İşletme | The Business Journal 2025, 6(2), 213-225

https://doi.org/10.57116/isletme.1737812 e-ISSN: 2757-9433

Stock Price Forecasting Using Single Multiplicative Neuron Model Artificial Neural Network (SMNM-ANN): A Case of Iron-Steel Sector in Türkiye

(Tek Çarpan Nöron Modeli Yapay Sinir Ağı (SMNM-ANN) Kullanarak Hisse Senedi Fiyat Tahmini: Türkiye Demir-Çelik Sektörü Örneği)

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Keyword:
Single Multiplicative Neuron Model, Artificial Neural Network, Stock Price, Machine Learning, Iron-Steel

Paper type:
Research

Abstract

This study employs the Single Multiplicative Neuron Model Artificial Neural Network (SMNM-ANN) Automatic Forecasting Method for Stock Price Prediction in Turkey's steel industry. Accurate financial forecasts are critical for businesses and investors, as the primary goal is to maximize profits through predicting future stock prices. A variety of methods are used in stock price predictions, with traditional techniques being complemented by artificial neural networks and machine learning methods in recent times. In this context, the SMNM-ANN method provides a flexible, nonlinear approach for predicting stock prices. The study utilizes 1101 stock closing price data between January 28, 2015, to May 30, 2025. To facilitate comparisons, machine learning techniques such as Boosted Tree, Decision Tree, and SVM are also employed. The application calculates forecast values for the next 10 data points, revealing that the SMNM-ANN-AFM method exhibits lower error rates. The obtained RMSE value is 0.6983, while the MAPE value is 2.5138. This research highlights the potential of SMNM-ANN to enhance decision-making processes and resource allocation in the steel sector, thereby contributing significantly to the industry.

Anahtar Kelimeler:
Tek Çarpanlı Nöron Modeli, Yapay Sinir Ağı, Hisse Senedi Fiyatı, Makine Öğrenmesi, Demir-Çelik

Makale türü:
Araştırma

Öz

Bu çalışma, Türkiye'deki demir-çelik sektöründe Hisse Senedi Fiyat Tahmini için Tek Çarpanlı Nöron Modeli Yapay Sinir Ağı (SMNM-ANN) Otomatik Tahmin Yöntemini kullanmaktadır. Doğru finansal tahminler, işletmeler ve yatırımcılar için kritik öneme sahiptir. Bu sürecin en önemli kısmı da gelecekteki hisse senedi fiyatlarını tahmin ederek elde edilecek karı maksimize etmektir. Hisse senedi tahminlerinde birçok farklı yöntem kullanılmaktadır. Geleneksel yöntemleri yanı sıra yapay sinir ağları ve makine öğrenmesi teknikleri son dönemlerde sıkça kullanılmaya başlanmıştır. Bu bağlamda, çalışmada kullanılan SMNM-ANN yöntemi, esnek ve doğrusal olmayan bir yaklaşım sunarak hisse senedi fiyatlarını tahmin etmektedir. Çalışmada, 28 Ocak 2015 ile 30 Mayıs 2025 tarihleri arasında 1101 hisse senedi kapanış fiyatı verisi kullanılmıştır. Çalışmada karşılaştırma yapabilmek için ayrıca makine öğrenmesi tekniklerinden Boosted Tree, Decision Tree ve SVM kullanılmıştır. Uygulamada, gelecek 10 gözleme ait tahmin değerleri hesaplanmış ve elde edilen sonuçlar, SMNM-ANN-AFM yönteminin daha düşük hata oranları sergilediğini göstermiştir. Elde edilen RMSE değeri 0.6983, MAPE değeri ise 2.5138 olarak belirlenmiştir. Bu araştırma, SMNM-ANN'nin demir çelik sektöründe karar verme süreçlerini ve kaynak tahsisini geliştirme potansiyelini açıkça vurgulamaktadır, böylece sektör için önemli bir katkı sağlamaktadır.

Başvuru/Received: 08.07.2025 | Kabul/Accepted: 23.09.2025 , iThenticate benzerlik oranı/similarity report: %17

Atıf/Citation: Kara, M. A, Bayyurt, D. (2025). Stock Price Forecasting Using Single Multiplicative Neuron Model Artificial Neural Network (SMNM-ANN): A Case of Iron-Steel Sector in Türkiye, *İşletme*, 6(2), 213-225.

