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Industrial process optimization through advanced HMI systems: exploring the integration of IoT and AI

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ABSTRACT

Facing the challenge of improving efficiency and stability in industrial processes, this study examines the impact of implementing advanced human-machine interface (HMI) systems, complemented by the internet of things (IoT) and artificial intelligence (AI). The integration of a PLC and HMI-controlled system has resulted in a 22.85% increase in efficiency, stabilizing production and reducing process variability. Tools such as PLCSIM and TIA PORTAL were crucial for validating control logic and programming. Additionally, the study explores the potential of AI and IoT to amplify these benefits, suggesting a significant advancement in automation that could transform operational efficiency and quality in related industries. These findings provide a relevant framework for companies looking to integrate emerging technologies into their operations, promoting continuous improvement and more informed management.

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1. INTRODUCTION

The evolution of industrial processes has been a key pillar in technological development, driving improvements in efficiency and productivity. Human-machine interface (HMI) systems have played a crucial role in this advancement, evolving from basic interfaces to sophisticated solutions that handle complex data and provide detailed analysis [1], [2]. These systems facilitate the supervision and control of automated operations, marking the transition towards more interconnected industrial environments [3], [4]. They have enabled more intuitive and responsive interfaces, allowing operators to interact more effectively with complex automation systems [5]-[7]. This highlights the importance of previous work that has laid the foundation for the effective integration of technologies in the industrial environment, addressing challenges such as usability, adaptability, and safety in human-machine interaction. Traditional HMI systems, while effective for basic control and supervision tasks, face significant limitations in the face of the challenges of the current digital era [8], [9]. These include restricted capacity for real-time data handling and analysis, insufficient adaptability to changing operating conditions, and a lack of autonomous learning [10], [11]. Although they have enabled notable advances in efficiency and safety, their standard design and limited functionality often prevent the full exploitation of data generated by modern industrial systems [12]. Comparators like traditional HMI systems, although effective in basic control tasks, are surpassed by the capabilities of advanced internet of things (IoT) and artificial intelligence (AI) systems.

The integration of the IoT and AI into HMI systems promises to overcome these barriers, transforming interaction with machines and how they adapt and respond to their environment [13], [14]. With IoT, HMI systems can become intelligent nodes that collect data from multiple sensors distributed throughout the industrial process, offering a holistic and detailed view of the operation in real-time [15]. AI enables these systems to learn from the collected data, anticipate problems, optimize operations, and adapt to new situations without human intervention [16], [17]. Practical applications include predictive maintenance and optimized resource management, significantly reducing downtime and operational costs [18]. Despite the potential benefits, the adoption of IoT and AI in HMI systems faces significant challenges, such as the need for robust technological infrastructure, concerns about data security and privacy, and the learning curve for operators [19].

Effective integration of these technologies into existing HMI systems requires a multidisciplinary approach that encompasses everything from interface design to systems engineering and organizational change management [20], [21]. It is essential to ensure that the implementation of innovative solutions is accompanied by practical and safe strategies, ensuring that the benefits of advanced automation are not overshadowed by unanticipated risks [22]. This article explores how the effective integration of IoT and AI into HMI systems can transform industrial processes, especially in the food industry, where efficiency, precision, and adaptability are critical. Through a literature review, the main contributors in the field of advanced HMI are identified, highlighting significant improvements in productivity and efficiency through the integration of these technologies. However, unresolved issues persist, such as the seamless integration of advanced systems into existing industrial environments and the training of personnel to handle these new technologies.

Our work addresses these areas of improvement, providing a guide for the effective and safe implementation of advanced HMI systems in the food industry, focusing on process optimization and waste reduction. The novelty of our research lies in the development of a conceptual framework that integrates IoT and AI into HMI to improve not only operational efficiency but also the adaptability and safety of food industry processes. The document is structured as follows: In Method, we describe the approach used to integrate IoT and AI into HMI systems, including the study design and evaluation methods. Results and discussion presents the findings of our research, analyzing how the implementation of these technologies impacts the efficiency and adaptability of food industry processes. Finally, in Conclusions, we summarize the key contributions of the study and discuss practical implications and future research directions.

