

Evaluating the Effectiveness of ARIMA and Radial Basis Function Neural Network Models in Sales Forecasting for a Cheese Supply Chain

تقييم فعالية نموذجي ARIMA ودالة الأساس الشعاعي (RBF) للشبكات العصبية في التنبؤ بالمبيعات لسلسلة توريد الجبن

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Received: 13/07/2025

Accepted: 24/09/2025

Published: 30/09/2025

Abstract:

Sales Forecasting is pivotal for improving logistics and enhancing the efficiency of supply chain management. Various forecasting methodologies have been developed, each with its strengths and limitations. This study aims to evaluate and compare the performance of two demand forecasting approaches: the Autoregressive Integrated Moving Average (ARIMA) model and the Radial Basis Function Neural Network (RBFNN). The analysis is based on daily cheese sales data obtained from a cheese factory in Maghnia. Model performance is assessed using the Root Mean Square Error (RMSE) metric. The experimental results indicate that the ARIMA model slightly outperforms the RBFNN model in forecasting accuracy for this dataset, underscoring the potential superiority of statistical methods in certain contexts

Keywords: Supply chain management, Sales Forecasting, autoregressive integrated moving average (ARIMA) Models, Radial Basis Function Neural Network (RBFNN).

Jel Classification Codes : c45 ; c53 ; q13 ; m31

ملخص:

تنبؤ المبيعات محوري لتحسين الخدمات اللوجستية وتعزيز كفاءة إدارة سلسلة التوريد. تم تطوير منهجيات التنبؤ المختلفة، ولكل منها نقاط القوة والقيود. تهدف هذه الدراسة إلى تقييم ومقارنة أداء نهجين التنبؤ بالطلب: نموذج المتوسط المتحرك المتكامل (ARIMA) المتكامل للانحدار والشبكة العصبية للوظيفة الشعاعية (RBFNN). يعتمد التحليل على بيانات مبيعات الجبن اليومية التي تم الحصول عليها من مصنع للجبن في Maghnia. يتم تقييم أداء النموذج باستخدام مقياس خطأ مربع الجذر (RMSE). تشير النتائج التجريبية إلى أن نموذج ARIMA يتفوق قليلاً على نموذج RBFNN في التنبؤ بدقة مجموعة البيانات هذه، مما يؤكد على التفوق المحتمل للطرق الإحصائية في سياقات معينة. الكلمات المفتاحية: إدارة سلسلة التوريد، التنبؤ بالمبيعات، نماذج المتوسط المتحرك المتكامل الانحداري التلقائي (ARIMA)، الشبكة العصبية لوظيفة الأساس الشعاعي (RBFNN).

تصنيف Jel: c45 ; c53 ; q13 ; m31

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Introduction :

Supply Chain Management (SCM) has emerged as a critical area of focus in contemporary business scholarship and practice, driven by the need to integrate and optimize processes across the entire supply chain from raw material suppliers and manufacturers to distribution networks and, ultimately, the end consumer. In today's highly competitive and globalized business landscape, supply chains have grown increasingly expansive and intricate. While individual entities within the chain, such as suppliers, manufacturers, or distributors, may prioritize locally optimal decisions, the overall efficacy and performance of the supply chain hinge on coordinated, system-wide optimization (Abolghasemi, 2020). A persistent challenge for decision-makers lies in the limited understanding of the operational dynamics and behavioral intricacies of supply chains, which underscores the need for robust analytical frameworks and advanced methodologies. Central to effective SCM is the practice of demand forecasting, which serves as a cornerstone for strategic and operational decision-making, particularly in the realm of inventory management. Accurate demand and supply forecasts are essential for maintaining optimal inventory levels: insufficient supply risks lost revenue due to stockouts, whereas excess supply incurs costs associated with markdowns or disposal of surplus stock. This delicate balance is especially critical in industries dealing with perishable goods, such as the cheese sector examined in this study, where inventory management directly influences profitability and competitive positioning (Niu, 2024). Consequently, the continuous monitoring and refinement of procurement and inventory strategies represent vibrant areas of research aimed at bolstering organizational resilience and market advantage. Demand forecasting has traditionally relied on statistical techniques, such as exponential smoothing and the Autoregressive Integrated Moving Average (ARIMA) models popularized as the Box-Jenkins methodology, which remain widely adopted due to their interpretability and computational simplicity. However, these conventional approaches often falter when applied to the non-linear, dynamic, and multifaceted nature of modern supply chains (Sarhani, 2014). In response, artificial intelligence (AI)-based methodologies have gained prominence as powerful alternatives for enhancing forecasting accuracy in complex systems. Among these, Artificial Neural Networks (ANNs) stand out as a leading technique, celebrated for their ability to model intricate patterns and relationships within data (Kochak A. & -1., 2015). Complementary AI approaches, including genetic algorithms, fuzzy logic, and support vector machines, have also been leveraged to address the limitations of traditional models, particularly in non-linear forecasting scenarios (Dash R. M.-5.). Within the ANN family, Radial Basis Function Neural Networks (RBFNN) have garnered particular attention due to their rapid training capabilities and effectiveness in capturing non-linear dynamics, making them a promising tool for supply chain demand forecasting. This study explores the evolving landscape of demand forecasting within SCM, with a focus on the application of advanced AI techniques to improve decision-making in the context of perishable goods. By addressing the limitations of traditional statistical models and highlighting the potential of AI-driven approaches, it aims to contribute to the growing body of knowledge on optimizing supply chain performance in an increasingly complex global economy.

