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Predicting production costs in procurement logistics: A comparison of OLS regression and neural networks in a Peruvian paper company

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A B S T R A C T

The purpose of this research work is to evaluate the use of statistical tools, specifically Ordinary Least Squares (OLS) and Artificial Neural Networks (ANN) and with the help of these tools to be able to independently and effectively predict the costs. of production in the context of supply logistics in the Peruvian paper industry. Both models that turn out to be different in their analysis, however, turn out to be complementary for a more exact and precise result, highlighting the ANNs for their superior performance in the precision of the evaluated metrics, where they managed to achieve an RMSE of 0.0171 and a MAE of 0.0122 compared to the OLS statistical model that achieved an RMSE of 0.0181 and a MAE of 0.2070. Likewise, the analysis between the dimensions studied, purchasing management stands out with a negative coefficient of -0.4978, which shows that its optimization will generate a positive impact on production costs, contrary to the case with the other two dimensions, which are: storage management and inventory management, which resulted in positive coefficients (0.7457 and 0.4667), which shows that their optimization does not necessarily generate a positive impact on production costs, but quite the opposite, that their inadequate management On the contrary, it can harm production costs. These results highlight the inherent need that Peruvian paper companies must have in being able to implement updated logistics systems, capable of integrating advanced statistical tools such as the use of ANN and MCO, which can scientifically help better decision making, allowing thereby improving your supply processes and thus being able to reduce your production costs.

1. Introduction

Corbos et al. (2023) and Jacob et al. (2024) highlight the strategic importance of adequate management of supply logistics, which allows a company to be able to maintain its operations efficiently, continuously and maintaining an adequate cost flow of its processes. According to Flores (2024), in this aspect the Peruvian paper industry is not the exception in terms of competitiveness, since, in a constantly changing market, measures must be implemented regarding its operational processes, thereby obtaining better conditions. to reduced prices, better quality standards and thus being able to be at the forefront and improve its positioning.

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There is a trend framed in sustainability Vegas et al. (2024) and Puma-Flores and Rosa-Díaz (2024) where caring for the environment plays a primary role. This not only implies compliance with current legal regulations, but is also a commitment to corporate social responsibility. In this scenario, in the constant search for alternatives for its care, such as the use of recycled products can be found as an effective and viable solution. This research seeks to compare the data obtained from a leading paper company in the Peruvian market through the statistical tools of Ordinary Least Squares (OLS) and Artificial Neural Networks (ANN) in order to know which of these tools can reach predict more optimally the influence that supply logistics exerts on production costs

Being one of the main problems that these types of companies face in their correct supply of cellulosic fiber as raw material. Taking into account that to obtain it, García et al. (2024), Bajpai (2021) and Chauhan & Meena (2021) maintain that cellulosic fiber can be obtained in two presentations, which are: virgin cellulosic fiber (eucalyptus and pine felling) where its acquisition is through imports, and recycled cellulosic fiber (recycling) which has a very competitive price compared to the previous one, however it can be acquired through the national and international market (Kumar et al., 2021). Flores (2024) and Flores-Vilcapoma et al. (2021) note that due to the country's limited recycling culture, recycled cellulose fiber is scarce in the Peruvian market. This scarcity often necessitates imports, which are more expensive than domestic options, yet still represent a considerable cost advantage compared to virgin cellulose fiber.

As mentioned above, these companies face significant challenges that directly impact their costs and even affect their ability to meet increasingly demanding market needs (Suriani et al., 2021). These challenges are closely tied to their dependence on raw materials, such as recycled fiber and virgin cellulose, whose prices and availability are subject to both internal and external market fluctuations (Wang et al., 2021). Implementing better procurement strategies could contribute significantly to reducing costs while ensuring uninterrupted operations.

The primary objective of this research is to analyze how procurement-related decisions directly impact production costs. This includes examining key aspects such as purchasing management, inventory management, and storage management. The study is supported by a review of both national and international literature to provide statistical evidence that scientifically explains how to make better decisions and implement improved procurement strategies.

