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INTELLIGENT CAPACITY SUPERVISION AND CONTROL SYSTEM IN INDUSTRIAL PROCESSES: INTEGRATION OF SCADA, AI, AND MACHINE LEARNING

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ABSTRACT
This study proposes a machine learning-based system for capacity supervision and control in industrial automation. The solution integrates high-precision sensors, programmable logic controllers (PLCs) and a SCADA (Supervisory Control and Data Acquisition) system, allowing real-time monitoring and adjustment of manufacturing processes. The methodology included the development of a software in C# in the Visual Studio 2015 environment, with an interface in a Mitsubishi CPU Q03UDV PLC, and the implementation of the system in a production line for practical evaluation.
The results demonstrated the system's ability to maintain the process capability indexes (CpK) above the critical limits (1.33) through the automatic correction of deviations. Key highlights include efficient integration with industrial networks and dynamic adaptation to production variabilities. On the other hand, limitations were identified, such as the dependence on a robust infrastructure and challenges in environments with high electromagnetic interference.
The discussion highlights the potential for scalability, application in other industrial contexts, and the inclusion of advanced algorithms, such as neural networks, to enhance predictive

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capacity. Future work suggests exploring more affordable implementations for small and medium-sized businesses, integration with IoT for predictive maintenance, and sustainability assessments. This research contributes to the advancement of intelligent automation, promoting consistent quality and operational efficiency in manufacturing.

Keywords: Supervision and control of industrial processes, Intelligent automation, Machine learning, SCADA, Industry 4.0.

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INTRODUCTION

Industrial automation is fundamental in the evolution of manufacturing, especially in the efficiency and precision of production processes. Since the beginning of the Industrial Revolution, the manufacture of all types of products has constantly sought ways to improve productivity and reduce operating costs.

The emerging technologies of Industry 4.0 are the state of the art of this effort, especially in the application of Artificial Intelligence (AI), Machine Learning (ML) and Deep Learning (DL) in robotic systems. Assembly robots, one of the most sophisticated applications of automation, have demonstrated an exceptional ability to handle complex tasks with a high degree of precision. However, the inherent variability of automated processes still presents significant challenges to maintaining consistent process quality and capability (SOORI et al., 2024).

In this journey, SCADA (Supervisory Control and Data Acquisition) systems have become mandatory components of manufacturing systems to monitor and control industrial processes, and increasingly aligned with modern automation projects through the interconnectivity between equipment and systems. This has created opportunities for the intensification of the development of AI and ML-based technologies.

However, interconnectivity still has elements that need to be overcome, such as failures in communication protocols and vulnerabilities in security configurations, which can compromise the efficiency and reliability of production systems. Recent studies show the existence of interest in cyberattacks targeting SCADA systems, for data hijacking, strategic information capture, and even piracy, making the need for accurate monitoring of process performance a priority (NAGARAJ, et al., 2023).

Added to all this context is the emergence of human-robot collaboration, represented by the use of collaborative robots (COBOTS), as one of the main trends in contemporary industrial automation. Designed to operate safely alongside humans, they combine the precision, accuracy, and consistency of traditional industrial robots with human flexibility and adaptability. The integration of COBOTS requires a new look at those of traditional line balancing methods, due to the weight that old and new variables, such as ergonomics and safety, start to play in the design of these lines (FATHI et al., 2024).

Key capabilities for the continued evolution of factory automation in Industry 4.0, such as autonomous navigation, object recognition, and predictive maintenance, have benefited from the facilitation of AI, ML, and DL applications. Thus, the accelerated

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development of areas such as Deep Learning (DP) Algorithms such as Convolutional Neural Networks (CNNs) enable robots to identify and classify objects with high accuracy and accuracy, while ML techniques are widely used to predict failures and optimize processes in real-time. These innovations not only increase the efficiency of industrial systems, but also provide greater adaptability to dynamic environments and changing conditions (ZAINEDIN et al., 2024).

However, despite the characteristic anxiety of industries for quick solutions to increase efficiency, there is still a lot of research and development work for these innovations to be mature enough for their general application and not only in specific users, (FUZZY et al., 2023):

- The need for large volumes of high-quality data to train AI/ML models is a known obstacle, especially in industries where the cost of data collection is high;
- The reliance on robust hardware, coupled with high power consumption, imposes practical limitations on the widespread adoption of these technologies; and
- Ethical and social challenges, such as the impact on employment and the economy.

This study seeks to address some of these challenges by proposing the development of a process capacity supervision and control system based on machine learning. The solution integrates sensors, machine learning algorithms, and SCADA systems to monitor and adjust industrial processes in real time, ensuring that quality and efficiency standards are maintained, even in the face of variations in processes.

Unlike conventional approaches, which often rely on static parameters, the use of machine learning allows the system to dynamically adapt to operating conditions, making it more effective in modern industrial environments. In addition, the development of fuzzy process capability indices has proven to be a promising solution to deal with uncertainties in industrial data and asymmetric tolerances. These indices offer a more robust and detailed analysis of process performance, contributing to more informed decisions about adjustments and interventions in production systems.

