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Increase in Operational Availability in Agricultural Fertilizer Production: A TPM Approach with Internet of Things (IoT)

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Abstract*– In this research, we aim to enhance production availability in an agricultural company specializing in fertilizers, including products like boric acid, 85% phosphoric acid, potassium chloride, and ammonium nitrate. The focus is on optimizing the production line of the top-selling fertilizer, potassium chloride. The project addresses equipment availability issues within the production process, with the main goal of reducing downtime and improving efficiency. To achieve this, we employ Total Productive Maintenance (TPM) methodology combined with Internet of Things (IoT) technology. TPM aims to maximize operational efficiency through preventive maintenance, employee involvement, and continuous improvement, while IoT enables real-time monitoring of equipment conditions, gathering data on critical factors like vibration, lubrication, wear, and temperature. By integrating these approaches, we aim to significantly enhance equipment availability, reduce downtime, and optimize operational efficiency in fertilizer production. The study results, validated through simulation, show a 2.55% increase in overall process availability, a monthly productivity boost of about 20.48 tons, and a reduction in economic losses per year. Additionally, there was a 7.26% and 5.41% increase in the availability of critical equipment, demonstrating the effectiveness of these methods and their potential application to other production lines, leading to improved sustainability and profitability for the company.

Keywords*-- TPM Methodology, Fertilizers, Optimization, Machinery Availability, Internet of Things (IoT).

I. Introduction

The study investigates the importance of agricultural mechanization and sustainability, highlighting significant environmental and economic impacts [1]. External events like the Russia-Ukraine war have disrupted imports and increased gas and oil prices, affecting fertilizer supply in Peru, as evidenced by the Food and Agriculture Organization and the Ministry of Agrarian Development and Risk [2][3]. The lack of support during agrarian reforms has exacerbated the fertilizer crisis, reducing the planting of key crops and increasing food prices, directly impacting the cost of living [4].

Political instability and the absence of alternative measures during recent agrarian reforms have led to a 300% increase in fertilizer prices, affecting trading companies, farmers, and consumers. The agricultural fertilizer trading company has faced operational challenges, particularly in the bagging area, with a 14.60% increase in delayed and unfulfilled orders due to low equipment availability, resulting in 327.7 hours of unproductive time annually.

The research addresses low equipment availability by proposing the application of TPM pillars, specifically focused improvement and autonomous maintenance, as a proactive tool to optimize equipment performance [5]. This approach aligns with the need for efficient production in the bagging line. The study emphasizes the importance of improving equipment efficiency, minimizing downtime, and optimizing maintenance [6].

The research aims to increase overall equipment availability to 95%, up from the current 89.14%, by focusing on preventive and corrective maintenance [7]. The integration of IoT technology with TPM allows real-time monitoring and data collection, enhancing operational efficiency in fertilizer production. The article is structured to present the improvement proposal, followed by validation and conclusions.

II. State of the Art

For the literature review, the theoretical foundation of the research is crucial as it supports results, facilitates debates, and advances scientific knowledge. To ensure its effectiveness, a rigorous methodology involving a systematic review of sources such as scientific articles, indexed journals, and recognized books is necessary. This includes thorough planning, searching multiple sources, and applying quality criteria to select relevant evidence. Formulating clear and precise research questions is essential to guide the review process, support research results, enable debates, and demonstrate scientific contributions. The methodology highlights the importance of a systematic review with diverse sources. Linares-Espinós stresses the need for at least two reviewers to minimize biases and eliminate irrelevant studies [8].

The search process is organized into phases: planning the review, conducting it, and presenting a detailed report, with meticulous documentation at each stage to ensure transparency and reproducibility. The planning phase involves formulating significant research questions that can drive changes in practice or challenge conventional beliefs. In this case, four questions are posed:

- What are the most recurring problems in agricultural fertilizer trading companies?

- What causes delays or late delivery of orders in these companies?

- What engineering tools help reduce unproductive times?

- What tools increase the efficiency of a production line in these companies?

The importance of a search protocol is emphasized, enabling meticulous planning, clear documentation, avoiding arbitrary decisions in data selection, and minimizing effort duplication [9]. This protocol includes research questions, inclusion and exclusion criteria, and a search strategy. Quality criteria focus on identifying limitations when evaluating articles for relevance. Following AMSTAR recommendations, it is advised to search at least two data sources, though expanding to more sources improves effectiveness [10].

