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Improvement of the Purchasing Process in a Spare Parts Trading Company through Forecasting, Supply Policy and RPA

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Abstract

This study presents an applied case of purchasing process optimization in a company dedicated to trading spare parts for heavy machinery. The research focused on high-rotation items, where three main inefficiencies were identified: the absence of demand forecasting, the lack of a structured inventory policy, and the manual handling of discrepancies caused by supplier part substitutions. To address these issues, an integrated solution was designed, combining demand forecasting, inventory management, and process automation. Machine learning models were applied to historical consumption data to estimate future demand and define essential stock parameters, including safety stock and reorder levels. Additionally, a Robotic Process Automation (RPA) bot was developed to standardize and automate the resolution of material discrepancies within the purchasing workflow. The proposal was validated through pilot tests in real operational settings and simulated scenarios, demonstrating significant improvements in efficiency and supplier compliance. The integration of forecasting, inventory control, and automation effectively reduced manual workload and enhanced purchasing performance. Overall, the results highlight the practical potential of data-driven and automated solutions to strengthen decision-making and operational reliability in industrial supply chains.

Keywords
Demand forecasting, Supply policy, Spare parts replenishment, Operational efficiency.

1. Introduction
The wholesale trade of machinery and spare parts has shown sustained growth in Peru, driven by new mining and manufacturing projects. According to INEI (2023), this sector grew by 3.17% compared to the previous year, and in March 2024 it advanced by 2.31% interannually, reflecting its strategic relevance for industries such as mining, construction, and agriculture. Heavy equipment, engines, tractors, and harvesters are among the main drivers of this expansion (INEI 2024). This trend highlights the importance of optimizing supply chains to ensure timely delivery of spare parts and maintain the operational continuity of critical sectors.

The company analyzed in this study is one of the country's leading distributors of machinery and aftermarket solutions, with more than 40,000 SKUs and an infrastructure that integrates centralized distribution, maintenance contracts, and real-time inventory systems. Despite these resources, the company faces persistent difficulties in its purchasing process. In 2023 it reported revenues of nearly USD 895 million and projected USD 935 million for 2024, with mining being the most important client, accounting for approximately 70% of income (Cruz 2024; Energiminas 2025). However, its order fulfillment rate remains below the 95% target (Gerrits et al. 2022), reaching only 90.37%, and the average monthly cost of emergency orders exceeds USD 112,000. Moreover, manual management of material discrepancies consumes around 33% of junior staff working hours, generating delays, inefficiencies, and additional costs.

These issues reflect structural gaps in purchasing management. First, the absence of a demand forecasting system prevents accurate anticipation of requirements and leads to stockouts or excess inventory. Second, the lack of a formal supply policy hinders standardized replenishment decisions. Third, the reliance on manual discrepancy handling increases workload, error rates, and contractual penalties. Together, these challenges elevate operational costs and compromise customer satisfaction.

To address these problems, this research proposes an integrated solution combining three components: a consumption forecasting model, a technical supply policy, and Robotic Process Automation (RPA) for discrepancy resolution. By integrating these tools, the study aims to improve forecast accuracy, strengthen inventory management, and significantly reduce operational workload. The ultimate objective is to optimize the purchasing process of spare parts in the heavy machinery sector and provide a replicable model for similar organizations.

1.1 Objectives

The present paper aims to optimize the purchasing process in a spare parts trading company for heavy machinery through an integrated approach. The objective is to develop a consumption forecasting model capable of analyzing historical demand data and selecting the most accurate algorithms to anticipate replenishment needs. Based on these results, a structured supply policy is designed, parameterized through reorder point, safety stock, and maximum inventory level, to standardize decision-making and reduce the incidence of emergency orders. Furthermore, a Robotic Process Automation (RPA) bot is implemented to automate the resolution of material discrepancies in purchase orders, reducing manual workload and errors. By validating these three components through functional tests and simulations, the research seeks to demonstrate that the combination of forecasting, supply policy, and automation strengthens efficiency, increases order fulfillment, and decreases operational costs, providing a replicable model for the heavy machinery spare parts sector.

