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A Comparative Study of Machine Learning and Statistical Methods for Demand Forecasting in Supply Chains

Une étude comparative des méthodes statistiques et d'apprentissage automatique pour la prévision de la demande dans les chaînes d'approvisionnement

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Abstract

The selection of an appropriate demand forecasting method is crucial for effective supply chain management (SCM), as accurate forecasts help optimize inventory, production, and logistics. However, in markets characterized by high uncertainty and constant change, traditional statistical techniques, such as the ARIMA model, may not be sufficient to generate reliable and accurate forecasts. In response to this challenge, artificial intelligence (AI) algorithms, such as artificial neural networks (ANN) and random forests, offer promising solutions to improve forecasting accuracy. Despite this potential, the existing literature often provides only general descriptions of AI methods without comparing their performance in demand forecasting. This paper thus offers a comparative analysis of three main approaches used for demand forecasting : artificial neural networks, random forests, and the ARIMA model, evaluating their respective performances in the context of supply chain management. By assessing the strengths and limitations of each method, this study aims to provide valuable insights into their effectiveness and help companies choose the most suitable technique for their demand forecasting needs.

Keywords : Demand forecasting ; Artificial Neural Networks (ANN) ; Random Forests ; ARIMA model ; Comparative analysis.

Résumé

La sélection d'une méthode appropriée pour prévoir la demande est cruciale pour une gestion efficace de la chaîne d'approvisionnement, car des prévisions fiables aident à optimiser les stocks, la production et la logistique. Toutefois, sur des marchés caractérisés par une grande incertitude et des changements rapides, les techniques statistiques traditionnelles, telles que le modèle ARIMA, peuvent ne pas suffire à générer des prévisions précises et fiables. Face à ce problème, les algorithmes d’intelligence artificielle, tels que les réseaux de neurones artificiels (ANN) et les forêts aléatoires, offrent des solutions prometteuses pour améliorer la précision des prévisions. Cependant, la littérature existante se concentre souvent largement sur les méthodes d’IA sans explorer leurs performances comparatives en matière de prévision de la demande. Cet article propose donc une analyse comparative de trois approches principales utilisées pour la prévision de la demande : les réseaux de neurones artificiels, les forêts aléatoires et le modèle ARIMA, évaluant leurs performances respectives dans un contexte de gestion de la chaîne d'approvisionnement.

Mots-clés : Prédiction de la demande ; réseaux neuronaux artificiels (ANN) ; forêts aléatoires ; Modèle ARIMA ; analyse comparative.

Introduction :

The era of stable markets is over. Companies today face highly complex situations, marked by unexpected phenomena such as monetary crises, pandemics, climate change, and supply shortages. Demand forecasting is a central issue for supply chain management. Recent studies have shown that the adoption of artificial intelligence in logistics significantly improves forecast accuracy, in particular by reducing errors and optimizing inventory (Jucha, 2021; Patier et al., 2014). Simultaneously, the increasing demand within exceptionally short timeframes complicates this situation. This growing complexity hinders the transparency of material and information flows among supply chain stakeholders, which remains essential for effective planning and optimal resilience of the value chain (Herburger, 2022).

The integration of artificial intelligence into supply chain management has given rise to new approaches that combine traditional time-series forecasting methods with machine learning techniques, including the use of artificial neural networks to optimize forecasting processes(Zhang et al., 1998).

This technological evolution has led to a re-evaluation of traditional demand forecasting methods, favouring the adoption of AI-based solutions for better anticipation of customer needs (Belkadi, 2025) .

Machine learning, a subfield of artificial intelligence, relies on algorithms capable of autonomously learning and improving their performance based on historical data(Schmidhuber, 2015).

These innovative tools have caused a true revolution in the industry, allowing companies to adapt more quickly to trends and make decisions based on accurate data (BELHAJ, 2023).

One area where these technologies have had a particularly significant impact is supply chain management, which is a fundamental element of contemporary economic operations. The primary goal of supply chain management is to improve the flow of goods, reduce logistics costs, and enhance operational efficiency (BELHAJ, 2023).

Accurate demand forecasting is one of the major challenges in supply chain management. By precisely anticipating customer requirements, companies can prevent overstocking, which immobilizes financial resources and occupies excessive space, while minimizing the risk of stockouts (Chris Chatfield, 2000), which could lead to decreased sales and customer dissatisfaction.

The integration of artificial intelligence into supply chain management presents significant benefits, particularly in terms of cost reduction and improved operational efficiency. However, it also poses challenges, such as the need for specialized skills and managing the risks associated with adopting new technologies(Wu et al., 2014).

Demand forecasting involves estimating future consumption of goods or services to plan production, optimize delivery schedules, and assess the economic viability of projects or enterprises. Forecasting relies on quantitative (historical data), qualitative (expert judgment), or mixed approaches (mathematical analyses combined with expert estimations). These forecasts directly influence inventory management, investment decisions, equipment acquisition, capacity planning, and the financial health of a company. Essential to production management systems, they determine the relevance of financial indicators and the overall performance of industrial processes, even though no method can guarantee complete reliability (Michael Gilliland, Len Tashman, Udo Sglavo, 2016).

Over the years, various methods have been developed to anticipate demand, ranging from statistical approaches to advanced techniques based on artificial intelligence (Maisonobe & Jeannot, 2023). This article focuses on three main approaches: artificial neural networks (ANNs), random forests, and ARIMA models. Each of these methods presents distinct but complementary perspectives for modeling and forecasting demand trends in dynamic contexts. Artificial neural networks excel in capturing complex relationships and non-linearities within data, while decision tree ensembles, such as random forests, combine multiple models to provide robust predictions (Breiman, 2001). Finally, ARIMA is widely regarded as the most popular traditional statistical model for time series analysis, particularly when the series exhibits a stationary structure (Rob J Hyndman and George Athanasopoulos, 2018).

This article presents a performance analysis of these three methods applied to a dataset, providing insights into their strengths and limitations in demand forecasting.

