Colegio de Postgraduados

Analysis of Inventories in the Agri-Food Sector through Probabilistic Models and application of Neural Networks

Heredia-Roldán, Miguel J.[1]; **Gurruchaga-Rodríguez, María E.**[1]; **Báez-Sentíes, Oscar**[1]; **Romero-Montoya, Mauricio**[1*]; **Bretón-Partida, Leticia**[1]

[1] Tecnológico Nacional de México, Orizaba. Instituto Tecnológico de Orizaba, Veracruz, México (94320).
* Correspondence: mauricio.rm@orizaba.tecnm.mx

ABSTRACT

Objective: To evaluate the effectiveness of this hybrid approach in improving forecasting accuracy and optimizing inventory decisions under demand uncertainty for the agri-food sector.

Design/methodology/approach: Based on the determination of the coefficient of variation, the Newsboy model was implemented, along with demand forecasting techniques using neural networks, allowing inventory levels to be adjusted according to demand fluctuations and reducing the risk of both overstocking and stockouts.

Results: This model and the neural network optimize product availability, balance inventory costs, and maintain a solid foundation for decision-making within the agri-food supply chain.

Limitations on study/implications: This study focuses on an agri-food company, where probabilistic inventory models are applied to improve certainty in managing product availability under demand variability.

Findings/conclusions: Inventory optimization is essential in the agricultural sector, where demand variability can significantly impact both costs and service levels.

Keywords: Inventories, neural networks, supply chain.

Citation: Heredia-Roldán, M. J., Gurruchaga-Rodríguez, M. E., Báez-Sentíes, O., Romero-Montoya, M., & Bretón-Partida, L. (2025). Analysis of Inventories in the Agri-Food Sector through Probabilistic Models and application of Neural Networks. *Agro Productividad*. https://doi.org/10.32854/gvxtjj33

Academic Editor: Jorge Cadena Iñiguez
Associate Editor: Dra. Lucero del Mar Ruiz Posadas
Guest Editor: Daniel Alejandro Cadena Zamudio

Received: July 12, 2025.
Accepted: November 17, 2025.
Published on-line: December 11, 2025.

Agro Productividad, 18(11). November. 2025. pp: 3-16.

INTRODUCTION

Given the dynamic and volatile nature of the agri-food sector, optimizing inventory management remains a persistent challenge for companies. The pressure to satisfy ever more demanding demands, together with the imperative to reduce operating costs, drives the continuous search for innovative solutions. However, traditional inventory management approaches often struggle to adequately capture the uncertainty and variability inherent in agri-food supply chains, especially under conditions of seasonality, perishability, and non-stationary demand behavior (Ahumada & Villalobos, 2009).

In recent years, the combination of probabilistic models and neural networks has emerged as a promising approach to enhance demand forecasting accuracy and thereby optimize inventory levels (Feizabadi, J. *et al.*, 2020). Yet, despite this potential, there is still

limited research on how exactly to integrate these techniques in the context of agro-food supply chains, leaving a gap that this study aims to address.

This paper reports a case study in an agri-food firm that implemented an inventory management system combining probabilistic models —such as the Newsvendor model— and neural networks for demand prediction. The objective of this study is to evaluate the effectiveness of this hybrid approach in improving forecasting accuracy and optimizing inventory decisions under demand uncertainty for the agri-food sector.

In our method, the coefficient of variation of demand is employed as a classification criterion, segregating products into those with relatively stable demand and those with high variability. Products classified as having probabilistic demand patterns are managed via the Newsvendor model, which adapts inventory levels to projected demand, thereby mitigating holding costs and the risk of stockouts. This methodological integration aims to deliver a practical decision support framework that balances operational efficiency with service-level improvements in perishable product management (Han, J., 2024).

Efficient inventory management in the agri-food sector is further complicated by the fluctuating and often uncertain demand for perishable products. Companies frequently face overstock and stockout situations, leading either to high storage costs or to lost sales opportunities. The high variability in demand requires advanced forecasting methods capable of adjusting inventory levels to complex and nonlinear consumption patterns —conditions under which empirical or traditional techniques often fail to perform adequately. To address these limitations, several companies have implemented product classification systems based on the demand coefficient of variation, distinguishing between deterministic and probabilistic demand. This classification enables the application of appropriate inventory models based on the nature of demand for each product.

Over the past two decades, a wide range of studies has examined inventory models aimed at improving accuracy and adaptability across various industries. Neural networks, for example, have been employed to enhance demand forecasting in education (Cruz & Correa, 2017), refrigeration, and retail sectors, consistently demonstrating that these methods can outperform traditional statistical approaches by capturing complex and irregular demand patterns. Similarly, probabilistic inventory models have proven effective in environments with uncertain and uncontrollable demand, allowing for better resource allocation and adaptive decision-making (Ríos *et al.*, 2008; Gelmi & Seoane, 2013). Other works have highlighted the role of hybrid approaches —combining methods such as Box-Jenkins, EOQ, and ROP— to continuously adjust inventory levels to real market conditions (Parreño Fernández *et al.*, 2002; Rodríguez Rodríguez *et al.*, 2014; Noriega, 2021; Jara Cordero *et al.*, 2017).