2. Literature Review

The literature highlights three main approaches relevant to the improvement of purchasing processes: Robotic Process Automation (RPA), demand forecasting, and supply policies. In the case of RPA, Flechsig et al. (2022) analyzed multiple case studies showing that automation decreases errors and cycle times by replacing manual tasks in purchasing, such as invoice checks and purchase order creation. Pyplacz and Žukovskis (2023) emphasized that organizational culture and leadership are critical for successful adoption, especially in small and medium enterprises, where resistance to change may arise. Similarly, Plattfaut et al. (2022) proposed a framework of critical success factors, distinguishing those unique to RPA from those shared with other digital technologies, which serves as a structured guide for implementation. These findings reinforce the potential of automation to standardize processes like the resolution of material discrepancies.

Forecasting has been identified as a key element for spare parts management due to the irregular and intermittent nature of demand. Saravanan et al. (2019) demonstrated that Auto ARIMA increased forecast accuracy by 40% compared to traditional approaches such as moving averages and exponential smoothing, highlighting the benefits of advanced time-series models. Hoffmann et al. (2022) compared statistical methods like Croston and Syntetos-Boylan with artificial neural networks, concluding that neural networks perform better under irregular demand scenarios, while classical methods are suitable for smoother patterns. In addition, Bandeira et al. (2020) showed that combining and automatically selecting forecasting models improves accuracy in intermittent demand cases. These results validate the need to test multiple algorithms and adopt the most accurate according to each SKU, which aligns with the approach applied in this research using Python and PyCaret.

Regarding inventory control, Tang et al. (2025) integrated maintenance planning with MRP and reorder-point policies, achieving improvements in spare parts availability and efficiency. Zhu et al. (2020) proposed a hybrid model that combines anticipatory maintenance data with forecasting methods, reducing costs by up to 51% in low-rotation parts. Both studies confirm that parameters such as reorder point (ROP), safety stock (SS), and maximum stock (NM) are effective for balancing inventory availability and operational costs.

In summary, the literature confirms that combining advanced forecasting techniques with structured inventory policies reduces uncertainty in demand planning, while RPA addresses inefficiencies derived from manual purchasing activities. Together, these approaches provide the theoretical foundation for the integrated solution proposed in this study to optimize spare parts purchasing management.

3. Methods

The study is framed within applied research, as it addresses a real problem related to low order fulfillment levels. A quantitative approach was adopted, based on the analysis of numerical data, and a quasi-experimental design that allows comparing results before and after the intervention.

The methodology was applied in a company dedicated to the commercialization of spare parts for heavy machinery, with centralized operations through SAP and presence in sectors such as mining, construction, and agriculture. The analysis focused on the Spare Parts Planning area, responsible for defining inventory levels and managing material discrepancies that arise in purchase orders.

To justify the use of the selected tools, a problem tree was designed to map the connection between the company's reduced profit margin and the operational and technical factors contributing to it. This visual framework served as the basis for identifying forecasting, supply policy, and RPA as targeted responses to the core challenges. Figure 1 summarizes the key problem, its economic impact, the root causes identified, and the corresponding tools proposed to address them.