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1.1 Research Problem

Drawing on the context provided, this study formulates the following research question: How effective is the application of ARIMA and Radial Basis Function Neural Network (RBFNN) models in forecasting sales within the cheese supply chain of a company?

1.2 Research Focus

This study focuses on enhancing demand forecasting accuracy within Supply Chain Management (SCM) by examining the limitations of traditional statistical methods, such as ARIMA, and evaluating the effectiveness of Artificial Intelligence (AI) techniques, particularly Artificial Neural Networks (ANNs) and Radial Basis Function Neural Networks (RBFNN). The research focuses on the perishable goods sector, where accurate demand predictions are essential for minimizing waste, optimizing inventory levels, and enhancing supply chain performance. By comparing traditional and AI-based forecasting models, the study aims to contribute to the development of more resilient, data-driven supply chains in today's complex and dynamic business environment.

1.3 Research Aim and Research Questions

The primary objective of this study is to explore and evaluate the effectiveness of advanced Artificial Intelligence (AI) techniques particularly Artificial Neural Networks (ANNs) and Radial Basis Function Neural Networks (RBFNN) in improving demand forecasting accuracy within Supply Chain Management (SCM), with a special emphasis on the perishable goods sector. By comparing AI-based models with traditional statistical methods such as ARIMA, the research seeks to enhance inventory optimization, reduce forecasting errors, and strengthen the responsiveness and efficiency of supply chains operating in complex and dynamic environments. Her research is designed to address the following questions:

- 1-What are the main limitations of traditional statistical models, such as ARIMA, in forecasting demand in complex supply chains?
- 2-To what extent can AI-based approaches-especially RBF Neural Networks-improve the accuracy of demand forecasting in the perishable goods industry?
- 3-How does improved forecasting accuracy affect inventory management and supply chain performance in sectors dealing with perishable products?
- 4-What are the practical implications of integrating AI-driven forecasting models into supply chain strategies for enhancing competitiveness and decision-making agility?

1.4 Literature Review

Modern supply chains are characterized by a high degree of complexity and uncertainty, stemming from a combination of factors such as supply network structure, partner interactions, shifting customer and competitor behavior, technological innovations, and new product development. Collectively, these factors contribute to increased supply chain volatility. This volatility leads to demand instability, making it essential to identify and predict sources of uncertainty to mitigate their negative impact on supply chain performance. Numerous studies have explored demand forecasting through diverse methodologies, employing both traditional

statistical techniques and advanced machine learning approaches. Below is a refined synthesis of key contributions from prior research:

(Mahin, 2025) Also proposed an innovative approach using machine learning algorithms. Among the tested models, the ensemble Voting Regressor outperformed the others, achieving the lowest RMSE (1.54) and the highest R^2 (0.9999), demonstrating superior accuracy and efficiency in sales forecasting.

(Ranawaka, 2024) Used LSTM networks combined with CNN, ARIMA, and BPNN for demand forecasting. The CNN-LSTM model proved to be the best, achieving the lowest MAE, MAPE, MSE, and RMSE, with hyperparameter tuning and cross-validation improving its accuracy.

(Borucka, 2023) compared several models for short-term demand forecasting of products with seasonal fluctuations, including seasonal ARIMA, ARIMA with Fourier terms, ETS, and TBATS. The study demonstrated that even with limited data, selected mathematical methods can effectively predict demand, offering an alternative to machine learning models. The results were compared, and the optimal solution for improving supply chain demand forecasting was identified.

Bousqaoui (2021) conducted in the context of a Moroccan supermarket, This study evaluated four forecasting models—ARIMA, Multi-Layer Perceptron (MLP), Long Short-Term Memory (LSTM), and Convolutional Neural Networks (CNN)—using historical demand data. The results demonstrated that CNN marginally surpassed LSTM in predictive performance, highlighting the potential of deep learning techniques in retail demand forecasting.

Husna (2021) focused on grocery sales in Ecuador; this research compared ANN, CNN, and LSTM models. The results identified LSTM as the top-performing approach, suggesting its strength in modeling temporal dependencies within sales data.

(Praveen, 2019) also aimed to accurately forecast demand using a multi-layer feed-forward neural network model with backpropagation, which helps address rapid changes in customer demand and reduce supply-demand discrepancies, ultimately leading to increased profit margins.

(Fattah, 2018) used the ARIMA model to predict future demand, finding that the ARIMA (1, 0, 1) model was the most effective for forecasting demand in food manufacturing.

(Vairagade, 2019) also aimed to forecast demand in Supply Chain Management (SCM) using machine learning techniques. The Random Forest model outperformed other models, including Artificial Neural Networks, in forecasting demand for grocery products. Performance was evaluated using R^2 , MSE, and MAE, with the Random Forest model demonstrating the highest accuracy.

(Shakti, 2017) Also used the ARIMA model to forecast tractor sales over ten years (2003-2014). He found that the ARIMA model effectively predicts sales for the next five years based on time series data patterns.

(Kochak A. & -1., 2015) Also used neural networks to forecast consumer product demand, demonstrating their effectiveness, especially over short forecasting periods, which helps improve production and inventory decisions.