2. METHOD

2.1. Level and design of research

This study employed an exploratory research methodology along with a detailed experimental design to investigate the untapped potential of advanced HMI systems integrating IoT and AI. The exploratory research helped identify and define new areas for further studies, while the experimental design facilitated the testing and observation of the effects of these technologies in controlled environments. This approach established a solid empirical foundation for understanding the effectiveness and impact of these integrations, crucial for progress in this emerging field.

2.2. Data collection technique and instrument

For data collection, a multifaceted approach was implemented to evaluate the performance of HMI systems through the analysis of operational records. These records served as the primary instrument for measuring industrial process efficiency and annual productivity. The evaluation of these data was carried out using the statistical software SPSS, which allowed for rigorous and detailed analysis. Additionally, an exhaustive literature review was conducted to compare our findings with improvements in HMI systems incorporating IoT and AI, using previous research in the area as a reference. This dual approach ensured a broad and deep understanding of the subject under study.

2.3. Validation and verification

The validation of the HMI system involved comparing operational results before and after its implementation to confirm productivity improvements. These results were aligned with similar studies to verify their validity and applicability. The reliability of the data was ensured by cronbach's alpha, supporting our conclusions about the effectiveness of the HMI system with precise measurements, as shown in Table 1. The analysis of cronbach's alpha in Table 1 showed a coefficient of 0.880, surpassing the reliability threshold of 0.7. This indicated that the measurements for production and efficiency in the automation process were highly consistent and reliable. Such a high level of reliability ensured that our findings were robust and could be confidently used to inform future research and practices in automation efficiency.

Table 1. Cronbach's alpha test

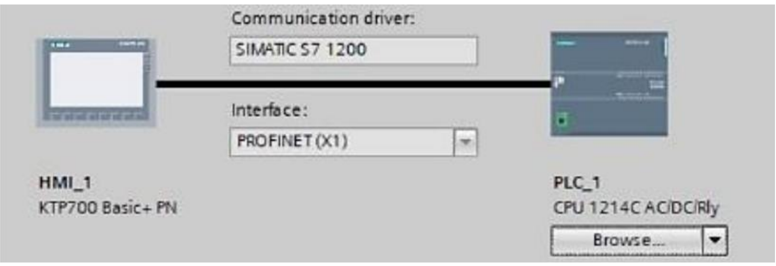
Cronbach's alpha	No. of elements
0.880	2

2.4. Description and configuration of the HMI system

The automated system employed the Siemens PLC CPU 1214C, recognized for its robustness and processing capability. Together with the HMI KTP 700 basic PN panel, an intuitive and highly responsive user interface was established. The communication between the two was carried out through the PROFINET network, a technical choice that ensured agile and secure data transmission, crucial for real-time supervision. Figure 1 illustrates the communication between the Siemens PLC CPU 1214C and the HMI KTP 700 basic PN panel.

TIA PORTAL V15 acted as the development environment where the complex control logics were configured and fine-tuned, which were crucial for efficient production management. The programming logic was structured in ladder diagram (KOP), a standard methodology in the industry for its clarity and effectiveness in representing logical sequences. This approach allowed for the detailed simulation of the production plant workflow, encompassing the sequential activation of components and the management of control signals. Iterative simulations refined the system's accuracy, ensuring that each sensor and actuator responded appropriately to the commands issued from the HMI.

To validate the integrity of the programmed design, PLCSIM was deployed as a comprehensive simulation tool. Here, the behavior of the inputs and outputs was meticulously examined, mimicking the system's operations in a controlled virtual environment. This preliminary phase was vital for identifying and correcting any discrepancies in the expected PLC behavior before implementation on the production site, thus ensuring the system's robustness and reliability. Finally, WinCC runtime complemented our suite of simulation tools. Figure 2 shows a dynamic representation of the process on the HMI screen.



