Machine Learning, MRP, and Lean Tools as an Internal Innovation Strategy to Improve Efficiency in a Bottling Company

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***Abstract*– The bottled water sector in Peru has shown sustained growth in recent years, driven by increased consumption and high seasonal demand, particularly during the summer. With a projected market value of $452.90 billion by 2029, companies in the industry face the ongoing challenge of adapting to a competitive and constantly changing environment. In this context, a bottling company identified improvement opportunities within its production system as it faced issues such as mechanical failures, supply shortages, planning errors, and rework, all of which compromised its operational efficiency. In response, strategies were promoted to optimize resource utilization, reduce unproductive time, and ensure product quality. These actions, driven from within the organization, reflected an intrapreneurial initiative focused on strengthening planning, preventive maintenance, and process standardization to enhance responsiveness to demand, particularly during peak months. Additionally, the company reinforced compliance with health and environmental regulations, contributing to the sustainability of its operations. As a result, the company achieved an 11% increase in operational efficiency, reduced losses, and enhanced its competitiveness. This experience illustrates how the pursuit of innovative solutions from within the work environment can transform traditional management practices, enabling organizations to adapt and thrive in a constantly evolving market while maintaining a commitment to efficiency, quality, and continuous improvement.**

***Keywords*— Autonomous Maintenance, Hybrid Forecasting, Machine Learning, MRP, Standardized Work**

I. Introduction

The bottled water industry in Peru has experienced steady growth in recent years, with a significant increase in consumption during the 2024 summer season, especially in the seven-liter format [1]. Likewise, according to a report, the global bottled water market will grow at a compound annual rate of 6.14%, reaching USD 452.90 billion by 2029 [2]. At the national level, the bottled water market continues to expand rapidly, driven by greater health awareness, urban population growth, and the development of the modern distribution channel. It is also estimated that this category will maintain a compound annual growth rate of 5.3% in volume until 2027, reflecting strong and sustained medium-term demand [3].

This surge in demand highlights the need to improve production planning in bottling companies. However, many of them face challenges due to the lack of adequate tools for accurate planning, which leads to inefficiencies and increases operational costs [4].

In the food industry, accuracy in demand forecasting and material planning is essential to minimize losses and optimize production. A study conducted in a Peruvian egg product company used the SARIMA model (Seasonal Autoregressive Integrated Moving Average) to analyze historical sales data and generate more accurate demand forecasts. This allowed the MRP system (Material Requirements Planning) to accurately plan the necessary raw materials, avoiding overordering and reducing product spoilage. The combination of SARIMA and MRP resulted in a 65.57% reduction in spoiled products and a 47.21% decrease in forecasting error, significantly improving operational efficiency. This integration of predictive technologies and resource planning demonstrates a replicable model for improving management in both food and bottled water industries [5].

Likewise, the application of standardized work in a bottling company leads to significant improvement in the execution of repetitive operations, allowing each task to be carried out in an orderly, clear manner and based on efficiency criteria. This directly contributes to optimizing production times and reducing non-value-adding activities, resulting in higher productivity and a lower margin of error. Furthermore, standardization enables personnel to follow the same sequence of steps, improving process control and the quality of the final product. According to the study, this tool made it possible to design a new work method with better space distribution, a defined ideal number of operators, and appropriate conditions to maintain consistent production, demonstrating its practical usefulness and sustainability in high-volume production industries [6].

Finally, autonomous maintenance is crucial to ensuring equipment operability in a water bottling company, as it facilitates the integration of technical knowledge from the maintenance department with the practical experience that operators acquire through daily machine handling. Thanks to this approach, operators can take care of basic tasks such as lubrication, cleaning, visual and manual inspections, as well as the replacement of certain worn components [7].

II. LITERATURE REVIEW

A. Machine Learning and Hybrid Forecasting Models

Machine Learning (ML), a branch of artificial intelligence, has become a key tool for analyzing large volumes of data and generating useful predictions. Unlike other AI approaches focused on task automation, ML aims for systems to learn directly from information [8].

Within its applications in time series, Long Short-Term Memory (LSTM) networks, an advanced type of recurrent neural network (RNN), are designed to handle data sequences and capture long-term dependencies that classical approaches cannot efficiently model [9]. Their architecture incorporates "gates" that regulate the retention or disposal of information, thereby facilitating long-term memory in sequential prediction tasks.

On the other hand, SARIMAX models constitute a statistical extension of ARIMA that incorporates seasonal components and external variables, allowing repetitive patterns to be represented more precisely [9].

Recent literature shows that the hybrid integration of these approaches significantly improves forecasting accuracy. In the Brazilian energy market, for example, a SARIMAX-LSTM model achieved an RMSE error of approximately 4.5%, demonstrating robustness against volatility and seasonality [10]. This type of result is particularly relevant for demand planning and materials management in production environments, as it provides a more reliable predictive framework for decision-making under conditions of uncertainty.

B. Material Requirements Planning and Production Management

Material Requirements Planning (MRP) is an essential methodology in production environments, as it allows for accurately determining the quantities and purchasing times of each component based on the product structure or Bill of Materials (BOM), ensuring that production aligns with planned demand [11]. In water bottling companies, efficient planning and scheduling are key to reducing idle hours, optimizing the use of human resources, and ensuring order fulfilment. For this purpose, the importance of integrating preventive maintenance with production order scheduling has been highlighted, which, together with mixed-integer programming (MIP) models, increases operational efficiency and responsiveness to demand variations [12].

