Trade Zone (ZFM) aligned with a complex set of laws, norms and guidelines that make it the most important industrial development center located in the northern region of Brazil. In this framework, the ZFM Information Technology Law stands out, which is responsible for attracting important industrial groups with global operations, through its tax attributes. Especially in the sector of consumer and electronic goods: mobile phones, computers, household appliances and even motor vehicles, Lima, A. K. C. (2015).

In this context of fostering development, actions related to the search for continuous improvement of process efficiency, quality and competitiveness are very important. Through Research and Development projects regulated by SUFRAMA (Superintendence of the Manaus Free Trade Zone) and guided by CAPDA (Committee for Research and Development Activities in the Amazon), with the encouragement and implementation of projects aimed at the development of products, processes, systems and technologies. All with the objective of fostering the constant search for competitiveness, through high levels of excellence in industrial operationalization, cost reduction and, today, also for sustainability,

Industry 4.0 is a global reality. Its fundamental technological capacity for cloud interconnection enables the monitoring of processes and their results at any time and place and makes it possible to observe in detail every space, component and action within a manufacturing facility. Its adoption has brought speed and precision to industrial process management systems in routine control and planning activities in the industrial day-to-day, with an unquestionable positive impact on organizations that have managed to fully adopt them.

However, this capacity is not yet a reality for the vast majority of industries located in the Manaus Industrial Pole (PIM). Most of the industries installed there work daily with constant challenges in production planning, logistical impasses in both supply and flow,

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quality control and predictive maintenance of the production line, but still without the facilities that the enabling technologies of Industry 4.0 can bring to industrial operations and their management. This happens not because of a lack of understanding of the benefits, or even resources, but because of difficulties in understanding how these technologies can be aligned assertively to deliver the necessary results, within certain limits of time and resources. Based on machine data analyzed in real time to stop the high incidence of unscheduled downtime in the production of high value-added goods, which compromises all sectors of industrial operations, Balluff Brazil. (2023) and Ramos, C. A., Ribeiro, P. F., Barboza, W. S., Dias, M. J., & Alcântara, G. A. M. (2024).

In addition, in the current world scenario and especially when we talk about the Amazon, it is essential to bring to the scope of industrial research and development projects the attributes and characteristics of industrial sustainability that must be contemplated in these continuous improvement processes, Almeida, O. C., Brilhante, J. C., Pinto, F. R., & Alencar, D. B. (2019). Here the linear thinking that industrial facilities and their equipment must be used at their maximum capacity, in an intelligent and even shared way, to reduce waste, is appropriate. Knowing how to maximize available resources is a vital sustainability action, but it requires deep knowledge of the processes and how to monitor them effectively. This is a demand that can be very well met through the deployment of the concept of "Digital Twins", as will be explored and developed in this industrial research and development work.

Having processes that can be monitored, understood and improved is the first step towards the application of clean technologies, because this type of transformation of the industrial environment demands the adoption of initiatives that are capable of planning, both internally and in the macro context, the integration of physical spaces, people and equipment things, Li, H., Pangborn, H. C., & Kovalenko, I. (2023).

This level of integration, characteristic of Industry 4.0, is capable of transforming work processes, but only if it is simplified for human interaction using accurate real-time performance metrics. These metrics are invariably complex to calculate and until today they were analyzed a posteriori. This almost completely nullified their importance and relegated them to illustrations of managerial work that had little chance of being implemented. The use of digital technologies for the analysis of high volumes of data, using even simple machine intelligence resources, allows automation of the calculation of

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performance metrics such as OEE (Overall Equipment Effectiveness), McKinsey & Company. (2023) and NVIDIA Corporation. (2023).

In this work, this solution path for the diffusion of Industry 4.0 capabilities will be explored, which can already be accessed without investments of impeding resources by most IMP industries, exploring the concept of digital twins in the case of an automated production plant in an electronics industry (high prevalence sector of PIM), able to accurately identify the times and reasons for their production interruptions ("stoppages").

