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Research Article

Developing Demand Forecasting Models for E-Commerce: Analyzing the Impact of Time Lags on Model Performance

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ABSTRACT

Time series are an important analytical tool used in many problems today. Particularly favored in regression problems such as demand forecasting, time series enable more accurate modeling of the impact of past data on future values through various lag options. Time lag is a method used in time series analysis or machine learning models to examine the effect of past (lagged) values of a variable on current or future values. Time lag options play a crucial role, particularly in the success of demand forecasts. This study aims to develop demand forecasting models that help e-commerce businesses gain a competitive advantage by accurately predicting demand and comprehensively analyzing the impact of time delay options on forecasting performance. In this context, an interface with hyperparametric flexibility has been developed, and the effects of the lag options "Use Best N," "Use Correlation," "Use All Delays," and "Selected Delay Lag" on forecasting performance have been analyzed using demand forecasting models. Models have been created for two different months and three different products. The performance of the developed models has been evaluated using the Mean Absolute Percentage Error (MAPE) metric. The lowest MAPE value for July has been obtained with the MQRNN model developed using product A, while the lowest MAPE value for August has been obtained with the MLP model developed using product B.

Keywords: Time-lag options, E-commerce, Demand forecasting, Machine learning

1. INTRODUCTION

Time series is a type of data that represents the values of a certain variable measured at regular intervals over time and is widely used in many fields, such as finance, economics, energy, health, and meteorology. This data is typically analyzed to examine the behavior of a particular event over time, identify trends and recurring patterns, and make future predictions [1].

Time series data serve as a fundamental building block for solving many problems today, with demand forecasting being one key application. Demand forecasting is a systematic analysis process that aims to estimate future product or service demand [2]. These predictions are made by considering past data, market dynamics, consumer behavior, and other economic factors. The use of time lags is crucial for enhancing the accuracy of demand forecasts. The time lag option used in time series analysis and machine learning models is an important tool for evaluating the impact of past (lagged) values of a variable on current or future values. By accounting for the role of past data in shaping future outcomes, dynamics such as trends, seasonal patterns, and autocorrelation are captured. This allows for a better understanding of the relationship between a variable and its past values. For instance, to predict the closing prices of a stock, data from previous days are included in the model, while in the energy sector, electricity consumption data from previous weeks are included in the model for demand forecasting. Past data not only improves forecast accuracy but also provides a deeper understanding of the system's dynamic structure. Additionally, incorporating past values into the model enables the management of complexity and enhances the generalization capacity without the need for data transformation.

These options can be applied in various ways depending on the dataset and the analysis objectives. Various lag options exist in time series, with the most commonly used being Fixed Lag, Rolling Lag, and Variable Lag. However, these

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methods have certain drawbacks. The fixed lag method can overlook important factors such as seasonal changes and dynamic patterns, making it challenging to apply to data that is sensitive to changing conditions. Since the rolling lag works with continuously updated historical data, it can lead to information loss and result in high computational costs. Moreover, the loss of older data may cause long-term trends to be overlooked. On the other hand, the variable lag method can increase model complexity, complicating the optimization process, and may lead to performance issues in cases of insufficient data, thus increasing the risk of overfitting.

In this context, the Use Best N, Use Correlation, Use All Lags, and Use Selected lag options stand out by offering more flexible and optimized solutions compared to fixed, rolling, and variable lag options. These options enable more dynamic and data-specific results compared to fixed lag and other traditional methods. This enables the model to effectively adapt to dynamic changes in the data and enhances its predictive accuracy.

Accurate demand forecasting is crucial, especially for e-commerce businesses. E-commerce businesses require reliable demand forecasts to effectively manage their inventory, accurately determine the quantity of products to be supplied, and efficiently conduct cost optimizations. In this context, accurate demand forecasting emerges as a critical strategic measure, enabling businesses to utilize resources effectively, enhance customer satisfaction, and gain a competitive advantage.

The aim of this study is to develop demand forecasting models that will help e-commerce businesses effectively meet customer needs by accurately predicting demand, gain a competitive advantage in the market, and perform cost optimizations accurately. For this purpose, an interface with hyperparametric flexibility has been developed, and the effects of the lag options on forecasting performance have been analyzed using demand forecasting models.

This study is organized as follows: Section 2 includes relevant literature. Interface with hyperparameter flexibility is presented in Section 3. Section 4 presents methodology. Dataset is presented in Section 5. Development of forecast models is given in Section 6. Results and discussion are presented in Section 7. Section 8 concludes the paper.