Recent research has focused on integrating probabilistic models with artificial intelligence techniques to improve both forecasting accuracy and decision-making efficiency. For example, Heredia Roldán *et al.* (2024) implemented the Newsvendor model jointly with EOQ to optimize inventory control in high-variability products, while Cardozo Rueda (2022) applied neural networks to predict coffee prices, demonstrating how AI can support strategic decisions in volatile markets. Moreover, Terán Villanueva *et al.* (2019) highlighted the expanding adoption of AI tools in industries such as textile and apparel, where automation enhances operational efficiency and market responsiveness.

Despite these advances, there remains limited empirical research on how to effectively integrate neural networks and probabilistic models within the agri-food context. This gap motivates the present study, which develops and evaluates a hybrid inventory management framework combining the probabilistic Newsvendor model with neural networks for demand prediction. The approach employs the coefficient of variation as a classification criterion to distinguish products according to demand variability, enabling adaptive inventory control that minimizes both holding costs and stockout risks.

The objective of this study is to assess the effectiveness of the hybrid probabilistic–neural model in improving demand forecasting accuracy and optimizing inventory decisions under uncertainty in the agri-food sector. The hypothesis is that combining probabilistic modeling with neural network forecasting enhances product availability and service levels while reducing total inventory compared to traditional methods.

Experimental procedures

To carry out this analysis, data on the historical demand of 165 agri-food products was collected over a period of 12 months (October 2022 - September 2023). Table 1 presents a summary of the ten relevant products, serving as the basis for classifying demand and applying inventory models.

Calculation of the Coefficient of Variation of Demand

As a first step, the historical demand for the products was analyzed to calculate the coefficient of variation (CV), an essential metric to classify demand according to its stability. Products with a CV less than or equal to 0.20 were considered to have deterministic demand, while those with a CV higher than this threshold were classified as having probabilistic demand (Romero, 2019). This classification made it possible to determine the products

Table 1. Historical record of units for the period October 2022-September 2023

Description (kg)	Oct-22	Nov-22	Dec-22	Jan-23	Feb-23	Mar-23	Apr-23	May-23	Jun-23	Jul-23	Aug-23	Sep-23
FATTENING SHEEP 40	616	586	873	991	943	975	581	920	929	568	334	289
BOVIPOP 40	126	200	156	151	108	242	176	100	135	34	37	18
SOYBEAN HUSK 35	1227	957	871	1184	909	837	725	626	544	717	485	489
CATLINE 15	1575	1272	1677	1530	1168	1068	1170	1014	737	1073	878	840
PIG FATTENING MIX 40	50	75	50	50	75	25	75	75	100	49	48	75
RABBIT GROWTH 40	1290	723	1051	1308	817	1816	1671	1664	1320	1216	990	1056
HIGH GENETIC GROWTH 20	134	140	146	168	123	264	168	306	294	197	264	240
HIGH GENETIC GROWTH 5	53	55	69	75	20	83	34	10	34	28	28	46
FLEXI GROWTH 20	444	458	287	362	210	520	239	336	360	376	280	344
DAIRY COW 12% 40	614	1276	1176	1735	1547	1674	2036	1516	1396	696	491	546

that required more flexible inventory management due to the high variability in demand, establishing a solid basis for applying appropriate probabilistic models.

To evaluate the fluctuation in demand for each product, the coefficient of variation in demand (CVD) was calculated, where those products with a higher CVD present higher level of uncertainty, which requires more careful inventory planning.

CVD measures the stability of demand over time: a higher CVD suggests greater relative variability, indicating possible significant changes in demand. For this analysis, sales data will be considered for an annual period, from October to September.

The formula used for the Coefficient of variation in demand is:

$$CVD = \frac{\sigma}{\mu} \times 100 \quad (1)$$

Where: σ=Represents the standar deviation of demand; μ=It is the average (or average) of the demand.

The initial calculation consists of obtaining the average sales. However, due to high demand, warehouses face challenges in meeting it; Therefore, dividing the data into weeks and calculating the weekly average helps to forecast demand over longer periods of time and avoids product shortages in the event of incomplete orders.

Calculation of the Average:

$$Mean = \frac{Sum\ of\ all\ values}{Quantity\ of\ values} \quad (2)$$

Subsequently, the standard deviation is calculated, considering only a sample of historical data, which requires the use of the sample formula.

$$\sigma = \frac{\sum_{i=0}^{n} \left(X_i - \mu\right)^2}{n} \quad (3)$$

Where: σ=Standard deviation of demand; X_i=represents each individual demand value in the dataset; μ=is the average of the dataset; n=is the total of values in the set; $\sum$=denotes the sum of the terms.