After defining critical questions and criteria, it is crucial to consider the data sources consulted. It is advisable to review and use the database of various sources such as Ebsco, Scielo, Web of Science, and Scopus. Furthermore, before creating the search equation, it is equally important to define search terms by using translations, synonyms, and specific engineering vocabulary. Additionally, standard search equations are recommended to be used, employing logical operators such as "OR," "AND," and "NOT" to combine and refine search terms. It is essential to consider various data sources and apply quality criteria to assess the relevance and reliability of selected studies.

During the next phase, called Conducting the Systematic Review, the protocol is developed and the actual review is conducted. See Figure 1. It is crucial to document this stage and visually represent it through a flowchart [11].

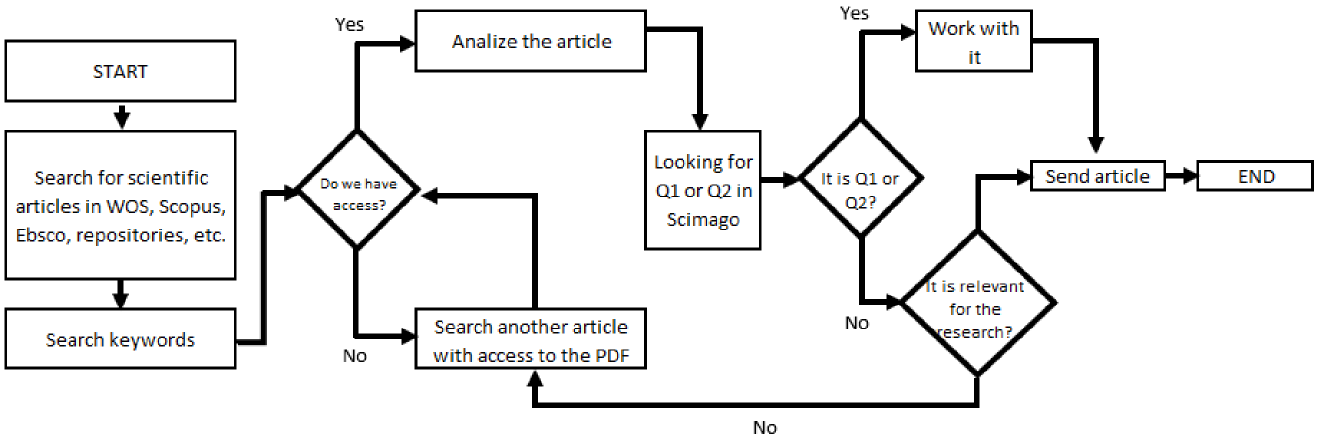

Figure 1. Flowchart: Systematic Review.

According to the above, the typologies considered for the research are:

1. Improvements achieved based on prediction and efficiency using technological focus and sustainability within the agricultural sector.
2. Increase in equipment lifespan and reduction of downtime through the application of TPM and maintenance technologies.
3. Increase in machinery performance through maintenance generated by the application of TPM in agricultural production processes.
4. Increase in operational efficiency through the improvement and planning of maintenance management in agricultural machinery.
5. Reduction of occupational accidents due to proper risk management and worker safety during preventive maintenance of machinery within the agricultural sector.

After categorizing the success cases, it is concluded that autonomous maintenance, focused on human capital, involves operators' participation in activities such as cleaning, lubrication, and equipment inspection, identifying wear on components early [6], [8], This early detection prevents unplanned shutdowns, increasing production. Regarding equipment availability orientation, the aim is to increase production hours by reducing unplanned downtime, significantly improving overall efficiency [10]. Success cases suggest achieving an equipment availability rate of 90% [12], and studies show that production efficiency increases with the implementation of autonomous maintenance under TPM methodology, including creating a positive work environment [13].