Communication driver: SIMATIC S7 1200

Interface: PROFINET (X1)

HMI_1
KTP700 Basic+ PN

PLC_1
CPU 1214C AC/DC/Rly

Figure 1. Communication between the Siemens PLC CPU 1214C and the HMI KTP 700 basic PN panel

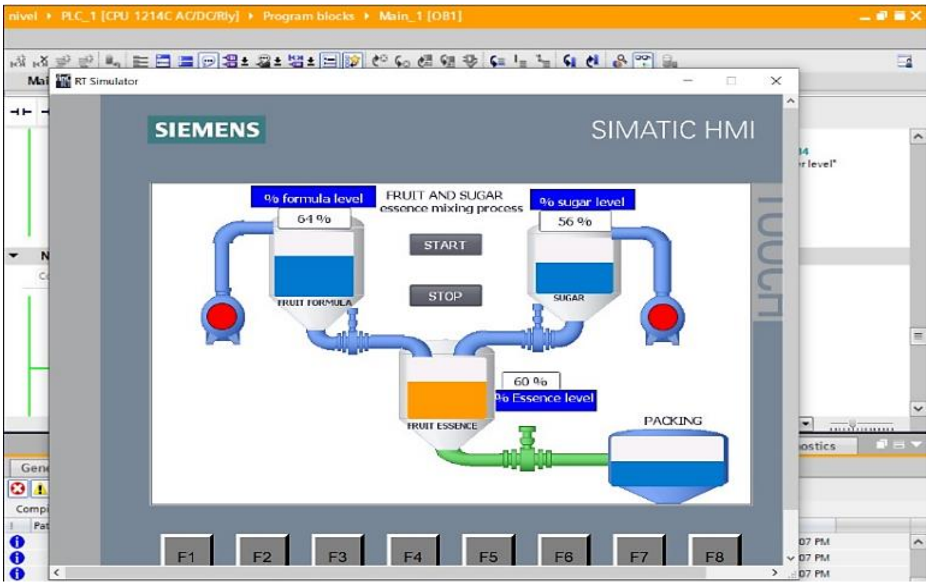


Figure 2. Dynamic representation of the process on the HMI screen

Operators could interact with this representation to gain a deep understanding of the system's operation, and anticipating the process dynamics became a practical exercise. This foresight and response capability not only improved operational efficiency but also prepared the ground for a smooth transition to the active production phase. Additionally, it allowed for the identification and resolution of potential issues before full implementation, thereby ensuring greater system stability and performance.

3. RESULTS AND DISCUSSION

3.1. Results

The adoption of advanced technologies has significantly improved industrial production, leading to higher efficiency and better product quality. Our research quantifies these advantages within the fruit juice production sector, comparing volumes over two periods (2022-2023). Figure 3 visually represents this increase in production, highlighting the positive effects of automation.