2. LITERATURE REVIEW

Nussipova [3] developed a hybrid approach combining machine learning, representation learning, and deep learning techniques to improve the accuracy of energy demand forecasting in modern electricity transmission systems and smart grids. The study highlights notable accuracy improvements achieved through the extraction of fundamental features in energy demand forecasting. In particular, it was observed that triple losses were effective for large margin sizes and long forecast periods. The study emphasizes the role of energy demand forecasting in areas such as renewable energy integration, system management, and market analysis, and states that these technologies contribute to practical applications. Rasul [4] introduced a general-purpose model called Lag-Llama, considering the development of basic models in time series forecasting. It was noted that Lag-Llama, based on a pure decoder converter architecture, focuses on univariate probabilistic time series forecasting. The model was pre-trained on a large time series dataset collected from various domains and demonstrated superior performance in zero-shot generalization. The study further mentions that with a small fine-tuning on new datasets, Lag-Llama surpassed previous approaches and achieved state-of-the-art performance. Lag-Llama stands out as the best general-purpose model for time series forecasting, thanks to its strong generalization capabilities, and it paves the way for future advancements in this field. Peláez-Rodríguez [5] examined the performance of machine learning and deep learning methods in forecasting bike sharing demand in Madrid and Barcelona and cable car demand in Madrid. The predictor variables were divided into four groups, and 12 different regression techniques were applied. The results demonstrate that both machine learning and deep learning methods achieve high accuracy, and these approaches can be applied to other urban mobility studies. Khatun [6] investigated the effectiveness of Convolutional Neural Network (CNN) – Long Short Term Memory (LSTM) and CNN-Gated Recurrent Unit hybrid models for short- and medium-term flow forecasting in the Mahanadi River basin in India. The hybrid models achieved higher accuracy compared to standalone models, and the impact of time lags on model accuracy was analyzed. The CNN-LSTM model accurately predicted flow trends and high peak flows. Additionally, it was highlighted that upstream discharges played an important role in improving the predictions. The study also emphasized that considering all input variables with a fixed time delay resulted in effective flood prediction, even with limited resources. Guo [7] proposed a forecasting model based on the Stacking fusion model combined with grid search to help businesses meet deadlines and reduce inventory costs. The Stacking Fusion model was constructed using "merchant - warehouse - commodity" time series data. Grid search and cross-validation techniques were used for parameter optimization, Extreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine, and Categorical Boosting machine learning models were included. The forecasting performance was evaluated using metrics such as Root Mean Square Error, goodness-of-fit coefficient, recall rate, and forecast accuracy. Li [8] proposed a cascaded hybrid neural network model based on multimodal data to improve the accuracy of commodity demand projections on e-commerce platforms. Historical order information and product evaluation data were combined as the dataset. In the model, Bidirectional Gated Recurrent Unit Networks and Bidirectional LSTM Networks have been combined. The results showed that the weekly Mean Absolute Error was 0.1682 for commodity forecasts and 0.8611 for long-term demand. When the results has been evaluated, it has been observed that the model provided high accuracy in commodity demand forecasting. Li [9] presented the Spatial Graph Neural Network (SGNN) method, which increased demand forecasting accuracy by using spatial correlations in online sales data. A geographically aware graph model was created using the dataset obtained from Kaggle, and forecasting accuracy was improved with attention methods. The model outperformed traditional methods. Experimental results verified the effectiveness of the GNN-based strategy and provided valuable insights in overcoming the complexities of the online marketplace. Liu [10] studied the e-commerce agricultural products feature dataset and applied data mining. A single model-based demand forecasting model was built using the e-commerce agricultural products feature dataset. To address the issue of irrational artificial fixed parameters in machine learning models, Auto Regressive Integrated Moving Average (ARIMA), LSTM, and Random Forest (RF) models were trained. Particle Swarm Optimization (PSO) and Bayes algorithms were used to optimize the LSTM and RF models, respectively, and the prediction model was created by selecting the most appropriate parameters. Liu [11] aimed to create the feature dataset for e-commerce agricultural products. To achieve this, preprocessing tasks such as data cleaning and filling, technical tools such as web crawlers have been used. The e-commerce agricultural products feature dataset underwent cluster analysis using the K-Means technique to obtain a multi-dimensional summary of sales factors, which provided data support for the prediction model. Considering the limitations of single prediction models, ARIMA, PSO-LSTM, and other combined models were constructed using arithmetic weighting and integrated learning methods. The weights of the model were determined using various arithmetic techniques to combine the prediction results. The combined model, which calculated the weight composition using the inverse error weighted average method, gave the best result in terms of prediction performance. Liu [12] aimed to forecast demand and optimize inventory for thousands of merchants, products, and supporting warehouses in the e-commerce platform. Firstly, an ARIMA time series model has been developed for the shipment of obsolete products over time, and through continuous iteration, the optimal parameters of the model have been obtained to predict the shipment of obsolete products. The final prediction findings were then classified using K-means clustering. The old products were replaced with new ones, and the final prediction values were obtained by cosine similarity analysis after extracting the feature values of both old and new products. Lv [13] developed a model to analyze inventory management problems in e-commerce platforms. While product demand was predicted with the ARIMA model, new product classification was evaluated with the K-means method, and the effect of promotions on demand was evaluated using the LSTM model. The results revealed that LSTM outperformed ARIMA. Trisolvena [14] proposed the application of time series forecasting algorithms to determine trends in 2024 and forecast product demand on the Temu platform. LSTM, Facebook's Prophet, SARIMA, and ARIMA algorithms were used to analyze daily sales data. The analysis revealed that the Prophet model and the SARIMA algorithm outperformed ARIMA and LSTM in terms of forecast accuracy. It was predicted that if the forecasting models were applied appropriately, Temu would increase operational efficiency, improve strategic decision-making processes, and reduce expenses by optimizing inventory control. Zhang [15] aimed to develop an accurate demand forecasting scheme to help merchants better understand their commodity needs. First, a commodity type analysis was conducted to determine how products were distributed across different industries. Then, focusing on the time series data of the best-selling commodities, the sales volume of each commodity was examined. Based on the study results, the sales of similar products supplied by different merchants in various warehouses were analyzed. The Cityblock Optimized K-Means method was used to group products with similar statistical properties. Finally, ARIMA models were applied to predict sales trends for the created clusters. Zhao [16] focused on e-commerce demand forecasting using the Seasonal Auto Regressive Integrated Moving Average (SARIMA) model and the K-means clustering algorithm. Using 1996 sales data, demand changes were predicted for the next 15 days. Initially, Linear Regression, ARIMA, and SARIMA models were evaluated. Then, SARIMA was selected as the most effective model. The K-means clustering method is applied to divide products into four distinct groups, and similar time series were integrated with cosine similarity. The findings showed that the SARIMA model accurately captured trends and seasonality, providing a reliable framework for e-commerce demand forecasting. Xu [17] presented a new method for forecasting demand during low-density periods. This method was developed by combining carefully selected proxy data with features obtained from a forecasting model based on Graph Neural Networks (GNNs). In the study, demand forecasting was formulated as a meta-learning problem. Using the relational metadata generated by GNNs and proxy data from off-density periods, the Feature-based First-Order Model-Agnostic Meta-Learning algorithm was constructed to learn feature-specific layer parameters. Theoretical analysis showed that the model accounts for domain similarities through task-specific metadata, reducing excessive risk as the number of training tasks increases. The method was evaluated with industry datasets, and the results showed that it significantly increased demand forecasting accuracy. Wang [18] proposed a time series feature-based forecasting model to forecast future product demand based on historical data. As the first step, data preparation was performed, and four regression models were trained using the first 90% of the data table: XGBoost, RF, Decision Tree (DT), and Multi-Layer Perceptron. With the second 10% of the data table, DT was selected as the best regression model. Finally, the demand for products from each merchant in each warehouse was predicted from 2023-05-16 to 2023-05-30. Using the K-means clustering technique, five classes were determined for classifying the time series generated by commodities, warehouses, and merchants. It was found that time series data belonging to the same class had similar demand characteristics.

3. INTERFACE WITH HYPERPARAMETER FLEXIBILITY

An interface with hyperparameter flexibility has been developed for forecasting models. This interface has been created using the Python programming language. The back-end utilizes TensorFlow, Keras, Pandas, Scikit-learn, Numpy, and Statsmodels libraries, while the front-end employs Tkinter, Pandastable, and Matplotlib libraries. The interface enables users to load datasets, select attribute and target variables, and partition the data for learning and testing stages. Additionally, it supports the optimization of method parameters and time delay values. Product demand forecasts are generated, and MAPE calculations are performed by comparing these forecasts with actual values. Furthermore, the interface allows for the visualization of forecast results by plotting graphs of predicted values against actual values. It has been tested using MLP and MQRNN models, and the most successful forecasting models have been identified through an evaluation of the obtained results. Interface with hyperparameter flexibility is shown in Figure 1 and 2.

The train dataset is loaded from the Get Train Set section, where the relevant variables are selected. Preferences such as how the data will be used, the proportion to be utilized, and whether intervals will be included are determined in the Customize Train Set section. Time delay options are categorized under four headings: Use All Lags includes all time delays within the specified range as independent variables in the model; Use Selected allows the user to add specific time delays to the model; Use Best N selects a certain number of delays with the highest autocorrelation with the target variable; and Use Correlation includes time delays with autocorrelation values above a specified threshold as independent variables in the model. Parameters such as the number of layers and neurons, output and activation functions, epoch, batch size, and learning rate are configured via the interface. The model is created using the Create Model button and tested with the Test Model button. Predicted values are displayed in the Values tab, while the comparison between actual and predicted values can be visualized using the Actual vs Forecasted Graph button.