The present study adopted a quantitative, cross-sectional, and non-experimental design. A convenience sample of 291 data points was selected, collected weekly from January 2018 to July 2023, from a prestigious paper company in Peru. This methodological approach enabled the collection of relevant data to evaluate the variables of supply logistics and production costs, ensuring representativeness within the defined temporal framework.

2. Literature Review

2.1 Procurement Logistics

Nguyen (2024) and Sebata (2024) state that procurement logistics ensures the efficient flow of essential supplies for a company's daily operations. According to Sakas et al. (2023) and Vaka (2024), its main processes include a thorough selection of suppliers, meticulous planning for material acquisition, and effective inventory management to ensure constant production without delays or interruptions. Rajabzadeh et al. (2024) argue that logistics is not only responsible for supplying inputs to the company for production but also must generate cost-benefit efficiencies to improve the organization's competitiveness. In the study conducted by Karabağ & Gökgür (2023), it is highlighted that due to the direct dependency on recycled cellulose fibers—a scarce type of raw material—many companies face constant challenges in their procurement logistics. These challenges are attributed to the ongoing fluctuations in prices and, more importantly, their availability, which directly impact production costs.

2.2 Production Costs

Hendarto et al. (2023) define production costs as all resources used to transform raw materials into finished products. In the competitive advantage model of Adama et al. (2024), it is emphasized that companies must prioritize maintaining and optimizing their costs, as these are crucial for their sustainability and market positioning. Similarly, Cen (2023) and Monjur (2023) highlight that the effective management of a company's logistical resources can positively impact production costs, generating significant savings across various industrial processes.

In Peru, previous studies by Pallete et al. (2022), Flores-Vilcapoma et al. (2021), and Pérez & Pena (2022) concluded that proper management of material acquisitions, combined with optimal warehouse management, allows manufacturing companies to significantly reduce their administrative and operational costs. Another perspective is offered by Khursheed et al. (2024) and Donyavi et al. (2023), whose studies warn that a lack of or inadequate planning in material and input acquisition by manufacturing companies can lead to cost overruns, directly affecting profitability.

2.3 Paper Industry

According to Pathak & Sharma (2023), Del Rio et al. (2022), and Dai et al. (2023), companies within the paper and cardboard sector continuously face supply issues due to their direct reliance on virgin cellulose fiber and recycled cellulose fiber. Palmer & Cohen (2020) concluded that the various fluctuations inherent to the supply of cellulose fiber, in any of its forms, have a direct impact on the operating costs of companies in this sector. Additionally, Smith (2023) and Hameri & Lehtonen (2001) argue that the growing demand for paper-based products increases the pressure on these industries to rethink and modernize their supply chains to meet market demands effectively.

In the Peruvian context, according to Vallenas (2022) and Flores (2022), the lack of domestic production of virgin cellulose fiber and the scarcity of recycled cellulose fiber due to a limited recycling culture create a scenario of complete dependence on the constant fluctuations of both national and international markets to ensure the continuous supply of raw materials.

2.4 Ordinary Least Squares (OLS) Regression

This method proves to be most effective in situations where the variables have a clear linear relationship and certain basic assumptions are met, such as data normality, equal variances (homoscedasticity), and the absence of strong correlations between independent variables (multicollinearity). Burton (2021) describes it as a widely used statistical technique today, which helps identify the linear regression between different types of variables. Lakshmi et al. (2021) argue that this technique aims to predict the values of the dependent variable based on the values of the independent variables, refining the analysis until the sum of squared differences between the observed values and the model's predicted values is minimized. Weisburd et al. (2022) highlight OLS as a statistical tool that stands out as long as the variables have a linear regression and meet certain conditions such as that the data must follow a normal distribution, the variances of the residual errors must be constant (homoscedasticity) and finally, the independent variables should not have a strong relationship with each other (multicollinearity).