THEORETICAL FRAMEWORK

THE EVOLUTION OF THE EO AND ITS IMPORTANCE IN INDUSTRY 4.0

OEE (Overall Equipment Effectiveness) is a core metric for measuring the effectiveness of industrial equipment. It evaluates three fundamental components: Availability (equipment operating time), Performance (equipment's ability to reach its maximum speed) and Quality (proportion of products that meet established standards). This concept emerged throughout the four Industrial Revolutions, being continuously improved to meet the demands of an increasingly complex and technological production environment (HANSEN, 2022).

OEE and the Industrial Revolutions

1st Industrial Revolution (18th and 19th centuries)

During this period, the introduction of the steam engine revolutionized production, replacing artisanal processes with mechanized ones. Although OEE did not yet formally exist, the idea of maximizing machine efficiency was a growing focus. The main goal was to minimize failures and downtime by prioritizing regular maintenance.

- Availability: The uptime of the steam engines was essential to keep production active. Unexpected downtime caused major impacts on productivity (HANSEN, 2022).
- Performance and Quality: Although they were not formally measured, there were efforts to increase the speed of machines and produce acceptable goods, albeit in a rudimentary way (HANSEN, 2022).

2nd Industrial Revolution (Nineteenth Century - Early Twentieth Century)

With electricity and the internal combustion engine, mass production and assembly lines rose to prominence. Scientific management methods, such as those proposed by Frederick Taylor, introduced studies of times and motions, standardizing processes and expanding attention to operational efficiency.

- Availability: Assembly line maintenance has been improved to ensure continuous operations (LEE; BAGHERI; KAO, 2015).
- Performance: There has been significant progress in reducing unnecessary movements and increasing the speed of machines, (HANSEN, 2022).
- Quality: It became vital to ensure that products met standards to avoid rework and waste, (HANSEN, 2022).

These advances brought the first indications of what would be formalized as OEE, with a more integrated view of production efficiency.

3rd Industrial Revolution (Mid-20th Century - Early 21st Century):

Industrial automation and digital technologies have transformed production. Computers and control systems allowed for real-time monitoring, while approaches such as Lean Manufacturing and Total Productive Maintenance (TPM) popularized the use of OEE.

- Availability: Automation has enabled predictive maintenance practices, reducing unexpected failures (MOURTZIS; VLACHOU; MILAS, 2016).
- Performance: Digital systems adjusted the speed of the machines with greater precision, optimizing production (PEREIRA; ROMERO, 2017).
- Quality: Automated controls have drastically reduced the occurrence of defects, ensuring consistency (PEREIRA; ROMERO, 2017).

OEE has become a widely adopted metric, allowing businesses to continuously monitor and improve their operations.

Industry 4.0 (21st Century)

Industry 4.0 has brought advances such as IoT, Big Data, Artificial Intelligence (AI), Machine Learning (ML), and Digital Twins, elevating the role of OEE to a predictive and

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real-time level. These technologies have connected all aspects of production, providing accurate insights and automated actions (PORTER; HEPPELMANN, 2014)

- Availability: IoT sensors continuously monitor equipment, while AI predicts failures before they occur (LEE; BAGHERI; KAO, 2015).
- Performance: Algorithms adjust parameters in real time, maximizing efficiency (MOURTZIS; VLACHOU; MILAS, 2016).
- Quality: Simulations with Digital Twins anticipate problems, ensuring high quality standards (FENZA et al., 2020).

The integration of these technologies has consolidated OEE as an indispensable metric in modern management.

OEE AND INDUSTRY 4.0 TECHNOLOGIES

Industry 4.0 connects physical and digital systems, enabling real-time analytics and automated decisions. OEE, which was historically calculated manually, has evolved into a dynamic indicator, automatically adjusted based on data collected by sensors and processed by AI (ARORA; PANDEY; KUMAR, 2019).

Applications of AI and ML in OEE Monitoring

Failure Prediction

Today's AI capabilities, already widely available in the automation components of its production lines and their connectivity, are capable of providing the analysis of significant historical and real-time data sets. This makes the regression analysis of monitoring variables reliable at a level that it becomes possible to predict imminent failures of equipment and processes, based on minimal observations (STOLZ; LORENZ; FISCHER, 2024). In addition to real-time strategies, it is also possible to acquire and build specific algorithms to identify patterns that indicate equipment degradation, allowing assertive preventive maintenance and, consequently, achieving benefits that were considered intangible: maximum use of equipment, life cycle monitoring, etc.