Introduction

Forecasting studies are of vital importance, particularly in the context of financial time series. Accurate predictions play a crucial role in ensuring both the sustainability of businesses and the decision-making processes of investors (Hezam et al., 2025). Financial forecasting is an important aspect of financial planning that involves predicting future financial outcomes using historical data, market trends and various economic indicators. This process serves as a roadmap for organizations, helping them effectively allocate resources, manage risks, and develop strategies for future growth (Brown et al, 2021). In recent years, the rapid economic growth has led to an increase in stock market investments by individuals. Making accurate predictions about stock price fluctuations can help investors mitigate risks and enhance their returns. Given the inherent volatility of the stock market, forecasting stock prices is typically regarded as a nonlinear time series problem. Numerous factors influence stock prices, which complicate predictions using straightforward models (Lu et al., 2021). Stock prices are influenced by various internal and external factors such as the domestic and international economic environment, global conditions, sector expectations, financial data of publicly traded companies, and the functioning of the stock market (Öztürk & Karacı, 2024). Moreover, machine learning methods are increasingly utilized in forecasting efforts. Due to the constantly changing nature of stock prices, developing forecasting systems that can consistently predict price fluctuations will enable investors to make informed decisions (Baek & Kim, 2018).

The literature indicates that a variety of methods are utilized for stock price prediction. Alongside classical approaches, emerging techniques like machine learning and deep learning have gained traction. Common traditional modeling techniques include autoregressive models, threshold autoregressive models, moving average models, and autoregressive-moving average models, which are frequently applied in financial markets (Box et al., 2015; Ballings et al., 2015). Despite their widespread application, these conventional models lack the flexibility needed to adapt to the dynamic nature of financial data, leading to often inaccurate prediction outcomes (Tang et al., 2022).

Artificial neural networks (ANNs) are employed for forecasting in time series analysis. These networks offer flexible, nonlinear, and complex modeling capabilities for predictions. Among the various types, multilayer perceptron neural networks are the most commonly utilized in existing literature. Recently, recurrent deep learning models have gained popularity in forecasting research (Eğrioğlu and Baş, 2022). This article introduces the SMNM-ANN method for predicting stock prices. Initially proposed by Yadav et al. (2007), the SMNM-ANN method addresses both forecasting and classification challenges. Subsequent research has enhanced this method by integrating different algorithms into its training and learning processes. Yeh (2013) developed an innovative swarm optimization technique for training SMNM-ANN. Additionally, Cui et al. (2015) created a hybrid learning system that combined differential evolution and glow-worm swarm optimization. Samanta (2015) proposed a gradient-based online learning approach. A robust learning technique using Mestimators was presented by Bas (2016). Furthermore, whereas Bas et al. (2016b) used the bat algorithm for training, Bas et al. (2016a) suggested a learning algorithm based on differential evolution. In their study, Egrioglu and Bas (2022) proposed a new automatic forecasting method utilizing SMNM-ANN with real-world data.

This study has two primary objectives. The first is to evaluate and compare the performance of the SMNM-ANN method with other forecasting techniques. The second is to showcase the effectiveness of the SMNM-ANN method in predicting stock closing prices. Additionally, the prediction performance of the proposed model has been assessed in relation to various machine learning methods.

The first section of the study discusses research on the method and topic. The second section presents the mathematical steps and algorithms of the method. In the third section, a real data set is used to predict the stock closing prices of a steel company. Subsequently, the results of the SMNM-ANN method are compared with those of machine learning methods using various metrics.

1. Literature Review

Recent research has investigated various approaches for predicting stock prices. For example, Lu et al. (2021) introduced the CNN-BiLSTM-AM method, which combines convolutional neural networks (CNN), bi-directional long short-term memory (BiLSTM), and an attention mechanism (AM) to forecast the next day's stock closing prices. Their study analyzed the Shanghai Composite Index over 1,000 trading days, finding that this method outperforms others in prediction accuracy. Similarly, Arslankaya and Toprak (2021) utilized machine learning and deep learning techniques to forecast stock prices, achieving the best results with the Random Forest algorithm using data from Ereğli Iron and Steel Works Co. Rezaei et al. (2021) proposed innovative hybrid algorithms, CEEMD-CNN-LSTM and EMD-CNN-LSTM, which extract deep features and time sequences to enhance prediction accuracy. Ji et al. (2021) developed a method that combines traditional stock financial indices with social media text features, employing Doc2Vec to generate text feature vectors and using wavelet transforms to clean the stock price data from noise. Yürük (2021) applied artificial neural networks to predict Turkish Airlines stock prices based on five key independent variables from daily data between 2014 and 2021. Koç Ustalı et al. (2021) aimed to forecast future stock prices for companies on the Borsa Istanbul 30 Index using ANN, Random Forest, and XGBoost algorithms, with XGBoost yielding the best results. Tokmak (2022) utilized Long Short-Term Memory networks for stock price predictions, testing four stocks from the Borsa Istanbul Technology Index over a dataset of 2,578 daily values from 2012 to 2022, achieving consistent results. Albayrak and Saran (2023) compared the Autoregressive Integrated Moving Average (ARIMA) model with three recurrent neural network models, finding that while ARIMA had a higher average error rate, the Gated Recurrent Unit (GRU) model performed slightly better than Long Short-Term Memory (LSTM) models. Lu and Xu (2024) introduced an efficient Time-series Recurrent Neural Network (TRNN) for stock price forecasting, utilizing trading volume and sliding windows to enhance model accuracy. Bardak et al. (2024) applied various machine learning techniques, including linear regression, random forests, and gradient boosting machines, to predict Kartonsan's stock price, with GBM achieving the highest accuracy. In their study, Akyüz et al. (2024) aimed to predict the values of the Borsa Istanbul (BIST) Forestry, Paper and Printing (XKAGT) index using the monthly closing values from 2002 to 2023. The author applied artificial neural networks, random forest, k-nearest neighbors, and gradient boosting machine techniques to forecast the index values of the XKAGT stock traded on BIST. Lastly, Çolak (2025) analyzed a dataset of Nike's daily trading data using four deep learning models: LSTM, GRU, RNN, and Multi-Layer Perceptron (MLP). Results indicated that LSTM provided the best performance with the lowest error metrics. In contrast, RNN and MLP models showed higher error rates and struggled to capture complex time series dependencies. Şimşek et al. (2025) proposed a hybrid model combining LSTM and GRU, demonstrating superior performance compared to other hybrid models in stock price prediction.