2.5 Artificial Neural Networks (ANNs)

Dastres and Soori (2021) highlight ANN Artificial Neural Networks as computational systems which are inspired by the complex functioning of the human brain, to be able to solve complex problems and address a wide variety of disciplines. They are designed to identify complex patterns and nonlinear relationships in data, making them particularly useful in scenarios where variables do not exhibit an evident linear relationship or when working with large volumes of multidimensional data (Suykens et al., 2012). These networks "learn" by adjusting the weights of the connections between neurons through an iterative process, with the goal of minimizing prediction errors.

3. Theoretical Perspective

Porter's competitive advantage model (2003) provides a solid and analytical foundation to understand how procurement logistics can directly influence production costs within an organization. It also helps to improve and strengthen a company's competitive positioning. Furthermore, Chopra and Meindl (2007) reinforce this stance, emphasizing the importance of integrating all components of the supply chain to enhance productivity and mitigate risks associated with uncertainty in resource and material provision. Finally, both perspectives highlight the critical role of logistics management in addressing and overcoming the specific challenges faced by paper companies, where effective cost control and a continuous supply of raw materials are fundamental to ensuring operational continuity.

4. Methodology

4.3 Econometric Model

4.3.1. OLS model

In order to evaluate the existing impact between the study variables and thus determine their significance, the OLS statistical tool was used since it is considered an appropriate tool for its evaluation through multiple linear regression modeling and in addition to its analysis of correlation that is very important to make a consistent estimate if it meets the conventional assumptions, by minimizing the sum of the squared errors.

$$y_t = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \varepsilon_t$$

where:
y_t: Production cost
x_1: Purchasing management

x_2: Storage management
x_3: Inventory management
ε_t: Disturbance term, $\varepsilon_{it} \sim iid(0, \sigma^2)$

The formula presented corresponds to the estimation through OLS, whose main purpose is to be able to reduce as much as possible the difference between the dependent variable and the estimated independent variable, thereby achieving more efficient forecasts for subsequent better decision making.

$$SSR = (y_t^T - \beta_t^T X^T)(y_t - X\beta_t)$$

where SSR is sum square of residuals, $\beta = [\beta_0, \beta_1, \beta_2, \beta_3]^T$ and $X = [1, x_1, x_2, x_3]$.

$$\beta = (X^T X)^{-1} X^T y_i$$

4.3.2. ANN model

The artificial neural network (ANN) model implemented corresponds to a feedforward neural network of the multilayer perceptron (MLP) type, specifically designed to capture complex patterns and nonlinear relationships between the independent variables and production costs. The model architecture comprises an input layer with three neurons, each representing one of the independent variables: Purchasing, Storage, and Inventory.

The hidden layer configuration was refined through experimentation with different neuron counts, with the final model incorporating 10 neurons and employing the Rectified Linear Unit (ReLU) activation function to effectively handle nonlinearities. The output layer consists of a single neuron responsible for predicting the Production Cost. The training process was conducted using the backpropagation optimization algorithm, with the Stochastic Gradient Descent (SGD) method. The selected hyperparameters include a learning rate of 0.01, 500 epochs, and a batch size of 32. Additionally, early stopping was applied to prevent overfitting by monitoring the validation set error and halting the training process when no significant improvement was observed in the model's performance.

5. Results

5.1. Statistics

Table 1 provides a descriptive analysis of the variables Production Cost, Purchasing, Storage, and Inventory, presenting key statistics such as mean, standard deviation, median, range, skewness, and kurtosis. The Production Cost variable shows a mean of 5.99 and a narrow range, indicating consistency across the dataset and a nearly symmetrical distribution (skewness of 0.01). The Purchasing variable has a mean of 3.96, with slight dispersion and a range of 0.57, demonstrating a symmetrical distribution (skewness of -0.05) and flatter tails compared to a normal distribution (kurtosis of -1.75).

