Journal of Physics: Conference Series

PAPER • OPEN ACCESS

Furniture market demand forecasting using machine learning approaches

To cite this article: P E Yaneva and H N Kulina 2023 *J. Phys.: Conf. Ser.* **2675** 012008

Furniture market demand forecasting using machine learning approaches

P E Yaneva and H N Kulina

Department of Mathematical Analysis, Faculty of Mathematics and Informatics, University of Plovdiv Paisii Hilendarski 24 Tzar Asen Street, 4000 Plovdiv, Bulgaria
E-mails: polinayaneva@uni-plovdiv.bg, kulina@uni-plovdiv.bg

Corresponding author's e-mail address: polinayaneva@uni-plovdiv.bg

Abstract. Researching consumer demand in the market for goods is essential for any business. The purpose of this study is to forecast the demand for furniture from a large manufacturer in Bulgaria. Significant factors influencing customer flow, both in the company and online stores, are investigated. Daily observations for nearly two years are modelled using CART Ensemble with arcing. The constructed models describe the demand for furniture with high goodness-of-fit statistics: coefficient of determination up to 93% and determine the order of the factors influencing the demand.

1. Introduction

The worldwide furniture market is expected to rise at a compound annual growth rate of 5.2% from 2021 to 2028 [1] and is now an important part of the global economy. In recent years, this has given furniture companies access to a lot of information that can be used to improve their development decisions. For example, they can use machine learning (ML) to better expectations of accurate furniture demand. This allows corporations to optimize their production techniques, inventory management, and advertising strategies.

Business strategies now have increasingly involved demand forecasting. Studies have proven that ML algorithms including regression evaluation, time series analysis, and neural networks can enhance the accuracy of demand forecasting [2,3]. For instance, to analyse the demand for different products in the furniture market, researchers [4-6] have used machine learning approaches such as deep learning, application of regression, and artificial intelligence methods to predict demand in a construction machinery company and application of artificial neural networks using the Bayesian training rule in sales forecasting for the furniture industry. These studies reveal that, unlike conventional statistical patterns, machine learning algorithms can improve demand forecasting accuracy. Paper [7] describes how a long short-term memory (LSTM) network is used to forecast sales in the supply chain of the furniture industry. The authors note that successful marketing forecasting is a challenging task because of the complex nature of supply chain operations and the wide range of consumer demand. They point out that using LSTM networks can help improve the accuracy of sales forecasts by taking seasonality and trends into account. A similar proposal, but for artificial neural networks (ANN) is demonstrated in the paper [8]. This shows the potential of these machine learning techniques in the supply chain and planning processes of the furniture industry. The authors also emphasize the importance of choosing the right input variables and network architecture for ANN models to improve results. Paper [9] developed a better demand forecasting model using deep learning methods and also proposed a supply chain solution integration strategy. To improve the accuracy of sales forecasts, [10] proposed a demand-based tensor factorization approach. The paper [11] uses data mining techniques to forecast customer demand for remanufactured products. The process of discovering patterns and relationships from large data sets is called data mining. The authors use machine learning techniques to determine the requirements for refurbished products (RPDP) with the highest accuracy and adaptability. The purpose of the research is to create an appropriate and successful marketing plan. Article [12] proposes demand forecasting using machine learning and ordered summation methods. The method includes many learning algorithms such as linear regression, random forests, gradient boosting, and regression trees. The combination of these makes a final prediction based on the predictions of the original models.

The use of machine learning-based demand forecasting methods compared to traditional mathematical time series models, such as autoregressive integrated moving average (ARIMA), also improves forecasting accuracy [13]. Some of the most frequently used demand forecasting techniques are random forest regression (RFR), decision tree regression (DTR), and support vector regression (SVR) due to their ability to handle non-linear interactions and massive data sets [14]. Traditional forecasting methods have conditions for capturing nonlinear relationships and handling massive and complex datasets [15]. They usually presume a linear relationship between variables and are incapable of determining more complex patterns and features in the data. In comparison, machine learning methods are intended to handle non-linear relationships. They can handle large amounts of data and thus are well suited for demand forecasting in the furniture business [16, 17]. Machine learning has a large range of applications and can significantly improve demand forecasting. For example, it can be used to optimize manufacturing and store management, lower waste, and minimize costs [18, 19]. To improve customer contentment, we can use machine learning to provide that the right product is supplied at the right time [20, 21]. In the furniture industry, predicting demand has the future to change the way companies work and improve profitability and productivity.

In this paper, we research the application of machine learning methods in furniture market demand forecasting. Specifically, we focus on classification and regression trees (CART) ensemble methods that use lagged variables of independent factors to capture the lagged effect of advertising on business purchase characteristics. The objective of this article is to gain insight into the future of these technologies for accurate demand forecasting.

2. Data and methods

2.1. Data

This work used daily data for a big furniture producer in Bulgaria. The period is from 01 January 2020 to 30 October 2021, or N=648 recordings. The investigated data are as follows: the flow of people in the store network for the day (Store_Traffic); the flow of people who visited the online store (website) per day (Web_ Traffic); advertisement on Facebook (FB_Ads), in BGN; advertisement in Google (Google_Ads), in BGN; advertisement in two big private TV groups (TV1_Group), (TV2_Group), in target rating point (TRP). The dependent variables are the flow of people in the store network for the day (Store_Traffic) and those who visited the online store per day (Web_ Traffic). Visitors to the company store network are counted by cameras placed at each site. Website visitors are counted with a visit counter. We have analyzed customer traffic in the stores and website, summarizing the findings in Table 1. The data shows notable fluctuations in Store_Traffic and Web_Traffic, indicating varying levels of customer engagement.