With this data, the CVD is calculated, of which it is obtained as a fraction, when multiplied by 100 it becomes a percentage, which allows better observation of demand patterns, supporting informed decisions on production, supplier management and distribution.

Based on historical demand data for 10 product-relevant agri-food products, the average and standard deviation of demand for each product were calculated. These values were used to determine the coefficient of variability (CV) of each, as shown in Table 2.

The results of the analysis of the coefficient of variability reveal that the demand for the vast majority of products (88%) is characterized by high variability, which indicates a probabilistic behavior. Given this situation, the implementation of a probabilistic inventory model is justified as the most appropriate strategy to deal with the uncertainty inherent in demand.

Newsboy Model Application

Through a probabilistic approach based on normal distribution and considering seasonal variability, the Newsboy model made it possible to optimize inventory levels for products with uncertain demand, determining the optimal quantity to be produced or acquired per period and thus minimizing the costs associated with excess or shortage of inventory.

Which calculates the optimal level of inventory per demand cycle, considering the variability reflected in the CVD and the costs of excess and shortage of inventory. The Newsboy model, also known as the Newsboy Model, is a tool in inventory theory and supply chain management. This model seeks a balance between the costs of maintaining additional inventory (storage, obsolescence) and the costs of opportunity and lost sales due to lack of inventory, thus minimizing total costs.

To calculate the optimal amount of inventory, the following formula is used:

$$Q = q = F^{-1}\left(\frac{p-c}{p}\right) = \mu + \sigma Z^{-1}\left(\frac{p-c}{p}\right) \tag{4}$$

Where: Q=Optimal quantity of inventory to order; q=Optimal amount of inventory to order, F^{-1}=Inverse cumunlative probability distribution function of demand D; p=Selling price of the product; c=Cost of the product; μ=Average demand; σ=Standard deviation of demand; Z^{-1}=Inverse quantile of the probability distribution associated with uncertainty in demand.

Table 2. Calculation of the Coefficient of Variability of Demand.

Description	Stocking	Standard deviation	CVD (%)	Classification
FATTENING SHEEP 40	717.08	252.47	35	PROBABILISTIC
BOVIPOP 40	123.58	68.77	56	PROBABILISTIC
SOYBEAN HUSK 35	797.58	248.07	31	PROBABILISTIC
CATLINE 15	1166.83	299.51	26	PROBABILISTIC
PIG FATTENING MIX 40	62.25	20.12	32	PROBABILISTIC
RABBIT GROWTH 40	1243.50	342.39	28	PROBABILISTIC
HIGH GENETIC GROWTH 20	203.67	66.44	33	PROBABILISTIC
HIGH GENETIC GROWTH 5	44.58	22.87	51	PROBABILISTIC
FLEXI GROWTH 20	351.33	91.11	26	PROBABILISTIC
DAIRY COW 16% FLEXI 40	2345.42	310.19	13	DETERMINISTIC

CVD: coefficient of variation in demand.

The mean (μ) and standard deviation (σ) of demand have already been calculated above. The value of Z^{-1} is determined using the Excel formula "DISTR. NORM. STAND. INV", which returns the inverse quantile of the standard normal distribution.

Newsboy model in normal distribution

The Formula, belonging to the Z^{-1} Determination Model, is presented

$$Q=(\mu)+(\sigma Z^{-1})\left(\frac{p-c}{p}\right) \quad (5)$$

Where: Q=Number of units to be ordered in inventory; μ=average demand; σ=Standard deviation of demand; Z^{-1}=Inverse quantile of the probability distribution associated with uncertainty in demand; p=The sale of each unit in inventory; Purchase costo of each unit in inventory; Demand for product in inventory $[\mu, \sigma]$. If D∼Normal $[\mu, \sigma]$

With the values obtained, optimal Q is calculated, using the mean plus the product of the standard deviation times Z. The results indicate that some products have a negative optimal Q, which reflects a low and variable demand; These products are recommended to be kept offline and produced only to order, thus reducing storage costs and risk of obsolescence.

Table 3 presents the calculations corresponding to the single purchase model with normal distribution, which has been selected as the most appropriate to manage demand uncertainty.

The value of Q is rounded up to tons due to production policies, which state that it can only be produced in multiples of tons. Products with a Q of zero will be kept offline to reduce costs.

Table 3. Calculation of Q of the single purchase model with normal distribution.