Table 1
Main statistics

Variables	n	mean	s.d.	median	min	max	range	skewness	kurtosis
Production cost	291	5.99	0.1	5.98	5.78	6.23	0.46	0.01	-0.9
Purchasing	291	3.96	0.19	4	3.65	4.22	0.57	-0.05	-1.75
Storage	291	3.31	0.07	3.34	3.15	3.45	0.3	-0.55	-0.88
Inventory	291	6.45	0.11	6.43	6.25	6.63	0.38	-0.04	-1.54

The Storage variable exhibits lower variability, with a mean of 3.31 and a range of 0.30, although it shows a slight left-skew (skewness of -0.55). The Inventory variable presents a mean of 6.45, low dispersion, and a symmetrical distribution (skewness of -0.04). Overall, the variables exhibit stable and consistent distributions, with limited extreme values, indicating homogeneity in the logistical processes analyzed and their relationship with production costs. These findings suggest that the logistical variables measured are well-structured, providing a reliable foundation for assessing their influence on cost optimization.

Fig. 1 reveals a significant shift in the company's logistics strategy around week 150. This change is likely associated with efforts to optimize procurement processes and inventory management, which, in turn, have a direct impact on production costs. The observed peaks in the purchasing and storage management graphs may reflect the company's adaptation to fluctuations in demand or variations in input costs. Furthermore, the stabilization trend seen in the final weeks suggests that the company has achieved a degree of control over its logistical processes and associated expenses. These patterns align with the core hypothesis of this study, demonstrating that improved supply chain management can effectively contribute to a reduction in production costs—an essential focus of our research.

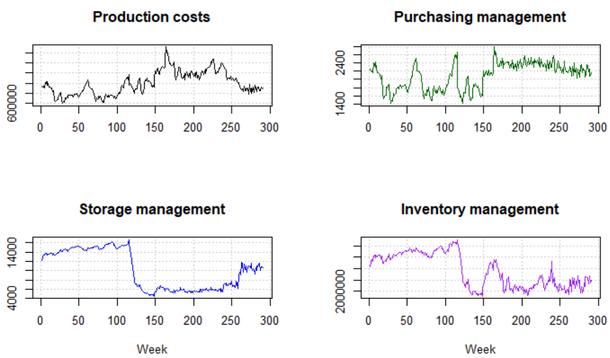

Fig. 1. Variables

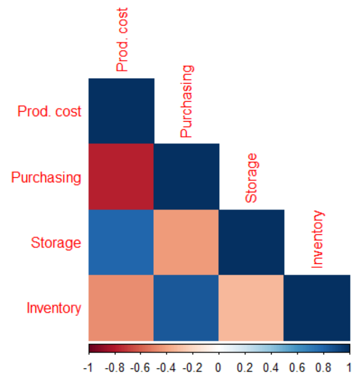

Fig. 2. Correlation matrix

The correlation matrix presented in Fig. 2 illustrates the relationships between four key variables: production cost, purchasing management, storage management, and inventory management. In order to interpret the correlation values, its range of values must be taken into consideration, which ranges between: -1 (strong negative correlation) which is represented with a dark red color and 1 (strong positive correlation) with a dark blue color, being the color scale which facilitates its interpretation and helps to distinguish strong relationships, whether positive or negative or perhaps closer to 0. In this sense, a strong negative correlation between production costs and purchasing management, which suggests that improvements in purchasing processes contribute significantly to the reduction of production costs. Similarly, moderate negative correlations are identified between production costs and both storage management and inventory management, indicating that optimization of these areas also contributes to cost reduction, although to a lesser extent.

Additionally, positive correlations are observed among the logistical variables, particularly between purchasing, storage, and inventory management. This indicates that improvements in one process are often accompanied by corresponding optimizations in the others. For instance, enhanced purchasing management is likely to facilitate more efficient storage practices and inventory levels. Collectively, these findings support the core hypothesis of this study, demonstrating that logistics process optimization plays a critical role in reducing production costs, ultimately enhancing the company's profitability and operational efficiency.