This leads us to formulate our research problem as follows: **How can the adoption of artificial intelligence in demand forecasting improve supply chain management while overcoming the challenges of integration and optimizing inventory and forecast accuracy?**

To address this problem, this study evaluates the performance of three demand forecasting models ANNs, random forests, and ARIMA on a selected dataset, analyzing their accuracy in predicting demand and their suitability for different supply chain contexts.

The article is organized as follows. First, we provide an overview of the three forecasting methods. Then, we detail the experimental setup and methodology used to assess their performance. Finally, we present the results of the performance evaluation, followed by a discussion of the findings and their implications for supply chain management.

1 Literature Review

1.1 Supply Chain Management and Forecasting

Forecasting techniques play a crucial role in efficient supply chain management and can be classified into four primary categories, each possessing unique features and uses:

- **Qualitative Methods:** These methods depend on human insight and expert evaluations. They are particularly advantageous when historical data is lacking or in novel situations, such as the introduction of a new product. However, their reliance on subjective judgment may introduce considerable biases.
- **Time Series Methods:** These methods utilize historical data to identify trends and temporal patterns. Examples include moving averages and exponential smoothing. While they are effective for univariate time series analysis, these techniques often operate under the assumption that future trends will replicate past behaviors, which can restrict their applicability in scenarios involving disruptions or intricate relationships.
- **Causal Methods:** These methods operate on the premise that demand is affected by specific external factors, including economic conditions, interest rates, and government regulations.
- **Simulation Methods:** These methods aim to simulate customer behaviors and decisions to forecast demand. While they can effectively model complex situations, they are costly and demand substantial computational resources (Hyndman & Athanasopoulos, 2018).

In the existing literature, time series and causal methods have frequently been preferred.

Demand forecasting is based on several theoretical approaches that structure methodological choices and prediction models. Among them, time series theory (Box & Jenkins, 1970) is commonly used to analyze past trends and anticipate future variations. In addition, the rise of machine learning (Schmidhuber, 2015)has paved the way for more complex models such as neural networks and random forests, capable of capturing non-linear dynamics. Finally, inventory management theory (Lee et al., 1997) emphasizes the importance of making reliable forecasts to avoid stockouts and unnecessary storage costs.

In 1997, Lee, Padmanabhan, and Whang demonstrated the bullwhip effect, a phenomenon where demand variability increases as it propagates through the supply chain, disrupting inventory and flow management(Lee et al., 1997). Chen, Drezner, Ryan, and Simchi-Levi

(2000) conducted a further analysis of this phenomenon within a two-tier supply chain involving retailers and manufacturers. Their findings indicated that forecasting errors and order delays significantly contribute to the amplification of this effect(Chen et al., 2000). They also showed that demand information can be centralized and that coordination between different actors in the chain can reduce this effect.

One significant challenge that organizations encounter is the necessity for substantial data to ensure the accuracy of most quantitative methods. While these methods can capture nonlinear relationships, including complex interactions among variables, anomalies may lead to distorted results (Jordan & Mitchell, 2015). Neural networks present a promising alternative to address these challenges. Their capacity to learn and model nonlinear and complex relationships makes them particularly effective in dynamic and uncertain environments (Schmidhuber, 2015). Mathematically validated to approximate any function, neural networks exhibit a high degree of versatility (Hornik et al., 1989).

The utilization of neural networks in demand forecasting creates new opportunities for improving accuracy and resilience within supply chains, especially in contexts characterized by increasing uncertainty. Demand forecasting is a vital component of supply chain planning (Croson & Donohue, 2003). While forecasting is more straightforward for mature products with stable demand, it becomes significantly more challenging for highly volatile products due to shorter sales cycles and a increased errors. Accurate forecasting of such products is crucial, as errors for stable products have less severe consequences. It is imperative for managers to comprehend the characteristics of forecasting in order to effectively design and manage their supply chains before detailing forecasting elements and methods in supply chain management (Christopher, Martin, et Towill, Denis R, 2000).

1.2 Forecasting and Artificial Intelligence in the Supply Chain :

The supply chain is essential to sourcing and procurement activities, which include demand planning and inventory management (Mentzer et al., 2001). It manages the distribution of products and services from suppliers, warehouses, and manufacturing sites to points of sale and end customers. The control of physical, informational, and financial flows is fundamental to supply chain operations, as highlighted by the Association for Supply Chain Management (Chopra & Meindl, 2019).

In recent years, there has been a notable increase in the amount of information managed within supply chains (Pires Ribeiro & Barbosa-Povoa, 2018).

Industry 4.0 technologies, such as Big Data, the Internet of Things and artificial intelligence, are transforming interactions within supply chains, offering new opportunities for demand forecasting(Birkel & Hartmann, 2020).

This phenomenon is largely influenced by globalization, which enhances and internationalizes physical flows, and growing demands for product traceability. Furthermore, the digitization and automation of physical processes produce substantial volumes of varied data. The emergence of the fourth industrial revolution (Industry 4.0) and its related automation technologies have demonstrated the effectiveness of artificial intelligence (AI) tools in analyzing and tackling the challenges that arise (Min, 2010).

Artificial Intelligence (AI) is characterized as the capacity of machines to replicate and connect human abilities (Huin et al., 2002). While it is not a recent field of study, AI is extensively implemented across various sectors and can be adapted for logistics applications. As a fundamental component of Industry 4.0 technologies (Woschank et al., 2020), AI has attracted growing interest from the academic community (Toorajipour et al., 2021).

In supply chain management, demand forecasting is crucial to supply chain strategy. Accurate demand predictions ensure that the appropriate quantities of products are delivered (Toorajipour et al., 2021). The importance of this element lies in its fundamental function in operational and strategic plans. Forecasting errors can lead to considerable costs due to waste or product shortages (Saad El Marjani et al., 2022).