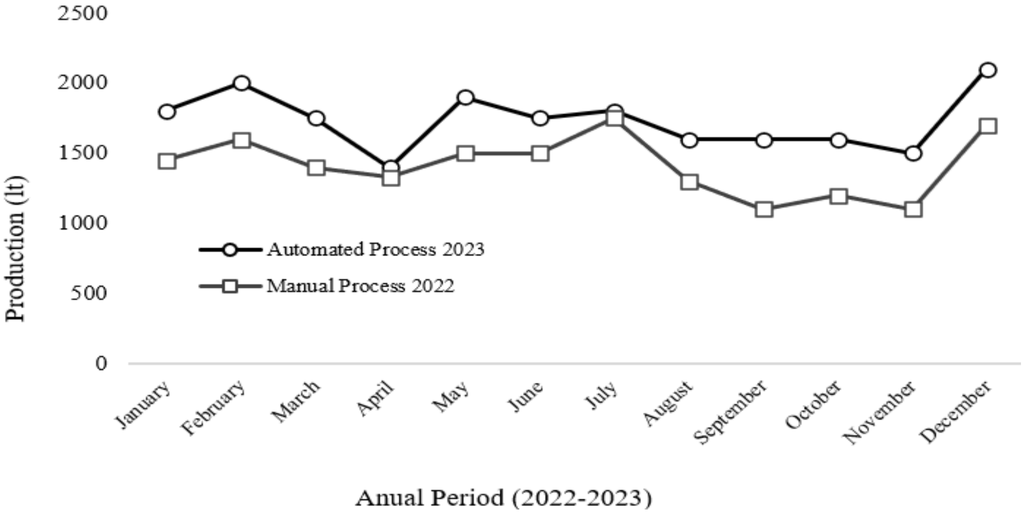


Figure 3. Production trends-manual vs. automated processes (2022-2023)

The trend analysis shown in Figure 3 reveals clear differences between the two periods analyzed. During 2022, when the processes were manual, production was more variable with fluctuations, which could be associated with the inefficiency inherent to human intervention and the variability of manual processes. In contrast, in 2023, with the introduction of an automated system integrating PLC and HMI, there is a general trend towards higher production, indicating a 22.85% improvement in efficiency. Additionally, the variability in production seems to decrease, suggesting that automation has contributed to stabilizing the production process and minimizing monthly discrepancies. This pattern is particularly evident in February, May, June, July, October, and December, where automated production significantly exceeds that of the previous year. These findings support the hypothesis that automation can substantially improve both the quantity and consistency of production in the industry.

To quantify the increase in production, a paired samples t-test was used. The results, shown in Table 2, compare the average of the manual process with the automated one, highlighting the improvement in efficiency and the reliability of the collected data. This statistical method underscores the advantages of automation, providing solid evidence of its positive impact on production.

The results from Table 2 show a significant increase in average production, moving from 1410.92 liters in the manual process to 1733.33 liters in the automated process. This notable increase evidences greater productive efficiency. Additionally, the comparable standard deviation and small standard error of the mean highlight an improvement in operational consistency following automation. Following the evidence of the impact of automation, a regression analysis is presented to better understand the relationship between manual and automated processes. Table 3 summarizes the linear and quadratic models. This offers a detailed look into the underlying dynamics of this relationship.

Table 2. T-test for paired samples

Statistics of paired samples				
	Mean	N	Standard deviation	Standard error mean
Manual process	1410.92	12	215.147	62.108
Automated process	1733.33	12	204.865	59.139

Table 3. Model summary and parameter estimates

Model summary and parameter estimates								
Equation	Model summary					Parameter estimates		
	R squared	F	gl1	gl2	Sig.	Constant	b1	b2
Linear	.620	16.310	1	10	.002	675.547	.750	
Quadratic	.622	7.391	2	9	.013	1045.886	.213	.000

The regression analysis showed that the linear model, with an R squared of 0.620, suggests that approximately 62% of the variability in automated production can be explained by the variation in the manual process, supported by a significant F-value indicating its statistical significance as a predictor of automated production. The model's constant and coefficient b1 indicate a direct, positive link between automation and increased production. Conversely, the quadratic model, despite a slightly higher R squared, does not significantly enhance prediction accuracy. The non-significant quadratic term (b2=0.000) suggests that the relationship between manual and automated processes might not be nonlinear, making the linear model a more fitting choice for describing their relationship.

3.2. Discussion

The results of our research show a significant increase in production, with a 22.85% improvement in average production due to the implementation of automated systems integrating PLC and HMI. This improvement highlights the effectiveness of automation in the fruit juice industry, providing solid evidence of its positive impact on production efficiency and consistency. Figure 4 shows the integration of AI and the IoT in automated process systems.