Continuous Optimization

The level of robustness of automation components in Industry 4.0 allows Machine Learning concepts to be implemented as continuous work methodologies, that is,

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incorporated into production work routines and no longer as subsequent studies of production data (CLEARPEAKS, 2023). This begins to make the ability to automatically adjust production parameters a reality: cutting speed, positioning, reference dimensions, temperature, i.e. any parameter beyond the production materials. This capacity maximizes the quality of processes, making the levels of production processes demanded increasingly higher. This dynamic analysis ensures that equipment operates at its optimal capacity (OEE: CALCULATING, 2023).

Digital Twins and OEE

The concept of Digital Twins is simple: the construction of virtual replicas that represent in real time the operation, performance, and interaction of equipment, lines, and production cells. The current level of automation and monitoring of these systems make it possible to deploy monitoring, simulation, and optimization strategies at an unprecedented level in the history of the Industrial Revolution, but make the construction of these digital environments increasingly complex (DIGITAL TWINS IN INDUSTRY 4.0, 2023). Especially if observed only from the reference of the highest technological level of human interaction, such as VR and AR (Virtual and Augmented Reality), and not at the pragmatic levels of application with a high level of return (cost-benefit), but with a lower level of visual impact. The present work goes exactly in the second alternative, in an attempt to demonstrate that pragmatic applications of technology can bring significant returns to the quality of industrial work, in all its attributes and characteristics.

But the search for maximum use of technology cannot be ruled out in this case, because the integration of Digital Twin environments with the ability to analyze AI and identify ML patterns has the potential to profoundly transform industrial work, through the following strategies:

Simulations

Test and evaluate working conditions, in different scenarios and configurations, before implementing changes in the real environment. This facilitates the process of choosing alternatives and making decisions with controlled risks.

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Monitoring

Constantly observing the work variables, synthesizing them into key process indicators (KPIs) and ordering their evolution over time within pre-established limits (CpK), in friendly and even immersive environments facilitate the understanding of the impact of each variable on the overall performance of the processes and, consequently, the detection of potential failures and the accurate adjustment of the work parameters. All this in real time (DIGITAL TWINS AND INDUSTRY 4.0, 2023).

Quality

The ability to simulate alternatives and monitor their performance in real time has the direct result of improving the stability of the processes, as each of the deviations from what was planned can be identified, evaluated and corrected. This in real terms leads to a decrease in process variations and, consequently, in the increase of quality levels.

This set can be considered the foundational tripod of the search for continuous improvement, under the paradigms of Industry 4.0.

PRACTICAL APPLICATIONS IN INDUSTRY

Pragmatically, the main benefit of implementing OEE in the manufacturing industry is the ability to observe the actual efficiency of the machines and properly manage the machine park. In addition, OEE monitoring allows for the identification and elimination of downtimes and failures, which translates directly into cost savings and increased production efficiency.

The implementation of OEE paves the way for further innovations in Industry 4.0, such as traceability systems, which enable even more precise management of production and product quality. Thanks to the infrastructure put in place to monitor OEE, it is easy to extend the functionality to additional modules, such as barcode scanners, which allow the tracking of specific batches of products.

The implementation of the OEE indicator is a key step on the path to the implementation of Industry 4.0 principles. In pursuit of these benefits, several sectors of the manufacturing industry are implementing innovative strategies and structures for monitoring, calculating, and analyzing OEE, such as:

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Automotive

Leading automotive companies, such as BMW, invest robustly and consistently in the development of solutions to monitor the availability, performance, and quality of their assembly lines and seek to increase the effectiveness of their predictive maintenance processes through AI.

Digitalisation is the enabler of transformation for BMW iFACTORY. Innovations in virtualization, artificial intelligence (AI) and data science enable the BMW Group to connect all relevant aspects of automotive production and use these innovations to design effective applications in production. The result: maximum data transparency, which makes highly effective digital process design possible. "The possibilities are growing rapidly – and we are taking advantage of them," says Milan Nedeljkovic. "With digitalization, we are achieving a new dimension of data consistency across the entire value chain and across all process chains." Applications can be deployed to any production location once developed.