2.2. Ensemble methods used in this study

Ensemble methods are machine learning techniques that combine several base models (such as CART, neural networks, etc.) to make the final decision, which is often better than individuals. These methods rely on "resampling" techniques to create different training sets for each of the models. According to how generated the base learners there are two popular methods for creating ensembles: sequential ensemble methods – boosting, where the base learners are generated sequentially, and parallel ensemble methods where the base learners are generated in parallel – bagging, represented by Breiman [22]. The parallel ensemble methods exploit the independence between the base learners and show that the error can be reduced. Ensemble methods are widely used in both classification and regression. In classification, the final decision is made by voting, and in regression, by averaging.

Table 1. Descriptive statistics of the used variables.

Variables	Minimum	Maximum	Range	Std. Deviation	Mean	
					Statistics	Std.Error
Store_Traffic (number)	720	5997	5277	974.008	2992.07	38.263
Web_Traffic (number)	14408	47390	32982	6000.337	28632.27	235.716

The arcing (arc-x4) framework is a sequential ensemble method introduced by Breiman in [23]. In the case of classification, arcing uses a simple mechanism for determining the probabilities of including observation in the training set. After the first K classifiers the next formula expresses the chance p_i that observation i will be picked for the training set of classifier K + 1 [23]:

$$p_i = (1+m_i^4)(\sum_{j=1}^{N}(1+m_j^4))^{-1}\ , \tag{1}$$

where the value m_i represents the number of times that the i^{th} observation was incorrectly included by the previous K classifiers. In regression, the probability is used as a weight for the i^{th} observation.

The advantage of arcing ensemble methods is that they can help to reduce bias and variance, especially when individual models. In general, ensemble methods are less sensitive to noise and outliers in the data. The combination of several models helps to smooth the errors of individual models. This increases the overall robustness of the predictions. The disadvantages of ensemble methods are that they often require more computational resources and time to train and predict than single models and can be challenging to interpret and explain.

In this paper, we use CART to build the base models in a regression model. Therefore, the predictions of the ensemble model are the arithmetic mean of the predictions of the trees of the ensemble. The hyperparameters set at the beginning of the analyses are the number of trees in the ensemble, the minimum number of cases in the parent node, and the minimum number of instances in a child node. Another main parameter that determines the algorithm is the cross-validation of the k-fold type.

This paper uses the Arcing ensemble algorithm for regression from the software engine CART ensembles and bagger of the Salford predictive modeler [24]. It also uses IBM SPSS Statistics [25].

2.3. Model evaluation metrics

When evaluating the performance of arcing, we utilize several predictive model evaluation measures. We chose: root mean squared error (RMSE), mean absolute percentage error (MAPE), and R-squared (R^2), using the formulas:

$$RMSE = \left(\frac{1}{N}\sum_{i=1}^{N}(Y_i - P_i)^2\right)^{1/2},\ MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{Y_i - P_i}{Y_i}\right|,\ R^2 = \frac{\left(\sum_{i=1}^{N}(P_i - \overline{P})(Y_i - \overline{Y})\right)^2}{\sum_{i=1}^{N}(P_i - \overline{P})^2 . \sum_{i=1}^{N}(Y_i - \overline{Y})^2} \tag{2}$$

where Y is the observed dependent variable (target), P is the model prediction, Y_i and P_i (i=1,2, …, N) are their values, respectively; $\overline{Y}$ and $\overline{P}$ are mean values, N is the sample size. A good predictive model should exhibit low errors, indicating accurate predictions with minimal deviation. Additionally, a high R^2 value suggests a strong explanatory power of the model, indicating a better fit for the observed data.

3. Results with discussion

3.1. Building ensemble models of Store_Traffic

Figure 1 illustrates the plot of the dependent variable Store_Traffic, revealing a noticeable upward linear trend. The plots also highlight numerous peaks in the variables, indicating potential factors such as the growing popularity of the store, an increasing number of customers, or successful marketing and advertising campaigns.