In the context of SMEs, several studies have demonstrated that the implementation of MRP in combination with tools such as 5S and forecasting models improves inventory management and synchronizes production with demand. A notable case is the bakery La Ciabatta, which, by applying these practices, increased its fill rate from 86% to 92%, reduced forecast error from 27% to 5%, decreased stockout levels from 14% to 5%, and increased inventory accuracy from 67% to 86% [13].

Furthermore, the integration of MRP with the Master Production Schedule (MPS), its extension MRP II, and Cyber-Physical Production Systems (CPPS) has shown significant impacts in reducing assembly times, increasing equipment utilization, and improving traceability, especially using simulators such as FlexSim and the development of digital twins [14]. Complementarily, in make-to-order companies, the application of MPS together with heuristic clustering algorithms has allowed for grouping similar products, reducing SKU variation by 9%, and decreasing master plan preparation time from one day to less than a minute, thereby improving operational efficiency and delivery punctuality [15].

C. Lean Manufacturing Tools for Process Optimization

Autonomous maintenance constitutes a pillar of TPM that seeks to empower operational personnel to identify abnormal equipment conditions, perform basic tasks such as cleaning, lubrication, and minor adjustments, and collaborate in preserving the functional state of machines [16]. Added to this is standardized work, aimed at defining a clear and repeatable sequence for process execution, eliminating non–value-added activities, reducing failures, and improving operation times, which contributes to production responding appropriately to market demand [6]. Complementarily, the Pareto diagram is a widely used tool in quality control, as it allows prioritizing the critical causes of defects and focusing efforts on the most significant factors to optimize processes [17].

Several studies support the effectiveness of these tools in different industrial sectors. For example, in a steel company, the implementation of autonomous maintenance increased productivity from 46.82 to 49.17 TM/h by prioritizing key problems and optimizing critical components [18]. Similarly, in the palm oil sector with an initial OEE of 73.27%, the integration of autonomous maintenance, SMED, and method studies reduced the Mean Time to Repair (MTTR) from 7.14 to 4.50 hours and raised OEE to 88.24%, achieving world-class standards, with availability of 91.01% and performance of 97.65% [19].

In the case of a plastic products company, low efficiency of 61.06% was attributed to long repair times and defects. The incorporation of 5S, SMED, and TPM, especially with autonomous maintenance, allowed operators to become directly involved in equipment care, which reduced repair times, improved operational availability, and increased efficiency to 73.65%, while decreasing defects due to burns [20]. Finally, a Peruvian textile SME implemented an improvement model based on Lean Manufacturing (SMED, 5S, standardized work, and ECRS). Using Arena simulation and a seven-week pilot, it managed to increase efficiency from 64.71% to 80%, reduce setup time by 10 minutes, decrease rework from 11% to 5%, and lower process variability to 6%, strengthening productivity and quality [21].

On the other hand, competitiveness in this sector depends on various strategic variables, such as environmental management, quality assurance, marketing, human talent, and information systems. Environmental management and quality are key to achieving sustainable growth and fostering customer loyalty in highly competitive environments [22].

Overall, the literature supports the integration of autonomous maintenance, material requirements planning, work standardization, and hybrid forecasting models as an effective approach to optimize efficiency in manufacturing companies. These precedents form the basis for the design and validation of the proposed model in the bottled water company.

III. Case Study

The bottled water company faces a systematic failure to comply with the production schedule due to unproductive time, rework, and delays on the production line. These deficiencies result in products not being delivered to customers on time, leading to returns and lost sales. Additionally, the company incurs overtime in production and dispatch, increasing operational costs.

TABLE I
Company Performance Efficiency

Month	Actual Production	Planned Production	Efficiency
January	133822	217416	62%
February	150983	231648	65%
March	125243	172640	73%
April	103959	158625.6	66%
May	69440	100880	69%
June	52862	84505.6	63%
July	58828	87360	67%
August	69000	84816	81%
September	71156	70296	101%
October	73808	90147.2	82%
November	70177	89400	78%
December	86220	86760	99%
	Average		75%

Currently, the average efficiency of the production process is 75% (Table 1), while according to the literature, the benchmark standard for this type of process is 88.98%. This difference reveals a gap of 13.98 percentage points, which translates into an estimated annual economic impact of 561,995.59 soles.

The main causes of this low production performance are unplanned downtime in the injection molding machine due to the lack of preventive maintenance, mechanical failures in the blow molding machines, delays caused by shortages of inputs, congestion of intermediate products resulting from deficiencies in production planning, and rework due to defects in the finished product.