Normal distribution	
Description (kg)	$Q=q=(\mu)+(\sigma Z^{-1})\left(\frac{p-c}{p}\right)$
FATTENING SHEEP 40	36
BOVIPOP 40	319
SOYBEAN HUSK 35	10
CATLINE 15	29
PIG FATTENING MIX 40	29
RABBIT GROWTH 40	297
HIGH GENETIC GROWTH 20	971
HIGH GENETIC GROWTH 5	622
FLEXI GROWTH 20	27
DAIRY COW 12% 40	99

The application of the Newsboy model, in its normal distribution approach, generated optimal inventory quantities adjusted to the probabilistic demand for each product. When comparing demand with results between these approaches, it was observed that the Newsboy model with normal distribution provided more accurate and consistent results in reducing inventory costs and preventing shortages, especially for fast-moving products.

Implementation of Neural Networks for Demand Prediction

To increase the accuracy of demand forecasting and support inventory optimization, neural networks were used, capable of identifying complex and non-linear patterns in historical sales data. The neural network was configured to adjust to seasonal fluctuations and trends of each product, providing an advanced tool that outperforms traditional prediction techniques. Based on this accurate prediction, the company was able to anticipate changes in demand, which facilitated proactive inventory management aligned with market needs (See Figure 1).

Evaluation of the Hybrid Model's Performance Against the Simple Moving Average Forecast Model

To verify the efficiency of the hybrid approach in comparison with the simple moving average forecast model, the forecast quality was assessed using the metrics Mean Absolute Percentage Error (MAPE), Mean Squared Error (MSE), and Mean Absolute Deviation (MAD).

The study was conducted considering a simple random sampling from a population of N=165 products. A sample size of n=20 (fraction f=12.1%) was established. With this size, for the estimation of proportions in the worst-case scenario (p=0.5) and applying the finite population correction, the maximum estimation error was ±20.6 percentage

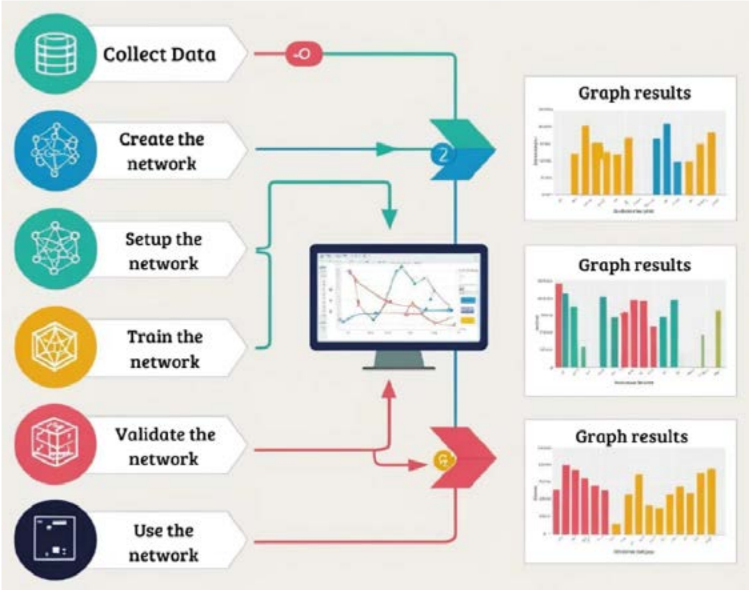

Figure 1. Methodology for network training.

points at a 95% confidence level (±17.3 p.p. at 90%). For means, the margin of error was approximately 0.412·s at 95% confidence.

This sample size was adopted based on feasibility criteria, providing sufficient precision for the study's exploratory objectives while accounting for time and resource limitations. The results are presented in Table 4.

In Table 4, it can be observed that the average MAPE was lower than 0.2673. According to Montes de Oca-Sánchez and Loza-Hernández (2025), MAPE is used as a key metric to compare the performance of forecasting methods, with models presenting lower MAPE values being considered superior. In the context of this study, establishing a threshold of MAPE <5% is regarded as a high-accuracy target, consistent with common practice in planning and forecasting.

To further reinforce the validity of the proposed model, and in accordance with de Castro Moraes, T., Qin, J., Yuan, X.-M., & Chew, E. P. (2023). Researchers propose hybrid architectures with evolutionary optimization for newsvendor-type decisions. A real-world case demonstrated up to 85% lower costs compared to a univariate benchmark and up to 40% savings relative to a simpler architecture, indicating better performance than traditional approaches and more basic neural network models. A comparison was carried out between the actual demand values and those forecasted by the neural network. Table 5 presents the results most relevant to the period October

Table 4. Calculation of the metrics MAPE, MSE and MAD.