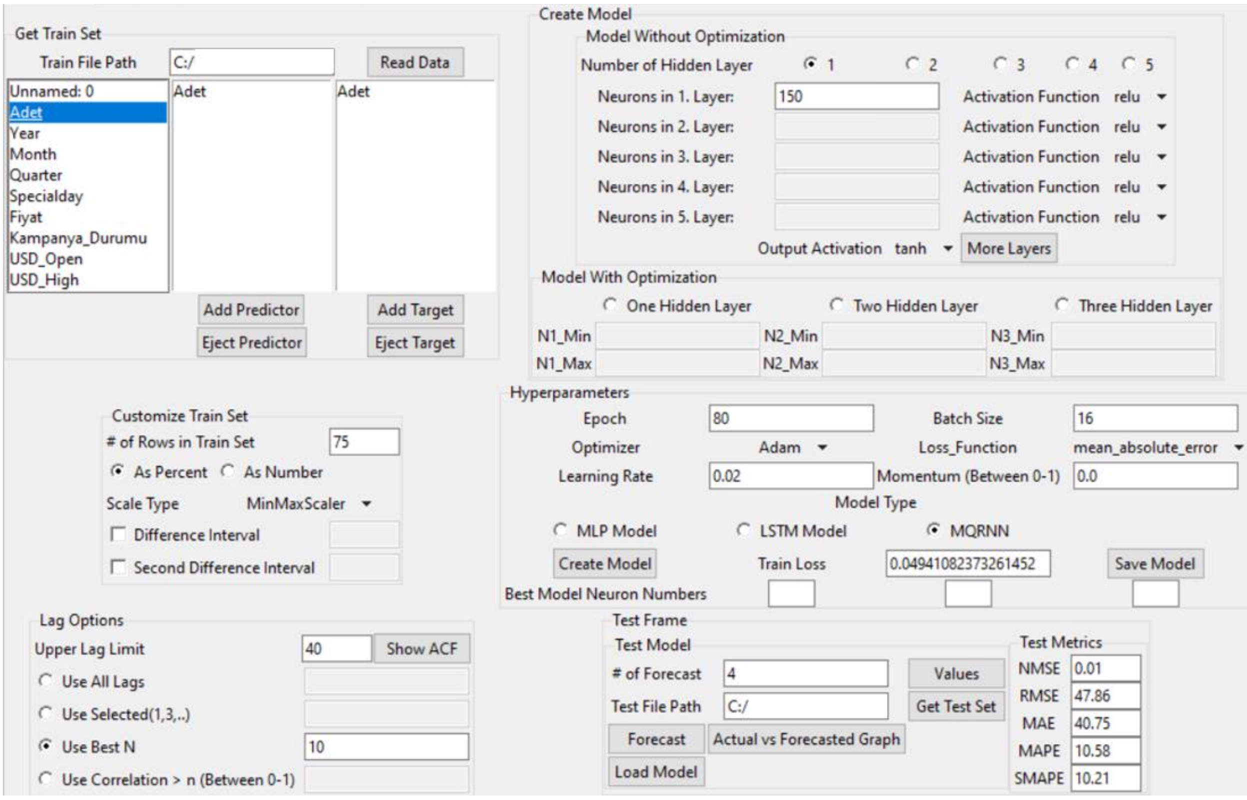

Fig 1. MQRNN screen

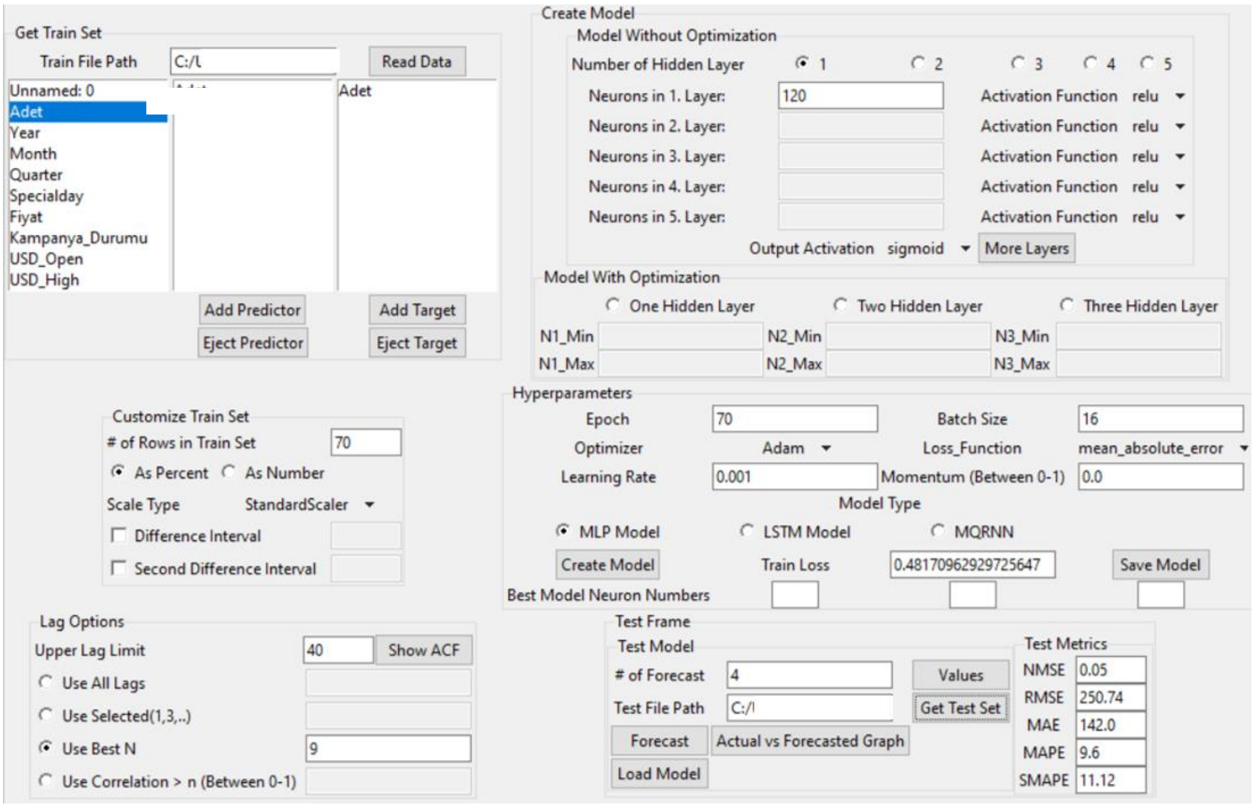

Fig 2. MLP screen

4. METHODOLOGY

4.1. Multi-Layer Perceptron

Artificial Neural Networks (ANNs) are generally divided into two fundamental categories: recurrent (feedback) networks and feedforward networks. Among these, the MLP, which follows a feedforward network architecture, is one of the most widely used types of ANN. MLP operates without making any assumptions about the structure of the output variable, the linearity of the predictor variables or output functions, or the distribution of the data. The MLP architecture comprises three primary components: the input layer (independent variables), the hidden layers (processing units), and the output layer (output variables). This structure is built by connecting multiple parallel layers of nodes with weighted connections. For instance, an MLP model might include three hidden layers containing 64, 32, and 16 neurons, respectively, as well as an output layer and an input layer with five input units [19]. MLP architecture is given in Figure 3.