2. Methodology

2.1. SMN-ANN

SMNM-ANN was first proposed by Yadav et al. (2007). This artificial neural network architecture consists of only one neuron. SMNM-ANN requires fewer parameters compared to other types of neural networks. The neuron model in SMNM-ANN is a multiplicative neuron model, and the aggregation function uses multiplication instead of addition. SMNM-ANN can be utilized for various purposes, such as classification and forecasting. When the aim is forecasting, inputs to SMNM-ANN are generally preferred as lagged variables. The architecture of SMNM-ANN for forecasting purposes is illustrated in Figure 1. The inputs are lagged variables with orders 1, 2, …, p. The network has weights W = (w_1, w_2, …, w_p) and biases B' = (b_1, b_2, ..., b_p). The target values of the network are x_t, where t = 1, 2, ..., n, and n represents the number of time-series observations. The outputs of the SMNM-ANN are calculated for learning samples.

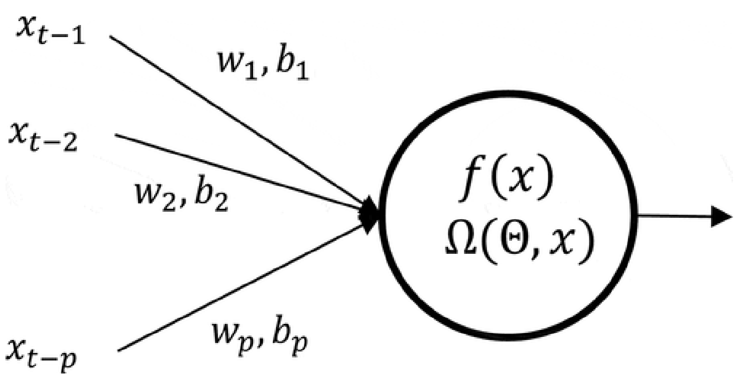

Figure 1. The architecture of SMNM-ANN for forecasting

2.2. *SMNM-ANN – AFM (Automatic Forecasting Method)*

SMN-ANN has been utilized to address nonlinear time series forecasting challenges in existing research. This method serves as a nonlinear multivariate forecasting technique, employing lagged variables from multiple time series as inputs (Eğrioğlu et al., 2023). Automatic Forecasting Method (AFM) relies on assessing input significance and evaluating model adequacy. It is specifically designed for time series that display various components, such as trends and seasonal patterns. The AFM can autonomously detect these components and implement preprocessing steps like differencing and seasonal decomposition (Eğrioğlu and Baş, 2022). The transformed data is processed using SMNM-ANN, while significant inputs are determined through input significance tests. A key advantage of this automatic forecasting method is that it estimates all hyperparameters automatically throughout the process.

The AFM proposed by Eğrioğlu and Baş (2022), with its steps detailed in Algorithm 1, is used for predicting stock closing prices.

The algorithm of the AFM is given in Algorithm 1.