n	Description (kg)	MAPE	MSE	MAD
1	FATTENING SHEEP 40	0.1405	1.2071	0.9092
2	BOVIPOP 40	0.0371	0.0011	0.0270
3	SOYBEAN HUSK 35	0.0017	0.0011	0.0129
4	CATLINE 15	0.0972	1.7864	1.1463
5	PIG FATTENING MIX 40	0.0490	0.6579	0.0184
6	RABBIT GROWTH 40	0.0118	0.0839	0.0869
7	HIGH-GENETICS GROWTH 20	0.0119	0.0007	0.0202
8	HIGH-GENETICS GROWTH 5	0.0440	0.0004	0.0164
9	FLEXI GROWTH 20	0.0073	0.0008	0.0242
10	DAIRY COW 12% 40	0.0138	0.0830	0.0858
11	STEER FATTENING 16% 40	0.0405	0.0002	0.0134
12	BLACK ROOSTER 10% 40KG	0.0135	0.0008	0.0229
13	PURPLE ROOSTER 29% 40	0.6553	0.0065	0.0715
14	SPECIAL MAINTENANCE ROOSTER BLUE 38	0.0458	0.0033	0.0436
15	POLLAZO 5	0.0195	0.0001	0.0096
16	EGG LAYER 5	0.2190	0.0010	0.0061
17	CITRUS PULP 40	0.0084	0.0009	0.0241
18	WHEAT BRAN 40	0.0288	0.0017	0.0319
19	SUPER WEANING 20	0.0457	0.0007	0.0169
20	GROWTH PLUS 40	0.2633	0.0003	0.0134

Table 5. Results of the hybrid model for the period October 2023-September 2024.

Description (kg)	Oct-23	Nov-23	Dec-23	Jan-24	Feb-24	Mar-24	Apr-24	May-24	Jun-24	Jul-24	Aug-24	Sep-24
FATTENING SHEEP 40	617	587	874	992	944	976	584	921	929	569	334	290
BOVIPOP 40	126	200	156	151	108	242	176	100	135	34	37	18
SOYBEAN HUSK 35	1227	957	871	1184	909	837	725	626	544	717	485	489
CATLINE 15	1573	1270	1675	1528	1167	1069	1170	1014	737	1072	877	839
PIG FATTENING MIX 40	50	75	50	50	75	25	75	75	100	49	48	75
RABBIT GROWTH 40	1290	723	1051	1308	817	1816	1671	1664	1320	1216	990	1056
HIGH GENETIC GROWTH 20	134	140	146	168	123	264	168	306	294	197	264	240
HIGH GENETIC GROWTH 5	53	55	69	75	20	83	34	10	34	28	28	46
FLEXI GROWTH 20	444	458	287	362	210	520	239	336	360	376	280	344
DAIRY COW 12% 40	614	1276	1176	1735	1547	1674	2036	1516	1396	696	491	546

2023-September 2024, which served as the basis for contrasting the outcomes of the Hybrid Newsboy-Neural Network model.

This analysis made it possible to identify the degree of fit and generalization capability of the model in reproducing actual demand fluctuations for agri-food products. By evaluating the absolute and relative differences between both datasets, a high correspondence was observed for most products, demonstrating the robustness of the model in contexts characterized by variable seasonality.

Figure 2 illustrates the comparative behavior between the actual demand model and the hybrid model outputs, revealing a strong alignment with the observed demand patterns.

Figure 3 shows the architecture of the network used as a feed-forward type with several hidden layers, using hyperbolic tangent as an activation function in the hidden layers and a linear function in the output layer. The descending gradient algorithm was used in the backpropagation learning process.

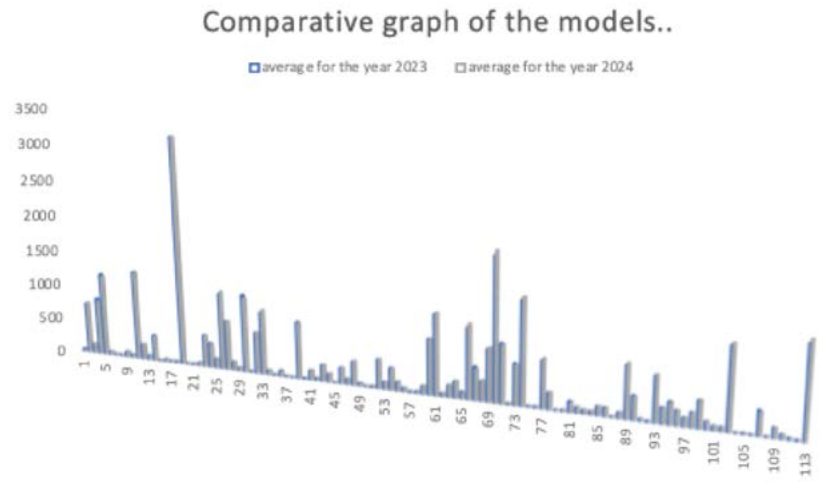

Figure 2. Comparative graph of the models.