Electronics

Leading companies in the development of automation technologies, such as Foxconn, have increasingly invested in the search for IoT integration solutions (sensors) and AI and ML strategies, to intensify the ability to predict failures, adjust processes, and ensure production performance (capability).

“Advanced manufacturing, supported by Industrial AI, is going to revolutionize how manufacturers compete in the global economy, upgrade skills, create jobs, and onshore business to the United States. - Keyi Sun, Head of FOXCONN iAI”, (FOXCONN INDUSTRIAL INTERNET, acesso 12.2024).

Food: Undeniably, the food industry is one of the main orchestrators of all economies and with significant investment capacity, especially with companies that take Coca-Cola's place in their value chain (food processing).

Digital twin technology represents a significant advancement, providing an accurate virtual model of production lines. This digital representation offers real-time insights and predictive analytics, revolutionizing decision-making with data-driven efficiency improvements and cost savings. To reduce dependence on suppliers, the company adopted 3D printing for the production of spare parts, with 386 designs implemented in 11 plants. This initiative generated substantial savings, reduced lead times, and improved the

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availability of production lines," COCA-COLA HELLENIC BOTTLING COMPANY, accessed 12, 2024."

These statements by leading companies in the global scenario of Industry 4.0 demonstrate the growing importance that their technological framework is acquiring, even in relation to sustainability issues. In all of them, ensuring equipment availability demonstrates how OEE has become a central metric in industries that demand high efficiency and accuracy.

BENEFITS AND CHALLENGES

When implementing artificial intelligence (AI) in manufacturing, key benefits include increased accuracy through real-time analytics and reduced human error, cost savings due to predictive maintenance that minimizes unexpected downtime, and improved quality through consistent automated systems. However, challenges such as integrating with legacy systems in older factories, ensuring data quality for accurate analysis, and the need for substantial training to develop a skilled workforce to operate advanced technologies are also significant.

Benefits

Increased Accuracy

AI algorithms can analyze data with superior accuracy than human, resulting in more reliable insights and decisions. As highlighted by Stackpole (2023), AI can monitor and improve production and quality control in factories, increasing the accuracy of operations.

Cost Reduction

Predictive maintenance, powered by AI, enables proactive repairs before equipment failures, minimizing downtime and associated costs. According to McKinsey & Company (2023), data-centric AI tools can accelerate the remediation of data quality with increased levels of automation, contributing to cost reduction.

Quality Improvement

Automated quality checks using AI can consistently identify defects in real-time, preventing defective products from reaching customers. The integration of AI technologies in manufacturing has the potential to transform operations by improving the quality and efficiency of production processes.

Challenges

Integration with Legacy Systems

Integrating AI systems with aging equipment can be complex and require significant modifications. The adoption of AI in manufacturing faces challenges, including the need to integrate new technologies with existing production systems.

Data Quality

Inaccurate or incomplete data can lead to unreliable analysis and poor decisions. Data quality is a critical factor in the success of AI initiatives in manufacturing, and is essential for accurate analysis and effective decision-making.

Need for Training

Implementing advanced AI technologies requires a skilled workforce, which can require significant investments in training. Digital transformation in manufacturing requires the development of specific skills, including empowering workers to operate and maintain AI-based systems.

All these challenges are very well discussed in VIAL et al., (2020).

This text demonstrated that OEE has evolved from a rudimentary concern with the availability of machines in the 1st Industrial Revolution to a predictive and automated metric in the era of Industry 4.0. Its integration with technologies such as IoT, AI, ML, and Digital Twins has made it indispensable for industrial competitiveness and sustainability. Now, in Industry 4.0, OEE is not just an operational indicator, but a strategic tool to identify opportunities, optimize processes, and ensure high quality standards.

MATERIALS AND METHODS

CONTEXTUALIZATION OF THE STUDY

The study was carried out in an assembly industry of boards for notebooks and computers located in the Industrial Pole of Manaus (PIM). The production of this type of component requires rigorous processes, with low fault tolerance, which makes it essential to adopt technologies that optimize production efficiency. The central objective was to

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automate the calculation of OEE (Overall Equipment Effectiveness) through sensors integrated with an Internet of Things (IoT) platform and Digital Twins.