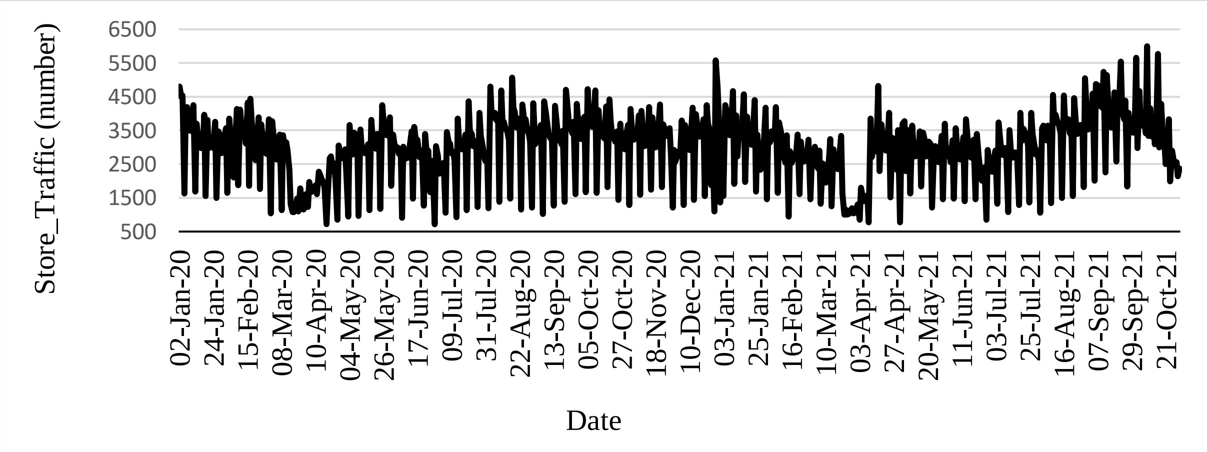

Figure 1. Observed values of Store_traffic.

The conducted Dickey-Fuller and Phillips-Perron tests showed a p-value < 0.01 rejecting the null hypothesis of non-stationarity, i. e. the time series is stationary. The study continues with the construction of the graph of the partial autocorrelation function (PACF) function in Figure 2.

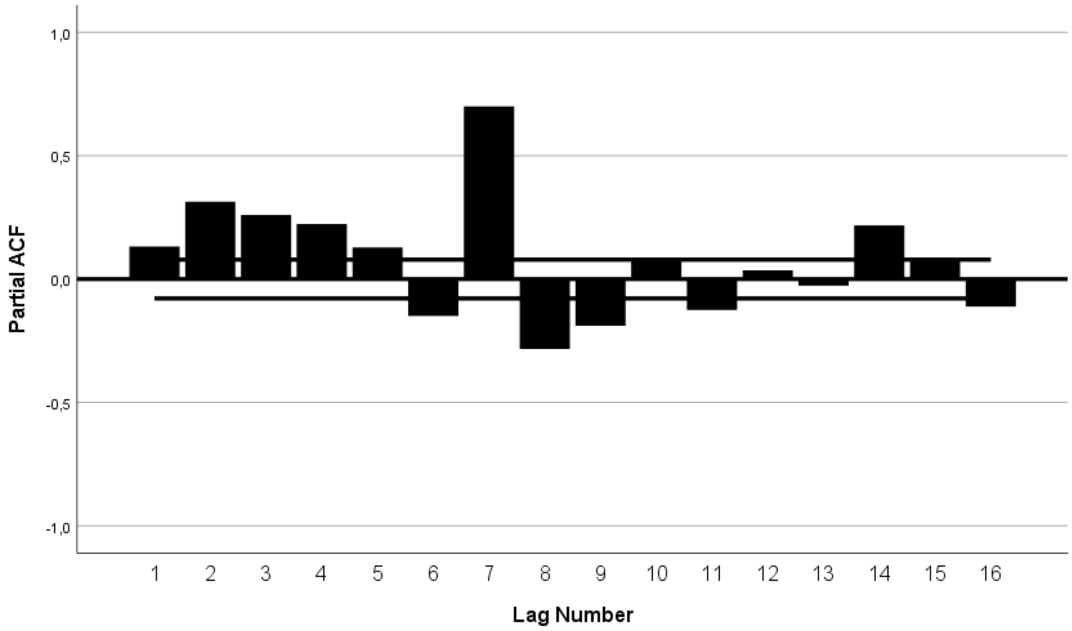

Figure 2. Partial autocorrelation function (PACF) of Store_Traffic.

From the PACF plots of the dependent variable Store_Traffic, we can observe that Store_Traffic lag 7 stands out with a relatively high partial autocorrelation coefficient. PACF shows us that we can use the lagged values of the variable for further analyses.

To validate the models, we constructed a new dependent variable called Store_Traffic_7. This variable was created by removing the last seven values from the initial time series, Store_Traffic.

For the model predictors, we conducted tests using various variables and identified the following lag values as the most influential: Web_ Traffic: lag 2, 4, and 7; Store Traffic: lag 1 and 7; Facebook (FB): lag 2 and 4; Google: lag 7; TV1_Group: lag 7; TV2_Group: lag 7. These lag values indicate the time intervals at which the predictors are most relevant and impactful in forecasting Store_Traffic_7. The hyperparameters of the ensemble models include a minimum number of cases in parent and child nodes of each tree – 5 and validation, which is performed by the 10-fold cross-validation algorithm. For each different choice of predictor, we compare models with different numbers of trees in the ensemble based on evaluation measures. We find that as the number of trees in the ensemble increases, R^2 increases and the corresponding MAPE decreases. Table 2 shows the prediction statistics of the results of ensemble models with 10, 20, 30, 40, 50, 60, and 70 trees.