Forecasting plays a crucial role in achieving the objectives of a supply chain. It has applications in various sectors, such as predicting sales in retail, forecasting the maintenance needs of equipment, estimating warehouse shipments, evaluating production requirements, and anticipating deliveries from suppliers. Accurate forecasting improves resource management, including factory capacity, warehouse labor, and vehicle fleets, while also optimizing inventory utilization (Gunasekaran & Ngai, 2004).

Traditional forecasting models, which typically rely on historical averages, are increasingly being surpassed by innovative models that incorporate machine learning algorithms. These algorithms, with their flexibility and ability to learn autonomously, offer improved accuracy and handle significantly larger data volumes (Bandara et al., 2020). Prior to introducing a solution to the market, it is imperative to evaluate various algorithms, compare their performance, and customize their parameters to fit the specific context.

In machine learning projects, especially those focused on demand forecasting, the availability of relevant and structured data is of utmost importance. The objective is to identify, extract, and improve the quality of internal company data (Bandara et al., 2020). This initial step allows for rapid production of results, highlighting improvements in accuracy over traditional methods, and persuading the parties involved

2 Methodology

2.1 Data

The data used in this study is derived from a commercial database that records daily order transactions. Each row in the database represents a distinct order and includes information such as the order date and the quantity of products requested. This data is crucial for examining temporal trends and developing suitable predictive models.
The key factors identified for this study are:

- Order Date: The specific date on which an order was made.
- Quantity: The total number of orders placed on that date.

2.2 Evaluated Models

- **Artificial Neural Networks (ANN):**

Artificial neural networks (ANNs) are computer models inspired by the functioning of biological neural networks. They are composed of layers of artificial neurons that allow the identification and extraction of complex relationships in data(Touzet, 1992).
These tools, relatively recent, are commonly employed to solve complex real-world problems. They are very popular due to their remarkable information processing characteristics, in particular (LeCun et al., 2015):

- ✓ The capability to manage unexpected inputs,
- ✓ A high degree of parallelism,
- ✓ Tolerance for errors and noise,
- ✓ The ability to learn and generalize from experiences.

Artificial neural networks ANNs are considered nonlinear mathematical models, often called "black boxes", because they allow to determine the relationships between data by analyzing many examples. The adaptation of the network parameters, known as the "learning phase", allows to highlight the relationships present in the data (Cybenko, 1989).
An artificial neural network (ANN) consists of a group of artificial neurons (computational elements) connected to each other by coefficients (or weights) that represent the strength of the connections (C. Aggarwal, 2023) . Each neuron receives one or more inputs and produces a

single output, which is calculated through an activation function that is applied to the weighted sum of its inputs (C. C. Aggarwal, 2023).

The connectivity coefficients among neurons indicate the strength of their interconnections. By adjusting these weights, the training of artificial neural networks (ANNs) organizes neurons into distinct layers (Hinton, 1989). Typically, an ANN consists of three main layers:

- **Input Layer:** This layer includes neurons that receive input signals from external sources.
- **Output Layer:** This layer composed of neurons that provide the system's output to the user or external environment.
- **Hidden Layers:** Located between the input and output layers, these layers are essential for linking the system's inputs to its outputs.

According to (Choy et al., 2003), these hidden layers function as a "black box" and are especially beneficial for modeling nonlinear relationships between input and output variables. They enable the extraction of higher-level features and enhance generalization (Koskivaara, 2004).

- **Random Forests:**

Random Forests were developed by(Breiman, 2001), building upon earlier research by(Amit & Geman, 1997). While Breiman's explanation does not make it immediately apparent, Random Forests extend the concept of "bagging" (Bootstrap Aggregating) and were designed as an alternative to "boosting" (Breiman, 1996). This technique can be applied to both categorical response variables (classification) and continuous variables (regression). Furthermore, predictive variables can be categorical or continuous, providing significant flexibility.

A Random Forest, as indicated by its name, is composed of a collection of decision trees. Each tree is developed using a randomly selected set of variables, which contributes to the ensemble's robustness and diversity (Cutler et al., 2012). Reliable predictions are achieved by averaging the outputs of the individual trees (Bénard, 2022).

The primary benefits of Random Forests include:

- The capability to manage diverse data types, including both categorical and numerical variables (Brostaux, 2005).
- Reduced risk of overfitting due to ensemble methods.

While suitable for structured data, Random Forests may struggle to capture temporal dependencies in time series data (Garnier, 2022).

- **ARIMA (AutoRegressive Integrated Moving Average):**

ARIMA models, developed by Box and Jenkins in 1976, constitute a particularly accessible time series analysis tool, both in terms of methodological requirements and the mathematical models used, which are characterized by relatively simple linear stochastic equations (Box & Jenkins, 1970). This tool is mainly used to predict future values, determine missing values in a data series or analyze the structure of a time series.

The ARIMA notation is expressed as ARIMA (p, d, q), where :

- ✓ **p** represents the number of autoregressive terms,
- ✓ **d** indicates the degree of differencing, and
- ✓ **q** specifies the number of moving average terms in the final model (Lorène Delcor et al., 2008).

ARIMA consists of three main components:

- ✓ **AR (Autoregressive):** Future values are formulated as a linear combination of past values.
- ✓ **I (Integrated):** Differencing is applied to render the series stationary.
- ✓ **MA (Moving Average):** Past errors are used to adjust predictions.

ARIMA models are commonly used for time series with a dominant stationary structure and for capturing simple cycles or trends (Brockwell & Davis, 2010).