Practical applications have demonstrated the effectiveness of this approach in sectors such as the automotive industry, where accuracy and reliability are critical for success (FUZZY et al., 2023). Finally, the study highlights the importance of a holistic approach to industrial automation, which takes into account not only the technical aspects, but also the social, economic, and ethical implications of emerging technologies. The

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successful integration of AI, ML, and DL in industrial automation requires a balance between technological innovation and the responsible management of the associated impacts.

THEORETICAL FRAMEWORK

OVERVIEW

Industrial automation, driven by Industry 4.0 technologies, stands out for the integration of intelligent systems for real-time monitoring and control. Programmable Logic Controllers (PLCs) play a central role, providing the flexibility and robustness needed for complex industrial environments. According to Borges (2009), PLCs are widely used due to their ability to integrate with sensors and actuators, ensuring high reliability in continuous operations.

High-precision sensors, such as those used to measure dimensions in manufacturing processes, are essential for maintaining quality and consistency. According to Lugli and Santos (2015), modern sensors allow the collection of data in real time, being crucial for the automated control of processes in advanced production lines.

In addition, SCADA systems have been widely used for supervision and data acquisition in industrial processes. UPADHYAY et al., 2020 highlight that the integration of SCADA with modern industrial networks, such as PROFINET, allows for real-time analysis and intervention, increasing operational efficiency.

Process capability analysis (CpK) is widely recognized as a key metric for assessing compliance with specifications. According to Fuzzy et al. (2023), the calculation of CpK provides a clear view of the stability and efficiency of the process, and is widely applied in the electronics and automotive industry.

On the other hand, reliance on robust infrastructure and vulnerability to electromagnetic interference are common challenges. SOORI et al. (2023) suggest that adopting machine learning algorithms can mitigate these challenges by providing greater accuracy and adaptability in harsh industrial environments.

The scalability and applicability of the system across different industries are critical factors for the adoption of emerging technologies. Pinto and Sousa (2020) highlight that integration with IoT and predictive maintenance can transform industrial automation, allowing remote monitoring and more efficient interventions.

Finally, sustainability in industrial automation is also a relevant issue. FATHI et al. (2023) argue that artificial intelligence-based solutions not only increase efficiency but also reduce waste by promoting more sustainable industrial practices.

CHALLENGES IN INDUSTRY 4.0

Industrial automation, integrated with Industry 4.0 technologies, represents a milestone in the modernization of production processes. However, challenges related to the cost and availability of equipment remain important barriers to large-scale implementation, especially in small and medium-sized enterprises (SMEs). These challenges are compounded by rapid technological evolution, which often renders devices obsolete before they are even widely adopted.

Cost Challenges

The acquisition of high-precision sensors, state-of-the-art PLCs, and SCADA systems represents a significant initial investment. SOORI et al. (2020) highlight that the reliance on robust infrastructure and advanced technologies can be an obstacle for companies with limited budgets. Additionally, emerging technologies such as machine learning and artificial intelligence require specialized hardware, such as high-performance GPUs, which increase operating costs.

The cost of maintenance is also a critical concern. Lugli and Santos (2015) point out that the need for frequent calibration of sensors and continuous software updating make systems more expensive throughout their life cycle. In addition, the implementation of industrial networks, such as PROFINET and EtherCAT, requires specialists, increasing the costs of training and hiring qualified personnel.

Equipment Availability

The availability of equipment in the global market is influenced by complex supply chains that are vulnerable to disruptions. UPADHYAY et al., 2020 (2023) report that recent events, such as the COVID-19 pandemic, have exacerbated the shortage of electronic components, negatively impacting the production and supply of essential devices for industrial automation.

Another aspect is the concentration of specialized manufacturers, which limits competition and raises prices. Pinto and Sousa (2020) highlight that, in many regions, the

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lack of local distributors makes it difficult to access modern equipment, forcing companies to import technologies at high costs and long delivery times.

Impacts on SMEs

For SMEs, which represent the bulk of businesses in emerging economies, these challenges are particularly significant. FATHI et al. (2023) suggest that creating low-cost solutions, such as sensors based on open technologies and streamlined industrial networks, can mitigate these barriers. In addition, infrastructure sharing initiatives and access to government funding programs have the potential to democratize automation.

Potential Solutions

To overcome these barriers, integration with Internet of Things (IoT) technologies and cloud-based platforms has emerged as a viable alternative ZAINELDIN et al., (2024) argue that cloud solutions allow access to high-performance resources without the need for large investments in on-premises hardware. In addition, predictive maintenance, enabled by machine learning algorithms, reduces costs by predicting failures and optimizing equipment usage.

Another solution is the development of modular devices, which can be upgraded or replaced individually, reducing obsolescence costs. According to Fuzzy et al. (2023), this approach not only minimizes waste but also improves scalability, allowing companies to increase their capabilities gradually.