Table 2. Prediction statistics of ensemble models of Store_Traffic_7

Model	Number of trees	RMSE	MAPE	R^2
Arc10	10	335.8009	11.6659	0.8929
Arc20	20	271.3181	9.3211	0.9337
Arc30	30	244.8294	8.2289	0.9462
Arc40	40	232.9647	7.7723	0.9514
Arc50	50	226.2525	7.5315	0.9542
Arc60	60	220.8948	7.2943	0.9564
Arc70	**70**	**218.3189**	**7.1542**	**0.957**

We have determined that the best model consists of 70 trees. Figure 3 displays a comparison between the observed values of the Store_Traffic time series, (represented by the red line,) and the predictions made by the Arc70 model, (represented by the blue dashed line.) This comparison focuses on the most recent 50 days of the time series. Beyond the vertical line in the plot, we find the forecasted values generated by the Arc70 model.

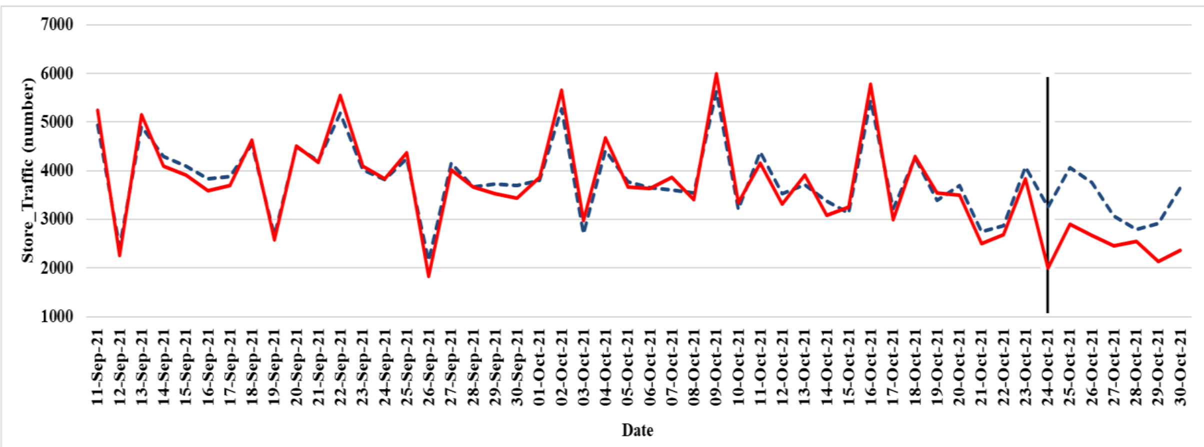

Figure 3. Comparison between observed values of the store traffic time series (red line) and predicted by the Arc70 model (blue dashed line). After the vertical line are the forecasted values.

The built model has a coefficient of determination R^2=0.957 (between Store_Traffic and predicted Store_Traffic _7) and explains around 96% of the change of the dependent variable Store_Traffic. The following performance measures are: RMSE = 218.3189, MAPE = 7.1542.

The importance of variables in the Arc70 model remains consistent regardless of the number of trees. The most significant influence on Store_ Traffic is the store traffic from 7 days ago with 100 points, as shown in Figure 4. The influence of the remaining variables is determined relative to it. The next highest importance is the website traffic from 2 days ago. FB advertising, website traffic, and Google advertising are subsequent variables in terms of their influence on store traffic. And finally, advertisements on television exhibit the least significant impact on store traffic according to the Arc70 model.

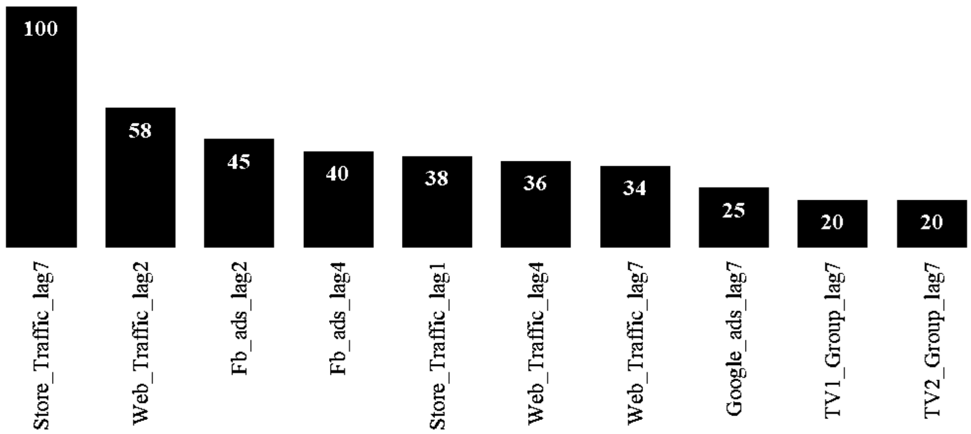

Figure 4. Relative variable importance of independent variables in the model Arc70.

Examination of the residuals for the selected model shows that they are close to normal distribution. This can be seen from the histogram of the residuals in Figure 5.