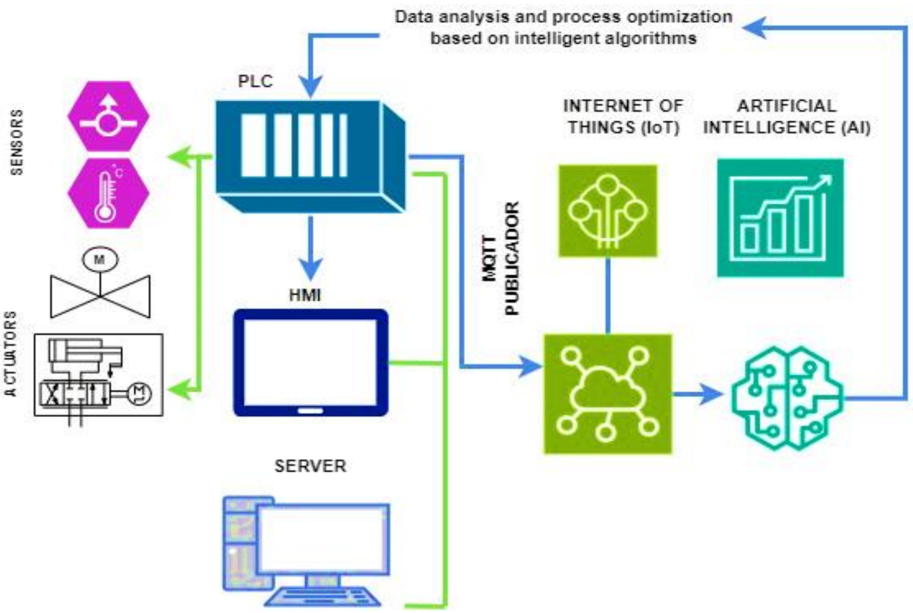


Figure 4. Integration of AI and the IoT in automated process systems

Figure 4 illustrates a qualitative leap in our pursuit of operational excellence through the incorporation of AI and IoT in automated process systems. The combination of AI and IoT offers systems capable of learning from data and improving over time, anticipating failures before they occur, and optimizing operations without human intervention. This synergy represents an acceleration of the trend towards intelligent automation and data-driven decision-making. The integration of AI and IoT in production systems not only increases productivity but also improves product quality and process sustainability. AI algorithms analyze real-time data to control fruit ripeness and storage conditions, ensuring that only the best quality pulp is used for production. Additionally, failing to integrate advanced technologies such as AI and IoT could result in a loss of market competitiveness, with companies unable to achieve the efficiency and quality that these technologies can offer.

Comparing our results with previous studies, such as those conducted in [23], we found that the precision and control associated with automation are consistent with our findings. Mateo and Redchuk [24] also highlights the reduction in operating costs and waste, aligning with our observations on energy efficiency. Additionally, studies like those in [25], [26] underscore the adaptability of control systems to specific production needs, supporting our conclusion that automation is a tool for continuous innovation.

A recent advancement in the integration of AI and IoT is the use of digital twins. A digital twin is a virtual replica of a physical process used to simulate, analyze, and optimize process performance in real-time. This allows companies to anticipate problems, test solutions, and optimize production without interruptions to the actual process. General Electric and Siemens have led the implementation of digital twins in manufacturing and energy management, showing significant improvements in operational efficiency and cost reduction.

Another promising development in the integration of AI and IoT is the implementation of predictive maintenance based on machine learning. This approach uses advanced algorithms to analyze historical and real-time data from machines and equipment, allowing for the prediction of potential failures before they occur. Companies like IBM and Microsoft have developed predictive maintenance platforms that are being used in various industries, from manufacturing to aviation. This type of maintenance significantly reduces unplanned downtime, decreases repair costs, and extends the equipment's lifespan. Moreover, by optimizing maintenance schedules, companies can operate more efficiently and sustainably. The ability to predict and prevent problems before they affect production not only improves system reliability but also provides a competitive advantage by minimizing disruptions and maximizing operational availability.