OEE is calculated from three main variables:

- Availability (effective line operating time),
- Performance (production rate relative to theoretical capacity) and
- Quality (percentage of products without defects).

The study was divided into stages: real-time data collection, automation of OEE calculation, scenario simulation, and validation of results.

REAL-TIME DATA COLLECTION

Sensors and Infrastructure

Data collection was carried out by motion, temperature and humidity sensors strategically installed along three SMT (Surface-Mount Technology) lines;

Motion Sensors:

They monitored the production cycle of each board; and

Temperature and Humidity Sensors

ensured the ideal conditions for the integrity of the components.

The sensors were integrated into the Siemens MindSphere platform, using communication protocols such as MQTT for fast data transfer. The platform enabled the remote visualization of metrics in real time through a Digital Twin system, which virtually replicated the production line.

Andon Board and Downtime Monitoring

The Andon Board tool was used to record critical events, such as downtime, actual production capacity and quality obtained. The record included the duration of the shutdowns, the description of the problem, and the corrective actions implemented.

With the data from the Andon Board, the Digital Twins system, integrated with Artificial Intelligence (AI) modules, identified patterns of repetitive failures and suggested proactive actions to the Engineering team.

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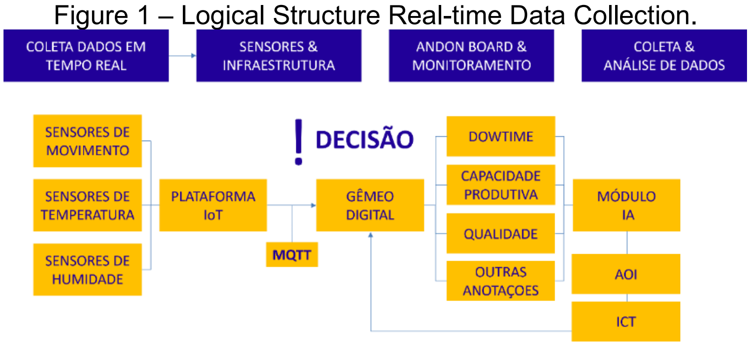
Collection and Analysis Cycle

Data collection occurred at defined intervals, starting with the passage of the plates through the first machine equipped with sensors. Variables such as cycle time, temperature, humidity and downtime occurrences were monitored.

The data fed into the Digital Twin system, allowing operators to track the status of lines in real-time and make quick decisions based on operating conditions. Figure 1 shows in the form of logical blocks the structure of Real-Time Data Collection.

Figure 1 – Logical Structure Real-time Data Collection.



Automated AOI (Automatic Optical Inspection) and ICT (In-Circuit Test) inspections complemented monitoring, allowing the automation of OEE calculation, detecting assembly and functional failures early, which minimized rework.

AUTOMATION OF THE CALCULATION OF THE STATE BUDGET

OEE was automated by integrating the variables capacity, quality and availability into a centralized system. With each new data collection, the OEE was recalculated, providing an accurate and up-to-date view of production efficiency.

Production Capacity

The capacity was monitored based on the UPH (Units per Hour), using motion sensors to account for the plates produced. The comparison with the theoretical target allowed us to identify bottlenecks and adjust production.

Product Quality

The quality was evaluated in two main stages: AOI, which identifies problems in the assembly of the components, and ICT, which analyzes the electrical functionality of the boards.

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The data collected helped to adjust processes, ensuring that the final products met quality requirements.

Line Availability

Availability was measured from downtime records. Each downtime was recorded with its duration and cause, allowing for detailed analysis and implementation of actions to reduce unscheduled outages.

SIMULATION AND VALIDATION OF RESULTS

Simulation with Digital Twins

Digital Twins allowed the simulation of production scenarios without interference on the factory floor. Variables such as increased demand, machine failures, and process changes were tested to predict impacts on production.