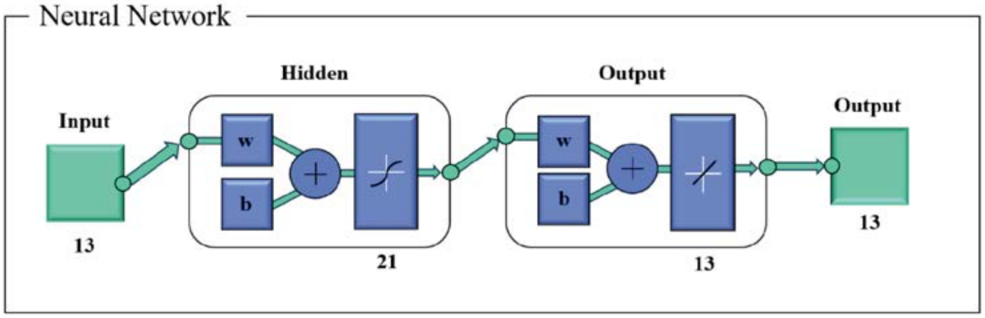

Figure 3. Network architecture.

In which a backpropagation neural network was developed in Matlab®, configured with 13 inputs, a hidden layer of 21 neurons, and the Levenberg-Marquardt algorithm for training. The dataset was divided into training and test subsets, and network parameters (number of neurons, learning rate, etc.) were adjusted to optimize its performance.

To justify the adopted architecture, parametric tests were implemented across different configurations of layers and neurons, as shown in Table 6. These tests allowed for the determination of the optimal structure, balancing accuracy and computational efficiency.

The evaluated configurations ranged from 14 to 23 neurons in the hidden layer, using the Levenberg-Marquardt training algorithm, which demonstrated faster convergence and lower fitting error compared with other available methods. Furthermore, the Levenberg-Marquardt algorithm was selected because it provides an excellent fit for linear, nonlinear, and regression problems, making it the most appropriate structure for modeling the behavior of the data analyzed in this study (regression).

Based on these results, the selected architecture —comprising 13 input variables, one hidden layer with 21 neurons, and one output node— achieved the lowest Mean Squared Error (MSE=0.00006) and correlation coefficients greater than 0.99 across all training,

Table 6. Tests of network properties and training parameters of the network.

Configuration number	Network properties		Training parameters			Network results			
Number	Layers	Neurons	Epochs	Goal	Max fail	Training	Validation	Test	MSE
1	2	14,13	9	0.0	6	0.07110	0.07149	0.05276	225636.87
2	2	15,13	15	0.0	6	9.99377	0.95705	0.97787	342.52988
3	2	16,13	8	0.0	6	0.51049	0.65764	0.58985	297786.9
4	2	17,13	10	0.0	6	0.57607	0.47044	0.669412	339136.5
5	2	18,13	16	0.0	6	0.96496	0.86668	0.93771	20190.5
6	2	19,3	40	0.0	6	0.99985	0.98297	0.97299	8.68784
7	2	20,13	1000	0.0	6	0.58097	0.65260	0.70595	24800.0
8	2	21,13	1000	0.0	0	0.99999	0.99918	0.99583	0.00006
9	2	22,13	1000	0.0	0	0.94885	0.72910	0.90635	22810.61
10	2	23,13	1000	0.0	0	0.99999	0.99678	0.99766	0.000006

validation, and testing datasets. Additionally, the demand data underwent a normalization and cleaning process, during which outliers were removed and missing records were completed through interpolation. The results of these tests are presented in Table 6.

Regarding data preprocessing, it was carried out using the Delphi method, following the approach described by Krajewski, L. J., Ritzman, L. P., & Malhotra, M. K. (2020). The process began with the first phase: Preparation or Planning, during which the general objective was defined: To identify the main factors that will influence the demand for agri-food products over the next five years and to estimate their expected behavior, to support production and inventory decisions.

Specific objectives were also established, followed by the selection of the expert panel, composed of 10 experts from the company's inventory department and agricultural associations. The selection criteria included a minimum of five years of experience in agricultural economics, marketing, or production planning. Anonymity among experts and commitment to participate in at least three rounds were also ensured. Subsequently, an initial open-ended questionnaire (Round 1) was designed, with questions such as: What will be the most determining factors influencing the demand for agri-food products over the next five years? What changes in consumer behavior will affect demand? Responses were collected through an electronic form, coordinated by a moderator.

In the second phase —Execution or Iteration of the First Round, open-ended responses were collected and analyzed. The research team grouped repeated ideas and classified factors into the following categories: Economic (prices, inflation, exchange rate), Productive (technology, efficiency, costs), Environmental (droughts, climate variability), Social (healthy preferences, local consumption), Political (subsidies, regulations). A consolidated list of 13 proposed variables or factors was then developed.

In the second round, the same experts were provided with a new structured survey using a Likert scale (1 to 5) to rate the importance and expected impact of each factor. Statistical indicators such as mean, standard deviation, and interquartile range were analyzed, and factors showing greater dispersion were marked for re-evaluation in the following round.

During the third round, the experts were presented with aggregated results and asked to reconsider their ratings, either maintaining or adjusting them based on group feedback, with the objective of reaching consensus and stabilizing the responses. A consensus criterion was established: Consensus was considered achieved when 80% of the experts assigned scores within a range of ± 1 point and the standard deviation was below 1.