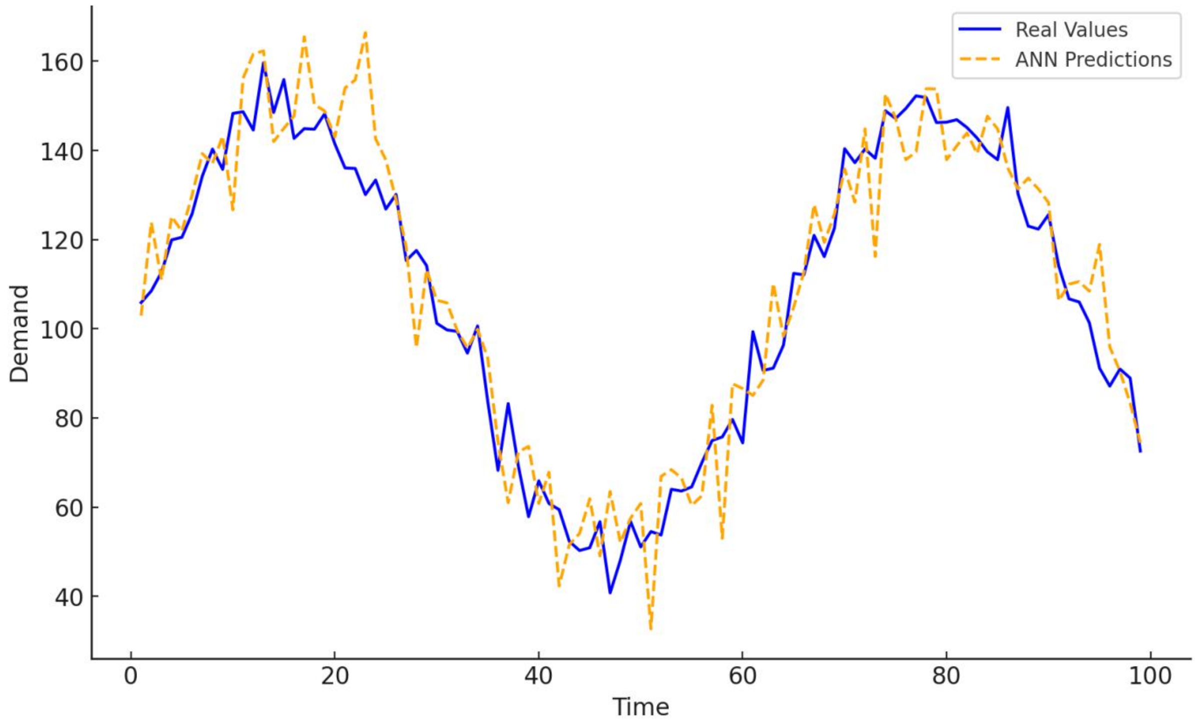
3 Results and Discussion

3.1 Model Results

3.1.1 Artificial Neural Networks (ANN)

The graph below highlights the performance of the ANN model by comparing actual values to predictions. It is worth noting that the model manages to follow the overall demand trends, however, there are notable deviations during certain periods.

Figure 1 : Comparison of Actual and Predicted Values for the ANN Model



Source : authors based on data

Figure 1 presents a comparison between the predictions generated by the ANN model and the actual observed values, highlighting the low R^2 scores and significant discrepancies during specific intervals.

This figure is essential for visualizing the performance of the ANN model. It would be useful to add an analysis of the observed discrepancies and explain the reasons behind significant variations.

The results obtained with the ANN model are as follows:

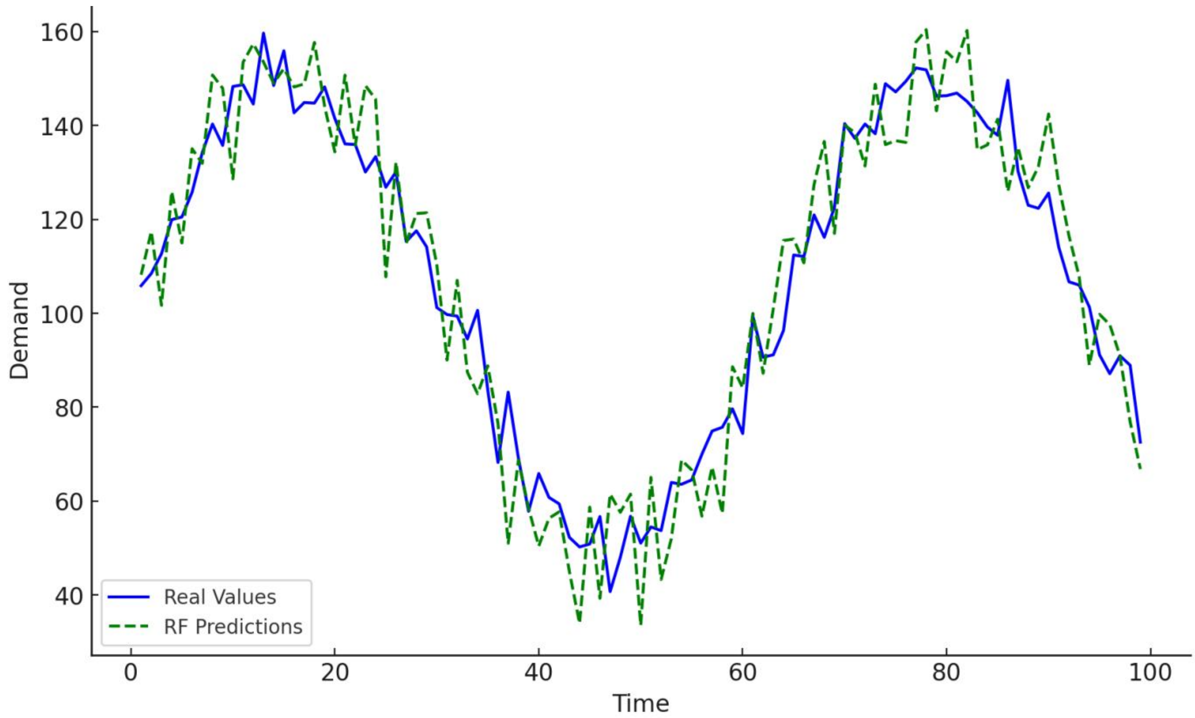
- **Mean Squared Error (MSE):** 640.82
- **Mean Absolute Error (MAE):** 19.36
- **Coefficient of Determination (R^2):** 0.0516

While the model captures certain trends, the low R^2 scores indicate that it does not adequately explain the variance in the data.