5.2. OLS result

Table 2 presents the results of a multiple linear regression model that evaluates the influence of Purchasing (Purchasing Management), Storage (Storage Management), and Inventory (Inventory Management) on Production Costs. The model indicates that all independent variables are statistically significant, with p-values of 0.000, confirming their relevance in explaining cost variations. The coefficient for Purchasing is -0.4978, suggesting that improvements in purchasing management contribute to a reduction in production costs. In contrast, the coefficients for Storage (0.7457) and Inventory (0.4667) are positive, implying that increased levels of storage and inventory management can raise production costs, potentially due to inefficiencies in these logistical processes.

Table 2
Multiple linear regression

Coefficients	Estimate	S.E.	t value	p-value
Intercept	2.4823	0.1899	13.07	0.000***
Purchasing	-0.4978	0.0223	-22.34	0.000***
Storage	0.7457	0.0325	22.93	0.000***
Inventory	0.4667	0.0353	13.22	0.000***

Note: *** Significance less than 1%.

The model demonstrates an excellent fit, with a multiple R^2 of 0.941, indicating that 94.1% of the variability in production costs is explained by the included variables. The residual standard error of 0.02213 confirms the accuracy of the model's predictions, with minimal deviations from observed values. Additionally, the F-statistic of 494.1 and its p-value < 2.2e-16 underscore the model's high statistical significance. Collectively, these findings provide robust evidence supporting the hypothesis that logistical processes, particularly purchasing management, have a substantial impact on production costs. Optimizing these processes is essential for enhancing operational efficiency and achieving cost reductions, making them critical areas of focus for improving overall business performance.

The results of the Jarque-Bera test applied to the residuals of the regression model indicate a test statistic of Chi squared equal to 0.44505, with 2 degrees of freedom and a p-value of 0.8005. Since the p-value is substantially higher than the commonly used significance level of 0.05, the null hypothesis of normality in the residuals cannot be rejected. This finding suggests that the residuals do not exhibit significant skewness or kurtosis, confirming that the model adheres to the normality assumption of errors, which is essential for ensuring the validity and reliability of linear regression results. Therefore, the model's predictions can be considered statistically robust and reliable, reinforcing the appropriateness of the applied methodology for predictive purposes.

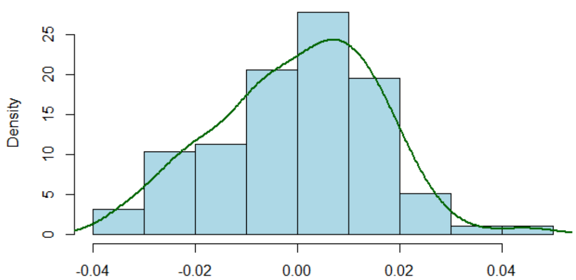

Fig. 3. Histogram of residuals and kernel curve

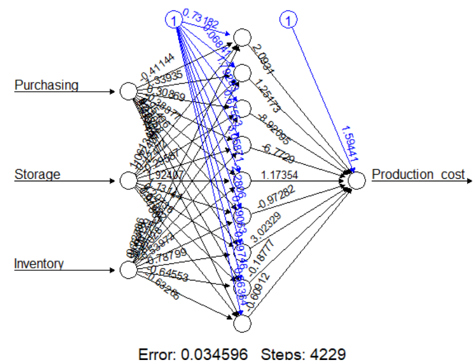

Fig. 4. The architecture of an **ANN**

Fig. 3 exhibits a distribution centered near zero, indicating that the errors are well-balanced around the expected value, which is a desirable property in regression analysis. The superimposed kernel density curve reveals a slight right skew, suggesting a minor deviation from normality. However, this deviation does not appear to be substantial enough to compromise the validity of the model. The absence of extreme values or outliers indicates that the residuals are reasonably random, satisfying one of the key assumptions of linear regression.

Overall, the results indicate that the residuals demonstrate an approximately normal distribution, reinforcing the reliability and robustness of the model's estimations. Although the slight skewness is not a critical issue, further refinement of the model could be achieved by applying transformations or reviewing additional predictor variables to address this asymmetry and potentially improve the model's performance.