Sustainability and Circular Economy

In addition to reducing costs, adopting circular economy practices can improve equipment availability. Lugli and Santos (2015) suggest that the reuse and remanufacturing of devices, such as PLCs and sensors, can relieve pressure on the supply chain, making automation more accessible and sustainable.

ETHICAL AND ECONOMIC DILEMMAS IN INDUSTRIAL AUTOMATION AND THE ROLE OF AI AND ML

The integration of automation, artificial intelligence (AI), and machine learning (ML) into industrial processes has generated significant discussions about their ethical and economic impacts. While these technologies promise unprecedented efficiency, quality, and

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scalability, they also raise concerns regarding the potential reduction of jobs and the economic inequality resulting from the replacement of human labor with automated systems.

ETHICAL DILEMMAS

1. Job Replacement: Automation and the use of AI in production processes, such as in the system described, where adjustments are performed automatically by PLCs and algorithms, reduce the need for direct human supervision. This, on the one hand, eliminates human errors and increases productivity, but on the other hand, it creates uncertainty for workers who previously performed these functions. According to RAMAIAH et al. (2019), the replacement of low-skilled jobs is an inevitable consequence of automation in labor-intensive industries.
2. Economic Inequality: Companies that adopt these technologies tend to gain significant competitive advantages, but this can create a greater economic disparity between large corporations, which have the capital to invest in automation, and small and medium-sized companies, which struggle to keep up with this transition.
3. Redefining the Human Role: Automation creates the need to rethink the human role in the industrial environment. Workers who previously operated machines need to be trained to perform more analytical and creative functions, such as monitoring data and managing automated systems. This requires significant investment in education and training, which is not always guaranteed.

ECONOMIC DILEMMAS

1. Employment Impacts: The reduction of direct jobs, particularly in sectors that rely on repetitive tasks, can lead to an increase in structural unemployment VAHDAT et al. (2024) note that while new positions are created in areas such as data analytics and systems maintenance, not all workers have access to the resources they need to upskill.
2. Concentration of Wealth: Automation tends to concentrate profits in companies that successfully implement the most advanced technologies, while workers and small businesses face greater difficulties in adapting. UPADHYAY et al., 2020 (2023) highlight that this concentration of wealth can intensify social and economic disparities.

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3. Transition Cost: Implementing and maintaining AI and ML systems requires high upfront investments. This presents an economic dilemma for many organizations that want to modernize their operations but lack sufficient financial or technical resources.

MITIGATION AND FUTURE PATHWAYS

1. Education and Reskilling: Investments in education for the reskilling of the workforce are essential. This includes programs that teach technical skills such as data analysis and programming, as well as behavioral competencies such as problem-solving and creativity.
2. Responsible Adoption of Automation: Companies can adopt a hybrid approach, combining automation with human oversight to create a more inclusive and balanced work environment. According to Pinto and Sousa (2020), keeping the human at the center of the process can minimize the social impact of automation.
3. Public Policies: Governments can introduce tax incentives for companies that invest in reskilling programs and create regulations that promote a just transition. Additionally, measures such as taxing robots or subsidizing SMEs can help balance the economic impact.

ETHICAL CONSIDERATIONS

While automation increases efficiency, it's crucial to address the ethical dilemmas associated with reducing jobs responsibly. Developing strategies that prioritize social well-being and economic inclusion, such as integrating corporate responsibility policies, can help build a more balanced transition.

MATERIALS AND METHODS

In this section, the materials and methods used to conduct the research are described, with the aim of providing sufficient detail for the study to be reproduced. The description covers the devices, tools, equipment, and systems employed, as well as the stages of the experimental process, data collection procedures, and statistical analysis used.

The methodological planning was developed in order to ensure the accuracy, reliability, and validity of the results, considering the variables and specific conditions of the study environment.

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All the methods adopted were carefully selected based on their adequacy to the research objective and their ability to answer the proposed questions.

LOCATION AND PERIOD OF THE SURVEY

The research was conducted on an automated production line of a manufacturing plant between the months of June and September 2023. The environment was selected for its serial production and advanced automation infrastructure, which allowed for real-time data collection and the implementation of automated adjustments.

FAI91 piece: The object of study was the FAI91 piece, whose dimensions were monitored and adjusted automatically based on the technical specifications (minimum limit: 86.973 mm; maximum: 88.133 mm; nominal: 87.628 mm.

UNIVERSE, POPULATION AND SAMPLE

The research universe comprised all FAI91 pieces produced during the study period, about 500 units per day, totaling 45,000 pieces. The sample was composed of 10% of the daily production, resulting in a final sample of approximately 4,500 pieces, representative for statistical analysis and evaluation of the quality of the process.

For the development of the industrial automation system, intended for the monitoring and automatic adjustment of the manufacturing process of parts, the following materials were used:

Computer and Software: A computer with Visual Studio 2015 software was used to develop the C# program responsible for controlling and automating the system.