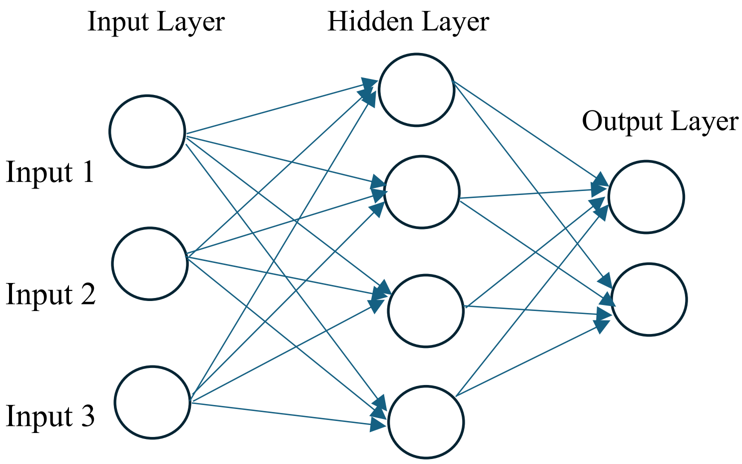

Fig 3. MLP Architecture

4.2. Multi-Horizon Quantile Recurrent Forecaster

LSTM functions as a convolutional encoder for each prediction horizon, generating the context vectors used in MQRNN. This method comprises three main components and is based on the Seq2SeqC architecture:

Encoder: The encoder creates a feature vector that represents the time series input. These feature vectors identify and extract patterns in the time series. The encoder is typically implemented using CNNs or recurrent neural networks (RNNs) with one or more layers.

Context Vector (Intermediate Vector): This vector, referred to as the context or intermediary vector, is generated by the encoder to compile the features of the input time series. The resulting vector is utilized by the decoder to generate predictions representing the time series.

Decoder: The decoder is usually implemented using an RNN or a similar model with one or more layers. It predicts values for the subsequent time steps based on the feature vector generated by the encoder. By employing various training methods, the decoder can be optimized to simulate and predict a specific percentage or distribution of the time series [20].

5. DATASET

The datasets were obtained from an Innovance customer. Daily sales data for three separate products (A, B, and C) were compiled between January 1, 2023, and August 25, 2024. Table 1 presents the characteristics and descriptions of these datasets.

Table 1. The main dataset

Attribute Name	Description
Quantity	Quantity of the products sold
Year	Year
Month	Month
Quarter	Quarter of the year
Specialday	Special days of the year
Price	Product prices during the sales period
Campaign_Status	Campaign status during the sales period
USD_Open	USD opening value
USD_High	Highest value of USD
USD_Low	Lowest value of USD
USD_Close	USD closing value
EURO_Open	Euro opening value
EURO_High	Highest value of Euro
EURO_Low	Lowest value of Euro
EURO_Close	Euro closing value
BIST_Open	BIST opening value
BIST_High	Highest value of BIST
BIST_Low	Lowest value of BIST
BIST_Close	BIST closing value

6. DEVELOPMENT OF FORECAST MODELS

In this study, the demand forecast models have been developed for products A, B and C in the FMCG sector. The models have been developed using MLP and MQRNN for the months of July and August. The effects of the lag option selection and the parameters used on the forecast performance have been also analyzed. The best value of hyperparameters has been found with grid search. The hyperparameter ranges used as a basis for developing prediction models are given in Table 2.

Table 2. Hyperparameter ranges

Method	Hyperparameter Range
MLP	"Percentage_Of_Rows_In_Train_Set": [70 - 100] "Difference_Interval": [7] "Second_Difference_Interval": [28] "Use_All_lags": [5 - 25] "Use_Selected": [1 - 7] "Use_Best_N": [6 - 20] "Use_Correlation": [0.1 – 0.5] "Number_Of_Hidden_Layer": [1] "Neurons_In_1_Layer": [60 - 200] "Epoch": [50 - 128] Batch_Size": [16 - 32] "Learning_Rate": [0.0005 – 0.005]
MQRNN	"Percentage_Of_Rows_In_Train_Set": [70 - 100] "Difference_Interval": [3 - 6] "Second_Difference_Interval": [4] "Use_All_lags": [2 - 15] "Use_Selected": [1 - 31] "Use_Best_N": [2 - 25] "Use_Correlation": [0.1 – 0.3] "Number_Of_Hidden_Layer": [1] "Neurons_In_1_Layer": [50 - 200] "Epoch": [50 - 150] Batch_Size": [8 - 64] "Learning_Rate": [0.001 - 0.02]

7. RESULTS AND DISCUSSION

The MAPE values of the models developed for July have been presented in Table 3, while those for August have been shown in Table 4. The real and forecast values of the most successful results obtained with the developed prediction models developed for July are presented in Figures 4 to 6. The real and forecast values of the most successful results obtained with the developed prediction models developed for August are presented in Figures 7 to 9.

Table 3. MAPE values of the models developed for July

Methods	Products	Lag Options	MAPE (%)
MLP	A	Use All Lags	8.42
		Use Selected	9.39
		Use Best N	9.71
		Use Correlation	9.41
	B	Use All Lags	10.34
		Use Selected	10.96
		Use Best N	9.6
		Use Correlation	10.3
	C	Use All Lags	31.14
		Use Selected	79.28
		Use Best N	41.86
		Use Correlation	44.04
MQRNN	A	Use All Lags	8.79
		Use Selected	9.8
		Use Best N	7.02
		Use Correlation	8.94
	B	Use All Lags	12.77
		Use Selected	12.59
		Use Best N	12.35
		Use Correlation	13.56
	C	Use All Lags	36.04
		Use Selected	92.81
		Use Best N	42.69
		Use Correlation	47.96