5.3. ANN result

Fig. 4 depicts the architecture of an ANN designed to model the relationship between the independent variables (Purchasing, Storage, and Inventory) and the dependent variable (Production Cost). The network is organized into three layers: an input layer, which contains the logistical variables under study; a hidden layer, where signals are processed through weighted connections; and an output layer, representing production costs. The connections between the nodes are annotated with synaptic weights, indicating the magnitude and direction of the influence exerted by each input variable on cost predictions. Positive weights imply that an increase in the input variable results in higher production costs, whereas negative weights suggest that increasing the input variable leads to a cost reduction.

The weight analysis highlights that Purchasing Management exerts the greatest influence on Production Costs, reinforcing previous findings on the importance of optimizing purchasing processes to achieve cost efficiency. Meanwhile, the variables Storage Management and Inventory Management also contribute significantly, though their impact is less pronounced compared to purchasing management. The reported error value of 0.034596 indicates a high level of model accuracy, reflecting the network's ability to minimize prediction errors during the training process. The total number of iterations, Steps: 4229, further illustrates the computational effort required to achieve this precision. These results validate the ANN model as an effective predictive tool for identifying the logistical factors that most significantly influence production costs, providing valuable insights for improving supply chain management strategies.

Fig. 5 presents scatter plots illustrating the relationship between the variables Purchasing, Storage, and Inventory with Production Costs. The analysis indicates a positive impact of these variables on production costs, albeit with varying degrees of intensity.

Among them, Purchasing Management emerges as the most influential factor, followed by Inventory Management, and lastly, Storage Management.

These findings provide empirical support for the hypothesis that optimizing logistical processes can significantly reduce production costs. By enhancing procurement practices and improving the management of inventory and storage, companies can achieve greater operational efficiency, which ultimately translates into cost savings.

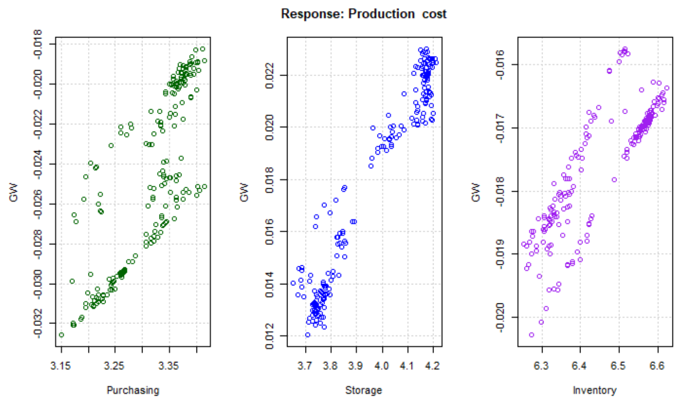

Fig. 5. Scatter plots

5.4. Prediction

Table 3
Comparison between models

	OLS model	ANN model
RMSE	0.0181	0.0171
NRMSE	0.0396	0.0375
R^2	0.9662	0.9702
Accuracy	0.9999	0.9998
MAPE	0.0021	0.0020
MAE	0.2070	0.0122

Table 3 compares the performance of a linear regression model (OLS) and an artificial neural network (ANN) using various precision and error metrics. The results show that the ANN model outperforms OLS in terms of Root Mean Square Error (RMSE) and Normalized RMSE (NRMSE), with values of 0.0171 and 0.0375, respectively, compared to 0.0181 and 0.0396 for OLS. This indicates that the neural network provides more accurate predictions. Both models achieve a high coefficient of determination (R^2), explaining over 96% of the variability in the data, with a slightly higher value for the ANN model (0.9702) compared to OLS (0.9662). Regarding accuracy, both models reach values close to 100%, with a marginal advantage for OLS (0.9999) over ANN (0.9998). However, the ANN model excels in percentage and absolute error metrics, such as Mean Absolute Percentage Error (MAPE) and Mean Absolute Error (MAE), showing lower error values (MAPE of 0.0020 and MAE of 0.0122) compared to OLS (MAPE of 0.0021 and MAE of 0.2070).