Visual Studio 2015 is an integrated development environment (IDE) from Microsoft, widely used to create applications in a variety of languages, including C#. In industrial automation, it offers a comprehensive set of tools that facilitate the development, debugging, and deployment of software that interacts with control systems, such as PLCs (Programmable Logic Controllers) and field devices, MICROSOFT (2024).

With support for the .NET Framework, Visual Studio 2015 enables the creation of robust and scalable applications that are essential for complex industrial environments. In addition, its compatibility with automation-specific libraries and frameworks enables efficient integration with industrial protocols and SCADA (Supervisory Control and Data Acquisition), PINTO, and SOUSA (2024) systems.

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Programmable Logic Controller (PLC): Equipment responsible for receiving automatic adjustment commands and implementing changes in the manufacturing process.

A Programmable Logic Controller (PLC) is an electronic device that is widely used in industrial automation to monitor and control processes and machines. It functions as the brain of the automation system, receiving inputs from sensors, processing the data based on pre-defined programs, and sending commands to actuators. PLCs are designed to operate in harsh industrial environments and offer high reliability, flexibility, and ease of integration with other industrial devices, such as SCADA systems and industrial networks, (NEPIN, 2024).

The **Mitsubishi CPU Q03UDV** is a central processing unit (CPU) belonging to the Q series of programmable logic controllers from Mitsubishi Electric. This series is recognized for its high performance and flexibility, being ideal for complex industrial applications with high processing speed, native connectivity to ETHERNET and SCADA communication, modularity and industrial resistance, (MITISUBISHI ELECTRIC, 2024).

The electronic component assembly industry works on detailed confidentiality agreements about its components, production line configuration, and processes. Up to this point, naming the specification of the components used does not cause any prejudice to these contracts, but the specification of sensors, communication interfaces and network equipment may infringe the rules of these contracts, because they begin to indicate the level of performance required in the manufacturing strategy of each product. It is not the objective of this work to detail the functioning of these components, but rather to build a strategy for the measurement of quality indicators capable of correcting the performance of a line with a high degree of automation in process. Thus, from this point on the description of the equipment will be in terms of the types and principles of operation.

Measurement Sensors: Image measurement sensors (dimensions and positioning), are known to be used in these applications, they are high quality devices when it is necessary to measure dimensions of manufactured parts in real time, ensuring continuous data collection.

The choice of the type of measurement required (dimensions, positioning or surface inspection) and environmental conditions such as lighting and material characteristics. Leading brands in the market, such as Cognex, Keyence, Basler, and Omron, are widely recognized for their reliability in applications characteristic of the electronics industry:

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internal alignment, external dimensions, and finish quality of cell phone batteries, ensuring final products within specifications, (THOMAZINI, 2020).

COMMUNICATION INTERFACE

The **communication interface** is a critical component in automation systems, as it acts as the conduit that connects sensors, programmable logic controllers (PLCs), and automation software. Its main function is to allow the exchange of information between devices, ensuring that the data captured by the sensors is efficiently transmitted to the controllers and supervisory systems (SCADA).

Communication interfaces are crucial in industrial automation, offering high transmission speed for real-time applications and low latency for quick responses to critical events. Its robustness ensures resistance to industrial interference, while reliability reduces failures and interruptions. In a factory, sensors measure the thickness of parts and send data to a PLC, which automatically adjusts parameters such as pressure or speed to ensure quality.

Among the technologies, Modbus is simple and widely used, while PROFINET caters to applications that require high speed. OPC UA facilitates integration between devices from different manufacturers. These systems bring operational efficiency, flexible integration of new devices, and cost savings with fewer errors and manual interventions.

INDUSTRIAL NETWORK

Industrial networks are communication infrastructures specifically designed to connect devices and systems in industrial environments, such as sensors, actuators, programmable logic controllers (PLCs), and SCADA systems. They ensure that data is exchanged reliably and in real time, even in harsh conditions such as high temperatures, electromagnetic interference, and vibrations.

Industrial networks are essential in automation due to their high reliability, operating continuously with minimal communication failure. Its low latency ensures immediate responses in real-time controls, while security mechanisms protect against unauthorized access. With scalability to integrate new devices and robustness against dust, moisture, and interference, they are ideal for harsh industrial environments. An example is the connection between sensors and PLCs in automobile factories, which synchronize welding robots with the position of the parts, ensuring precision and efficiency in the production process.

Main logic blocks

This work takes advantage of the opportunity of technological development that requires the improvement of business objectives, improvement of efficiency and manufacturing quality, made available in a robust and large-scale production line. All the components presented and mentioned have their fundamental principles known in the market, although specifically, due to the cost, they are not common in universities and laboratories.

In this alignment, its development contribution is to demonstrate how all these components should be aligned, both functionally and in a programmable logic structure, in order to ensure the measure of interest, its quality and the calculation routine for automation and human interaction.