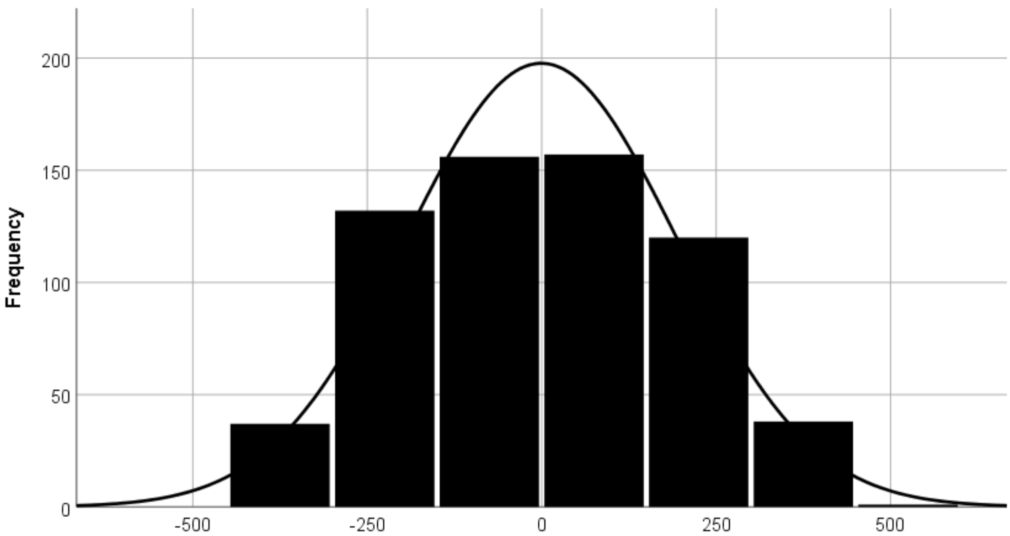

Figure 5. Histogram of residual scores of Store_Traffic for Arc70 model.

3.2. Building ensemble models of Web_Traffic

Like any large chain, the company offers its customers to view and purchase goods from the online store. Website visits are an indicator of customer interest and demand. Figure 6 illustrates the plot of the dependent variable Web_Traffic.

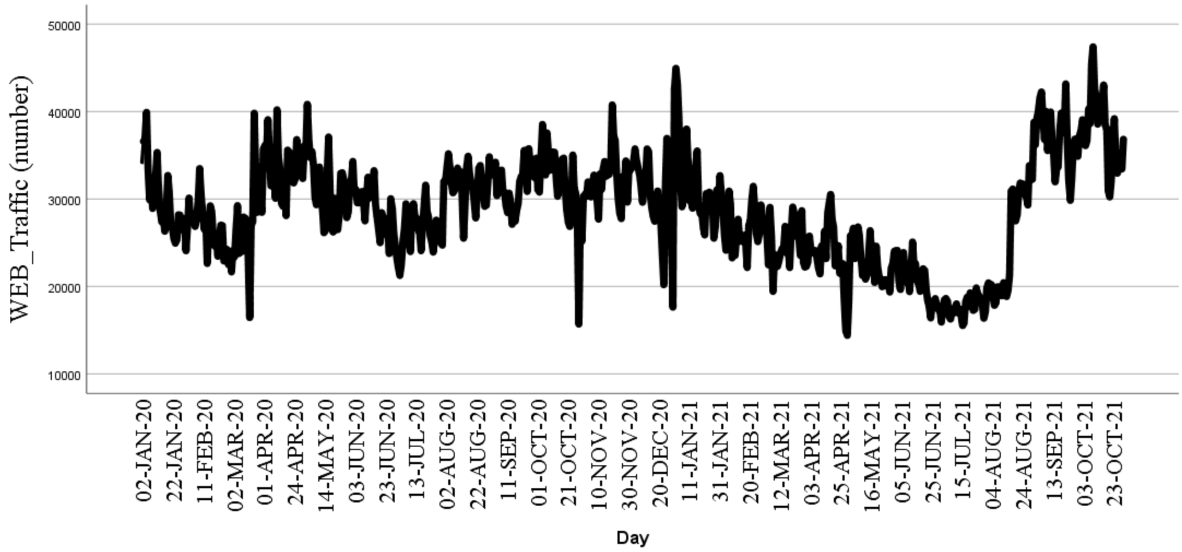

Figure 6. Observed values of the Web_Traffic.

The Dickey-Fuller, and Phillips-Perron tests performed showed a p-value > 0.05, indicating that the time series is non-stationary. Figure 7 showcases the PACF plot of the dependent variable Web_Traffic. Lag 1 has a high positive partial autocorrelation coefficient. Lags 4, 5, and 6 also exhibit significant partial autocorrelation, although with smaller coefficients, suggesting some correlation between the current value and the values at those lags. This gives us reason to include the corresponding lagged variables in the construction of the arcing models.