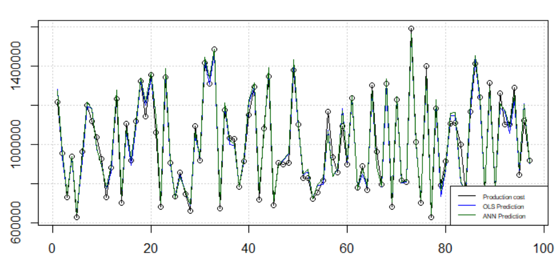

Fig. 5. Production Cost Predictions of a Paper Company in Peru

This confirms that the ANN model delivers more efficient predictions with reduced average error. Overall, these results suggest that neural networks offer a more robust alternative to linear models, particularly for complex problems where non-linear relationships between variables are more significant. Consequently, ANN models can improve predictive accuracy and better capture intricate patterns within the data, making them an effective tool for enhancing forecasting performance in practical applications. Fig. 5 illustrates the evolution of production costs for a paper company in Peru over a period of 100 weeks, comparing the observed values (Production cost) with the predictions generated by two models: OLS regression and ANN model. The blue curve represents the actual production costs, while the black curve corresponds to the OLS predictions, and the green curve depicts the ANN predictions. Both models demonstrate an adequate fit to the observed data, capturing the weekly fluctuations in production costs. However, when considering the performance metrics presented in the previous table, the ANN model exhibits superior predictive accuracy and lower average error. This is evident in its greater ability to replicate sharp peaks and troughs in the data compared to the OLS model. While the OLS model follows the general trends, it shows larger deviations from the observed values in certain weeks. This observation aligns with the RMSE, NRMSE, MAPE, and MAE values from the table, which confirm that the ANN model provides a better fit and more accurate predictions. In summary, the figure reinforces that the Artificial Neural Network model is more effective at capturing complex and non-linear variations in production costs, making it a more robust tool for operational cost forecasting in dynamic environments.

6. Conclusions

This research work concludes that two statistical modeling was used to estimate how supply logistics can impact production costs in a Peruvian paper company, whose modeling used were Artificial Neural Networks (ANN) and Regression by Ordinary Least Squares (OLS). It should be noted that both statistical tools present different approaches, but in the end they also turn out to be complementary when it comes to making a correct and more precise estimate of the data presented. Among both tools, the ANNs stood out since they turned out to obtain lower degrees of error compared to the OLS, thereby demonstrating that this statistical tool turned out to be significantly more precise.

What was stated in the previous paragraph is evident when knowing the data obtained in both statistical tools where, as indicated above, the ANNs managed to have a highly accurate performance, since a Root Mean Square Error (RMSE) of 0.0171 was obtained. and a Mean Absolute Error (MAE) of 0.0122 compared to that obtained by the OLS statistical tool that achieved an RMSE of 0.0181 and a MAE of 0.2070. Although according to the results obtained, it can be seen that the OLS analysis also turns out to be very effective, but its precision is lower compared to the ANN, especially in the MAE, where the difference between the two is very wide

The statistical results obtained with respect to each of the dimensions of supply logistics, it is possible to highlight the purchasing management dimension, which obtained as a result a significant negative coefficient of -0.4978, which indicates that if this dimension is improved or achieved Increasing its effectiveness will result in direct and significant savings on production costs. On the other hand, the results obtained in the storage management and inventory management dimensions were obtained as positive coefficient results respectively (0.7457 and 04667) whose results indicate that, instead of reducing production costs, they have the possibility of increasing them if not are managed appropriately.

Finally, with the results obtained and analyzed, it is possible to demonstrate a great need for companies of any kind to be able to update their logistics processes using statistical tools with advanced analytical capabilities in order to be able to predict the costs in the different logistics processes that they may have. This is especially reflected in those companies that present serious difficulties when it comes to acquiring their inputs for their normal operation, as is the case of companies in the paper sector, where the combination of modern tools such as ANN and traditional tools such as MCOs can achieve greater precision and more solid arguments when it comes to making decisions and efficiently facing the various changes that these types of markets have.

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