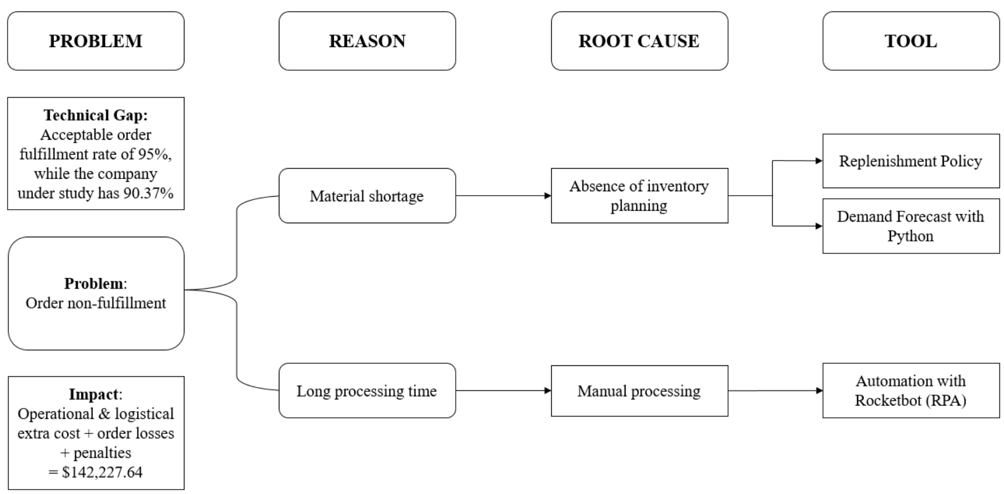

Figure 1. Problem tree linking causes and tools used in the proposed solution

In this scenario, each tool was implemented over real organizational processes: the forecast was built using historical consumption records available in SAP, the supply policy was designed as a formal guide for inventory replenishment, and the RPA was programmed to automate the flow of discrepancy resolution due to code changes, a task usually carried out by an intern under the supervision of a planner.

In the present study, Python was used for demand forecasting in order to address the problem of material insufficiency. The forecasting workflow was built in PyCaret's regression module, which automatically compared multiple algorithms, including ARIMA, Prophet, Extra Trees, and LightGBM, to identify the model with the lowest MAPE for each SKU. This automated model-selection approach ensured that each high-rotation code was forecasted using the method best suited to its historical demand pattern. For the automation of discrepancy resolution due to code replacement, Rocketbot was employed. Likewise, a supply policy was defined using technical parameters based on average demand and historical lead time (LT).
Safety stock (SS) was calculated as the product of average consumption and lead time:

$$SS = Average\ consumption \times LT$$

The reorder point (ROP) was set as the expected consumption during the lead time, plus the previously calculated safety stock:

$$ROP = (Demand \times LT) + SS$$

Similarly, the maximum inventory level (NM) was estimated by adding the projected demand during the replenishment interval to the reorder point:

$$NM = ROP + (Demand \times LT)$$

Finally, the macro design of the proposed solution is divided into three components, as shown in Fig. 2.