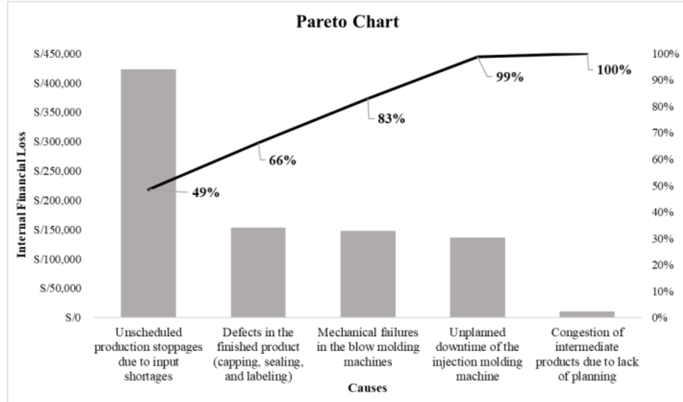

Fig. 1 Pareto Chart of the Causes

Figure 1 shows that stoppages due to lack of input represent the main cause of loss, accounting for 49% of the total, followed by defects in the finished product and mechanical failures in the blow molding machines, which together amount to 83% of the total impact. According to the Pareto principle, these three causes should be addressed as a priority, as they explain a large portion of the production delays, rework, and unproductive time that affect efficiency. Addressing them will help reduce internal losses, improve compliance with the delivery schedule, and optimize operational resources.

IV. Contribution

The model proposed in this study was designed with the aim of optimizing production management in a bottled water company, focusing on improving planning accuracy, minimizing downtime, and strengthening autonomous maintenance practices. The methodology integrates data analysis tools, demand forecasting techniques, material planning, and process standardization. The proposal is structured in three sequential phases: diagnosis, proposal design, and implementation and validation (Figure 2)

A. Phase 1: Diagnosis

In this phase, an in-depth analysis of the current state of the plant was carried out. Historical production data were collected and analyzed, identifying the main operational problems using the Pareto chart.

Subsequently, using a problem tree, a deeper analysis was conducted to identify the root causes affecting order fulfillment, causing production delays, and leading to economic losses associated with the return of products not delivered on time.

B. Phase 2: Proposal Design

Based on the findings from the diagnostic phase, the following tools and solutions were designed and integrated:

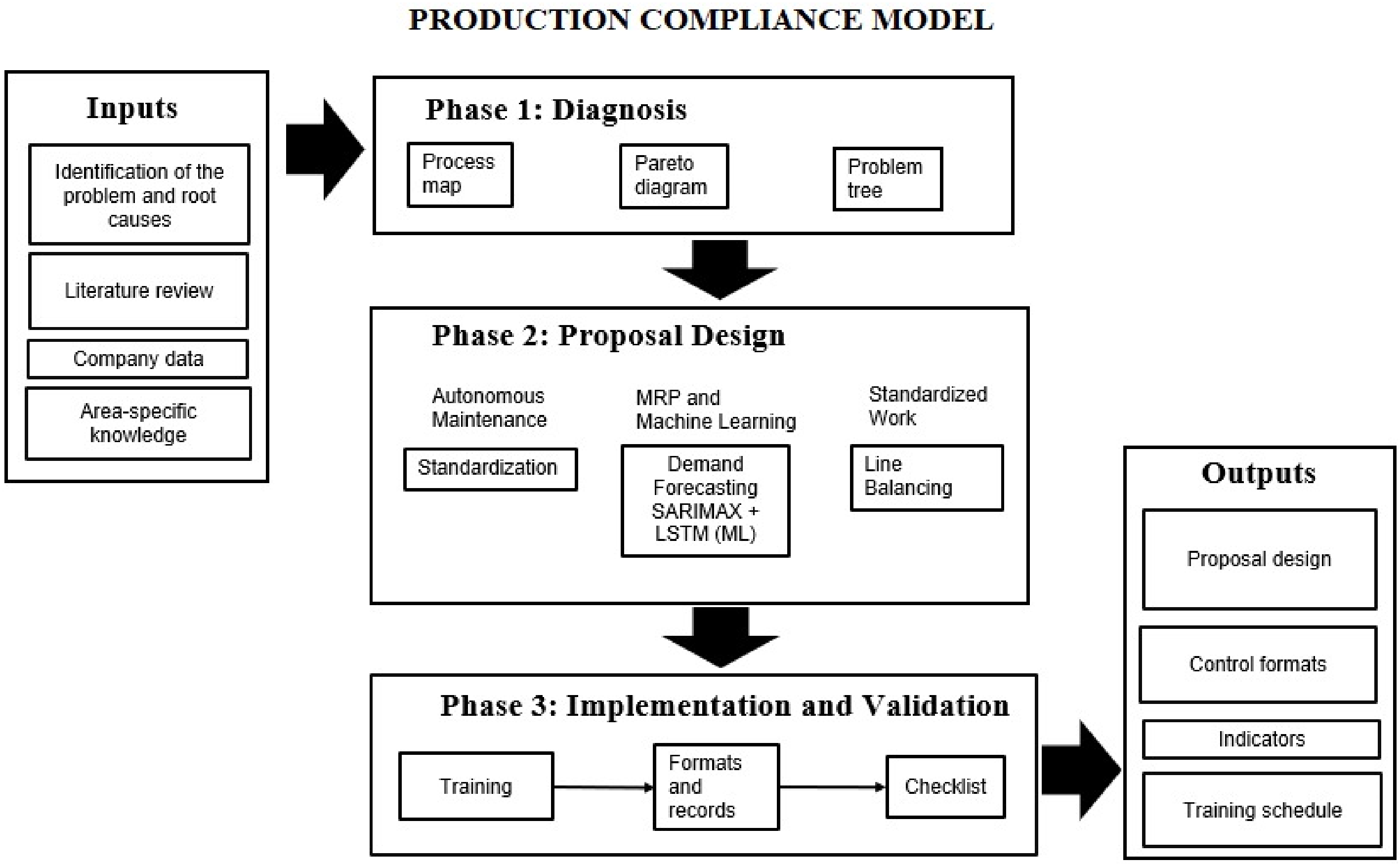

Fig. 2 Model for the Design of the Problem-Solving Proposal

1) Autonomous Maintenance: Deep cleaning routines for the machines were implemented, including the removal of contaminants and the optimization of access to critical areas to facilitate preventive inspections. Standardized procedures were developed for cleaning, lubrication, adjustment, and inspection, complemented by color-coded inspection tags and periodic checklists. In addition, production personnel were trained in basic inspection tasks, early detection of anomalies, and prevention of major failures.

2) MRP System with Machine Learning: To feed the MRP system, advanced SARIMAX statistical models were first applied, which made it possible to capture the seasonality and trend of the historical demand for the products. Subsequently, Long Short-Term Memory (LSTM) neural network models (Machine Learning) were incorporated to improve predictive accuracy in the face of nonlinear patterns and dynamic market variations. Based on the forecasts generated, the MRP system enabled the planning and coordination of raw material procurement, minimizing both shortages and inventory surpluses, and ensuring the timely availability of materials to meet projected demand.

3) Standardized Work: Clear operating procedures, defined cycle times, quality standards, and specific task assignments for each operation were developed to minimize operational errors, reduce variability, and ensure the stability of production processes.

C. Phase 3: Implementation and Validation

In this final phase, the gradual implementation of the proposals was carried out, including staff training, the use of daily, weekly, and monthly inspection checklists, and the establishment of follow-up formats and maintenance records. These tools enabled the monitoring of compliance with scheduled activities, the verification of proper execution of procedures, and the validation of the improvements' impact on the plant's production performance.

V. VALIDATION

A. Validation Rationale

According to [23], the validation of planning models such as MRP requires a pilot phase prior to full implementation, as it allows for the evaluation of the model's behavior under real conditions. In a study involving a small enterprise in the food service sector, historical sales data were used, and Excel-based simulations were conducted to compare to inventory strategies. This phase was essential for identifying necessary adjustments and confirming the model's feasibility, highlighting that the result analysis requires considerable time, which reinforces the importance of pilot testing as a verification mechanism in similar projects.

On the other hand, a study applying the PDCA cycle included a twelve-week pilot test aimed at evaluating the effectiveness of the Lean Service-FLD model. During this phase, tools such as layout redesign (FLD), standardized work (STW), and autonomous maintenance were employed. Through daily monitoring and time studies, key indicators such as productivity, efficiency, and rework levels were tracked. As a result, an 18% improvement in productivity, a 27% increase in efficiency, and a 50% reduction in rework were achieved [24].

Likewise, it has been demonstrated that a pilot test enables the empirical validation of the effects of autonomous maintenance as a pillar of TPM. In a case applied to a small manufacturing enterprise, the implementation of the model over an extended period allowed for the measurement of concrete improvements in productivity, efficiency, setup times, and equipment availability. The results showed a 10% increase in productivity, a 23.8% improvement in efficiency, and a 32.04% reduction in changeover time, confirming the effectiveness of this pilot-based approach [8].

B. *Validation Design*

To validate the improvement proposal, a pilot test was carried out over a 12-week period, between January and March, applied to the highest-demand product. This phase enabled the implementation of the proposed actions under real operating conditions and the assessment of their technical impact. During the pilot, previously defined key performance indicators were monitored to verify improvements in operational performance, resource availability, and compliance with the production schedule.

1) Validation of MRP with Machine Learning:

The validation of demand forecasting is an essential step in assessing the effectiveness of MRP implementation after applying Machine Learning techniques to forecasting. For the validation process, a comparison was made between actual demand and forecasted demand using models such as SARIMAX and LSTM (Long Short-Term Memory). The objective is to determine the accuracy of these models and their ability to anticipate future production needs. In this process, the Mean Absolute Percentage Error (MAPE) is used as the primary metric to evaluate prediction accuracy.

TABLE II
COMPARISON BETWEEN FORECASTED AND ACTUAL DEMAND

Week	Forecasted Demand (units)	Actual Demand (units)	Absolute Error (%)
1	19,181	17,473	9.78%
2	21,474	17,311	24.05%
3	20,517	19,120	7.31%
4	18,335	18,434	0.54%
5	24,478	17,018	43.84%
6	21,704	18,507	17.27%
7	19,683	19,449	1.20%
8	19,314	20,548	6.01%
9	19,491	20,053	2.80%
10	21,618	21,363	1.19%
11	16,431	16,667	1.42%
12	14,070	14,193	0.87%
	MAPE		9.69%
	Effectiveness		90.31%

According to the results presented in Table 2, the MAPE was 9.69%, indicating high forecast accuracy for the first months of the year, with a forecast effectiveness of 90.31%. These results demonstrate that the Machine Learning models were effective in predicting demand with a high degree of accuracy, enabling the application of MRP with more efficient planning of inputs and production, reducing error margins and improving responsiveness to demand.