III. CONTRIBUTION

A. Background

The study aims to optimize operational availability in fertilizer production by applying TPM methodology and introducing a model to enhance preventive maintenance in parallel production systems. This model incorporates maintenance policies, repairers, and spare units, utilizing a genetic algorithm [14] [17]. The methodology identifies and addresses factors affecting equipment availability, reducing unproductive times and increasing production capacity [11]. The integration of IoT technology allows real-time monitoring, early detection of potential failures, and timely corrective actions [8]. This combined approach innovates preventive maintenance, enhancing production and maintenance efficiency [16]. The methodologies are crucial in agricultural production, particularly in Peru's fertilizer industry, by addressing machinery efficiency and availability [14]. TPM, with its focus on autonomous maintenance, is essential for optimizing equipment performance throughout its lifecycle, mitigating unproductive times, and increasing operational availability [15]. Additionally, AI and ML significantly impact agriculture by enhancing resource efficiency, reducing water waste, optimizing fertilizer management, and increasing productivity [16]. These technologies enable more effective weed control and provide efficient agricultural data [21]. Integrating IoT and AI techniques in fertilizer production improves equipment availability and reduces unplanned downtime. IoT sensors on critical machines collect real-time data on various parameters, enabling predictive and preventive maintenance with 97.75% fault detection accuracy. This reduces maintenance costs and increases operational efficiency, proving economically viable. Long-term maintenance and improvement strategies include personnel training, constant monitoring, a predictive maintenance program, and regular system updates, aligning with TPM methodology goals. Implementing advanced technologies in agricultural production enhances efficiency and sustainability, directly impacting productivity and profitability. Optimization in resource utilization, maintenance cost reduction, and increased equipment lifespan benefit the sector economically and environmentally. The study also emphasizes the educational and practical applications in industrial engineering, reinforcing skills in planning, designing, implementing improvement strategies, and operations management. This experience strengthens academic training and develops practical professional competencies.

B. Model detail

Below is a model based on the application of IoT and a pillar of the TPM methodology to increase the availability of equipment based on two critical components. See Figure 2.