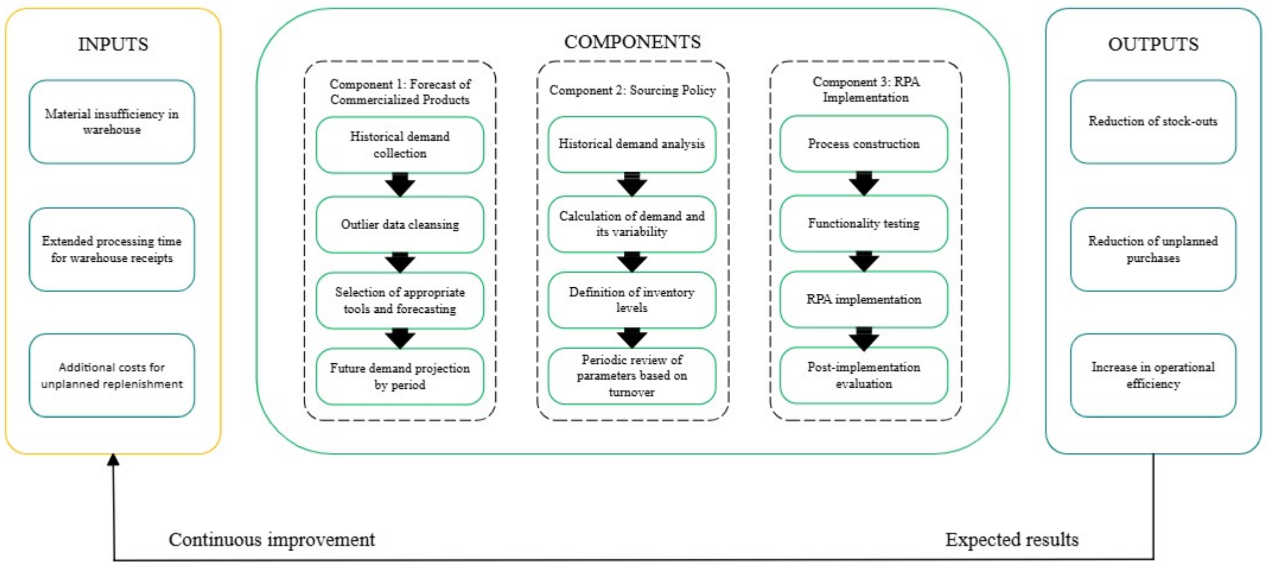

Figure 2. Overall design of the proposed solution

4. Data Collection

The population considered in this study corresponds to high-rotation spare parts (class A), identified through historical consumption data from the last 24 months. From this population, a non-probabilistic sample of 30 items was selected for the forecasting and supply policy tools, prioritizing those with the highest request frequency and operational criticality in maintenance processes. In parallel, for the Robotic Process Automation (RPA) tool, a random sample of 221 materials with code-replacement observations was used, given the variability in demand. These data provided the basis for the implementation and validation of the proposed solution.

Forecasting models were developed using 24 months of monthly consumption data per SKU, covering class-A spare parts with high operational criticality. A three-month forecasting horizon was adopted to align with procurement lead times. PyCaret's 10-fold cross-validation was applied to ensure model robustness, and metrics such as MAPE, MAD, and RMSE were averaged across folds to obtain representative performance values. This approach is consistent with recommended validation practices in predictive analytics for supply chains (Seyedan and Mafakheri, 2020).

To illustrate the process of identifying class A items, a Pareto chart was developed in Figure 3, showing the concentration of demand in a small subset of codes. This analysis justified the focus of the forecasting and supply policy on these items.

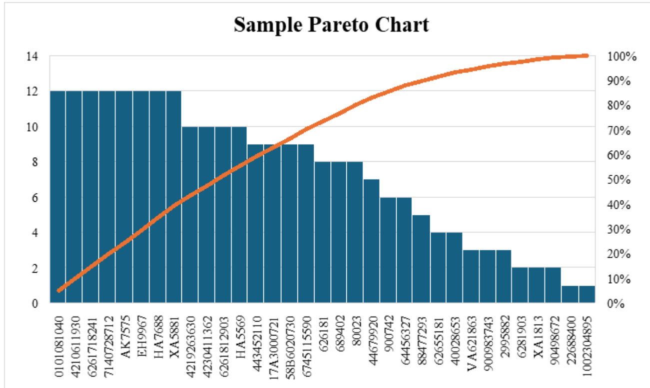

Figure 3. Sample Pareto chart

Once the codes were defined, historical consumption data were extracted directly from SAP and later processed in Python, as shown in Figure 4. These datasets served as the foundation for the development of forecasting models and the calculation of inventory parameters such as reorder point, safety stock, and maximum stock level.

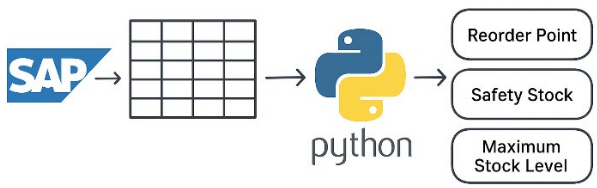

Figure 4. Data Processing Flow

In addition to consumption data, the company's internal records of discrepancy cases were collected and standardized, generating a structured dataset that served as training and validation input for the automation tool. This process, as illustrated in Figure 5, represents the standardized workflow for handling material discrepancies.

No.	Activities	Material Discrepancy Resolution (Standardized)						Notes
		○	⇨	D	□	▽	Time (minutes)	
1	Review the supplier report and flag the lines whose part number differs from the requested one.	X					2	
2	In SAP, check whether the purchase was created as a replenishment-to-stock line or as an order-assigned (commercial) line.	X					3	
3	Retrieve the purchase requisition data in SAP.					X	7	
4A	Replenishment-to-stock line: create a requisition with the substitute material.	X					6	Replenishment-to-stock cases
5A	Link the new line item to the purchase order and delete the previous one.	X					4	Replenishment-to-stock cases
6B	Order-assigned (commercial) line: email the requester to create the new line item on the order.	X					9	Order-assigned line cases
7B	Wait for the requester's confirmation.			X			15	Order-assigned line cases
8B	Associate the newly created line with the order and remove the old one.	X					4	Order-assigned line cases
	TOTAL						50	

Figure 5. Standardized process for material discrepancy resolution

This structured data collection ensured the representativeness of the study, supported the calibration of forecasting models, parameterization of the supply policy, and functional validation of the RPA bot.