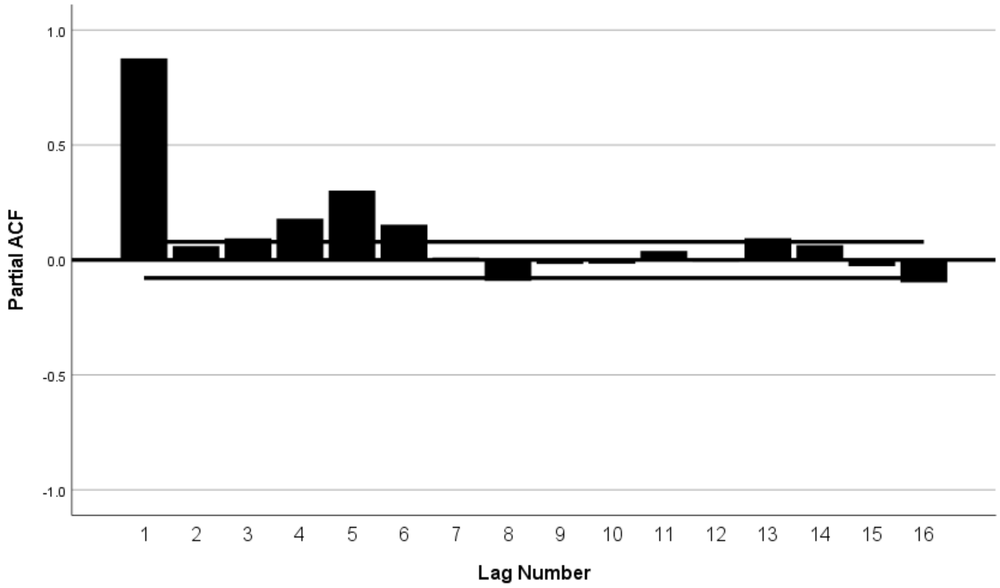

Figure 7. Partial autocorrelation function (PACF) of Web_Traffic.

To validate the models for the Web_Traffic variable, we created a new dependent variable called Web_Traffic_7. This variable was derived by removing the last 7 values from the initial time series, Web_Traffic. We tested various predictors and selected the following variables: Web Traffic: lag 2, 4, and 7; Store Traffic; Facebook (FB): lag 2 and 4; Google; TV1_Group; TV2_Group. The hyperparameters used in this evaluation process are the same as those employed for the arcing model of Store_Traffic. Table 3 shows the prediction statistics of ensemble models with 10, 20, 30, 40, 50, and 60 trees.

Table 3. Prediction statistics of ensemble models of Web_Traffic_7.

Model	Number of trees	RMSE	MAPE	R^2
Arc10	10	1672.211	5.2553	0.930516
Arc20	20	1359.629	4.2876	0.95676
Arc30	30	1239.262	3.9311	0.96539
Arc40	40	1163.306	3.6997	0.970065
Arc50	50	1128.799	3.5686	0.971628
Arc60	**60**	**1108.679**	**3.513**	**0.960**

For each different choice of predictor, we compare models with different numbers of trees in the ensemble based on evaluation measures. We can see that after the Arc10 model, the corresponding mean absolute percentage error decreases and is under 5%.

The best model for forecasting Web_Traffic_7 is the one with 60 trees. This model demonstrates the following performance measures: RMSE = 1108.679, MAPE = 3.513, R^2 = 0.960. They highlight the accuracy and precision of the chosen model in forecasting Web_Traffic_7.

Figure 8 shows the comparison between observed values of the Web_Traffic time series (red line) and predicted by the Arc60 model (blue dashed line) for the last 50 days. The forecasted values are after the vertical line.

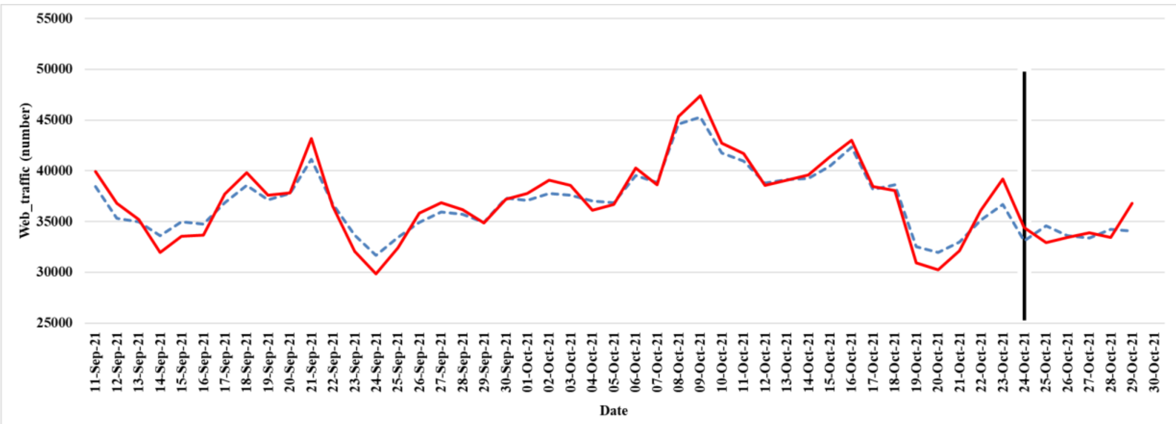

Figure 8. Comparison between observed values of the web traffic time series (red line) and predicted by the Arc60 model (blue dashed line). After the vertical line are the forecasted values.

The analysis of variable importance within the selected ensemble model reveals that the influence of variables remains consistent across different numbers of trees – 10, 20, 30, 40, 50, and 60. For the chosen model, a significant influence on the Web_Traffic variable has website traffic from 2 days ago. Following are the website traffic from 7 and 4 days ago, indicating that recent web traffic patterns strongly impact the current web traffic levels. Advertisements on television have the least significant impact on the Web_traffic variable.