This configuration can be visualized, for your general understanding, from the definition, location and explanation of three logical blocks.

1st Logical Block: Integration and communication of line control, measurement systems and process validation

This block comprises the integration of all the physical components of the proposed control system, on the existing assembly line itself. That is, a measurement system was built, with specific characteristics, on top of the existing system itself. This is expanding the inference about the control variables, in this case a specific measurement measure, and taking advantage of the robustness of the installed equipment.

All the steps of configuring the PLC's communication with the industrial network are established: control and definition of the instance in the network, communication configuration (IP, communication ports and logic) and supervision of the system's connection to the Cloud. This set must guarantee the unique processing capability of the PLC (open/close) at the time of reading the measurement sensor (accuracy of 0.001 mm).

Finally, the three data reading validity checks are established: device concurrency, data conversion, and spelling (ENUM).

Table 1 shows the structure of this configuration.

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Table 1 – Configurations of the Logical Block for integration and communication of line control, measurement systems and process validation.

INTEGRAÇÃO COMPONENTES DA LINHA	DEFINIÇÃO DA INSTÂNCIA DE COMUNICAÇÃO COM O PLC
	ATRIBUIÇÃO DO IP DO PLC NA REDE ETHERNET
	DEFINIÇÃO PORTA TCP/IP PLC
	CONFIGURAÇÃO DA ESTAÇÃO LÓGICA
	DEFINIÇÃO SENHA PLC
CONFIGURAÇÃO COMUNICAÇÃO PLC	COMANDO DE CONEXÃO COM O PLC
	DEFINIÇÃO DE CÓDIGO DE ERRO
	ROTINA DE FECHAMENTO DO PLC
	COMUNICAÇÃO DE ERRO
	COMUNICAÇÃO DE SUCESSO
	PROCEDIMENTO DE DESCONEXÃO DO PLC
	FECHAMENTO PLC
	AVALIAÇÃO FECHAMENTO DO PLC
VERIFICAÇÕES DE COMUNICAÇÃO PLC E ESTAÇÃO (NUVEM)	VERIFICAÇÃO DISPONIBILIDADE DO PLC
	COMANDO DE SOLICITAÇÃO EM ANDAMENTO
	GARANTIA ACESSO EXCLUSIVO AO PLC
	LEITURA E VERIFICAÇÃO DOS DADOS (ENUM)
	COMUNICAÇÃO DE SUCESSO DE LEITURA

2nd Logical Block: Data Collection and Auto-Tuning

This block works from the capacity established, in the previous block, to simultaneously locate, access and manage the control, the PLC and the sensors, in the correct order through the industrial communication network.

Specifically, locating, commanding, and returning the sensor readings stored in the PLC and converting them to the analysis job format. In this process, possible reading errors are also identified through the spelling evaluation (ENUM).

This entire set is built so that the performance of the process, from the measurement of the quota of the chosen component, can be compared with a pre-defined capability curve (CpK 1.33). The measurement history is used in the automatic correction of the process, in the previous stations of the line.

Table 2 shows the structure of this configuration.

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Table 2 – Logical Block Settings: data collection and automatic adjustment.

LEITURA DOS DADOS NO PLC	VERIFICAÇÃO DO ESTADO DO PLC
	ENVIO DA SOLICITAÇÃO DE LEITURA
	COMANDO DE ACESSO EXCLUSIVO
	LEITURA DOS DADOS
	AVALIAÇÃO DO PROCESSO DE LEITURA
	MENSAGEM DE SUCESSO
CONVERSÃO E COMUNICAÇÃO DOS DADOS	ARMAZENAMENTO DOS DADOS
	CONVERSÃO DO FORMATO DOS DADOS PARA MANIPULAÇÃO
	COMUNICAÇÃO DO PACOTE DE DADOS FORMATADO
	VERIFICAÇÃO DE ERROS DE COMUNICAÇÃO
AJUSTE DE PARÂMETROS	PROCESSAMENTO DOS DADOS (MÉDIA, DESVIO-PADRÃO E CpK)
	AVALIAÇÃO CpK
	CÁLCULO DO AJUSTE
	COMANDO DE AJUSTE
	CONFIRMAÇÃO DO AJUSTE

3rd Logical Block: Data Analysis and Inference

This block specifically takes care of the analysis of data after the monitoring and process adjustment actions, with three objectives:

- Evaluation of general trends, variations, and potential causes of process deviations. This is done using Descriptive Analysis strategies;
- Verification of the consistency of CpK values and the impact of external variables such as different work shifts. This is done by means of statistical, parametric and non-parametric analysis; and
- Search and identification of relationships between the results (set of measurements, statistics and calculation of CpK) and the operating conditions. This is done through regression analysis.

Table 3 shows the structure of this configuration.

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Table 3 – Logical Block Configurations: data analysis and inference.