Data Validation

The data generated in the simulated scenarios were compared with the real data collected directly from the machines. This validation ensured that the Digital Twin system accurately represented the conditions of the production line, giving reliability to the process. Figure 2 schematically shows the logical structure of OEE Calculation Automation.

Figure 2 – Logical Structure Established for the Automation of OEE Calculation.

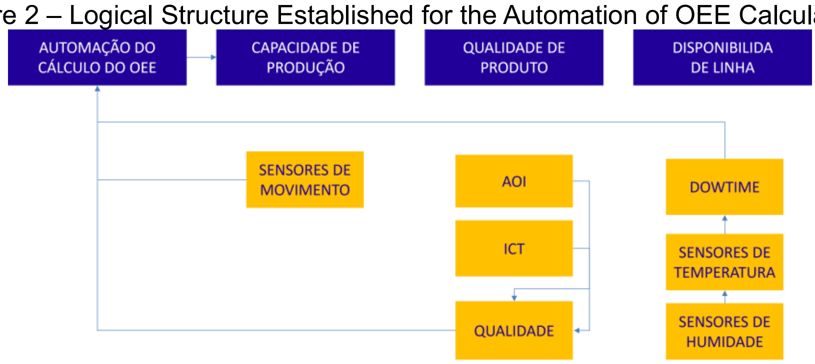

Figure 3 sequentially presents the operations of the production line, with each station identified by its main work equipment ("machine"), description, layout, and the variables that are monitored.

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Figure 3 – Monitoring and simulation structure.

All this construction allowed the beginning of the implementation of automated OEE calculation and the consolidation of the database for the beginning of simulation through a "Digital Twins" environment.

RESULTS

The first moment of implementation of the proposed solution went through the stages of testing and stabilization of the entire data collection system, integration and validation of data, going through initial moments of high variability and reaching the clear ordering of priority of attention. Figures 4 and 5 show these two moments.

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Figure 4 – Initial moments of the implementation of the system for monitoring and automating the calculation of OEE.

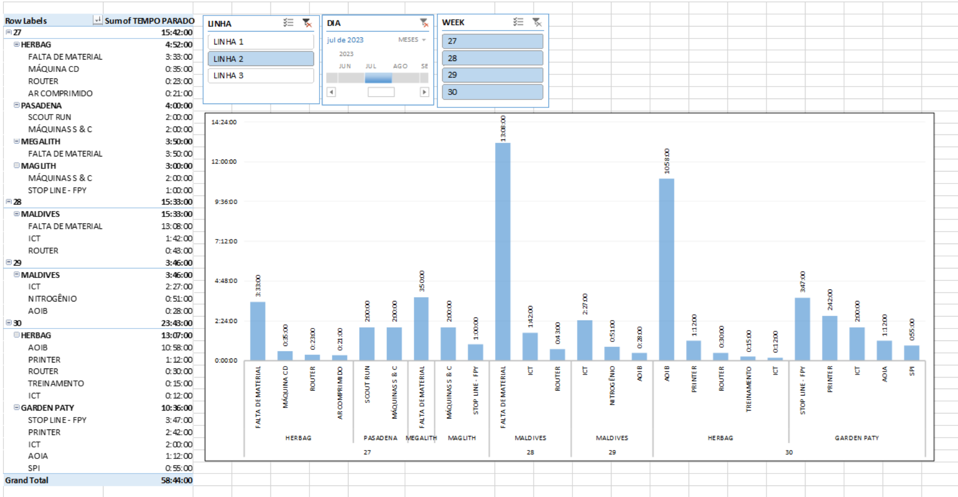
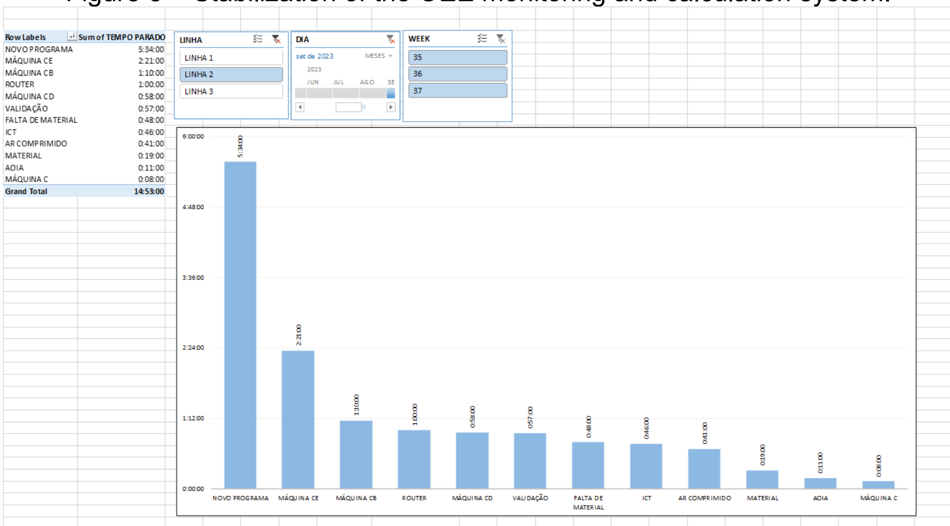