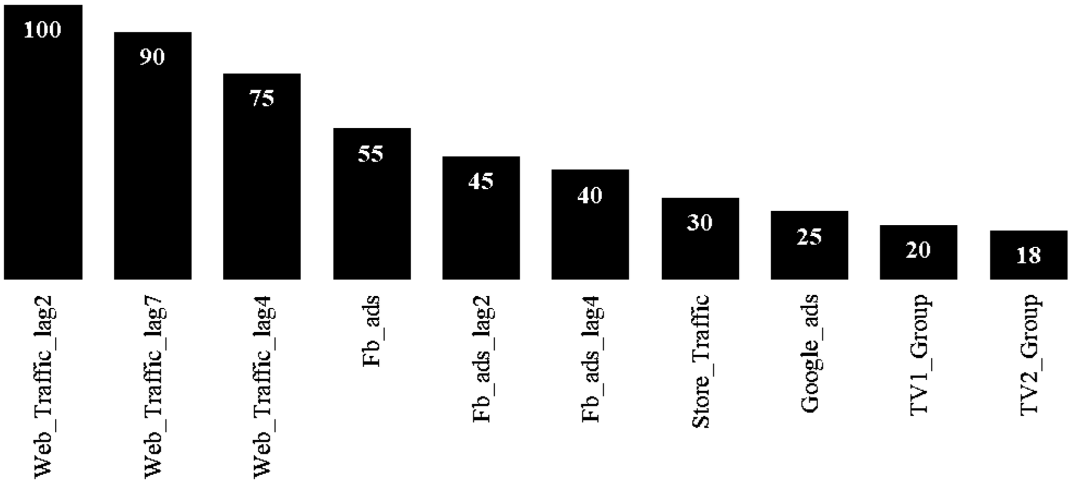

Figure 9. Relative variable importance of independent variables in the model Arc60.

Examination of the residuals for the selected model shows that they are close to normal distribution. This can be seen from the histogram of the residuals in Figure 10.

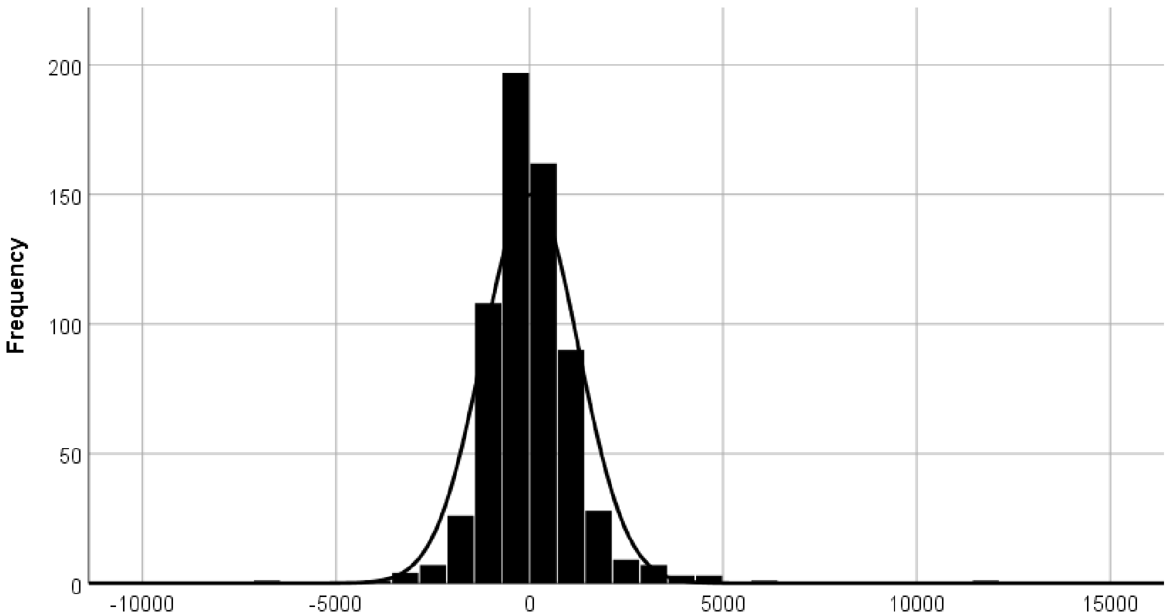

Figure 10. Histogram of residual scores of Web_Traffic for Arc60 model.

4. Conclusion

In conclusion, our study focused on utilizing machine learning techniques for furniture market demand forecasting. We evaluated the performance of these models on the Store_Traffic and Web_Traffic variables, providing valuable insights into the accuracy of our predictions.

Based on the analysis and interpretation of the results, it can be concluded that website traffic has the greatest influence on the demand for furniture, followed by online advertisements. This suggests that the online presence and marketing efforts of the furniture store significantly impact the demand for their products. It is likely that customers are increasingly relying on online channels to explore and make purchasing decisions. On the other hand, TV commercials have the least impact on demand. Furthermore, it was previously discussed that store traffic has the greatest impact on store turnover. This finding suggests that customers have a preference for physically visiting the store before making a purchase**.**

Acknowledgments
This study was supported by the Bulgarian National Science Fund, Grant KP-06-N52/9.