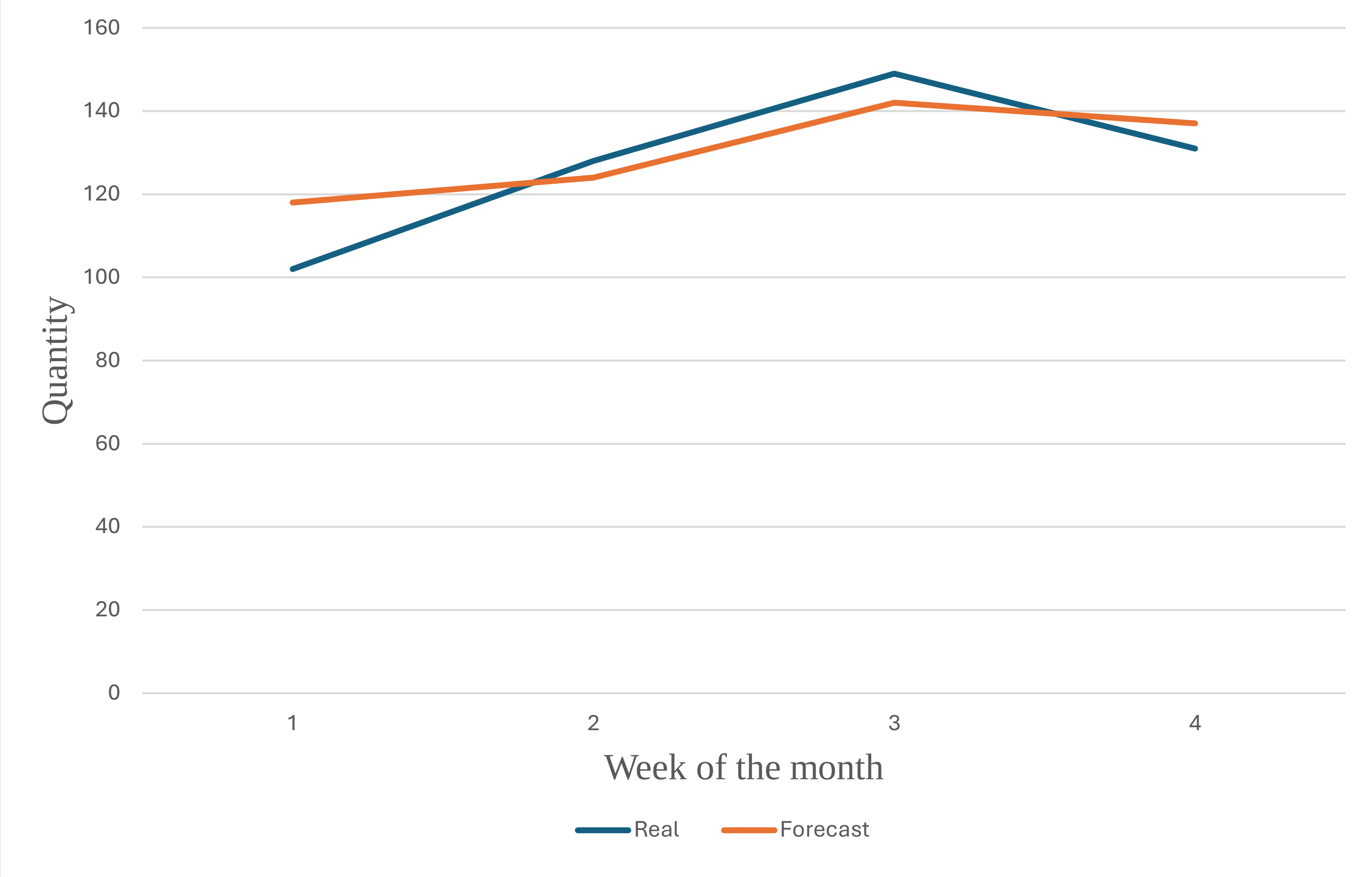

Fig 4. The real and forecast values of the model developed using MQRNN with the Use Best N for product A

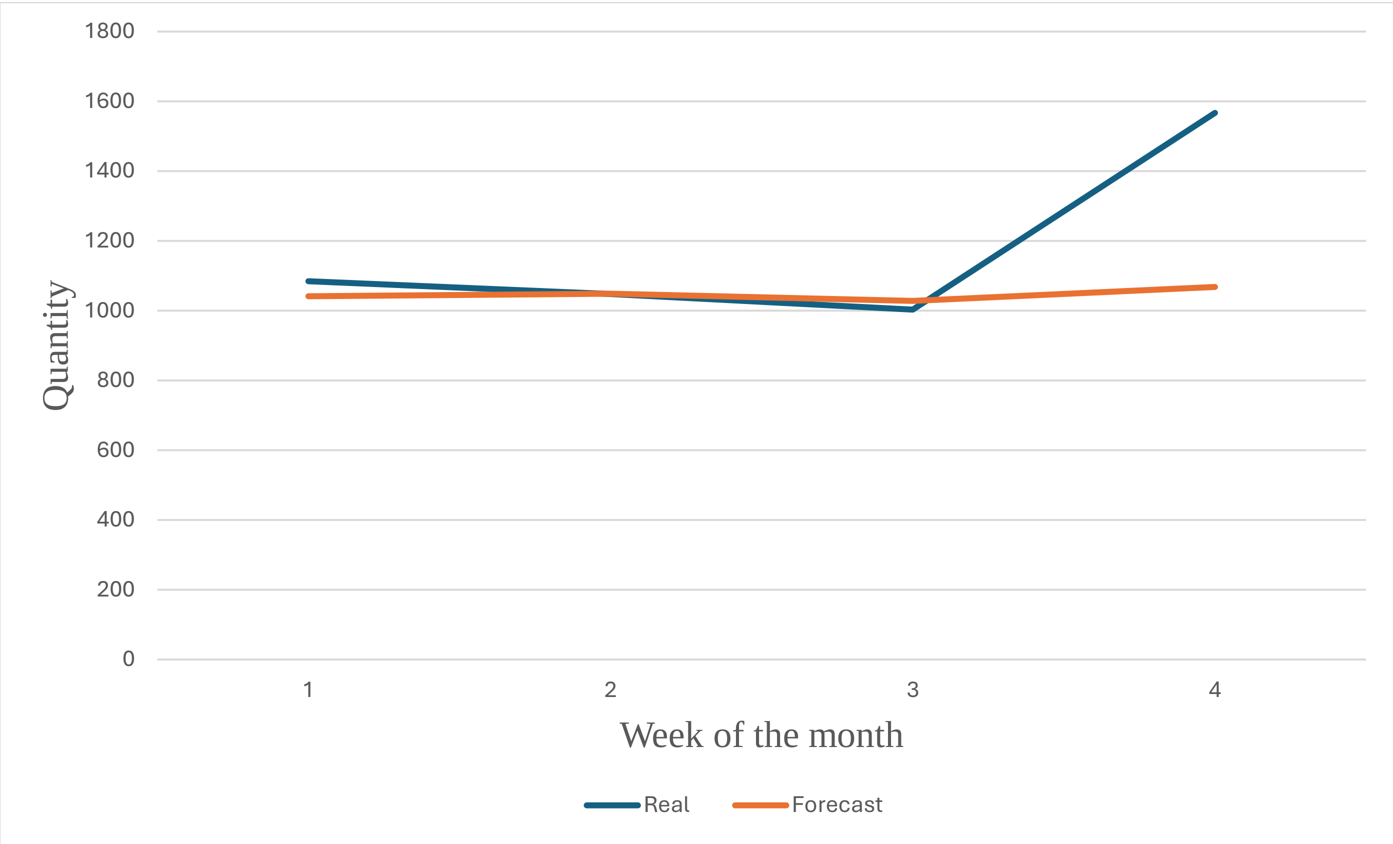

Fig 5. The real and forecast values of the model developed using MLP with the Use Best N for product B