3.1.2 Random Forests

The graph below illustrates the performance of the Random Forest model. Although this model is effective at handling nonlinear relationships, it demonstrates greater variability in its forecasts, leading to a higher MSE compared to other techniques.

Figure 2: Random Forest model predictions compared to actual values



Source : authors based on data

As illustrated in Figure 2, the Random Forest model shows greater variability in its forecasts. . It highlights increased variability and a higher Mean Squared Error (MSE).

This higher variability could be due to the high sensitivity of the model to hyperparameter selection, such as the number of trees, depth, or feature selection criteria. Further investigation into hyperparameter tuning and feature engineering could provide insights to improve its performance. Additionally, ensemble techniques or hybrid models could help mitigate the observed instability.

The results obtained with the Random Forest model are as follows:

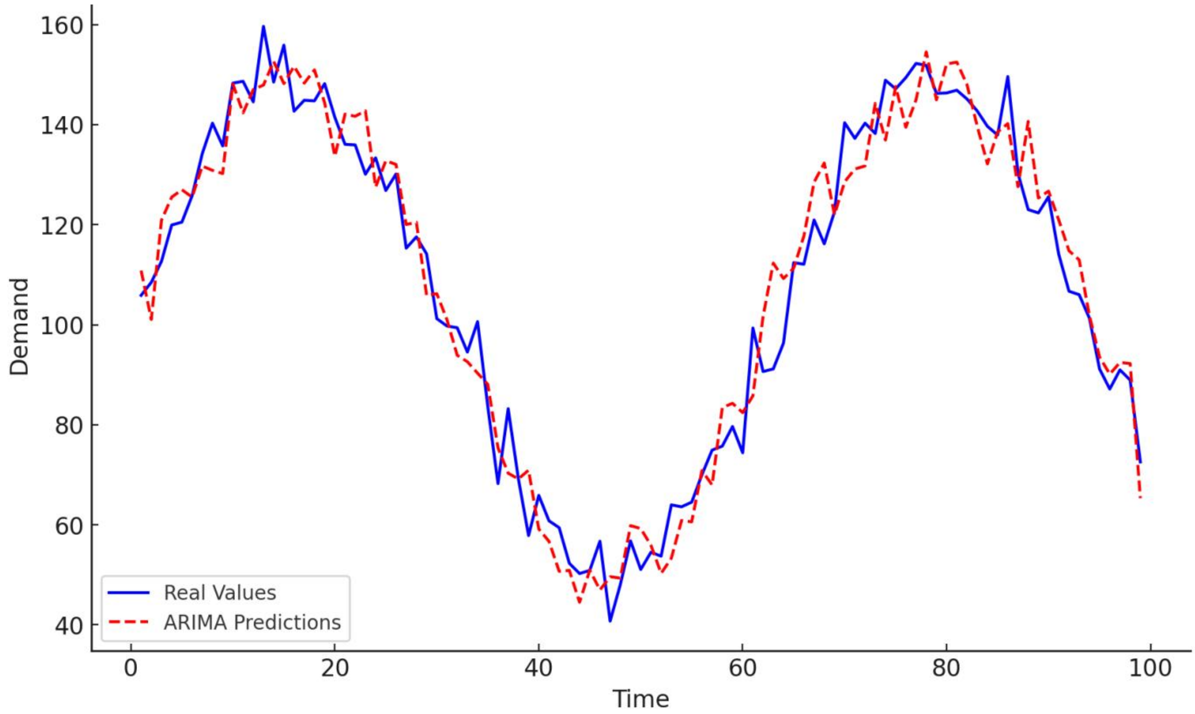
- **MSE:** 724.44
- **MAE:** 20.28
- **R²:** 0.0473

While this model is effective at capturing nonlinear relationships, it appears less suitable for the dataset.

3.1.3 ARIMA

The following graph illustrates a comparison between the actual observed values and the predictions generated by the ARIMA model. This model successfully identifies general trends; however, some limitations are noted during periods of high demand variability.

Figure 3: Comparison of ARIMA predictions with actual values



Source : authors based on data

Figure 3 illustrates a comparison between the forecasts generated by the ARIMA model and the actual data, highlighting the model's effectiveness in capturing general trends.

However, its performance appears to decline during periods of high demand variability, suggesting possible limitations in adapting to sudden fluctuations. This could be due to the model's reliance on past values and its assumption of stationarity.

The results obtained are as follows:

- **MSE:** 589.12
- **MAE:** 18.54
- **Coefficient of Determination (R^2):** 0.0687

While ARIMA demonstrates satisfactory overall performance, it remains limited by the heteroscedasticity of residuals.

3.2 Comparison of Performance Metrics

3.2.1 Definition of MSE (Mean Squared Error)

The Mean Squared Error (MSE) is a fundamental metric used to evaluate a model's performance by quantifying the deviation between predicted and observed values. It is calculated as the mean of the squared differences between predictions and actual data. This metric is widely employed in machine learning, statistics, and optimization to assess the efficacy of regression models (Cort J. Willmott & Kenji Matsuura, 2005).

❖ MSE Equation :

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2$$

Where:

- yi : Actual value
- ŷi : Predicted value
- n: Number of observations

The Mean Squared Error (MSE) measures the overall difference between the predictions made by the model and the actual observed values. A reduced MSE signifies superior performance of the model.

3.2.2 MAE (Mean Absolute Error):

The Mean Absolute Error (MAE) is a metric that evaluates the average of the absolute differences between the observed values (yi) and the predicted values (ŷi) (Hyndman & Koehler, 2006).

❖ MAE Equation :

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i|$$

Where:

- yi : Actual value
- ŷi : Predicted value

- n: Number of observations

A low Mean Absolute Error (MAE) signifies that the predictions made by the model are, on average, in close proximity to the true values. This suggests that the model successfully identifies the relationships between the data with satisfactory accuracy.