Finally, the third and last phase —Analysis and Synthesis— presented the expected results, identifying the 13 critical variables that reached the highest level of agreement. The panel of experts concluded that agri-food demand will remain on a growth trend but will become more volatile, particularly for healthy and locally sourced products. The Delphi method results can serve as an input for a demand forecasting model in the agri-food sector, providing a foundation for adjusting inventory parameters or supply strategies.

Performance metrics to quantify the effectiveness of the model

To support the effectiveness of the model, statistical performance metrics were incorporated to evaluate the predictive accuracy of the neural network objectively. The results presented in Table 7 show that the model achieved a Mean Squared Error (MSE) of 0.00068 for the training set, 0.97098 for validation, and 0.30993 for testing, maintaining in all cases a correlation coefficient (R) greater than 0.99.

These values demonstrate a high generalization capability, confirming that the neural network effectively learned the nonlinear relationships between the input variables and the resulting demand. Moreover, the consistency of the R values across the three datasets supports the stability of the model, indicating that overfitting was successfully avoided.

Thus, the inclusion of these metrics complements the previous qualitative analysis and provides robust empirical evidence validating the performance of the Hybrid Newsboy-Neural Network approach in demand forecasting.

Neural networks possess a remarkable ability to identify underlying patterns in data and to distinguish signal from noise, even in highly variable environments. This property enables the model to maintain stable performance when dealing with noisy or imperfect data (Goodfellow, Bengio, & Courville, 2016).

Unlike traditional statistical methods, neural networks can process incomplete or noisy information due to their distributed structure and the redundancy of their connections (Haykin, 2009).

RESULTS AND DISCUSSION

The application of the Newsboy model, in its normal distribution approach, generated optimal inventory quantities adjusted to the probabilistic demand for each product. When comparing demand and results across these approaches, it was observed that the Newsboy model with a normal distribution provided more accurate and consistent results in reducing inventory costs and preventing shortages. The results obtained show a high accuracy in the prediction of demand, corroborated by the correlation coefficients (R) close to 1 in the training, validation, and test sets. Neural networks, trained on historical demand data, have demonstrated an exceptional ability to identify complex patterns and seasonalities in data, which has been crucial for optimizing inventory levels.

The combination of neural networks with the coefficient of variation and the Newsboy model has resulted in a highly effective inventory management strategy. The coefficient of variation has made it possible to classify products according to their level of uncertainty, while the Newsboy model, adjusted with the predictions of neural networks, has provided the optimal inventory levels for each product.

Table 7. Performance metrics to quantify the effectiveness of the model.

Datasets	Samples	MSE	R
Training	75%	0.00068	0.99999
Validation	15%	0.97098	0.99958
Testing	15%	0.30993	0.99992

The analysis of the graphs (Table 7) confirms the excellent performance of the neural networks. R values close to 1 across all datasets indicate a high correlation between predicted and actual values, suggesting that the model has accurately captured demand dynamics. Based on these results, the selected architecture —comprising 13 input variables, one hidden layer with 21 neurons, and one output node— achieved the lowest Mean Squared Error (MSE=0.00006) and correlation coefficients greater than 0.99 across all training, validation, and testing datasets.

As far as the implementation of neural networks is concerned, it has been essential to improve the accuracy of demand predictions and, consequently, optimize inventory management. The synergy between neural networks and probabilistic models has enabled the development of a robust solution adaptable to market fluctuations.

The results of this study support the idea that neural networks, combined with probabilistic models such as the Newsboy model, can revolutionize operations management across various sectors. In the specific case of the agri-food industry, this approach offers a competitive edge by enabling more informed and efficient decision-making. Similar to the work of Cardozo Rueda (2022), where neural networks were used to predict coffee prices to optimize decision-making in complex economic markets, this study also employs a forecasting model. It allows for analyzing cases where demand is uncertain, which is also essential in the agri-food sector.

The findings of this research profoundly demonstrate the efficacy of integrating neural networks with probabilistic models, such as the Newsboy model, to enhance inventory management within agri-food enterprises. The application of this methodology to the organization resulted in a considerable increase in the precision of demand forecasting, which consequently led to a reduction in operational costs and an elevation in product availability. This exemplifies that continuous model updates enable alignment with actual demand and enhance customer service, as supported by Noriega (2021) and Jara Cordero *et al.* (2017).

However, it is essential to note that the successful implementation of these tools requires adequate data collection and processing, as well as specialized knowledge. In addition, it is critical to monitor results and adjust models as market conditions change continuously.