5. Results and Discussion

5.1 Numerical Results

The demand forecasting models developed in Python using PyCaret achieved a Mean Absolute Percentage Error (MAPE) of 35.81%, indicating moderate forecasting accuracy. A lower MAPE reflects better predictive performance, and in this case the value remained below the internal maximum acceptable error threshold of 50%, which had been established by the company as the upper limit for operational use. Comparable research reports MAPE values as low as 20% for supply-chain forecasting using advanced learning models(Jahin et al. 2024) and average 1-month to 3-month item-level forecasts around 40% in industrial contexts (Weller and Crone, 2012).This positions the present result within the typical industry range, while clearly improving upon the prior manual average-based estimation previously used by the organization.

Beyond statistical improvement, the increase in fulfillment from 90.37% to 97.62% is operationally significant. In supply-chain operations, service-level gains above 5 percentage points are commonly linked to substantial reductions in backorders, emergency purchases, and associated costs. In this case, the enhancement implies fewer production stoppages, reduced penalty exposure, and a measurable increase in customer satisfaction. This finding aligns with evidence summarized by Seyedan and Mafakheri (2020), who highlight that forecasting accuracy directly supports higher service-level performance across manufacturing supply chains.

5.2 Graphical Results

Figure 6 presents three-month horizon forecast for Part Number 0101081040, 1 of 16 forecasts generated with PyCaret.

```
[81] # plot forecast for 36 months in future
     plot_model(best, plot = 'forecast', data_kwargs = {'fh' : 6})
```

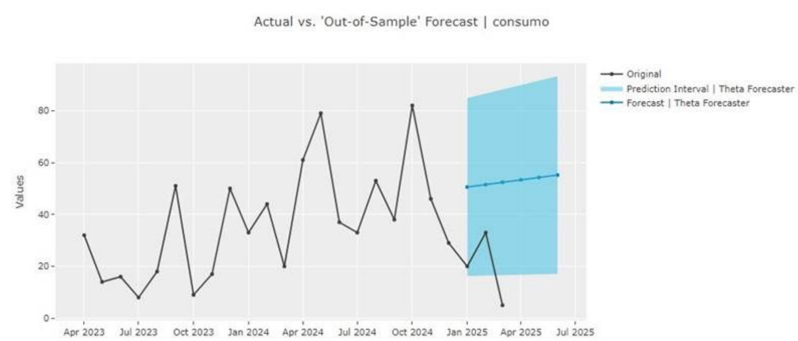

Figure 6. Forecast with a 3-Month Horizon – Part Number 0101081040

Figure 7 compares forecasting models using error metrics (MAPE, MAD, RMSE), highlighting the technical criteria applied to select the most accurate model.

```
[78] # compare baseline models
     best = compare_models()
```