The average stockout rate in 2024 was 30.47%, significantly affecting production due to supply shortages. With the validation of the MRP during the first quarter of 2025, the indicator decreased to 20.60%, evidencing improvements in input planning and availability, as well as in the efficiency of the production flow.

Furthermore, after the implementation of MRP as a pilot test for the planning of the 8.5-liter product, which has the highest demand, its manufacturing was prioritized, and weekly production was scheduled more appropriately. Although the MRP tool was not directly applied to the 10-liter product, it was positively affected, as unnecessary overproduction was avoided. As a result, the average inventory duration of 10-liter bottles decreased from 19.43 days in 2024 to 7.31 days in the first quarter of 2025, significantly reducing warehouse accumulation and improving operational efficiency.

TABLE III
MRP AND MACHINE LEARNING METRIC RESULTS

Tool	Indicator	As Is	To Be	Validation Results
MRP/Machine Learning	Stockout Rate	30.47%	21.53%	20.6%
	Inventory Duration (days)	17.78	7	7.31

2) Validation of Standardized Work:

The validation of the standardized work tool through a pilot test was conducted by analyzing the production line consisting of eight consecutive operations, from the initial transport of bottles to their final transfer to the warehouse. Each of these tasks was compared against a standard takt time of 9 minutes, which represents the pace required to meet customer demand.

TABLE IV
CURRENT LINE BALANCE

Operation	Operator	Description	Time (min)	Takt time (min)
1	Operator 1	Transport of bottles from the warehouse	8.76	9
2	Operator 2	Placement and filling of bottles	12.48	9
3	Operator 3	Capping	7.18	9
4	Operator 4	Sealing	10.12	9
5	Operator 5	Labeling	4.24	9
6	Operator 6	Visual quality inspection	4.37	9
7	Operator 7	Placement of finished product on pallet	8.21	9
8	Operator 8	Transfer to warehouse	4.91	9

This comparison made it possible to identify both critical operations and improvement opportunities within the process. The operation that represents the main bottleneck is the placement and filling of bottles, performed by Operator 2, with a cycle time of 12.48 minutes, significantly exceeding the takt time. This delay affects the continuous flow of the production line and leads to work-in-process accumulation in the subsequent stages.

Similarly, the sealing operation presents a cycle time of 10.12 minutes, which also slightly exceeds the takt time and could contribute to the overall imbalance if not addressed in a timely manner. Additionally, several operations exhibit cycle times well below the takt time, such as labeling (4.24 minutes), visual quality inspection (4.37 minutes), and final transfer to the warehouse (4.91 minutes). These activities show high idle capacity, representing an opportunity to redistribute workloads and enhance human resource utilization.

The initial transport operation (8.76 minutes) and pallet placement (8.21 minutes) fall within the optimal range, as they align with the takt time without exceeding it, contributing to a balanced process flow.

Based on this analysis, the future line balancing was developed using a strategic task grouping approach. This validation enabled the reorganization of activities by combining tasks with low workloads into a single workstation and splitting those that exceeded the available time. As a result, the tasks of labeling and visual inspection were integrated into a single station, achieving a combined workload close to the takt time.

TABLE V
OPERATION GROUPING

Operator	Time (min)	Operations
A	6.67	1
B	10.33	2
C	8.13	3
D	9.33	4
C	7.77	5,6
D	10.16	7,8

In the case of the final operations, such as the placement of the finished product on the pallet and its transport to the warehouse, their grouping was considered. However, since this exceeded the time limit, it was recommended to support the process with auxiliary transport or to redistribute functions. This reconfiguration allowed the workload across stations to be balanced, eliminated idle times, and avoided unnecessary overloads. Moreover, the result of the analysis was used as the basis for structuring standardized work, enabling the establishment of defined, repeatable, and easy-to-train sequences. Additionally, the number of operators was reduced from 8 to 6, which is favorable for the company.

As a result, substantial improvements were observed in terms of operational efficiency. In the initial process diagnosis, an inefficiency level of 19% was identified, reflecting high variability, rework, and bottlenecks. With the validation of the pilot test, this value was reduced to 13%, representing a relative improvement of 32% compared to the initial condition. This improvement demonstrates that task standardization, visual controls, combined with proper staff training and the documentation of procedures, contribute to reducing execution variability, increasing efficiency, and ensuring quality in outcomes.

TABLE VI
STANDARDIZED WORK METRIC RESULTS

Tool	Indicator	As Is	To Be	Validation Results
Standardized Work	Rework Rate (%)	19%	12%	13%

3) Validation of Autonomous Maintenance:

The autonomous maintenance tool was implemented in response to recurrent stoppages in the injection molding machine, primarily caused by component wear, inadequate lubrication by personnel, and the absence of standardized procedures. To validate its effectiveness, a pilot test was conducted. This initiative promotes operator autonomy by encouraging active participation in the daily maintenance of equipment, including the identification and correction of minor deviations, as well as the execution of basic activities such as cleaning, lubrication, inspection, and adjustment of components.

The validation was carried out using the One-Point Lesson (OPL), which was placed on the injection molding machine. This visual tool served as a standardized guide containing clear images and step-by-step sequences that enable quick and accurate understanding of the tasks to be performed, thereby reducing reliance on verbal instructions and minimizing the risk of human error.