PAINEL DE DESEMPENHO (KPI – DASHBOARD)	AVALIAÇÃO CpK 1,33
	CÁLCULO DO AJUSTE
	CONTROLE DO NÚMERO DE FALAHAS APÓS O AJUSTE
	AVALIAÇÃO DOS TEMPO DE RESPOSTA (ESTABILIZAÇÃO DO PROCESSO)
AVALIAÇÃO DE CAUSAS – Cpk BAIXO	AJUSTE DA PARÂMETROS
	CALIBRAÇÃO DE LEITURA SENSOSRES
	CALIBRAÇÃO SERVO MOTORES (LINHA)
	ANÁLISE E FILTRAGEM DOS DADOS
ANÁLISE DE DESEMPENHO	REDUÇÃO DA VARIAB
	AVALIAÇÃO CpK
	MELHORIA DOS TEMPOS DE RESPOSTA
	OTIMIZAÇÃO DA QUALIDADE DO PRODUTO FINAL
	EXIBIÇÃO EM TEMPO REAL DAS DIMENSÕES

The methods described were implemented and tested in a real industrial environment, allowing a detailed analysis of the effectiveness of the proposed system.

The data collected during the validation period provided valuable insights into the performance of the automated control, especially in maintaining the dimensional conformity of the manufactured parts.

Next, the Results section presents an analysis of the performance of the system developed and implemented, highlighting the efficiency of the system in ensuring the stability of the production process, as well as the adjustments made to optimize the operation in real time.

RESULTS

The general objective of the technological development project to which this article corresponds was fully fulfilled, as the implementation of a supervisory and process capacity control system was achieved, using the structure of the production system already implemented and taking advantage of its robustness for the implementation of machine learning routines.

Figure 1 shows the entire architecture of the supervision and control system, installed on the components of the line, associated with the components of the three logical blocks presented in the description section of the methodology.

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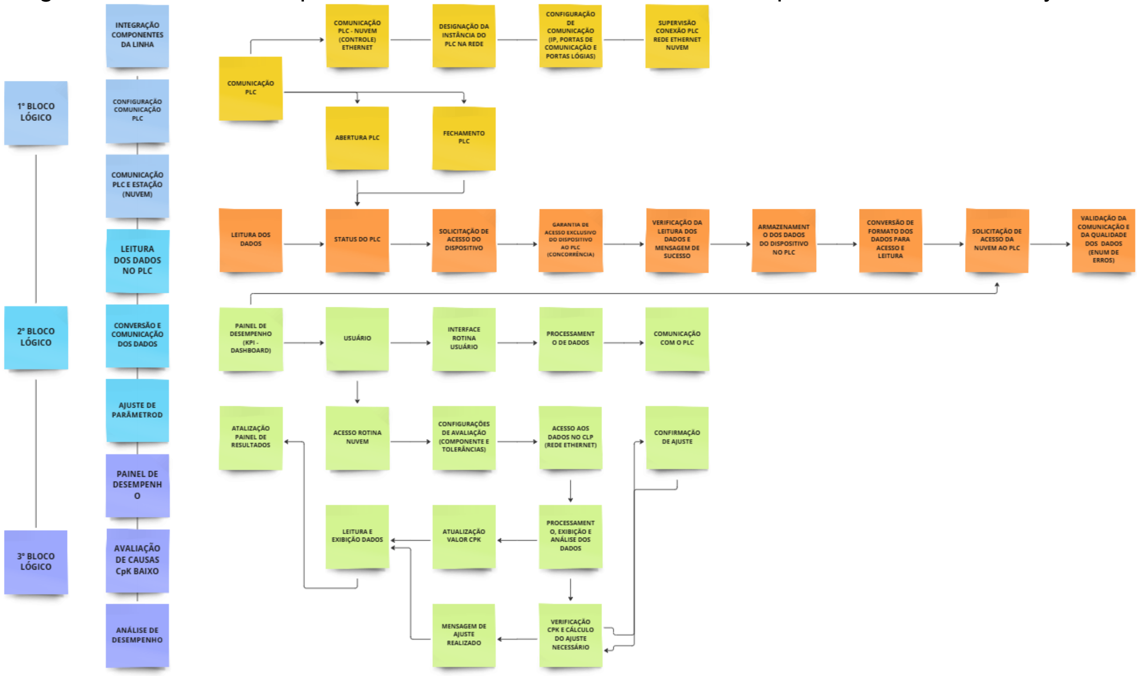
Figure 1 – Schematic representation of the architecture of the supervision and control system.