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Dhini (2015). This research examined consumer demand forecasting within an Indonesian consumer goods company over two years. The study compared ARIMA, ANN, and a hybrid model combining the two. Findings indicated that ANN achieved superior accuracy compared to both the hybrid approach and ARIMA, underscoring the efficacy of neural networks in capturing complex demand patterns.

Benkachcha (2014). This investigation sought to enhance forecasting accuracy by comparing ANN with Multiple Linear Regression (MLR). The results affirmed ANN's greater efficiency, positioning it as a more effective tool for demand prediction compared to traditional regression techniques.

Kandananond (2012). This study contrasted ANN and Support Vector Machines (SVM) for demand forecasting in Thailand, utilizing Mean Absolute Percentage Error (MAPE) as the evaluation metric. The findings favored SVM, indicating its superior capability in minimizing forecasting errors in this context.

Aburto (2007). This study focused on demand forecasting for a Chilean supermarket, Economax, by integrating Autoregressive Integrated Moving Average (ARIMA) models with Artificial Neural Networks (ANNs) to create a hybrid framework. The findings revealed that ANNs outperformed standalone ARIMA models, while the hybrid approach yielded the highest accuracy. This enhanced precision enabled Economax to optimize inventory management and elevate service quality by reducing stockouts and sales losses.

Doganis (2006). This study proposed a non-linear sales forecasting model combining ANNs with genetic algorithms, applied to fresh milk sales data. The hybrid methodology exhibited robust forecasting performance, demonstrating the value of evolutionary optimization techniques in enhancing ANN-based predictions.

Based on the results of previous studies, there is no consensus on a specific method that is considered optimal. Therefore, this study aims to compare the ARIMA model with RBFNN forecasting sales within the cheese supply chain of a company.

2. Materials and Methods

To answer the research problem, this study adopted both descriptive and applied approaches. Two forecasting models, ARIMA and Radial Basis Function Neural Network (RBFNN), were employed, both grounded in mathematical logic for data analysis and processing. A quantitative approach was implemented by using these models to forecast sales, based on daily cheese sales data collected from a distribution company for the period from March 1, 2022, to May 31, 2022. This modeling aimed to identify the optimal forecasting method capable of enhancing forecast accuracy and supporting inventory decision-making.

2.1. Forecasting Models

2.1.1 ARIMA Models:

Autoregressive Integrated Moving Average (ARIMA) models, pioneered by Box and Jenkins (1970), are a cornerstone of time series forecasting, frequently referred to as Box-Jenkins models (Khatrı, 2024). These models are distinguished by their inductive approach, relying solely on historical data without presupposing specific patterns, making them versatile for both stationary and non-stationary time series. (Dash, 2020). The ARIMA framework encompasses

four iterative stages: model identification, parameter estimation, diagnostic checking, and forecasting. (Guha, 2016).

Model Identification: This initial step involves determining the appropriate orders of the ARIMA model, autoregressive (p), differencing (d), and moving average (q) denoted as ARIMA(p,d,q). Autocorrelation function (ACF) and partial autocorrelation function (PACF) plots are employed to infer preliminary model parameters by analyzing the time series' temporal dependencies (Atique, 2019)

Parameter Estimation: Once a tentative model is specified, parameters are estimated using methods such as least squares or maximum likelihood estimation. These techniques optimize the fit of the model to the observed data, ensuring robust statistical inference

Diagnostic Checking: The adequacy of the fitted model is evaluated using information criteria such as the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC), defined as:

$$AIC = -2 \log (\text{maximum likelihood}) + 2k$$

where (k) represents the number of parameters.

$$BIC = -2 \log (\text{maximum likelihood}) + 2 \log N$$

And (N) denotes the sample size.

Lower AIC and BIC values indicate a better balance between model fit and complexity.

Forecasting: The final step involves generating predictions based on the validated model, leveraging its ability to capture underlying patterns in the data. (Gebretensae, 2021)

ARIMA comprises autoregressive (AR) components of order (p), moving average (MA) components of order (q), and differencing (I) of order (d), denoted as ARIMA(p,d,q). Its equation is: (Yasmin, 2024)

$$\hat{y}_t = \mu + \phi_1 y_{t-1} + \dots + \phi_p y_{t-p} - \theta_1 e_{t-1} - \dots - \theta_q e_{t-q}$$

2.1.2 Radial Basis Function Neural Network (RBFNN)

The Radial Basis Function Neural Network (RBFNN) is a type of feedforward neural network, initially proposed by Broomhead and Lowe in 1988 (Zheng, 2013). It is characterized by its capacity for both supervised and unsupervised learning, alongside exhibiting hybrid properties when compared to other neural network architectures.