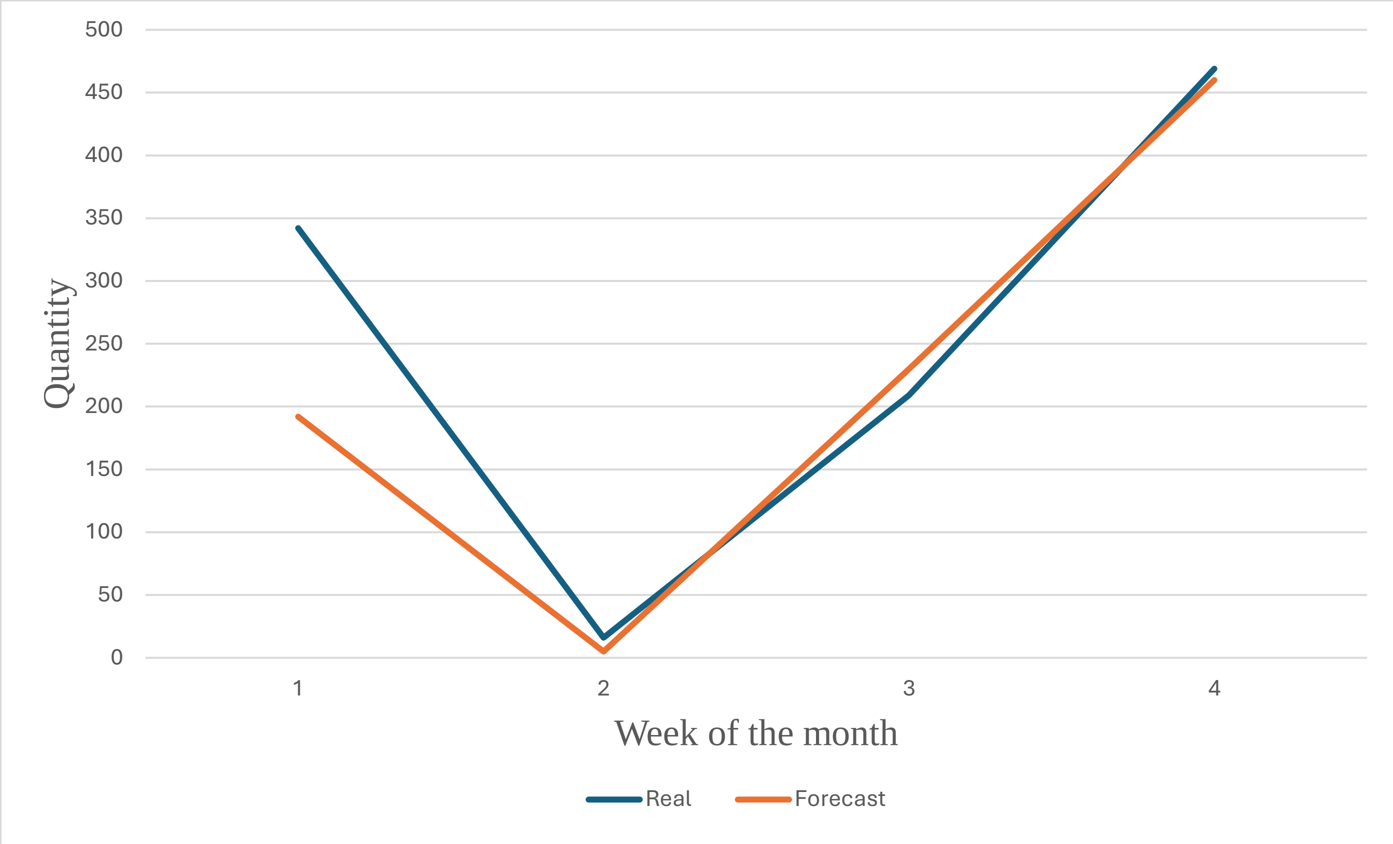

Fig 6. The real and forecast values of the model developed using MLP with the Use All Lags for product C

Upon examining the results of the models developed using MLP:

- The most successful result for Product A was achieved with the Use All Lags, yielding a MAPE of 8.42%. The Use Selected, Use Best N, and Use Correlation demonstrated similar performance.
- For Product B, the best performance has been observed with the Use Best N, achieving an error rate of 9.6%. This suggests that utilizing a specific subset of lags (Best N) improves model accuracy.
- For Product C, the Use All Lags resulted in a MAPE of 31.14%, while the worst performance has been observed with the Use Selected, which had an error rate of 79.28%.

When the results of the models developed using MQRNN have been examined:

- For Product A, the lowest MAPE value, 7.02%, has been achieved with the Use Best N.
- For Product B, the performance difference among the options was minimal. The Use Best N yielded the lowest error rate of 12.35%, while other methods produced similar results, ranging between 12.59% and 13.56%.
- For Product C, MAPE values were notably high, indicating lower model performance compared to other products. Although the best result has been achieved with the Use All Lags, with an error rate of 36.04%, the error rate remains significantly high.

Table 4. MAPE values of the models developed for August

Methods	Products	Lag Options	MAPE (%)
MLP	A	Use All Lags	16.55
		Use Selected	19.17
		Use Best N	13.9
		Use Correlation	18.1
	B	Use All Lags	6.68
		Use Selected	11.55
		Use Best N	9.84
		Use Correlation	10.28
	C	Use All Lags	11.35
		Use Selected	13.03
		Use Best N	13.88
		Use Correlation	26.32
MQRNN	A	Use All Lags	14.15
		Use Selected	18.64
		Use Best N	14.85
		Use Correlation	16.57
	B	Use All Lags	11.39
		Use Selected	16.62
		Use Best N	12.58
		Use Correlation	13.39
	C	Use All Lags	18.74
		Use Selected	22.24
		Use Best N	10.58
		Use Correlation	21.72