This construction allowed the production line managers to:

- Access and accumulate enough data for machine learning to be able to effectively adjust the production parameters for CpK correction, within the expected performance limits (CpK 1.33), including failure rate and the required response time for the stabilization of the adjustments associated with the number of parts to be reworked;
- Relate, through machine learning (statistical and regression analysis, in real time) the dimensional errors to the set of process parameters and promote the appropriate adjustment, compensating for external variables beyond the possibility of control, including calibration of the data reading, the set of servo motors for adjustment and data filtering (transmission noises), once again isolating false results of low CpK;
- Improve the reliability of the reduction of failures, the value of response time to adjustments and, with this, guarantee of the quota of the measure in question and the consequent optimization of product quality; and
- Finally, to make the supervision and adjustment of a critical process independent of human action, depending on the limits of adjustment of the quota of the measure in question, significantly reducing the number of components out of quality due to non-action in the correction at the necessary time, or in an erroneous way. At the same

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time, it provides worked and validated data for the human interface to seek assertive improvement paths.

This set of results showed that it is possible to build, on the already installed components of a robust electronic component assembly line with a high degree of automation, an advanced statistical process control (SPC) system that calculates the process capacity index (CPK) in real time. The data analysis takes place from data formatted in a .csv file, verified in relation to access and transmission errors to the control (Cloud), which identifies which parameter values are out of specifications and automatically adjusts the performance of the set of positioning servo motors, correcting deviations without human intervention. The routine of data manipulation, from its capture as electrical impulses to its conversion into a high-level data manipulation (.csv) file is an important achievement of the work, because it demonstrates that all the noises (electromagnetic, mechanical and environmental) inherent to a complex and extensive automated production line can be isolated, without the acquisition of new equipment.

Figure 2 shows the configuration of the system monitoring dashboard and its key components:

- The CpK control history, recalculated for each part and which immediately enables the identification of extreme variations in the process that can put the integrity of the entire line at risk (table to the left of the reader – "CPK FAI9I Control");
- The process data in relation to the batch in production (central tanela – "Process Data"), where the CpK of the whole batch is displayed against its position relative to the boundary lines (USL & LSL) and the nominal value;
- The field for accessing the CpK status and the adjustment decision (table to the right of the reader – STATUS CpK – TARGET 1.33); and
- In the lower field of the screen, the CpK control chart, an essential tool for starting the search for ways to improve.

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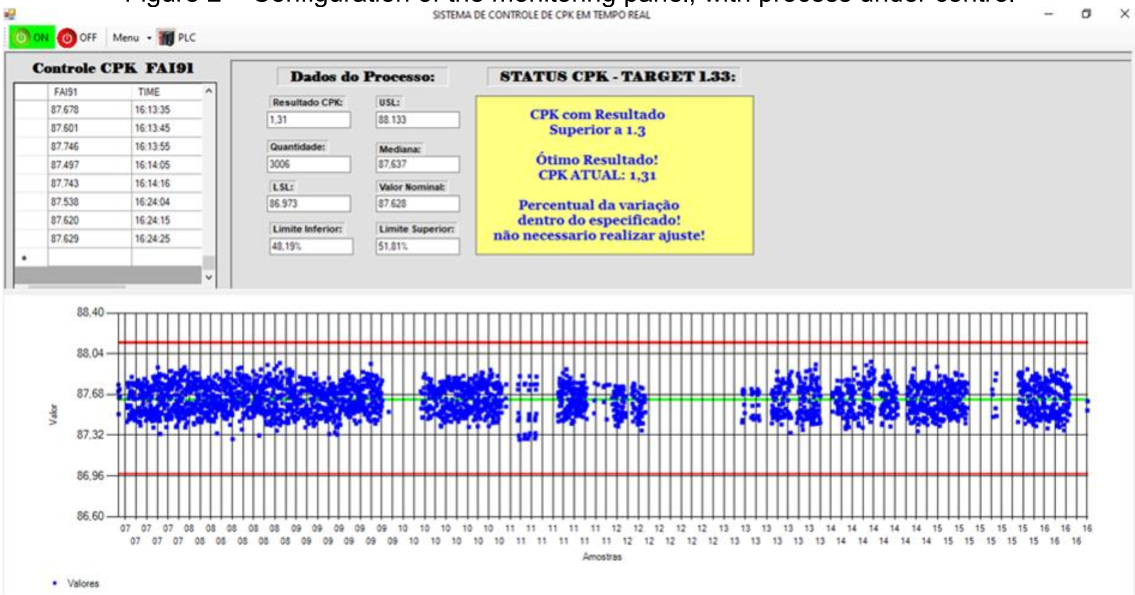
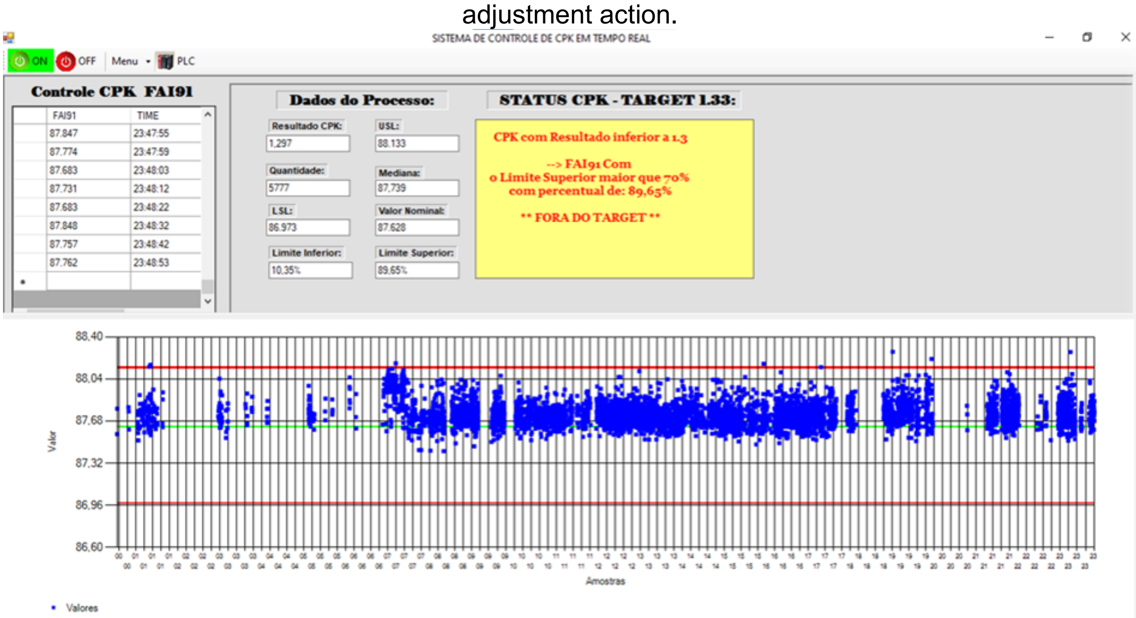
Figure 2 – Configuration of the monitoring panel, with process under control