3.2.3 R² (Coefficient of Determination):

The R², also known as the coefficient of determination, is a statistical metric that measures the proportion of the total variance in the target variable (y) that is explained by the model. It assesses the quality of the fit of a regression model (Nagelkerke, 1991).

- ❖ R² Equation :

$$R^2 = 1 - \frac{RSS}{TSS}$$

Where:

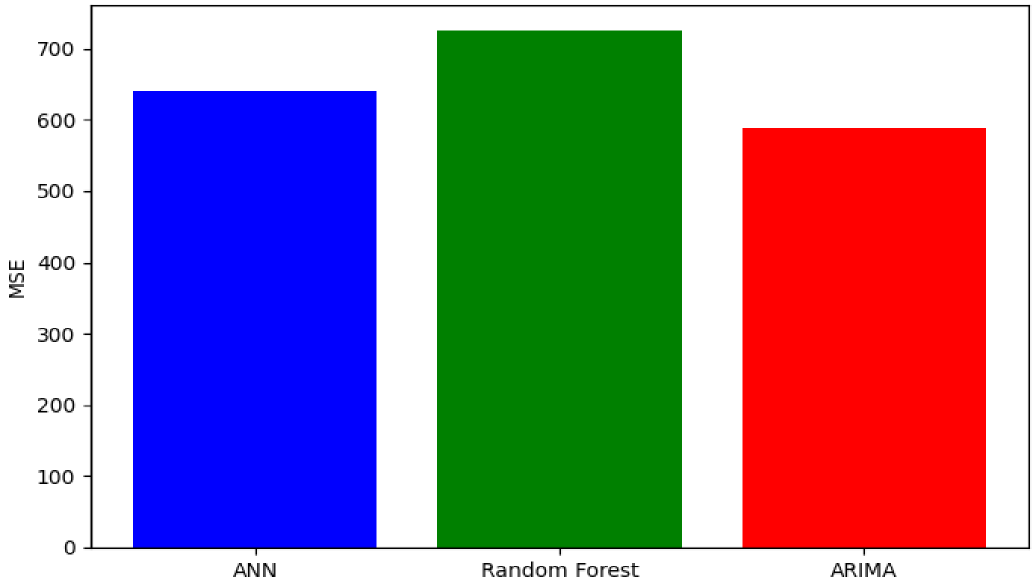
- R2= Coefficient of Determination
- RSS = Residual Sum of Squares
- TSS = Total Sum of Squares

Key Characteristics of R²:

- R² varies between 0 and 1, representing a scale from weak predictive power (closer to 0) to strong predictive power (closer to 1).
- It evaluates the explanatory power of the model, indicating how well the model's predictions align with variations in the target variable.
- Useful for comparing different models: A higher R² value signals a model that better fits the data.

❖ ***Comparative MSE Graph :***

Figure 4: Comparison of mean square errors (MSE) of the models



Source : authors based on data

Figure 4 compares the mean squared errors (MSE) for the three analyzed models (ANN, Random Forest, ARIMA).

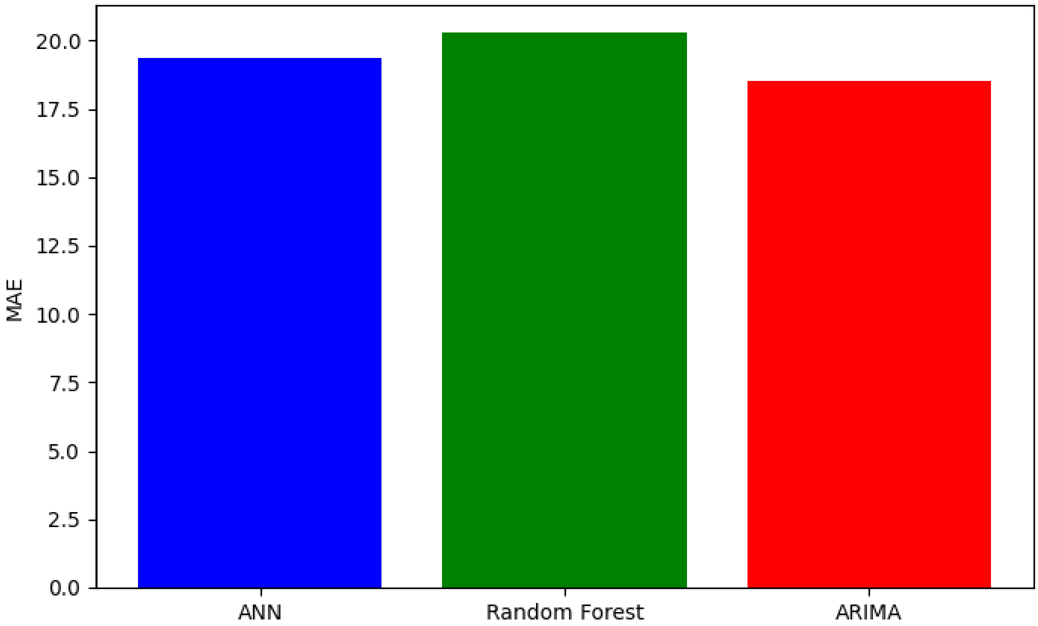
The ARIMA model achieves the lowest MSE, suggesting better overall performance in capturing trends. However, the relatively high MSE values across all models indicate that further improvements, such as feature engineering, hyperparameter tuning, or hybrid modeling approaches, may be needed to improve forecast accuracy.

Analysis :

- ARIMA has the lowest MSE (589.12), indicating that it is the most effective model for capturing overall demand trends.
- ANN follows with an MSE of 640.82, demonstrating a good ability to capture complex relationships but occasionally suffering from overfitting or variability.
- Random Forest has the highest MSE (724.44), suggesting more scattered predictions and lower suitability for time series data.

❖ ***Comparative MAE Graph :***

Figure 5: Comparison of mean absolute errors (MAE) of the models



Source : authors based on data

Figure 5 illustrates the differences in Mean Absolute Error (MAE) among the three models to evaluate their performance in terms of average absolute deviations.