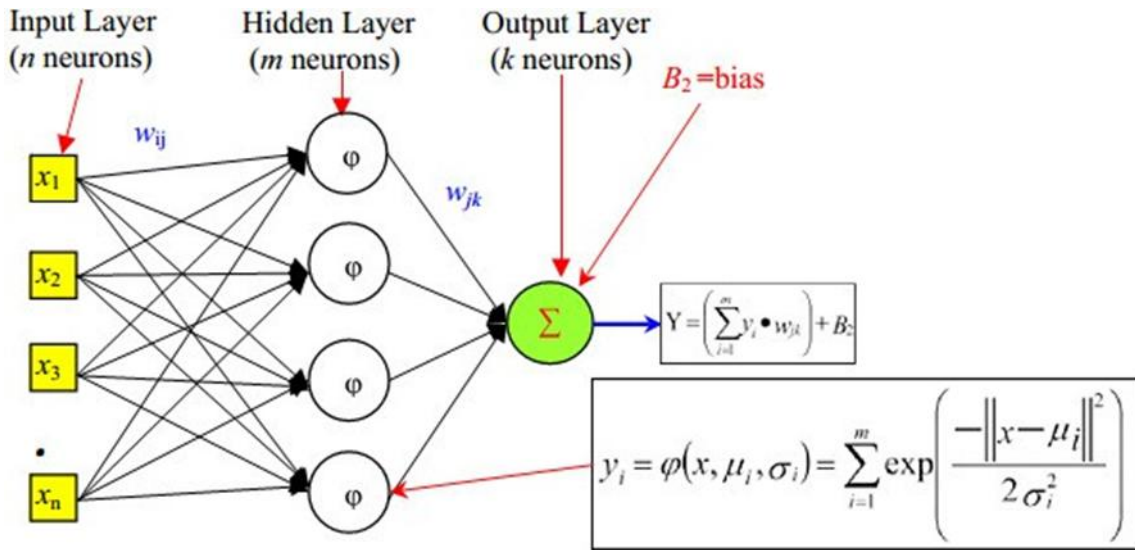
Furthermore, RBFNN serves as an approximation function, distinguished by its ability to model complex, multidimensional nonlinear systems with robust generalization performance, utilizing a relatively small number of radial basis functions. Additionally, it is noted for its rapid learning capabilities (Sideratos, 2020).

Structurally, RBFNN comprises three layers: an input layer, a single hidden layer, and an output layer. The activation function of the hidden layer must inherently be a radial basis function (Singh, 2014).

The diagram below illustrates the fundamental architecture of RBFNN, where data flows sequentially from the input layer, through the hidden layer, to the output layer. The input and output layers of RBFNN employ linear activation functions, whereas the neurons in the hidden layer utilize radial basis activation functions. Among the most commonly applied activation functions in practical applications is the Gaussian function.

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Figure 1: Radial basis function neural network (RBFNN) structure



Source: Heddarn, S. (2016). Simultaneous modelling and forecasting of hourly dissolved oxygen concentration (DO) using radial basis function neural network (RBFNN) based approach: a case study from the Klamath River, Oregon, USA. *Modeling Earth Systems and Environment*, 2(3), 1-18.

where:

$$\phi_i(x) = \|x - \mu_i\| \quad i = 1, 2, \dots, N$$

The term $\phi_i(x)$ refers to the output of the i -th hidden neuron, while $\|\cdot\|$ denotes the Euclidean distance. x is the input vector, μ_i is the center (vector) of the i -th hidden neuron, and ϕ refers to the activation function.

The activation function used in the hidden layer, as mentioned earlier (Gaussian), is written as follows:

$$\phi_i(x) = \exp\left(-\frac{\|x - \mu_i\|^2}{2\sigma_i^2}\right) \quad i = 1, 2, \dots, N$$

Finally, the output of the RBFNN model can be calculated as follows:

$$Y = \sum_{j=1}^N w_{ij} \phi_i(x) + B_2$$

Where:

w_{ij} refers to the weighted connections between the neurons of the radial basis function and the output of the neurons, (N) is the number of neurons in the hidden layer, and B_2 refers to the constant, representing the bias.

3. Analysis of Findings:

This research is based on the daily cheese sales data from the company, spanning from March 1, 2022, to May 31, 2022, encompassing a total of 92 observations. The primary objective is to conduct forecasting by employing Autoregressive Integrated Moving Average (ARIMA) models alongside Radial Basis Function (RBF) neural network models.

3.1 Descriptive Statistical Analysis and Graphical Representation of the Sales Time Series:

The statistical characteristics of the daily data for the time series utilized in this study will be analyzed to provide a comprehensive understanding of the dataset. The table below summarizes these statistical measures.

Table 1: Descriptive statistics for daily cheese sales data

	MEAN	MEDIA N	MAXIMU M	MINIMU M	STD. DEV.	SKEWNE SS	KURTOS IS
SALES	1322566.	1361630.	1.712878	839059.3	225423.7	-0.141149	1.942002