	Model	MASE	RMSSE	MAE	RMSE	MAPE	SMAPE	R2	TT (Sec)
theta	Theta Forecaster	0.9137	0.9430	18.2417	22.2912	0.3598	0.3595	-1.3406	0.0467
rf_cds_dt	Random Forest w/ Cond. Deseasonalize & Detrending	0.9172	0.8760	18.5042	20.8939	0.3990	0.3648	-2.1716	0.2933
xgboost_cds_dt	Extreme Gradient Boosting w/ Cond. Deseasonalize & Detrending	0.9206	0.9170	18.7707	22.1264	0.4154	0.3536	-3.5814	0.1567
gbr_cds_dt	Gradient Boosting w/ Cond. Deseasonalize & Detrending	0.9402	0.8643	19.1386	20.8439	0.4246	0.3884	-3.4895	0.1700
ada_cds_dt	AdaBoost w/ Cond. Deseasonalize & Detrending	0.9469	0.8889	19.1460	21.2792	0.4365	0.4007	-1.7209	0.1767
croston	Croston	0.9734	1.0037	19.1124	23.4832	0.3163	0.3966	-1.2432	0.0300
dt_cds_dt	Decision Tree w/ Cond. Deseasonalize & Detrending	0.9904	0.9693	20.0435	23.3143	0.4955	0.4175	-2.9439	0.1233
huber_cds_dt	Huber w/ Cond. Deseasonalize & Detrending	0.9977	1.0076	19.9974	23.8982	0.4141	0.3924	-2.0375	0.1900
ridge_cds_dt	Ridge w/ Cond. Deseasonalize & Detrending	0.9978	0.9911	20.0560	23.5439	0.4230	0.3899	-1.9646	0.1133
omp_cds_dt	Orthogonal Matching Pursuit w/ Cond. Deseasonalize & Detrending	0.9978	0.9911	20.0560	23.5440	0.4230	0.3899	-1.9647	0.1833
lr_cds_dt	Linear w/ Cond. Deseasonalize & Detrending	0.9978	0.9911	20.0560	23.5440	0.4230	0.3899	-1.9647	0.3633

Figure 7. Comparison of Forecasting Models – Part Number 0101081040

The supply policy was applied using the defined formulas for reorder point, safety stock, and maximum stock level. This policy was validated through simulation in Arena, comparing the inventory behavior under the policy against the actual demand. As shown in Figure 8, the blue line represents the inventory level resulting from the applied policy, while the red line corresponds to the real demand, providing a visual verification of the model's performance.

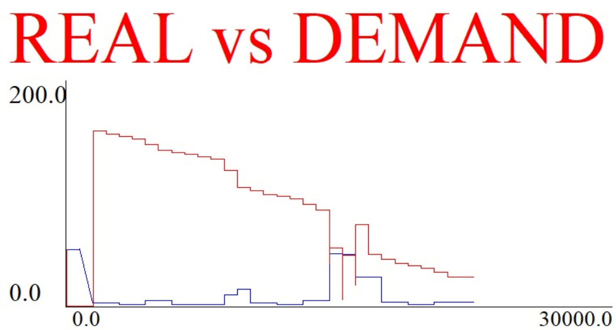

Figure 8. Validation of the supply policy in Arena

Robotic Process Automation (RPA) was implemented through the Rocketbot platform, which made it possible to configure and execute the automated flow designed to address material discrepancies. Figure 9 displays the interface used during the bot setup, where tasks such as price updates, database validations, and email notifications were programmed.

The figure shows the sequence of commands configured in Rocketbot for the discrepancy-handling process, including steps such as connecting to SAP, reading configuration files, cleaning folders, sending automated emails, downloading and uploading reports, and executing the main RPA flow