This is the screen that shows the process under correct working conditions and without the need for automatic adjustment.

Figure 3 shows the same configuration as the monitoring dashboard, but in the situation where the process has started to show a tendency to overshoot the process upper limit (USL).

Figure 3 - Configuration of the monitoring panel, with process outside the established limit and automatic adjustment action.



This set of results demonstrates the validity of the initial idea, by demonstrating its ability to maintain the conformity of the process, even in the face of variations in the

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parameters of the production process. The process capability (CpK) metrics proved to be consistent for this objective, showing that there are still development paths for the identification of data patterns.

In the following section, the implications of this construction will be discussed, as well as its limitations and opportunities for future applications in different industrial contexts.

DISCUSSION

The results obtained confirm the feasibility of the system proposed for industrial automation, highlighting its ability to monitor and adjust production processes in real time. The integration between high-precision measurement sensors, the programmable logic controller (PLC) and the developed automation software proved to be effective in maintaining the process capacity indices (CpK), overcoming critical limits at times of greater variability. This approach contributed significantly to the stability of the process and the final quality of the manufactured parts.

INTERPRETATION OF RESULTS

The CpK values calculated throughout the experiment indicated that the system was able to react quickly to variations in the production process, adjusting critical parameters such as pressure and speed with high precision. This behavior underscores the importance of using machine learning algorithms and real-time control as key tools for modern automation. However, the reliance on advanced technological infrastructure, such as high-precision sensors and robust industrial networks, presents scalability challenges, especially for small and medium-sized businesses that may not have access to such resources.

STUDY LIMITATIONS

Although the system has shown promising results, some limitations have been observed. First, the analysis was conducted in a specific production environment, with well-defined characteristics. The applicability in production lines with greater complexity or with greater variability in materials and processes still needs to be investigated. In addition, the reliance on stable communication between sensors, PLC, and software can compromise performance in environments with significant interference, such as factories with high electromagnetic load.

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SUGGESTIONS FOR FUTURE WORK

Based on the results and the limitations observed, the following directions are suggested for future research:

1. **Exploration of New Algorithms**: Investigate the use of more advanced machine learning algorithms, such as convolutional neural networks (CNNs), to improve pattern detection and failure prediction in industrial processes.
2. **Multi-Sector Application**: Evaluate the performance of the system in different industrial sectors, such as the automotive sector and the food industry, which have different demands for automation and quality control.
3. **Reduction of Technological Dependence**: Develop solutions that use sensors and devices at a more affordable cost, making the system more attractive to small and medium-sized companies.
4. **IoT Integration and Predictive Maintenance**: Explore system integration with Internet of Things (IoT) platforms to enable remote monitoring and predictive maintenance, increasing efficiency and reducing unplanned downtime.
5. **Sustainability Assessment**: Investigate the environmental and energy impacts of the system, with the aim of making it more sustainable, reducing energy consumption and material waste.

PRACTICAL IMPLICATIONS

The research reinforces the crucial role of intelligent automation in the modernization of the industry, offering solutions that increase productivity and quality. However, its implementation requires careful planning to ensure that the technological benefits are accompanied by economic and social considerations, including the impact on the workforce and sustainability.

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