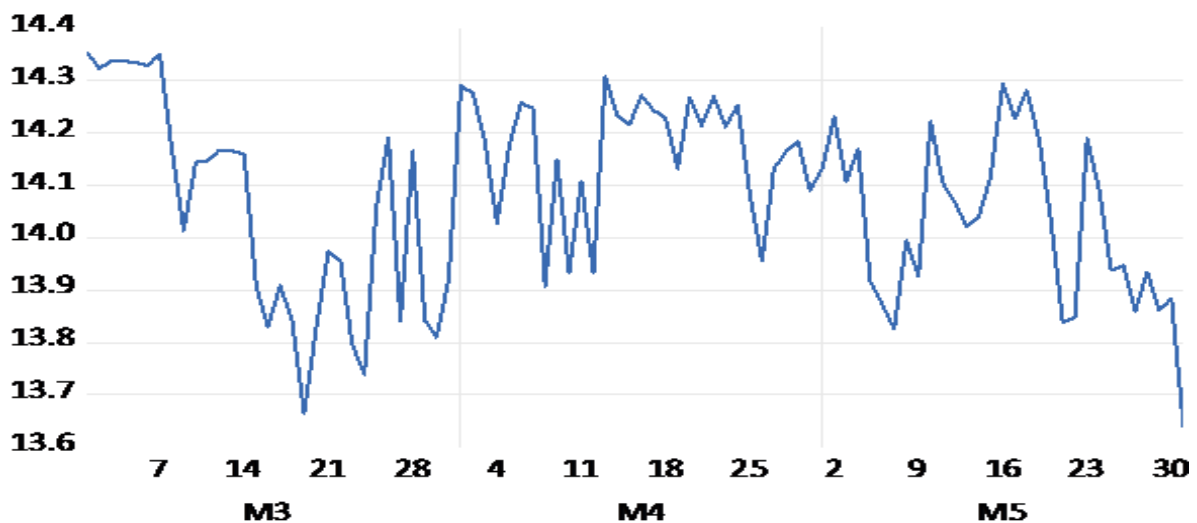
Source: Prepared by researchers using the Eviews 13 results

Based on the data presented in the table above, it is evident that the maximum value for daily sales amounted to 1.712878, with the minimum recorded at 839059.3. The arithmetic mean of the sales series was calculated to be 1322566, while the median and standard deviation were determined to be 1361630 and 225423.7, respectively. Furthermore, the kurtosis and skewness coefficients were computed as -0.141149 and 1.942002, respectively.

Notably, the kurtosis value, being less than 3, suggests a platykurtic distribution, indicating a relatively flattened curve for the data.

Figure 2 shows the time evolution of cheese sales, where the natural logarithm was applied to the data to reduce the effect of extreme values resulting from sudden increases in sales and to stabilize the variance of the time series.

Figure 2: Cheese sales chain
LNVENTE



Source: Prepared by researchers using the Eviews 13 results

Results

3.2 ARIMA Modeling and Box-Jenkins Methodology

For the application of the ARIMA model using the Box-Jenkins methodology, the time series was partitioned into a training set comprising 69 observations and a test set consisting of 23 observations.

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3.2.1 Training Phase: Stationarity Assessment

The stationarity of the series was evaluated during the training phase. Visual inspection of the time series plot (Figure 3) revealed a discernible trend and heteroscedastic behavior, indicative of non-stationarity. To formally test this hypothesis, the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests were conducted, both of which corroborated the presence of non-stationarity in the series

Table 2: ADF and PP test results

	AFD		PP	
	Level	First Difference	Level	First Difference
With Constant	-4.0514*** Prob. 0.0022	-7.5612*** Prob. 0.0000	-3.8870*** Prob. 0.0036	-21.6810*** Prob. 0.0001
With Constant & Trend	-4.0773** Prob. 0.0109	-7.6256*** Prob. 0.0000	-3.9785** Prob. 0.0143	-25.7957*** Prob. 0.0001
Without Constant & Trend	-0.3642 Prob. 0.5494(No)	-7.6115*** Prob. 0.0000	-0.3737 Prob. 0.5460(No)	-21.3551*** Prob. 0.0001

Notes:

a: (*) Significant at the 10%; (**) Significant at the 5%; (***) Significant at the 1% and (no) Not Significant

b: Lag Length based on SIC

c: Probability based on MacKinnon (1996) one-sided p-values.

Source: Prepared by researchers using the Eviews 13 results

The empirical findings delineated in the aforementioned table indicate that the sales time series exhibits non-stationarity, as evidenced by the results of both statistical tests. To render the series stationary, first-order differencing was applied, with the outcomes reported in the same table, confirming that the sales series achieved stationarity for both tests. To specify an appropriate ARIMA model, the autocorrelation function (ACF) and partial autocorrelation function (PACF) were graphically analyzed. Model selection was conducted by comparing candidate models using the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). After proposing several models, it became clear that the model that gives the lowest value of the Akaike and Schwarz criteria is the ARIMA (3,1,0) model.

Upon determining the most appropriate ARIMA specification for forecasting cheese sales, the subsequent stage entailed parameter estimation, which was conducted using the maximum likelihood estimation method. The results of this estimation process are presented in the table below.

Table 3: Model estimation

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.002954	0.008056	-0.366627	0.7152
AR(1)	-0.452816	0.102541	-4.415950	0.0000
AR(2)	-0.307923	0.125058	-2.462233	0.0167
AR(3)	-0.329595	0.096551	-3.413701	0.0012
SIGMASQ	0.017942	0.003325	5.395400	0.0000
R-squared	0.242693	Mean dependent var	-0.002868	
Adjusted R-squared	0.191351	S.D. dependent var	0.155139	