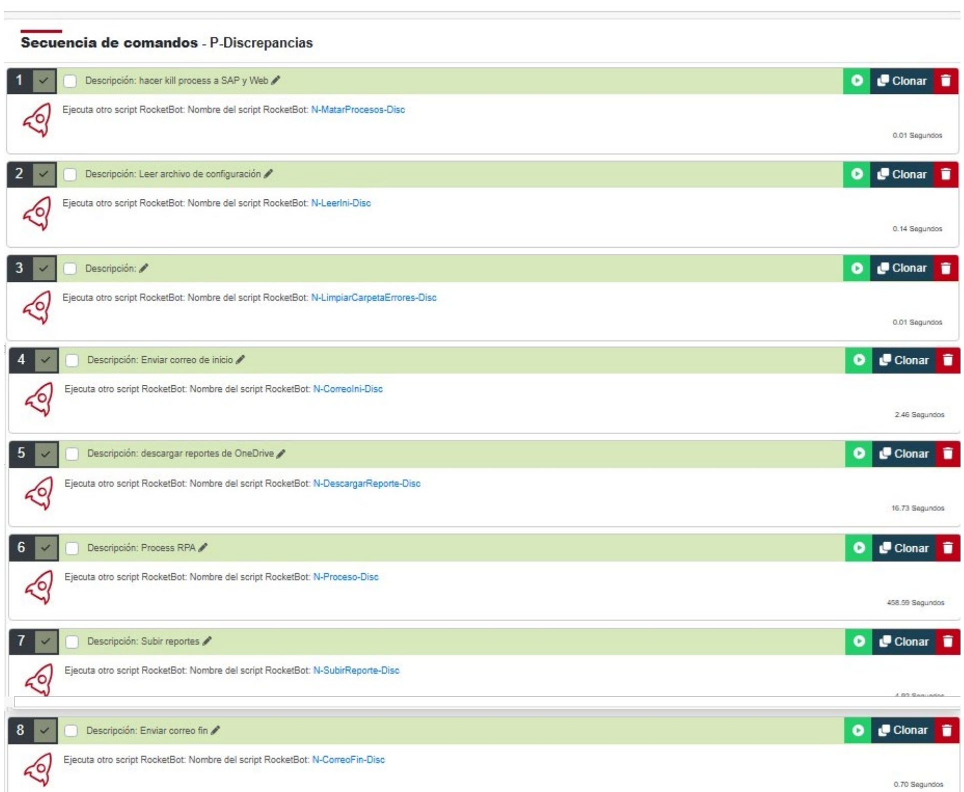

Figure 9. Rocketbot interface for process configuration

In parallel, Arena was used to model and simulate the improved version of the process, as shown in Figure 10. Although Arena does not execute the bot, the simulation helped evaluate the expected operational impact of automation, particularly in terms of processing time and workload reduction. The Arena model reflects the logic of the standardized flow implemented in Rocketbot and was essential for validating the proposed improvements.

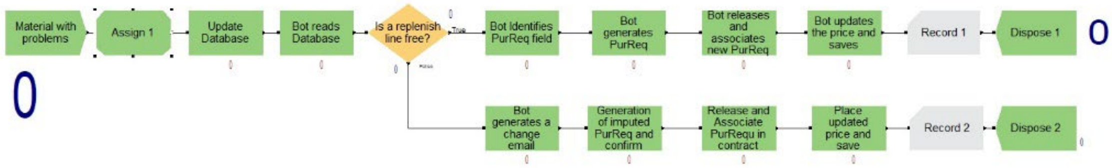

Figure 10. Proposed automated flow for purchase order modification using RPA

To evaluate the impact of automation, the average resolution time was analyzed before and after the bot implementation. Using the Output Analyzer tool, 95% confidence intervals were calculated for both scenarios. Figure 11 presents the results obtained, comparing the time required by the employee to resolve the discrepancy (Output 3) manually versus the time achieved by the bot (Output 1).

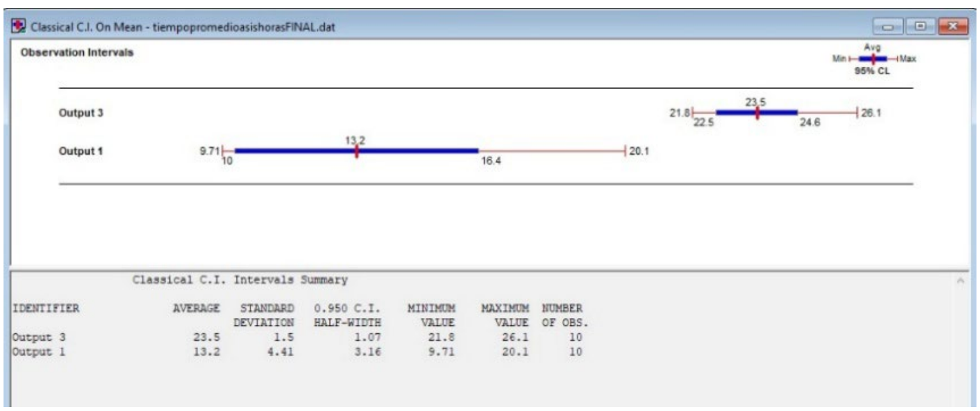

Figure 11. Comparison of Scenarios using Output Analyzer

5.3 Proposed Improvements

The proposed improvements include:
Updating forecasting models periodically with new historical data, ensuring adaptation to variability in demand.
Extending the supply policy to other item categories beyond Class A, adjusting safety stock and reorder points according to operational criticality.