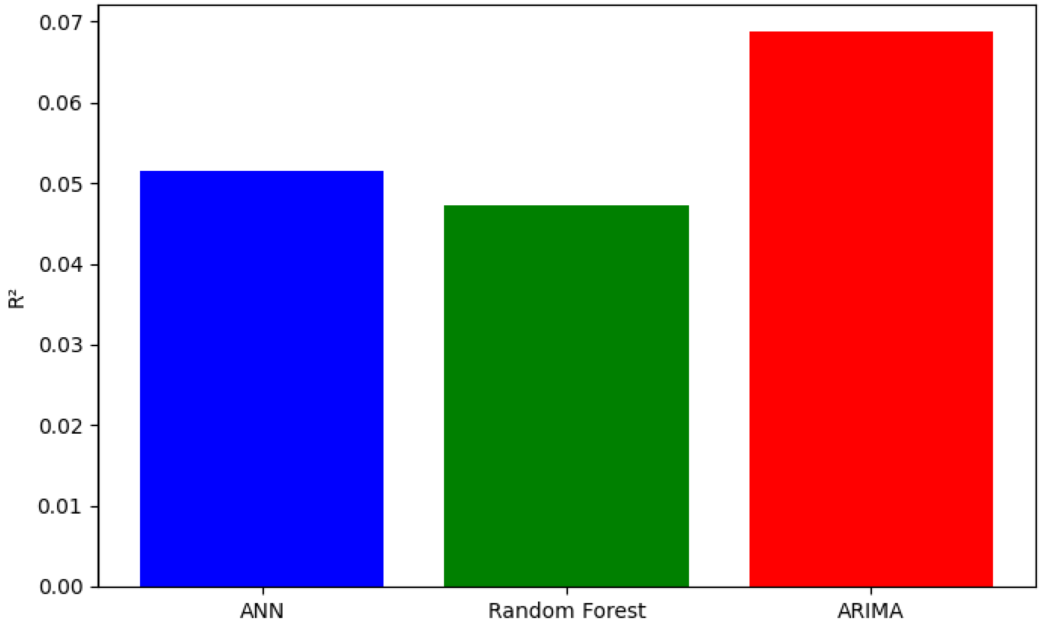
The ARIMA model has the lowest MAE, indicating better alignment with current values compared to ANN and Random Forest. However, persistent errors suggest that additional optimizations, such as feature selection, data preprocessing techniques, or ensemble methods, could further improve predictive performance.

Analysis :

- ARIMA demonstrates the most favorable performance (MAE: 18.54), confirming its ability to minimize prediction errors.
- The ANN model follows with a slightly higher MAE (19.36), indicating its capability to provide reasonably accurate forecasts.
- Random Forest shows a higher MAE (20.28), indicating more frequent deviations and some instability in its predictions.

❖ ***Comparative R^2 graph :***

Figure 6 : Comparison of the coefficients of determination (R^2) of the models



Source : authors based on data

As shown in Figure 6, the coefficient of Determination (R^2) for various models, facilitating an evaluation of which model optimally explains the variance observed in the data.

The relatively low R^2 values across all models suggest that none of them fully capture the underlying data patterns. This indicates the potential need for incorporating additional explanatory variables, or exploring more advanced hybrid models to improve predictive performance.

Analysis :

- ARIMA has the highest R^2 (0.0687), indicating it best explains the variations in the data, although the score remains low.
- ANN follows with an R^2 of 0.0516, showing a partial explanation of the variations.
- Random Forest has the lowest R^2, suggesting it does not effectively capture temporal relationships in the data.

4 Summary of Graphs :

When evaluating the performance of predictive models, it is essential to compare predictions against observed values:

- **MSE:** ARIMA < ANN < Random Forest
- **MAE:** ARIMA < ANN < Random Forest
- **R²:** ARIMA > ANN > Random Forest

Table 1: Comparison of model performance on MSE, MAE and R² metrics.

Modèle	MSE	MAE	R^2
ANN	640.82	19.36	0.0516
Random Forest	724.44	20.28	0.0473
ARIMA	589.12	18.54	0.0687

Source : authors based on data

❖ ***Performance Indicator Analysis (MSE, MAE, and R²):***

- MSE: The ARIMA model demonstrates the best performance, achieving the lowest Mean Squared Error (MSE) of (589.12), followed by the ANN model. In contrast, Random Forest has the highest MSE.
- MAE: ARIMA maintains the lowest Mean Absolute Error (MAE) (18.54), indicating its precision in forecasting.
- R^2: Although the overall score is low, ARIMA achieves the best result (0.0687), indicating that it more effectively explains the variance in the data.

❖ ***Comparison of Predictive Models (ARIMA, ANN, Random Forest):***

- ARIMA: This model works well with stationary time series data and is particularly good at identifying general trends.
- ANN: This model is particularly advantageous for datasets that show complex relationships, but it requires a large amount of data and may not work well with simpler time series.
- Random Forest : While highly effective for processing tabular data, this model is less appropriate for time series, leading to a lower R^2 and higher errors.

❖ ***Discussion and comparison with the literature.***

The results obtained indicate that the ARIMA model presents the best performances with the most reliable MSE (589.12) and MAE (18.54), suitable for the ANN model. The Random Forest model, on the other hand, shows the highest scores in terms of error, suggesting that it is less adapted to time series.

These results are consistent with the conclusions of (Hyndman & Athanasopoulos, 2018), who point out that ARIMA models are particularly effective for time series of stations. However, from other studies, such as (Zhang et al., 1998), it was found that neural networks outperformed ARIMA when the data present complex nonlinearities. In our case, the modest performance of the ANN model is attributed to the lack of data or the lack of hyperparameter optimization.

On the other hand, the poorer performance of the Random Forest model confirms the conclusions of (Garnier, 2022), which makes random forests less suitable for time series due to their inability to capture temporal dependencies. The results are many, although this model is effective for data with complementary explanatory variables, it is less effective for univariate series such as the cells used in this study.