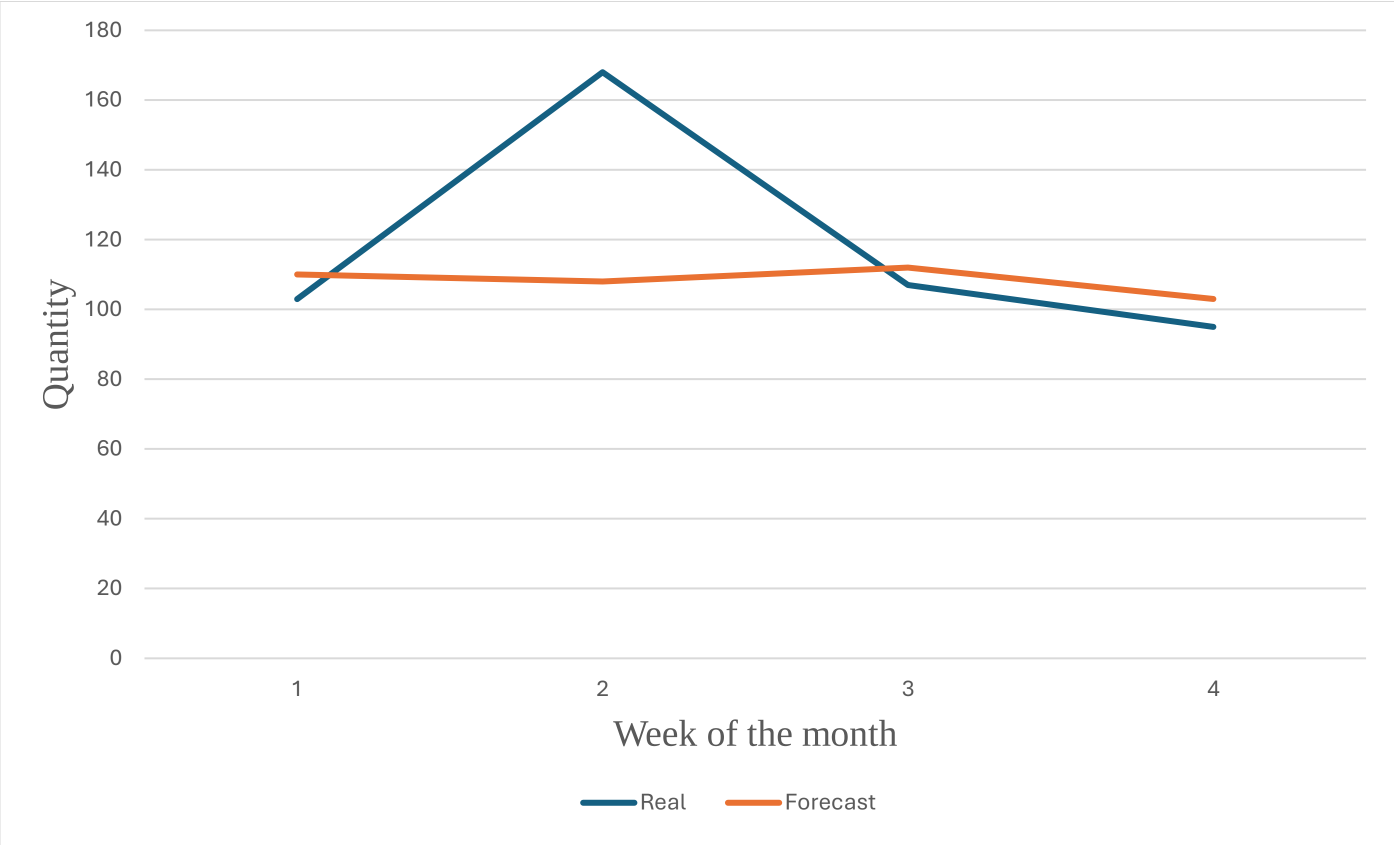

Fig 7. The real and forecast values of the model developed using MLP with the Use Best N for product A

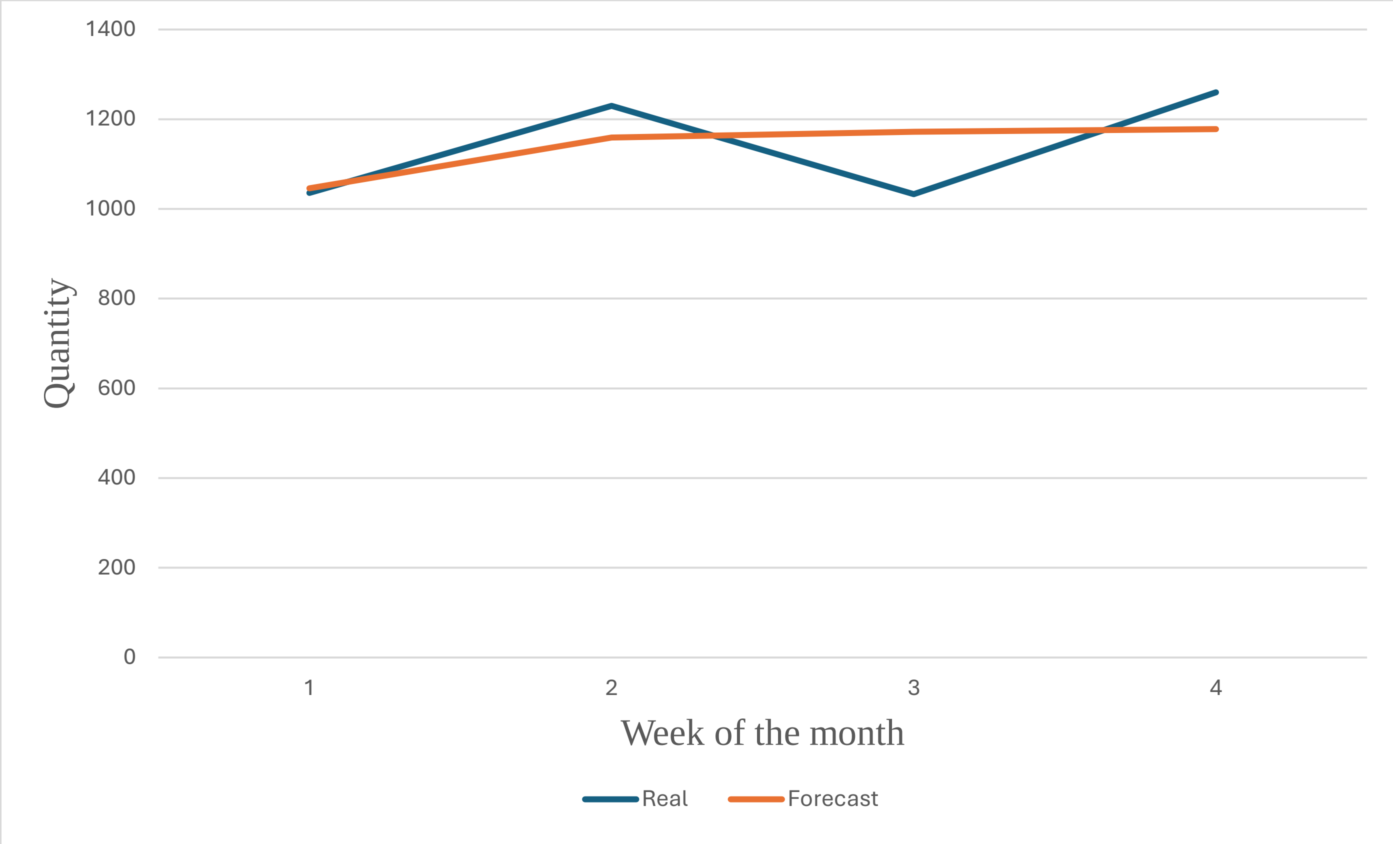

Fig 8. The real and forecast values of the model developed using MLP with the Use All Lags for product B