Scaling RPA implementation to other purchasing processes, such as invoice validation and supplier interaction, to replicate the observed efficiency gains.

5.4 Validation

Validation was conducted through Arena simulations and Output Analyzer results. Statistical tests confirmed significant differences at a 95% confidence level between AS-IS and TO-BE scenarios.

In addition, the forecasting phase was validated through cross-validation consistency checks across folds, confirming the stability of model performance prior to integration with the Arena simulation.

The discussion aligns these findings with prior studies. Nguyen et al. (2023) highlighted that RPA in SAP reduces processing times up to threefold, while this study achieved a 93% reduction in manual workload, surpassing the results reported in that research. Similarly, Syed et al. (2020) noted that RPA decreases human participation in repetitive tasks by 20–50% and reduces costs by 30%. The results presented here confirm and extend these findings, as automation nearly eliminated manual intervention.

In terms of efficiency, Encinas et al. (2023) suggested RPA eliminates between 20% and 60% of manual work, while in this study nearly the entire weekly workload was removed. Other studies, such as Santos et al. (2020), reported cost reductions up to 70% through automation. These outcomes are consistent with the observed reduction of errors and cost savings.

Furthermore, Osman (2019) identified improvements of up to 30% in costs and up to 50% in workload reduction, which are in line with the results of this research, especially in terms of error reduction and improved traceability in SAP. Palaniappan (2024) emphasized the importance of error detection mechanisms in RPA solutions, which were integrated into the implemented workflow.

Finally, the study also corroborates organizational perspectives highlighted by Sobczak (2022), who pointed out that RPA strengthens institutional resilience by allowing agile responses to changes. The achieved order fulfillment level of 97.62% reflects this benefit.

6. Conclusion

The research addressed the main problems in the purchasing management of a spare parts trading company, such as the lack of consumption planning, the absence of formal replenishment guidelines, and the manual handling of material discrepancies, understood as inconsistencies between what was requested and what was invoiced. The diagnosis revealed significant operational and economic impacts, including high levels of discrepancies, rework, and low order fulfillment, which are consistent with findings in studies on logistical inefficiencies in repetitive processes (Bédard et al. 2024).

An integrated solution was designed, composed of three complementary tools: a consumption forecasting model developed in Python using the PyCaret library, a supply policy defined through technical parameters by code, and an RPA system implemented in Rocketbot to automate discrepancy resolution. The simulation validated in Arena confirmed its feasibility and allowed for comparison with the current scenario. The forecasting model achieved a Mean Absolute Percentage Error (MAPE) of 35.81%, which indicates moderate predictive accuracy and aligns with acceptable industry ranges. Studies have reported MAPE values between 20% and 40% for demand forecasting in logistics and industrial supply chains (Jahin et al. 2024; Weller and Crone, 2012). Although slightly above the lowest benchmark, the result represents a significant improvement over the company's prior manual estimation method and confirms the model's capability to generalize across high-variability items.

The results demonstrated significant improvements. The supply policy incorporated parameters such as reorder point, safety stock, and maximum stock level, standardizing replenishment and reducing uncertainty. The automation of discrepancy resolution reduced the operational workload by more than 90%, validating the expected benefits of using RPA in repetitive tasks (Bédard et al. 2024; Syed et al. 2020). From an economic perspective, the proposal proved sustainable, with an initial investment of USD 380 without licenses and benefits that largely exceeded the operational costs.

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Biographies

Maria Fernanda Gómez holds a Bachelor's degree in Industrial Engineering from the University of Lima, ranking in the top third of her class. She specializes in logistics and supply chain management, with experience at Komatsu-Mitsui Maquinarias Perú in planning and spare parts operations. Her work focuses on optimizing import purchasing, improving process efficiency, and reducing non-compliance in restricted cargo management. Proficient in Excel, Python, SQL, Power BI, and fluent in English with intermediate Mandarin, she applies strong analytical and problem-solving skills to enhance supply planning and continuous improvement.

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