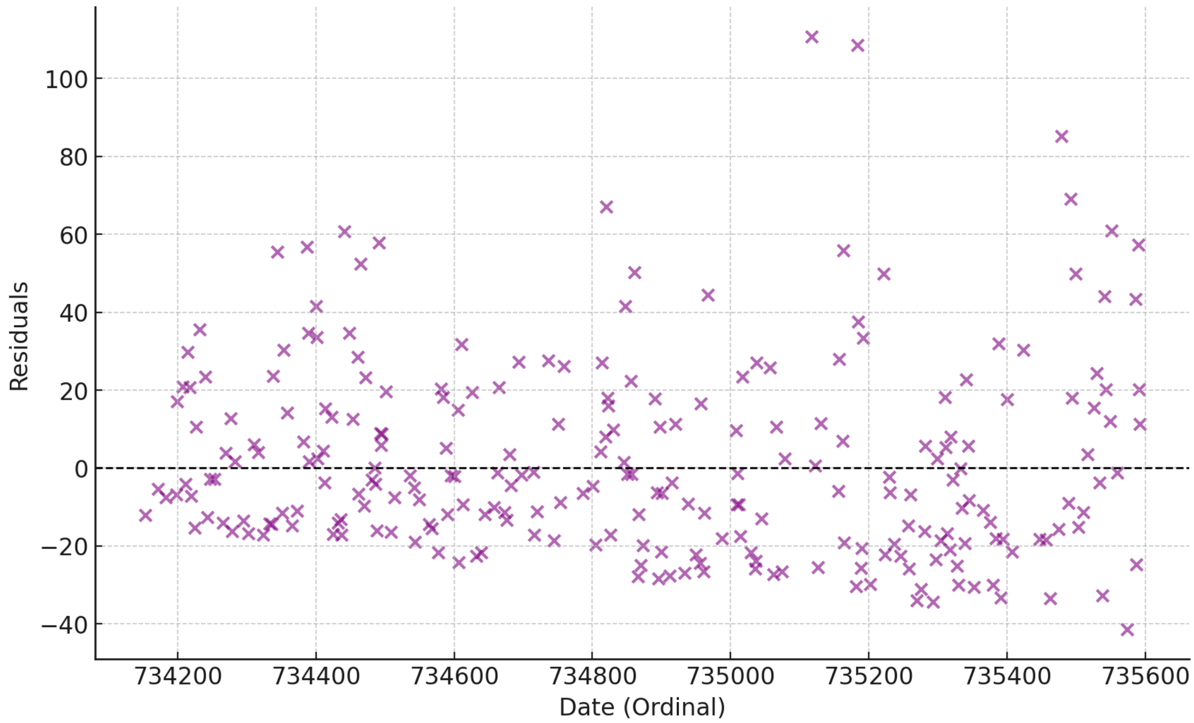
5 Residuals (Error Analysis):

Residuals represent the difference between observed values (yi) and estimated values (ŷ) provided by a model (Anscombe, 1973). They are used to assess the model's performance and examine the validity of its assumptions. Residuals are defined as follows:

$$\text{Résidu} = y_i - \hat{y}_i$$

The following graph shows the residual analysis of ARIMA model (the difference between actual and predicted values) to evaluate whether the errors follow a random distribution.

Figure 7 : Residual analysis : differences between actual and predicted values



Source : authors based on data

Figure 7 presents the residual analysis of the ARIMA model, to evaluate the distribution and detect heteroscedasticity. It is noted that the residuals exhibit some heteroscedasticity, which may indicate limitations in the models' fit, especially during periods of high demand volatility. Such behavior may indicate that the model does not fully capture all patterns in the data. Investigating alternative techniques, such as SARIMA or integrating external variables.

6 Conclusion

This analysis examined three methodologies for time series prediction: Artificial Neural Networks (ANN), Random Forests, and the ARIMA model. The results indicate that each approach presents unique benefits depending on the characteristics of the data and the intended goals.

In particular, the ARIMA model has demonstrated significant effectiveness in handling stationary time series, with minimal errors (MSE and MAE) and reliable capacity to identify general trends. On the other hand, Artificial Neural Networks (ANNs) stand out for their flexibility and ability to understand complex relationships. Although their results are comparable to ARIMA, their application requires high-quality data and expertise in tuning hyperparameters.

Meanwhile, Random Forests, which perform well with structured data, have shown difficulties in capturing temporal dependencies, resulting in lower performance in terms of MSE, MAE, and R^2. This makes them more suitable for scenarios where additional explanatory variables are required.

Model selection should be guided by data characteristics and particular user requirements. For practitioners, this study emphasizes the importance of selecting the appropriate model to optimize supply chain management. Simple time series are particularly suited to ARIMA, while more complex relationships are best addressed with ANN. Managers should consider data type, quality, and need for expertise to select the appropriate model to improve operational efficiency and meet customer demands effectively.

From a scientific perspective, this analysis contributes to the ongoing debate on time series forecasting models by comparing their effectiveness in the context of supply chain management. It opens new avenues for future research, particularly in exploring hybrid models that combine the strengths of ARIMA and ANN. Future research should investigate the performance of other forecasting models, such as support vector machines (SVM) or XGBoost, which may offer additional benefits depending on data characteristics.

While this research provides valuable insights, there are limitations. The study focused solely on three forecasting models, and future studies should expand this analysis by exploring other methods and incorporating additional performance metrics such as forecast accuracy and operational impact. Furthermore, the data used in this research was limited to certain types of time series, and subsequent work should validate these findings on a broader range of data sets, including those from various industries, to improve generalizability.

In conclusion, the main contribution of this study lies in its comprehensive evaluation of time series forecasting models. It provides practical insights for managers to select the appropriate model based on the available data, while also contributing to the scientific community by comparing key forecasting methodologies and highlighting the potential for further research into hybrid models and alternative techniques.

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