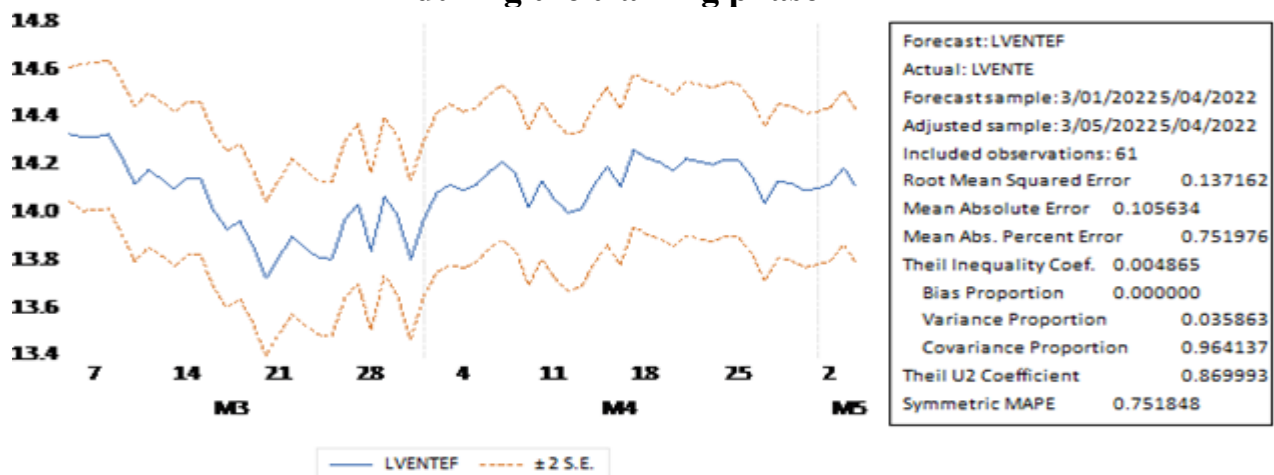
S.E. of regression	0.139509	Akaike info criterion	-1.018219
Sum squared resid	1.148303	Schwarz criterion	-0.849556
Log likelihood	37.58299	Hannan-Quinn criter.	-0.951774
F-statistic	4.726921	Durbin-Watson stat	1.980448
Prob(F-statistic)	0.002240		
Inverted AR Roots	.12+.68i	.12-.68i	-.69

Source: Prepared by researchers using the Eviews 13 results

The results presented in the aforementioned table indicate that the standard error (Std-Error) associated with the AR (3) term is notably lower than those for AR (1) and AR (2). Moreover, both the overall and individual parameter estimates demonstrate statistical significance, as evidenced by the student's t-test and Fisher's F-test, with p-values below the 0.05 threshold. The coefficient of determination (R^2) for the estimated model of cheese sales is calculated at 0.24, indicating that 24% of the variability in the series is explained by the model. Additionally, the absence of residual autocorrelation is substantiated by the Durbin-Watson (DW) statistic, which yields a value of 1.98, closely approximating the ideal value of 2 and residing within the acceptable confidence interval.

The culminating phase of the Box-Jenkins methodology involves forecasting. Following the estimation, diagnostic checking, and validation of the model to ensure its adequacy, the ARIMA (3,1,0) model is deemed suitable for generating predictions of future cheese sales. The subsequent figure delineates the forecasted values derived from this model, accompanied by an assessment of the forecasting accuracy based on the model's performance during the training phase.

Figure 3: Forecasted values obtained using the ARIMA (3,1,0) model, along with the assessment of forecast accuracy based on the estimated model during the training phase



Source: Prepared by researchers using the Eviews 13 results

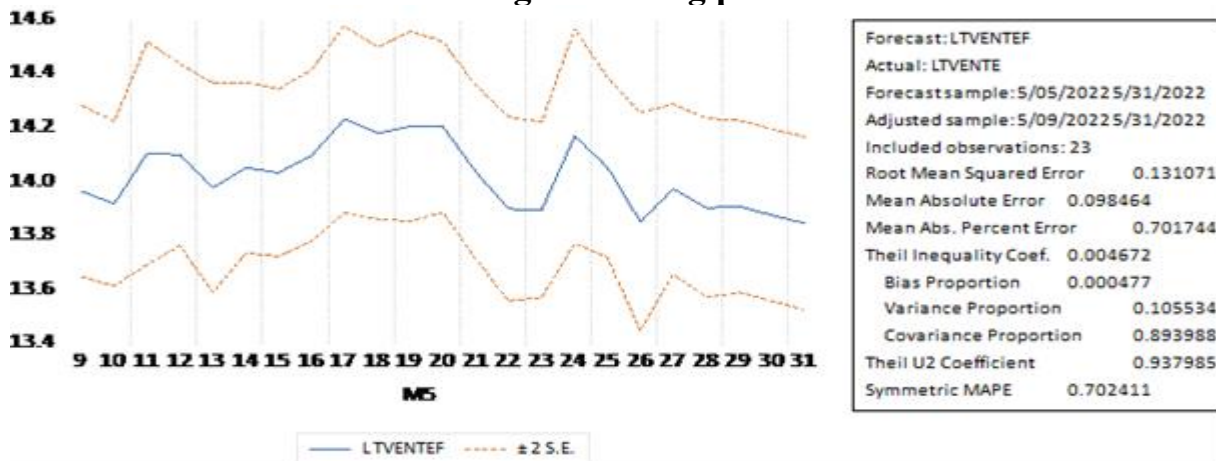
The analysis of the aforementioned figure reveals that the fitted ARIMA (3,1,0) model consistently resides within the confidence bounds delineated by one standard deviation, thereby supporting the inference that the model maintains statistical significance throughout the entire time series. Moreover, the divergence between the observed and forecasted values, quantified by the root mean square error (RMSE) of 0.137162, is minimal, underscoring the model's robust predictive precision.