In addition, time measurements were conducted for each work element to validate the duration required by operators to perform machine cleaning, lubrication, parameter inspection and adjustments, anomaly labeling, and monitoring.

Furthermore, the number of breakdowns during the first quarter of the year was recorded.

During the development of the pilot test, a machine availability of 97.71% was achieved, exceeding the proposed target by 1.171%, as indicated in [7]. This outcome was made possible through continuous training of plant workers and close monitoring of each operation. The result reflects a significant improvement in the operational availability of the equipment, resulting from the systematic application of activities such as cleaning, inspection, and lubrication carried out by operational personnel.

The validation of the autonomous maintenance tools demonstrated a significant improvement in the operational reliability of the sealing machine, reflected in the increase of its MTBF (Mean Time Between Failures). MTBF is an indicator that measures the average time between consecutive equipment failures, and its purpose is to reduce the frequency of breakdowns through timely preventive and corrective actions.

At the beginning of the study, the recorded MTBF was 23.48 hours. After the implementation of autonomous maintenance, this value increased to 41.13 hours, representing an absolute improvement of 17.65 hours. This increase reflects a lower occurrence of failures, attributable to the active participation of operators in basic tasks such as cleaning, lubrication, inspection, and adjustment. These actions help prevent premature component wear, detect deviations in a timely manner, and maintain optimal operating conditions of the equipment, thereby increasing the availability and efficiency of the production process.

TABLE VII
AUTONOMOUS MAINTENANCE METRIC RESULTS

Tool	Indicator	As Is	To Be	Validation Results
Autonomous Maintenance	Availability (%)	89%	96%	97.17%
	MTBF (hours)	23.48 h	113.27 h	41.13 h

VI. DISCUSSION

The results obtained in the pilot test demonstrate that the integration of Lean tools (autonomous maintenance and standardized work) with materials requirements planning (MRP), supported by predictive Machine Learning models (SARIMAX + LSTM), constitutes an effective strategy to improve the efficiency of the 8.5-liter bottled water production line. This format accounts for 94.48% of the company's total production volume, representing a critical point of intervention in its production management.

The observed 11.98% increase in efficiency, raising the average from 75% to nearly 87%, is close to the 88.98% reported in the literature as a reference for similar processes. These findings are consistent with previous evidence indicating that the adoption of Lean methodologies enhances production performance in the food and beverage sector [24]. However, the improvement achieved was slightly lower than in studies that incorporated layout redesign and SMED techniques, suggesting that the focus was limited to the 8.5-liter format and the absence of physical interventions in the plant constrained the impact obtained.

The SARIMAX + LSTM hybrid model achieved a forecasting accuracy of 90.31% (MAPE: 9.69%), which reduced stockout-related downtime by 97% and significantly improved inventory turnover. This performance is consistent with [23], which demonstrated that hybrid Machine Learning models significantly reduce prediction errors. Nevertheless, the reliance on reliable historical data and the short validation window (12 weeks) limits the robustness of the model for long-term applications.

The 32% reduction in rework confirms the effectiveness of standardized work and staff training, consistent with studies in manufacturing SMEs that reported reductions of up to 70% in process variability [22]. The lower magnitude observed here can be explained by the company's operational maturity level and the initial resistance to change.

In terms of autonomous maintenance, the availability of blow molding machines increased to 97%, and the MTBF of the injection machine improved by 17.65 hours. These results are consistent with [7], which evidenced that integrating TPM with Industry 4.0 technologies can raise equipment availability above 95%. However, the MTBF obtained in this study remains below the target (113.27 hours), highlighting the need to strengthen predictive maintenance through online monitoring and advanced data analysis.

The study focused exclusively on the 8.5-liter production line, excluding other product formats, distribution logistics, and human resource management. Although this scope was necessary to ensure analytical depth, it restricts the generalization of the findings. Therefore, future research should extend model validation to other production lines and incorporate emerging technologies, such as IoT and digital twins, to enhance traceability and support real-time decision-making.

VII. CONCLUSIONS

The application of the proposed management model increased production efficiency from 75% to 86%, evidencing an 11% improvement that contributed to reducing bottlenecks and optimizing installed capacity. This demonstrates that the integration of Lean Manufacturing tools with predictive analytics can significantly enhance operational performance in the beverage industry.

Autonomous maintenance raised the availability of blow moulding machines to 97.17% and improved the MTBF of the injection machine by 17.65 hours, confirming the effectiveness of operator involvement in basic maintenance activities. However, opportunities remain to achieve world-class reliability standards, particularly by strengthening predictive and condition-based maintenance practices.

The standardization of operational tasks reduced the rework rate from 19% to 13%, consolidating process stability and ensuring greater consistency in product quality. This highlights the role of structured procedures and workforce training in reducing variability and errors, thereby promoting sustainable improvements in efficiency.

The hybrid forecasting model (SARIMAX + LSTM) enabled MRP to anticipate demand with 90.31% accuracy, reducing stockout-related downtime by 97% and optimizing work-in-process inventory to 7.31 days. These findings validate the potential of combining traditional planning systems with advanced Machine Learning techniques to align production more closely with market demand.

The study confirms the technical and operational feasibility of the proposed model; however, its scope was limited to the 8.5-liter production line, meaning that the results cannot be generalized to other product formats or to the logistics chain.