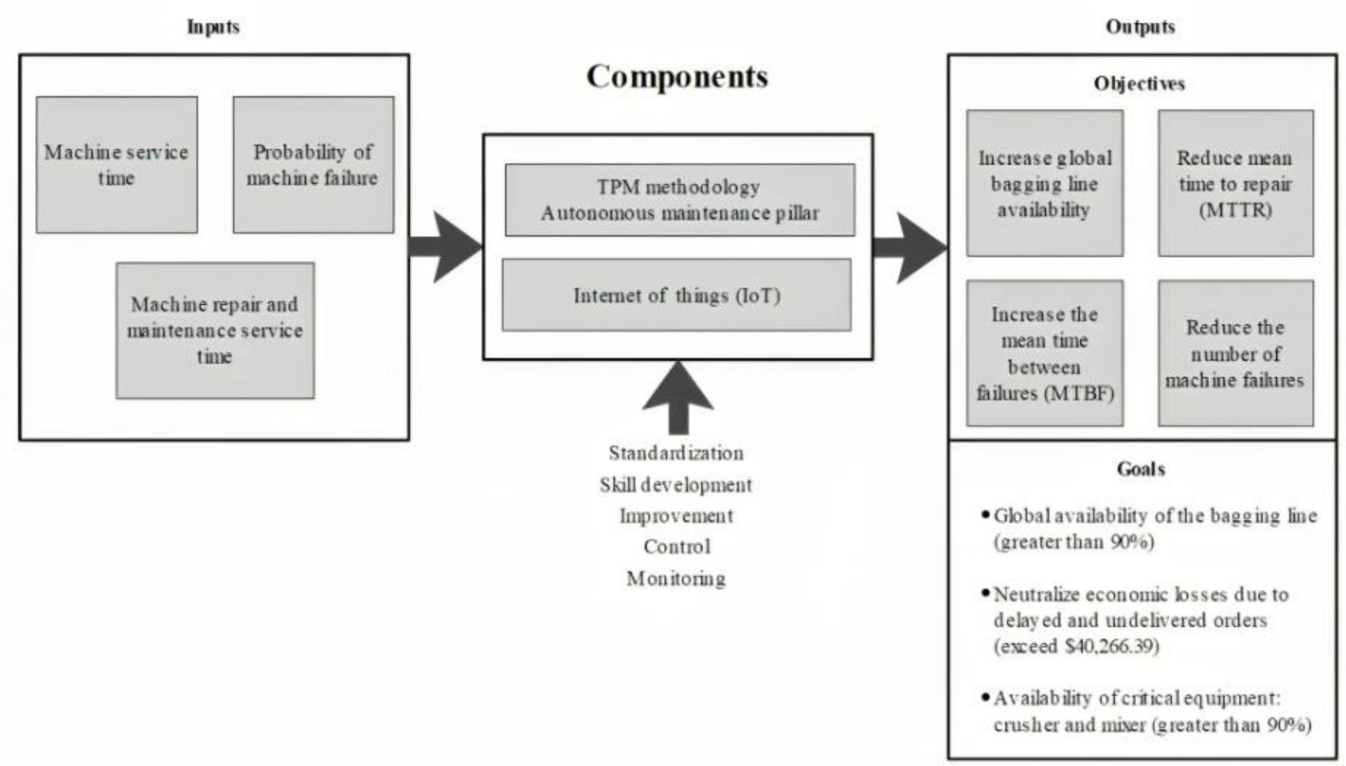

Figure 2. Conceptual model for the implementation of TPM and IoT in the company.

The main contribution of this work is optimizing operational availability in fertilizer production operations. Applying TPM methodology has proactively identified and addressed factors affecting equipment availability, reducing unproductive time, and increasing production capacity. This improvement translates to increased productivity and profitability for agricultural companies, contributing to their growth. Additionally, IoT technology provides real-time monitoring, enabling early fault detection and informed decision-making, improving resource utilization efficiency, reducing maintenance costs, and extending equipment lifespan, positively impacting the agricultural sector's economic and environmental sustainability.

The current availability of critical machinery, as shown in Table 1, is 83.99% and 86.68%, respectively. This is mainly due to the waiting time generated by each of them, which is approximately 81.00 hours per year for the mixer and 89.30 hours per year for the crusher. Furthermore, the total theoretical operating time is considered to be 3,014.40 hours per year. See Table 2. It is important to highlight that, although these are not the machines with the longest waiting time, they are the ones that contain causes that have a more significant impact on order delays.

	AS IS	TO BE
Mixer machine	83.99%	93.59%
Crusher machine	86.68%	94.67%

Table 1. AS IS and TO BE availability of critical machines.

	Crusher machine	Mixer machine
Unproductive time per year	89.30	81.00
Theoretical total operating time	3,014.40	

Table 2. Comparative table of unproductive times in critical machines.

This project aims to enhance asset management efficiency by implementing Total Productive Maintenance (TPM) principles alongside IoT (Internet of Things) technology. This combination provides a detailed perspective on equipment performance, facilitating informed decision-making and proactive responses to potential availability and performance issues [20].

The new monitoring method utilizes special sensors installed on the company's main machinery. These sensors monitor critical aspects such as vibration, lubrication levels, wear, and temperature [19]. The collected data are analyzed based on predefined criteria to ensure they remain within optimal ranges. Alerts are generated if deviations are detected, enabling technical personnel to intervene and inspect the machinery. This proactive approach helps identify and address potential issues before they become severe, thereby improving efficiency and extending equipment lifespan [22].

Criteria were established for implementing IoT technology on the most important machines, including sensor installation for monitoring critical aspects like vibrations, lubrication, wear, and temperature. A robust network infrastructure is necessary to connect these sensors to an IoT platform capable of real-time data reception, storage, and processing [24]. Standard communication protocols must be established to ensure interoperability and information security [23]. The sensor parameters provide detailed insights into unexpected vibrations, lubrication levels, wear, and temperature, as described in the operation flow in Figure 3.

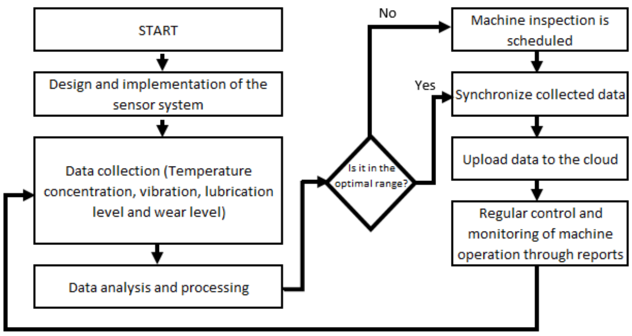

Figure 3. IoT Monitoring System Diagram.

The implementation of the TPM tool is divided into several key stages:

The proposal includes several measures to enhance maintenance and organization. Staff will inspect and classify items, identifying critical and non-critical items with red and yellow cards for removal or relocation. Specific places will be designated for each object to reduce travel times and improve organization. Cleaning shifts will be assigned, and a checklist created to ensure all activities are completed. Standards and procedures will be documented with visual indicators to maintain optimal conditions. Continuous improvement will be integrated through annual audits to suggest corrective, preventive, and improvement measures. Finally, a management meeting will be held to analyze audit results and make decisions, which will be communicated to all stakeholders.