A recent analysis in [27] examines how human-robot collaboration improves efficiency in the manufacturing sector in Ireland, aligning with Industry 5.0 ideals. It discusses the nuanced impact of human-robot collaboration on manufacturing processes, emphasizing the need for upskilling workers to maximize the benefits of these advanced technologies. In the automotive industry, companies like Tesla use AI and IoT not only to improve vehicle manufacturing but also to optimize vehicle performance. Cars are equipped with a variety of sensors that collect real-time data, which is then processed using AI to optimize everything from fuel efficiency to vehicle safety [28]. In agriculture, companies like John Deere implement AI and IoT solutions to revolutionize precision farming. Tractors and harvesters are equipped with sensor technology and GPS, along with AI platforms that analyze terrain data and crop conditions, allowing farmers to make informed decisions about planting, irrigation, and harvesting [29]. The energy industry also leverages AI and IoT to move towards a more sustainable future. Companies like Siemens and General Electric use these technologies to create smart grids that can predict energy demand and automatically adjust distribution to improve efficiency and reduce costs [30]-[32]. Additionally, studies like those in [5], [7] underscore the adaptability of control systems to specific production needs, supporting our conclusion that automation is a tool for continuous innovation.

It is important to consider alternative explanations for the findings. While the improvement in production can largely be attributed to automation, other factors such as staff training and equipment maintenance may have also influenced the results. Environmental conditions and raw material quality also play significant roles. Additionally, the initial investment in automated equipment is substantial, although long-term operational savings are expected to offset these costs. Proper training of personnel to handle and maintain these advanced systems is crucial to maximizing the benefits of automation and ensuring its long-term success.

Looking to the future, the integration of AI and IoT with existing automation systems promises to transform manufacturing. These technologies not only enhance production capacity and quality through their predictive and adaptive capabilities but also offer unprecedented visibility and remote control. AI’s predictive capabilities can transform preventive maintenance from a reactive to a proactive approach, minimizing downtime and maximizing operational efficiency. The adaptability provided by these technologies facilitates more agile and flexible production, improving responsiveness to consumer demands and optimizing resource use, aligning with sustainability practices. Additionally, the possibility of remote monitoring and control allows companies to manage globally distributed operations, improving coordination and reducing response times.

In conclusion, the adoption of AI and IoT in industrial processes marks a before and after in automation. These technologies introduce unprecedented levels of precision and control, allowing automated systems to perform tasks more effectively while learning and adapting over time. The ability of AI to analyze large volumes of data and optimize processes in real-time, coupled with IoT connectivity, transforms decision-making and enhances production sustainability. Companies that adopt these innovations will be better positioned to face future challenges and seize opportunities in the digital era. These studies collectively highlight a significant evolution in industrial processes driven by the incorporation of IoT and AI technologies. They particularly focus on perfecting human-machine interfaces, aiming to boost productivity, sustainability, and safety. Additionally, these technological advancements will enable greater customization and adaptation of industrial processes, responding more efficiently to changing market demands and consumer expectations.

4. CONCLUSION

The main objective of this study was to investigate the effects of integrating AI and the IoT into the automated systems of the fruit juice industry, evaluating how these technologies can improve efficiency, product quality, and process sustainability. The research has demonstrated that implementing automated systems integrating PLC and HMI, combined with advanced technologies such as AI and IoT, can significantly increase average production by 22.85%. Additionally, the integration of AI and IoT not only enhances production quantity but also its consistency, reducing monthly variability and optimizing resource use. These findings underscore AI's ability to predict and adapt, and the real-time connectivity provided by IoT enables more informed and rapid decision-making, optimizing both production and sustainability.

The integration of AI and IoT in automated processes represents a significant advancement in the food industry. This study has identified that automation not only increases productivity and improves product quality but also promotes more sustainable and efficient practices. AI's predictive capabilities can transform preventive maintenance from a reactive to a proactive approach, minimizing downtime and maximizing operational efficiency. Additionally, the visibility and remote control provided by IoT allow for more effective resource management. These technological advancements position companies that adopt them favorably to face future challenges and seize opportunities in the digital era. Further research in other industrial sectors is recommended to evaluate the applicability and benefits of integrating AI and IoT in different contexts, as well as long-term studies to better understand the continuous impacts of these technologies.

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