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REFERENCES

[1] D. Peves, “El consumo de agua embotellada se dispara un 19%: ¿Qué pasa con los precios?,” *Gestión*, 14 mar. 2024. [Online]. Available: https://gestion.pe/economia/empresas/consumo-de-agua-embotellada-crece-19-y-los-precios-empresas-verano-calor-r-noticia/?ref=gesr

[2] Mordor Intelligence, “Tamaño del mercado de agua embotellada y análisis de participación, tendencias de crecimiento y pronósticos,” *Mordor Intelligence*, 2024. [Online]. Available: https://www.mordorintelligence.com/es/industry-reports/bottled-water-market

[3] Argentina-Uruguay-Retail Mascotas, “Agua embotellada en Perú: crecimiento acelerado hacia el 2027,” América Retail, 5 jan. 2024. [Online]. Available: https://america-retail.com/paises/peru/agua-embotellada-en-peru-crecimiento-acelerado-hacia-el-2027/

[4] European Knowledge Center for Information Technology, “Planificación de la producción,” *TIC Portal*, 6 feb. 2023. [Online]. Available: https://www.ticportal.es/glosario-tic/planificacion-produccion

[5] K. Carbajal-Vásquez, R. Piscoya-Alvites, J. Quiroz-Flores, Y. García-Lopez y S. Nallusamy, “Minimization of smashed products in sustenance industries by lean and machine learning tools,” *International Journal of Mechanical Engineering*, vol. 10, no. 10, oct. 2023, doi: 10.14445/23488360/IJME-V10I10P102. [Online]. Available: https://www.internationaljournalssrg.org/IJME/paper-details?Id=444

[6] K. Pajuelo, J. Quiroz-Flores y S. Nallusamy, “Minimization of product distribution delays through an integration model of Lean Manufacturing tools and A3 report: Case study,” *SSRG International Journal of Mechanical Engineering*, vol. 10, no. 9, pp. 31–43, sep. 2023, doi: 10.14445/23488360/IJME-V10I9P103. [Online]. Available: https://www.internationaljournalssrg.org/IJME/paper-details?Id=440

[7] D. Mendes, P. Gaspar, F. Charrua-Santos y H. Navas, “Integrating TPM and Industry 4.0 to increase the availability of industrial assets: A case study on a conveyor belt,” *Processes*, vol. 11, no. 7, art. 1956, jun. 2023, doi: 10.3390/pr11071956. [Online]. Available: https://www.mdpi.com/2227-9717/11/7/1956

[8] W. Forero-Corba y F. Bennasar, “Técnicas y aplicaciones del Machine Learning e Inteligencia Artificial en educación: una revisión sistemática,” *RIED-Revista Iberoamericana de Educación a Distancia*, vol. 27, no. 1, jan. 2024, doi: 10.5944/ried.27.1.37491. [Online]. Available: https://revistas.uned.es/index.php/ried/article/view/37491

[9] S. Malik, S. Malik, I. Singh, H. V. Gupta, S. Prakash, R. Jain, B. Acharya y Y.-C. Hu, “Deep learning based predictive analysis of energy consumption for smart homes,” *Multimedia Tools and Applications*, vol. 84, pp. 10665–10686, apr. 2025, doi: 10.1007/s11042-024-18758-z. [Online]. Available: https://link.springer.com/article/10.1007/s11042-024-18758-z

[10] C. Alondra-Torres, J. Quiroz-Flores y S. Nallusamy, “Enhancement of productivity and efficiency through a service model with lean service tools—Case study,” *SSRG International Journal of Mechanical Engineering*, vol. 10, no. 9, pp. 18–30, sep. 2023, doi: 10.14445/23488360/IJME-V10I9P102. [Online]. Available: https://www.internationaljournalssrg.org/IJME/paper-details?Id=439

[11] E. Farhang, R. Ehtesham y D. Gharakhani, “Optimization mixed procurement model for MRP and JIT with hybrid particle swarm algorithm and genetic algorithm,” *Journal of Applied Research on Industrial Engineering*, vol. 11, no. 3, pp. 471–486, sep. 2024, doi: 10.22105/jarie.2023.355444.1500. [Online]. Available: https://www.journal-aprie.com/article_185936.html

[12] A. Sifaleras, A. Karakalidis y Y. Nikolaidis, “Shift scheduling in multi-item production lines: a case study of a mineral water bottling company,” *International Journal of Systems Science: Operations and Logistics*, vol. 9, no. 1, pp. 75–86, sep. 2020, doi: 10.1080/23302674.2020.1818144. [Online]. Available: https://www.tandfonline.com/doi/full/10.1080/23302674.2020.1818144

[13] M. F. Collao-Díaz, M. V. Saavedra-Cielo, W. D. Calderón y D. Reimer, “Optimizing fill rate and inventory control in Peruvian bakery SMEs through 5S and MRP integration,” *SSRG International Journal of Mechanical Engineering*, vol. 11, no. 11, pp. 24–33, nov. 2024, doi: 10.14445/23488360/IJME-V11I11P103. [Online]. Available: https://www.internationaljournalssrg.org/IJME/paper-details?Id=537