Finally, the corresponding improvements are planned for the crusher and the mixer, critical machines within the packaging process. For the crushing machine, it is proposed to regularly program relief valve adjustments with a pressure limit of up to 4000 psi and check hydraulic cylinders every 250 hours of operation. Additionally, wear sensors will be implemented in critical areas with an IoT-based monitoring system to track them every 95 hours. Staff will be trained in adjustment procedures every 2 months, and an annual preventive maintenance management system will be established, alongside continuous monitoring of air compressor pressure between 80 to 120 psi. For the mixing machine, a regular lubrication program will be conducted every 70 hours, with protection devices and filters installed around the engine every 860 hours. A monthly cleaning schedule will be maintained, staff trained in machine use every 2 months, and key parts inspected for wear every 135 hours. Operational data will be recorded and analyzed using SAP EAM software on a weekly basis.

IV. VALIDATION

According to the methodology, we will start by collecting data and then analyze important indicators such as mean time to repair (MTTR) and mean time between failures (MTBF) [26]. These indicators will be critical to evaluate the results of our proposal. See Table 3.

Indicator	AS IS	TO BE
Mean time between failure (Minutes)	168.35	212.28
Average holding time (Minutes)	21.62	18.35
Global availability (%)	89.14	95.00
Mixer availability (%)	83.99	93.59
Crusher availability (%)	86.68	94.67
Average number of failures (unit)	13.25	12.36

Table 3. AS IS and TO BE indicators.

Firstly, to obtain the data necessary to model the current scenario, a total sampling of the times between arrivals of production orders is required, as well as the processing times of each of the production stations and the machinery maintenance times. due to faulty stops.

This will allow an adequate assignment of statistical distributions that reflect the real behavior of the company's operations system. With a horizon of n=1000 sample collections, the list of variables studied is presented, which includes the necessary parameters to determine, through simulation, the feasibility and impact of the present study. To guarantee the functionality and adequate behavior of the stochastic simulator, it is essential to have an orderly and supported approach. This involves presenting the model entities, their related attributes, and the activities that will be carried out throughout the simulation. See Table 4.

Entities	Attributes	Activities
Production order	Time between arrivals (TELL) Quantity demanded (CDEM)	Arrival at operations area From queue j (j=1,2,3,4,5,6,7) Occupy station resource I (i=1.2.3.4.7) Send delayed due to scale failure Send to delay due to crusher failure Send to delay due to mixer failure Send to delayed due to failure in manual bagger Send to delay due to failure in serving machine Get out of the system
Supplier	Waiting time (LT)	Fulfill order to warehouse
Store	MP Stock Pending orders (PEDPEN) Pending lawsuit (DEMPEN) Inventory position (POSINV)	Meet demand Increase pending demand Review inventory position Generate orders to supplier Meet pending demand
Station Resource i (i= 1…7)	Station resource service time i Probability of maintenance failure (i=2.3.4.5.6) Maintenance time i (i=1,2,3,4,5,6)	Wait for order from station i (i=1,2,3,4,5,6,7) Serve order from station i (i=1,2,3,4,5,6,7) Hold order until sufficient stock i (i=1) Perform maintenance fault on i (i=2,3,4,5,6) Perform corrective maintenance on i (i=2,3,4,5,6)

Table 4. Table representation of the company's current operations model.

Figure 4 illustrates the behavior of the current operations system of the study company, showing the flow of processes throughout the production stations and inventory management through the reorder point. Each production station is subject to probabilities of breakdowns associated with the machinery in use. In the proposed system, the raw material enters from the supplier, and if there is not enough quantity, the order is retained until the material requirement can be met.