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3.2.2 Testing Phase

Following the validation of the model's adequacy, it was applied to the test set, comprising the remaining 23 observations. The resultant findings are depicted in the subsequent figure.

Figure 4: Forecasted values obtained using the ARIMA (3,1,0) model, along with the assessment of forecast accuracy based on the estimated model during the testing phase



Source: Prepared by researchers using the Eviews 13 results

The analysis of the aforementioned figure indicates that the fitted ARIMA (3,1,0) model consistently falls within the confidence bounds established by one standard deviation, thereby affirming the statistical significance of the model across the entire time series. Furthermore, the divergence between the observed and forecasted values, as measured by the root mean square error (RMSE) of 0.131071, is minimal. Notably, the RMSE obtained during the training phase is lower than that observed in the testing phase, providing additional evidence of the model's robustness and superior predictive precision.

4. Radial Basis Function Neural Network (RBFNN) Model

The development of the RBFNN model entails adherence to the following methodological stages:

4.1. Data Partitioning Stage

The time series dataset will be segmented into training and testing subsets utilizing SPSS-25 software. This partitioning process will be executed through random allocation of observations. The proportions assigned to each subset are delineated in the table below.

Table5: Data partitioning stage

Groups	Percentageof Observations	Number of Observations
Training Set	70.8%	63
Testing Set	29.2%	26
Total Observations	100%	89

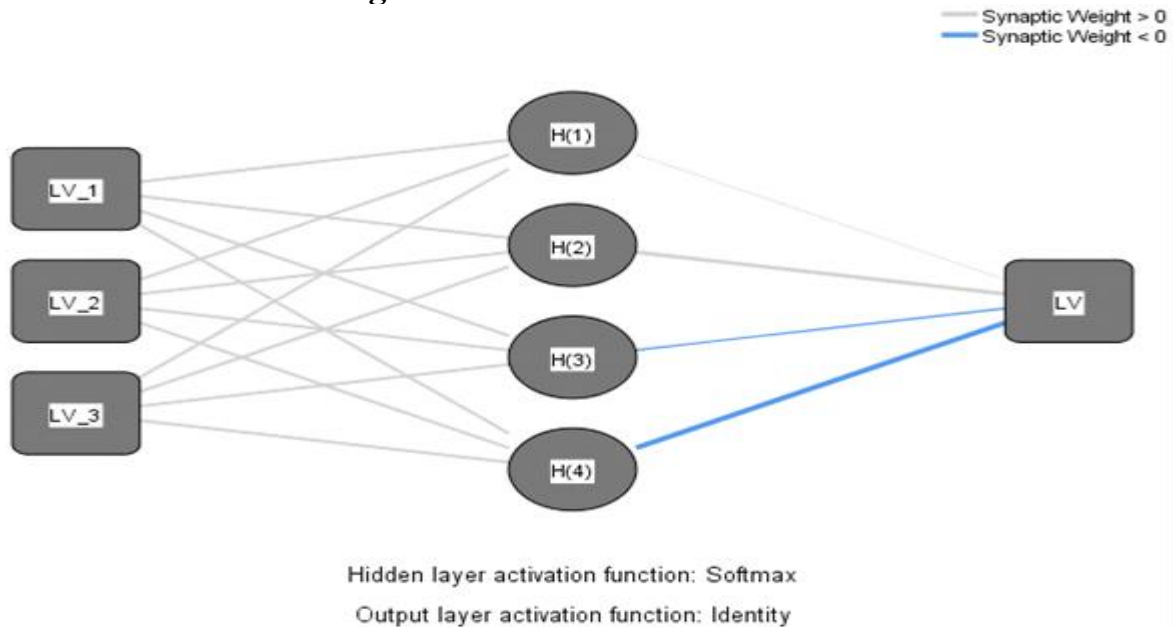
Source: Prepared by researchers using the SPSS 26 results

4.2 Architecture Specification Stage

A comprehensive evaluation of multiple prospective neural network configurations was conducted to ascertain the optimal architectural framework. Model selection was guided by the

minimization of the sum of squared errors (SSE) criterion. Empirical analysis revealed that the RBFNN (3,4,1) configuration produced the lowest SSE, thereby establishing it as the most appropriate model. This selected architecture is depicted in the figure below.

Figure 5: RBFNN architecture



Source: Prepared by researchers using the SPSS 26 results

Analysis of the figure reveals that the most effective architecture is structured across three layers: an input layer comprising three processing units, corresponding to the lag order, which was determined through optimization of the error function, specifically the sum of squared errors (SSE). A hidden layer incorporates four processing units, utilizing the non-linear normalized radial basis function as the activation mechanism. Lastly, an output layer consists of a single processing unit, employing the linear identity function as its activation function.

4.3 Model Summary

The subsequent table delineates the sum of squared errors (SSE) obtained during the training and testing phases.

Table 6: Sum of squared errors in the training and testing phases

	Sum of squared errors (SSE)
Training phase	21.602
Testing phase	5.669 ^a

Source: Prepared by researchers using the SPSS 26 results

Based on the results shown in the table, we note that the SSE value in the training phase is higher than the SSE value in the testing phase, which confirms the adequacy of the selected network.

5. Comparison Between the ARIMA Model and the RBF Neural Network

To evaluate the forecasting accuracy of the two models, the Root Mean Square Error (RMSE) criterion was employed. The following table summarizes the comparison results for the training and testing phases.