[14] A. Chakroun, Y. Hani, A. Elmhamedi y F. Masmoudi, “A proposed integrated manufacturing system of a workshop producing brass accessories in the context of industry 4.0,” *The International Journal of Advanced Manufacturing Technology*, vol. 127, pp. 2017–2033, jul. 2023, doi: 10.1007/s00170-022-10057-x. [Online]. Available: https://link.springer.com/article/10.1007/s00170-022-10057-x

[15] R. Diar y T. Jin, “Clustering-based heuristic algorithm for production planning alignment with container delivery schedules in make-to-order manufacturing,” *Management Systems in Production Engineering*, vol. 32, no. 1, pp. 45–55, sep. 2024, doi: 10.2478/mspe-2024-0037. [Online]. Available: https://sciendo.com/article/10.2478/mspe-2024-0037

[16] R. Florez-Cáceres, C. Huamán-Echevaría, y J. Quiroz-Flores, “Improving productivity in an SME in the metalworking sector through Lean Manufacturing and TPM tools: A case study in Peru,” South African Journal of Industrial Engineering, vol. 35, no. 2, pp. 91–109, Apr. 2024. [Online]. Available: https://sajie.journals.ac.za/pub/article/view/3013

[17] D. Widodo y P. Wahyudi, “Production process analysis to reduce defective products through the application of Pareto diagram and the eight disciplines problem solving method,” *Heuristic*, vol. 21, no. 2, pp. 219–228, oct. 2024, doi: 10.30996/heuristic.v21i2.12036. [Online]. Available: https://jurnal.untag-sby.ac.id/index.php/heuristic/article/view/12036

[18] S. Rathi, M. Sahu y S. Kumar, “Implementation of lean manufacturing methods to improve rolling mill productivity,” *International Journal of Advanced Technology and Engineering Exploration*, vol. 11, no. 111, pp. 243–256, mar. 2024, doi: 10.19101/IJATEE.2023.10102004. [Online]. Available: https://accentsjournals.org/paperinfo.php?journalPaperId=1638

[19] J. Herrera-Uribe, D. Rivero-Davila y M. Saenz-Moron, “Model based on TPM to increase the overall efficiency of equipment in an oil company,” en *Leadership in Education and Innovation in Engineering in the Framework of Global Transformations: Integration and Alliances for Integral Development*, LACCEI International Multi-Conference for Engineering, Education, and Technology, Buenos Aires, jul. 2023, doi: 10.18687/LACCEI2023.1.1.1050. [Online]. Available: https://laccei.org/LACCEI2023-BuenosAires/meta/FP1050.html

[20] V. Allca-Chauca, A. Yauri-Mendoza y M. Saenz-Moron, “Improvement model to increase efficiency through the use of 5S, TPM and SMED tools in a plastic SME company,” en *Leadership in Education and Innovation in Engineering in the Framework of Global Transformations: Integration and Alliances for Integral Development*, Buenos Aires, jul. 2023, doi: 10.18687/LACCEI2023.1.1.1052. [Online]. Available: https://dx.doi.org/10.18687/LACCEI2023.1.1.1052

[21] M. Torres-Mestanza, N. Guerrero-López y M. Saenz-Moron, “Improvement model to increase the efficiency of the sewing area in a

textile SME by applying SMED, 5S and Standardized Work – A Peruvian case study," en *Proceedings of the 2023 LACCEI International Multi-Conference for Engineering, Education and Technology*, vol. 1, no. 8, apr. 2024, doi: 10.18687/LACCEI2023.1.1.1051. [Online]. Available: https://proceedings.laccei.org/index.php/laccei/article/view/3226

[22] M. Cabezas, F. Pozo y O. Aldaz, "Competitividad de empresas envasadoras de agua en Santo Domingo," *Universidad y Sociedad*, vol. 14, supl. 2, pp. 290–299, apr. 2022. [Online]. Available: https://rus.ucf.edu.cu/index.php/rus/article/view/2784

[23] F. Monteiro, S. Monteiro, C. Rodrigues, J. Reis, U. Bezerra, M. Tostes y F. Almeida, "A hybrid methodology using machine learning techniques and feature engineering applied to time series for medium- and long-term energy market price forecasting," *Energies*, vol. 18, no. 6, art. 1387, mar. 2025, doi: 10.3390/en18061387. [Online]. Available: https://www.mdpi.com/1996-1073/18/6/1387

[24] D. Celi, N. Mendiola y E. Cabrera, "Mejora en la gestión de abastecimiento, planeamiento y control de la producción a través de las herramientas Material Requirements Planning y Master Production Schedule en una mype Dark Kitchen," *Ingeniería Industrial*, no. 46, pp. 83–103, jun. 2024, doi: 10.26439/ing.ind2024.n046.6875. [Online]. Available: https://revistas.ulima.edu.pe/index.php/Ingenieria_industrial/article/view/6875

[25] H. Tadesse, B. Singh, H. Deresso, S. Lemma, G. K. Singh, A. K. Srivastava, N. Dogra y A. Kumar, "Investigation of production bottlenecks and productivity analysis in soft drink industry: a case study of East Africa Bottling Share Company," *International Journal on Interactive Design and Manufacturing*, jun. 2024. doi: 10.1007/s12008-023-01715-9. [Online]. Available: https://link.springer.com/article/10.1007/s12008-023-01715-9