Once the graphic modeling was proposed, the simulator was designed using the ARENA program for the production system of the company under study. To do this, a minimum number of simulations necessary to obtain results close to reality was calculated. This is achieved by statistically calculating runs from an expected value of error in the mean. In this validation case, the aim is to obtain values with a confidence level of 95% and an error in the mean of 10%. The figure shows the confidence intervals for each output data of the operations system of the company under study, which allows us to conclude that the minimum number of runs will be executed for the current model, which is at least 139. It is important to note that for this analysis an initial value of 30 simulations was taken, so this value will be used to obtain the most realistic data possible

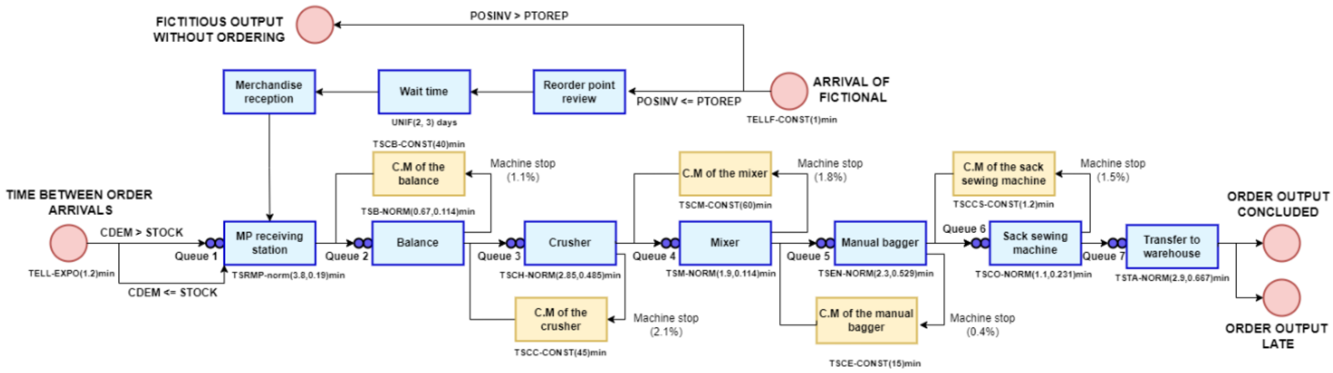

Figure 4. Graphic representation of the current model.

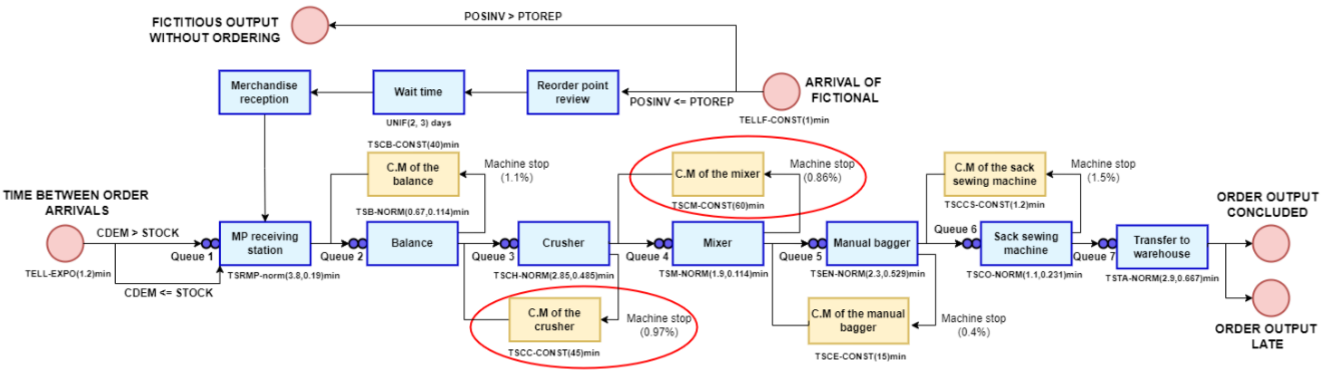

Figure 5. Graphic representation of the proposed model.

This allows evaluating the impact of the implementations proposed in the project. Therefore, changes will be made to the system to evaluate the metrics modeled in this validation case. To validate the implementation scenario, it is crucial to highlight the changes in the model that are reflected from the development of the improvement plan. Therefore, modifications were made compared to an initial scenario, focusing especially on inputs related to machinery repair service time and its probability of failure. See Table 5.

Machines	Statistical distribution	Crusher machine	Mixer machine
Mixer	Constant	29	0.86%
Crusher	Constant	32	0.97%

Table 5. Modification of inputs for proposed scenario.

The graphic representation of the discrete event simulation model for the proposed improvement scenario is presented below, which reflects the changes previously proposed regarding the Mixing and Crushing stations following an implementation of a focused improvement plan, autonomous maintenance, and the use of the Internet of Things (IoT). See Figure 5.