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Table 7 : Comparison results between ARIMA and RBFNN in the training phase

Models	RMSE
ARIMA	0.137162
RBFNN	0.59027058

Source: Prepared by researchers

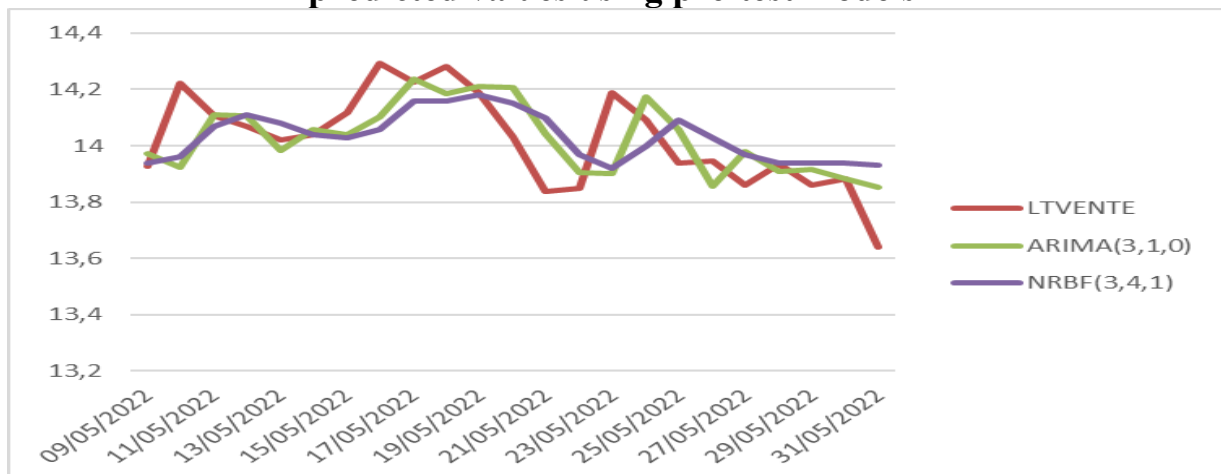
Table 7 presents the results of the comparison between the ARIMA and RBFNN models during the testing phase. Additionally, Figure 9 provides a graphical representation of the actual daily cheese sales alongside the predicted values generated by the aforementioned models for the testing phase.

Table 8 : Comparison results between ARIMA and RBFNN in the testing phase

Models	RMSE
ARIMA	0.131071
RBFNN	0.46694589

Source: Prepared by researchers

Figure 6: Graphical representation of actual daily cheese sales and predicted values using pre-test models



Source: Prepared by researchers using the Eviews 13 results

From the aforementioned figure, it is observed that the curve of the predicted values generated by the ARIMA model closely resembles the curve of the actual values for cheese sales, which were subjected to a natural logarithm transformation, in comparison to the curve of the predicted values obtained using the RBFNN neural network.

6. Discussion

Although significant emphasis was placed on Artificial Intelligence (AI) techniques, particularly neural networks such as RBFNN, the results indicate that traditional statistical models like ARIMA may still outperform AI-based models in certain contexts. This highlights the importance of aligning forecasting model selection with the specific characteristics of the data.

The superior performance of the ARIMA model in this study can be attributed to the nature of the data, which exhibits linear behavior and relative stability, making it well-suited to the characteristics of this statistical model. In contrast, the performance of the RBFNN model was less accurate, which should not be seen as a weakness of the model itself, but rather may be related to specific conditions such as the limited sample size or the lack of complex behavior

in the data. It is important to note that intelligent models, such as RBFNN, are more effective in cases characterized by nonlinearity or when complex patterns are difficult to capture using classical models. Therefore, these results do not diminish the importance of RBFNN, but rather suggest the need for further exploration of its performance in more dynamic contexts or with datasets that are more diverse and volatile, which may better highlight its predictive capabilities.

7. Conclusion

In this study, two forecasting approaches were proposed: one based on statistical models and the other leveraging modern techniques through Artificial Neural Networks (ANN). The first approach utilized the ARIMA model, widely recognized for its application in time series forecasting following the Box-Jenkins methodology. The second approach employed the Radial Basis Function Neural Network (RBFNN) model. Both methods were applied to predict daily cheese sales over the period from March 1, 2022, to May 31, 2022. For each method, experimental results were presented and analyzed based on the statistical criterion of Root Mean Square Error (RMSE). A comparative analysis between the statistical ARIMA model and the proposed RBFNN model revealed that the ARIMA model yielded lower errors and higher forecasting accuracy for time series data during both the training and testing phases.

Based on the findings, the following recommendations are proposed:

Conducting a comparative analysis between parametric and non-parametric models to identify the most effective models for modeling and forecasting cheese sales.

Exploring hybrid models that integrate the Radial Basis Function Neural Network with ARIMA models to enhance the accuracy of cheese sales predictions.

For future research, the development of additional models using a combination of qualitative and quantitative techniques is planned to achieve more reliable forecasts and improve prediction accuracy. Furthermore, an investigation into another type of artificial neural network, namely the Group Method of Data Handling (GMDH), will be undertaken to compare its performance with the ARIMA model, thereby validating the forecasting capability of the GMDH network for cheese sales.

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