References

[1] Furniture Market Size, Share & Trends Analysis Report By Product (Beds, Tables & Desks, Sofa & Couch, Chairs & Stools, Cabinets & Shelves), By Material (Metal, Wood, Plastic, Glass), By Application, By Region, And Segment Forecasts, 2022 – 2030 https://www.grandviewresearch.com/industry-analysis/furniture-market
[2] Alsharari N M, Al-Shboul M and Alteneiji S 2020 Implementation of cloud ERP in the SME: evidence from UAE *Journal of Small Business and Enterprise Development* **27**(2) 299–327
[3] Al-Haidari R, Al-Rawashdeh S, Zeidan A, Omambala J and Nagarur N 2023 Impact of Covid-19 pandemic on demand and demand forecasting in a furniture wholesale company *Preprints* **2023040144**, https://doi.org/10.20944/preprints202304.0144.v1
[4] Deng W, Patil R, Liu F, Daji E and Shi Y 2021 Exploring freight loading management by deep learning: a case study in home furnishing industry *Annals of Data Science* **9**(2) 213–228
[5] Aktepe A, Yanik E and Ersöz S 2021 Demand forecasting application with regression and artificial intelligence methods in a construction machinery company *Journal of Intelligent Manufacturing* **32(6)**1587–1604
[6] Yucesan M, Gul M and Erkan E 2017 Application of artificial neural networks using bayesian training rule in sales forecasting for furniture industry *Drvna Industrija* **68**(3) 219–228
[7] Pliszczuk D, Lesiak P, Żuk K and Cieplak T 2021 Forecasting sales in the supply chain based on the LSTM network: the case of furniture industry *European Research Studies Journal* XXIV(Special Issue **2**) 627–636
[8] Bibaud-Alves J, Thomas P and Haouzi H B E 2019 Demand forecasting using artificial neuronal networks and time series: application to a French furniture manufacturer case study, *Conf. Proc. International Joint Conference on Computational Intelligence* **2019**
[9] Kilimci Z H, Akyuz A O*,* Uysal M, Akyokus S, Uysal M O, Bulbul B A and Ekmis M A 2019 An improved demand forecasting model using deep learning approach and proposed decision integration strategy for supply chain *Complexity* **2019** Article ID 9067367
[10] Bi X, Adomavicius G, Li W and Qu A 2022 Improving sales forecasting accuracy: a tensor factorization approach with demand awareness *Informs Journal on Computing* **34**(3) 1644–1660
[11] Van Nguyen T, Zhou L, Loong Chong Y A, Li B and Xiaodie P. 2020 Predicting customer demand for remanufactured products: A data-mining approach *European Journal of Operational Research* **281**(3**)** 543–558
[12] Tugay R and Oguducu S G 2020 Demand prediction using machine learning methods and stacked generalization *arXiv:2009.09756 (Cornell University)*
[13] Fattah J, Ezzine L, Aman Z, El Moussami H and Lachhab A 2018 Forecasting of demand using ARIMA model *International Journal of Engineering Business Management* **10**
[14] Birim S, Kazancoglu I, Mangla S K, Kahraman A and Kazancoglu Y 2022 The derived demand for advertising expenses and implications on sustainability: a comparative study using deep

learning and traditional machine learning methods *Annals of Operations Research* **Jan 7**, 1-31
[15] Younis H M, Sundarakani B and Alsharairi M 2021 Applications of artificial intelligence and machine learning within supply chains: systematic review and future research directions *Journal of Modelling in Management* **17**(3) 916–940
[16] Rosienkiewicz M, Kowalski A, Helman J and Zbieć M 2018 Development of lean hybrid furniture production control system based on glenday sieve, artificial neural networks and simulation modeling *Drvna Industrija* **69**(2) 163–173
[17] Abbasimehr H, Shabani M and Yousefi M 2020 An optimized model using LSTM network for demand forecasting *Computers & Industrial Engineering* **143** 106435
[18] Makkar S, Devi G N R and Solanki V K 2020 Applications of machine learning techniques in supply chain optimization *ICICCT 2019 - System Reliability, Quality Control, Safety, Maintenance and Management* ed V K Gunjan, V Garcia Diaz *et al* (Singapore: Springer Singapore) pp 861–869
[19] Song Y, Cao Q and Zhang C 2018 Towards a new approach to predict business performance using machine learning *Cognitive Systems Research* **52** 1004–1012
[20] Ersöz T, Güven İ and Ersöz F 2022 Defective products management in a furniture production company: A data mining approach *Applied Stochastic Models in Business and Industry* **38**(5) 901– 914
[21] Hernández N N M, Cano-Olivos P, Sánchez-Partida D, Martínez-Flores J L and Caballero-Morales S O 2020 Demand forecasting: a challenge for furniture SMEs *Handbook of Research on Developments and Trends in Industrial and Materials Engineering* ed P Sahoo (IGI Global) pp 1-21
[22] Breiman L 1996 Bagging predictors *Machine Learning* **24**(2) 123–140
[23] Breiman L 1996 Bias, variance, and arcing classifiers *Technical Report* **460**, Statistics Department, University of California, Berkeley, CA
[24] *Salford Predictive Modeler* www.minitab.com/en-us/products/spm/
[25] *IBM SPSS Statistics*, https://www.ibm.com/products/spss-statistics