Figure 5 – Stabilization of the OEE monitoring and calculation system.



Over two months of development, the monitoring of the entire line, as detailed in item 3 of this article, allowed the training of the entire framework of analysis and decision automation, as presented in Figures 1 and 2. This process took place between October 1st and December 11th, 2024.

Figures 6 and 7 show the "Digital Twin" environment of the monitoring and simulation framework detailed in Figure 3. On October 10, 2024, for each process and time, there was already, based on the data initially collected, a simulation of the parameters that could be achieved. Missed goals are visually indicated by the color red. The mismatch between the goals established and the results achieved on October 1, 2024 is clear, observing these indicators, shown in Figure 6.

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Figure 6 – "Digital Twin" environment for the modeled assembly line (electronic boards for notebooks and chargers), on October 1, 2024.

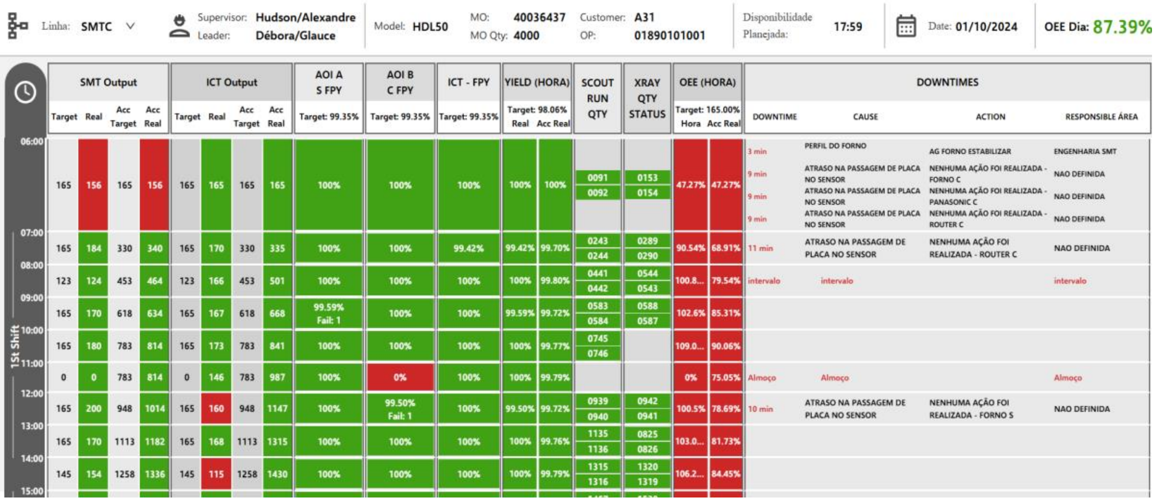

Figure 7 shows the same dashboard, but now after all the work of supervision, debugging the models, and adjusting projects over the almost 80 days of development (October 1 to December 11, 2024).

Figure 7 – "Digital Twin" environment for the modeled assembly line (electronic boards for notebooks and chargers), on December 11, 2024.

The operation of the state of these two panels, Figures 6 and 7, shows the clear evolution of the line's capacity to meet the stipulated OEE targets.