CONCLUSIONS

Product classification based on the coefficient of variation proved to be a key tool for tailoring inventory strategies to the specific characteristics of each product. The Newsboy model, adjusted with the predictions of neural networks, proved to be particularly effective in managing the uncertainty inherent in the demand for agri-food products. The integration of neural networks has enhanced the accuracy of predictions, as it facilitates the identification of seasonal patterns and intricate fluctuations in demand that conventional empirical methods are unable to detect. This AI-driven approach complements probabilistic models by providing the agri-food company with a more detailed and calibrated perspective on future demand, thereby supporting more informed decisions in inventory management. In conclusion, this study opens up new perspectives for supply chain optimization in the agri-food sector. The application of advanced data analysis and techniques allows companies to improve their efficiency, reduce costs, and offer a better service to their customers. Future research is recommended to explore the application of these methodologies in other sectors and evaluate the long-term impact of these solutions.

REFERENCES

Ahumada, O., & Villalobos, J. R. (2009). Application of planning models in the agri-food supply chain: A review. **European Journal of Operational Research, 196**(1), 1-20. https://doi.org/10.1016/j.ejor.2008.02.014

Cardozo Rueda, K. (2022). Application of artificial neural networks for coffee forecasting. *Colombian Journal of Advanced Technologies*, 39.

Cruz R, R. S., & Correa, C. (October-December 2017). Intermittent demand forecasting with time series methods and artificial neural networks: Case study. *DYNA*(84), 9-16. doi:https://doi.org/10.15446/dyna.v84n203.63141

De Castro Moraes, T., Qin, J., Yuan, X.-M., & Chew, E. P. (2023). Evolving Hybrid Deep Neural Network Models for End-to-End Inventory Ordering Decisions. *Logistics, 7*(4), 79.

Feizabadi, J., et al. (2020). Machine learning demand forecasting and supply chain performance. **International Journal of Production Research**. https://doi.org/10.1080/13675567.2020.1803246

Gelmi, M. E., & Seoane, R. S. (2013). Deterministic and probabilistic models for the estimation of nitrate load in a rural basin. *Journal of the Faculty of Agrarian Sciences, 45*(2), 245-255. Retrieved from http://www.redalyc.org/articulo.oa?id=382837655008

Goodfellow, I., Bengio, Y., & Courville, A. (2016). Deep Learning. MIT Press.

Han, J. (2024). Deep Neural Newsvendor. *SSRN Working Paper*. https://doi.org/10.2139/ssrn.4582188

Haykin, S. (2009). Neural Networks and Learning Machines (3rd ed.). Pearson Education.

Heredia Roldán, M., Baroja Payán, E., Gurruchaga Rodríguez, M., & Báez Sentíes, O. (2024). Application of a Probabilistic Inventory. Model to Industrial Band Families in the Supply Chain. *International Journal of Combinatorial Optimization Problems and Informatics*, 113-124.

Jara Coredero, S., Sánchez Partida, D., & Martínez Flores, J. (2017). Analysis for the improvement of inventory management of a marketing company. *Journal of Industrial Engineering*, 1-18.

Krajewski, L. J., Ritzman, L. P., & Malhotra, M. K. (2020). Administración de operaciones: Procesos y cadenas de suministro (10.ª ed.). Pearson México.

Martínez Noriega, H. (September 2021). Evaluation of Artificial Intelligence techniques for the forecasting of coastal flooding due to sea penetration. *University of Computer Science Scientific Series, 14*(9), 16-27.

Montes de Oca-Sánchez, J. A., & Loza-Hernández, J. M. (2025). Comparativo de métodos de pronóstico en series de tiempo para la demanda de repuestos automotrices. *Revista Ingeniería, Innovación y Desarrollo, 5*(2), 45-60.

Parreño Fernández, J., De la Fuente García, D., & Pino Díez, R. (2002). Influence of forecasting methods on inventory management. Logistics.

Ríos, F., Martínez, A., Palomo, T., Cáceres, S., & Díaz, M. (2008). Probabilistic inventories with independent demand for continuous review, models with new orders. *Science Ergo Sum*, 15, 251-258. Retrieved from http://www.redalyc.org/articulo.oa?id=10415303

Rodríguez Rodríguez, R., Gómez Gasquet, P., & Oltra Badenes, R. (2014). Model of indirect transfer of manufacturing options between. *Bulletin of the Spanish Society of Ceramics and Glass*. doi:http://dx.doi.org/10.3989/cyv.332014

Romero, M. (2019). Optimización de la gestión del inventario usando programación matemática en una empresa de muebles. *Revista de Investigación Aplicada en Ingeniería UPB/UPTap, 4*(1), 1-10. ISSN 2448-5896

Terán Villanueva, J. D., Ibarra Martínez, S., Laria Menchaca, J., Castán Rocha, J. A., Treviño Berrones, M. G., García Ruiz, A. H., & Martínez Infante, J. E. (January-March 2019). Study of neural networks for the prediction of the demand for subjects. *Journal of the Faculty of Engineering*, 28, 34-43. doi:https://doi.org/10.19053/01211129.v28.n50.2019.8783