From the data presented in the proposed discrete event simulation report, it is possible to identify the proposed evaluation metrics, as shown in Table 6, which reflects the improvements resulting from the implementation of the improvement tools.

Indicator	AS IS	TO BE	RESULTS
Mean time between failure (Minutes)	168.35	212.28	217.34
Average holding time (Minutes)	21.62	18.35	9.71
Global availability (%)	89.14	95.00	91.69
Mixer availability (%)	83.99	93.59	91.25
Crusher availability (%)	86.68	94.67	92.09
Average number of failures (unit)	13.25	12.36	9.28

Table 6. Functional validation indicators.

With this, it is concluded that the implementation of the TPM methodology together with IoT technology to improve predictive and preventive maintenance allows detecting and preventing problems before they occur; since it increases the availability by 7.26% and 5.41% of the critical mixing and crushing machines, respectively.

Furthermore, with the implementation of the improvement proposal, global availability was increased from 89.14% to 91.69%. Likewise, the monthly production volume for potassium chloride increased from 610.08 Tn to 630.56 Tn, highlighting an increase of approximately 20.48 Tn.

V. Discussion

A. Main results

The main results of this research demonstrated a significant improvement in bale line availability following the implementation of autonomous TPM maintenance along with IoT technologies. Specifically, an increase of approximately 3 per cent was observed in the overall availability of the line; and, with respect to the availability of critical machines, improved 7.26% in the mixer and 5.41% in the crusher, which translates into a considerable reduction in unplanned downtime. These results underscore the importance of integrating emerging technologies such as IoT sensors into standalone maintenance programs to optimize operational performance and overall efficiency.

B. Scenario vs results

Prior to implementation, the packing line faced frequent interruptions due to unexpected failures in critical machines. Lack of visibility in machine condition and reliance on reactive maintenance resulted in an average availability of 89.14%. Following the implementation of autonomous TPM maintenance and the use of IoT sensors, global availability increased to 91.69%. Sensors allow real-time monitoring, identifying problems before they become critical failures, allowing for proactive intervention and more effective maintenance planning.

The analysis of the results was based on several criteria, which include the reduction of failure frequency, mean times between failures (MTFB) and average maintenance time (MTTR). The data showed a reduction of 29.96% in the frequency of failures, an increase in the mean time between failure of 29.10% and a decrease of 55.09% in the average maintenance times. These findings are consistent with previous studies indicating that IoT integration into maintenance programs, where operational efficiency can be significantly improved [25], [27], [29]. In addition, the implementation of autonomous maintenance of the TPM empowered operators, improving their knowledge and ability to manage and prevent problems, which is aligned with the literature that highlights the value of autonomous maintenance in improving staff performance [24].

C. Future work

For future work, we propose exploring machine learning implementation; since, integrate machine learning algorithms to predict more complex failures and further optimize predictive maintenance. According to studies, this could improve the accuracy of interventions and further minimize downtime [30]. On the other hand, we propose to evaluate the extension of autonomous maintenance of TPM and IoT in other production lines within the same plant or in different industries to validate the generalizability of the results obtained. Finally, a detailed analysis of the economic and environmental impact of the implementation of these technologies is proposed, quantifying the savings in operating costs and the reduction in carbon footprint due to greater efficiency in the use of resources. With this, these proposals will not only expand current knowledge, but could also contribute to the continuous improvement of industrial operations using advanced technologies

VI. CONCLUSIONS

The adoption of practices such as autonomous maintenance of the TPM and IoT technologies generates positive benefits in environmental, legal and occupational safety aspects, reducing noise and vibrations, improving compliance with regulations and reducing accidents at work.

It is decided to use the COK financial indicator to evaluate the cost of external financing, considering a bank loan to finance the investment, resulting in a value of 15.43%, and the conditions of the loan are established, such as the term of 12 months and a TEA of 8%.

The VAN is positive ($103,058.00), the IRR exceeds the COK (120% > 15.43%) and the cost-benefit indicator is greater than 1 ($5.25), concluding that the project is viable.

The investment recovery time is estimated at 1.70 years, approximately 1 year and 9 months.

The economic impact is analyzed in relation to penalties for late orders, showing a significant reduction of 28.95% in penalties, equivalent to $11,655.75.

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