The visualization of the more than 80 evolution dashboards of this journey are a rich source of indicators and triggers of process improvements, which were used for its performance optimization. But which will be presented and discussed in future works.

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DISCUSSION AND CONCLUSIONS

The results obtained in this study showed the effectiveness of the implementation of enabling technologies of Industry 4.0, with emphasis on Digital Twins and the automated calculation of OEE (Overall Equipment Effectiveness), in the optimization of production processes in an assembly line of electrical and electronic boards in the Industrial Pole of Manaus (PIM).

ALIGNMENT WITH INITIAL OBJECTIVES

The main objective of the work was to implement a solution that would make it possible to identify, in real time, the times and reasons for production stoppages through the automation of the OEE calculation and the use of Digital Twins. The results achieved over the 80 days of monitoring (Figures 6 and 7) prove the success of this approach, especially in reducing unscheduled interruptions and improving the production efficiency of the line.

At the beginning of the study, the OEE indicators showed a significant mismatch between the established goals and the observed results (Figure 6). This scenario reflected the difficulties identified in data integration, operational variability and lack of predictability regarding the causes of the stoppages.

As the study progressed, it was possible to stabilize the system, adjust the predictive models, and optimize the processes, as evidenced by the evolution of the indicators in the Digital Twin (Figure 7). This transformation has demonstrated that the combination of IoT sensors, real-time analytics, and virtual simulation allows for a clearer and more structured view of productive performance.

OBSERVED IMPACTS

Reduction of Unscheduled Downtime

The implementation of sensors and the Digital Twin system made it possible to identify patterns and predict equipment failures, allowing for faster and more assertive corrective actions. This improvement is directly attributed to the automation of OEE calculation and the use of historical data to feed Machine Learning models (MOURTZIS; VLACHOU; MILAS, 2016).

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Continuous Adjustment of Production Parameters

The algorithms developed made it possible to dynamically adjust production parameters, such as speed and temperature, maximizing performance without compromising quality (ARORA; PANDEY; KUMAR, 2019). The reduction in *downtime* had a direct impact on the increase in the availability and performance of the monitored lines.

Improvement of Product Quality

The integration of AOI and ICT inspections made it possible to detect and correct non-conformities in early stages of the production process, avoiding rework and waste. Predictive analytics based on Digital Twins has made it possible to simulate scenarios and anticipate possible problems (FENZA et al., 2020).

SUSTAINABILITY AND ENERGY EFFICIENCY

Another important result was the contribution to industrial sustainability, one of the objectives initially highlighted. Maximizing operational efficiency and using resources such as energy and inputs at optimized levels reduced waste and environmental impact, aligning with the concept of sustainable industry (DIGITAL TWINS IN INDUSTRY 4.0, 2023). This practice is in line with global trends, as observed in initiatives by Coca-Cola and the BMW Group (COCA-COLA HELLENIC BOTTLING COMPANY, 2023; BMW GROUP, 2022).

CHALLENGES OVERCOME

Key challenges identified included:

- Integration with Legacy Equipment: It was necessary to adapt the sensors and IT infrastructure for compatibility with previous generation machines, a common limitation in traditional industrial environments (STACKPOLE, 2023).
- Data Quality and Consistency: Improving data collection and filtering was key to ensuring accurate measurements, minimizing noise and unwanted variations in indicators (LI; PANGBORN; KOVALENKO, 2023).
- Technical Training of the Team: The development of specific skills for the operation of the system was a critical step to ensure the adherence of employees to the new methodology.

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CONCLUSION OF THE DISCUSSION

The results presented demonstrate that the implementation of Digital Twins and the automation of the OEE calculation represent a significant advance in the search for operational excellence and productive efficiency in the Electrical and Electronic Industry of the PIM. By connecting real-time data with predictive analytics and simulations, it was possible to not only proactively identify and solve problems, but also to lay a solid foundation for continuous improvement of industrial processes.

In this way, the study proves that the enabling technologies of Industry 4.0, when applied in a pragmatic and accessible way, offer substantial benefits, such as cost reduction, resource optimization and greater sustainability, aligning with the strategic and competitive objectives of the Manaus Free Trade Zone.

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