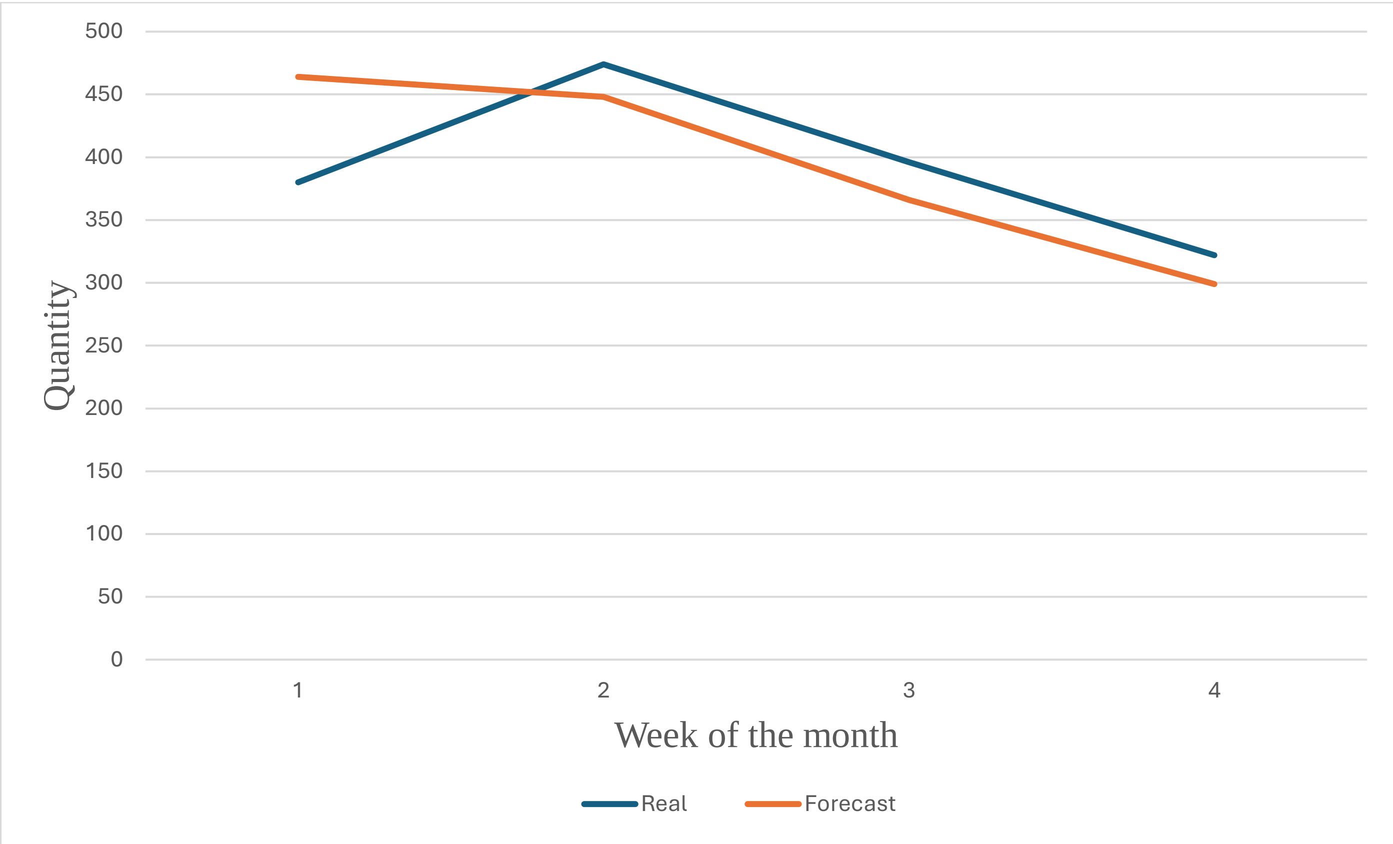

Fig 9. The real and forecast values of the model developed using MQRNN with the Use Best N for product C

When the results of the models developed with MLP have been examined:

- The lowest error rate for Product A was achieved with the Use Best N (13.9%).
- For Product B, the lowest error rate was obtained with the Use All Lags (6.68%), demonstrating very high success.
- The best performance for Product C has been observed with the Use All Lags (11.35%). However, the Use Correlation stands out with a significantly higher error rate of 26.32%, clearly separating it from the other options.

When the results of the models developed with MQRNN have been examined:

- For Product A, the lowest error rate was achieved with the Use All Lags (14.15%), closely followed by the Use Best N (14.85%).
- The best performance for Product B was observed with the Use All Lags (11.39%).
- The lowest error rate for Product C was obtained with the Use Best N (10.58%).

In the forecast models developed for July, the MLP method performed better with the Use All Lags option, while the MQRNN method achieved superior results with the Use Best N option. For the models developed for August, the MLP method again demonstrated superior performance with the Use All Lags option, whereas the MQRNN method showed comparable performance between the Use All Lags and Use Best N options. These analyses show that the performance of time delay options varies based on the method employed. These results help us understand the impact of seasonal performance variations and the methods used on prediction success. The lower MAPE values for Products A and B in July suggest that this period provided more consistent results for the models, while the higher success observed for Product C in August highlights the influence of seasonal factors and product-specific dynamics on model performance. Furthermore, the better performance of MLP compared to MQRNN in August underscores the importance of considering data structure and temporal dynamics when selecting models.

8. CONCLUSION

Time series data are encountered in many different problems today, one of which is demand forecasting. Since correctly modeling the effects of past data on future demand directly influences the accuracy of forecasts, the use of time lags in demand forecasting is of great importance. Time lags help capture future trends, seasonal changes, and other dynamics based on past data. Choosing the right lag parameters enhances the model's flexibility and improves forecast performance, leading to more reliable results. Therefore, choosing the appropriate time lags is critical. In this study, demand forecasting models have been developed to help e-commerce businesses gain a competitive advantage in the market by accurately predicting demand and the effect of time lag options on forecast performance has been analyzed comprehensively. An interface with hyperparametric flexibility has been developed for the forecasting models. Models have been created for two different months and three different products, and their performance has been evaluated using the MAPE metric. The lowest MAPE value for July has been obtained with the MQRNN model developed using product A, while the lowest MAPE value for August has been obtained with the MLP model developed using product B. These findings offer valuable insights for future model development, serving as a strategic guide to improve forecast accuracy and identify the most suitable method for each product. Contrary to the [21], this study offers a comprehensive analysis of the effects and role of lag options on demand forecasting of 3 different products, A, B, C. Furthermore, the structure and functionality of the hyperparametric interface employed in the analysis are thoroughly elucidated. Future studies could enhance forecast accuracy by analyzing the performance of different time lag options on complex data structures across various sectors and integrating external factors into the models. Additionally, the effects of time lag selection and hyperparameter optimization on forecast performance can be studied in greater depth. This approach can lead to more accurate forecast results and make significant contributions to the literature.

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