Algorithm 1. AFM based on Input Significance Tests

Step 1. Initially, preprocessing techniques are applied to the time series data to evaluate its seasonality. The series is categorized as seasonally different, meaning D=0, if the given criteria is met. The condition is defined as follows:

$$|ACF_m| > 1.645\sqrt{\frac{1+2(ACF_1+\sum_{i=2}^{m-1} ACF_i^2)}{n}} \tag{1}$$

Seasonal differencing is carried out using the formula:

$$z_t = (1 - B^s)^D x_t \tag{2}$$

In this equation, s represents the seasonality period. Augmented Dickey-Fuller test is then applied to the zt series. If the series exhibits a unit root, further differencing is performed as indicated by the following equation:

$$z_t = (1 - B)^d z_t \tag{3}$$

Step 2. In this step, the SMNM-ANN is trained utilizing lagged variables. The appropriate number of lags is determined through the assessment of partial autocorrelation coefficients, where the lag count corresponds to coefficients that exceed the $\pm 2SE$ limits. These identified lags are subsequently used as inputs for the SMNM-ANN.

Step 3. This step focuses on evaluating model adequacy and testing the significance of inputs. If the model is found to be inadequate, the optimal p value is set to 1, implying the absence of significant inputs for the ANN. Conversely, if the model satisfies adequacy criteria, significant lag numbers are identified through input significance tests. If all inputs are deemed significant, the process advances to Step 5.

Step 4. In this stage, after applying the SMNM-ANN to the significant lagged variables found in Step 2, Step 3 is revisited.

Step 5. Finally, forecasts are generated using the trained SMNM-ANN model. These forecasts are adjusted in accordance with the preprocessing steps implemented earlier. A flowchart depicting the proposed automatic forecasting method is illustrated in Figure 2.

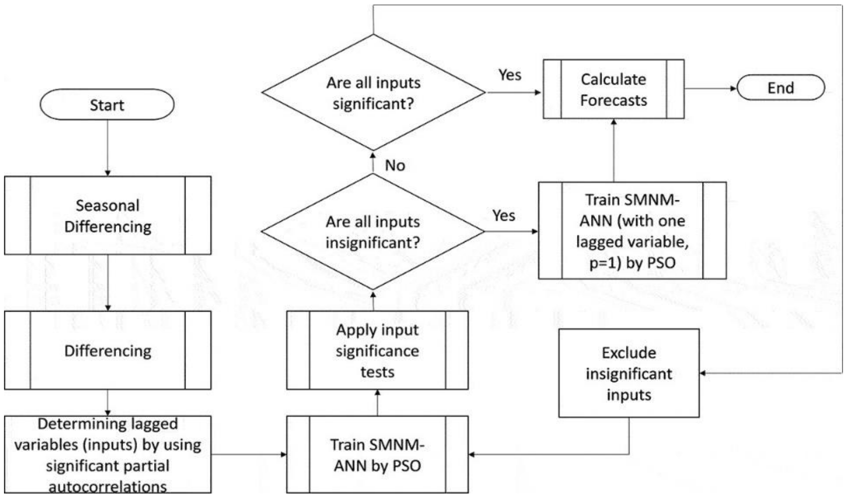

Figure 2. The flowchart of the used AFM

Source: Eğrioğlu and Baş (2022).

2.3. Machine Learning Methods Used in the Study

The study employs several machine learning algorithms, including Boosted Tree, Decision Trees and Support Vector Machine (SVM). The study utilized the Regression Learner Toolbox in MATLAB 2023b.

Decision Trees: Decision trees are used to predict continuous target variables in regression problems. They partition the data into a tree structure, making decisions at each node based on specific criteria. This approach is particularly effective in capturing the complexities within the dataset (Loh, 2011).

Support Vector Machine (SVM): While SVM is commonly used for classification tasks, it can also be applied to regression problems (Pisner & Schnyer, 2020). Support Vector Regression (SVR) is a regression technique derived from support vector machines (SVM). The goal is to find the function that best fits the given training data. SVR keeps the data within a curve of width ε (epsilon), ignoring errors that are within the tolerance and only penalizing errors that are outside the curve.

The decision function for any hyperplane is as follows:

$$f(x) = w^t x_i + b \quad (4)$$

In this function, x_i represents a point on the hyperplane, x_i represents the weight vector, and b represents a constant term.

The objective function is as follows:

$$|\xi|_{\mathcal{E}} = \begin{cases} 0 \; if \; |\xi| \leq \mathcal{E} \\ |\xi| - \mathcal{E} \; otherwise \end{cases} \quad Minimize \; \frac{1}{2}(w.w) + C \sum_{i=1}^{N} (\xi_i^+ + \xi_i^-) \quad (5)$$

In this function, ξ_i^+ and ξ_i^- represents slack variables indicating out-of-tolerance deviations, C represents penalty parameter.

Constraints is as follows:

$$\begin{cases} w.x_i + b - y_i \leq (\xi_i^+ \\ y_i - (w.x_i + b) \leq \xi_i^+ \; i = 1,2,\ldots,N \\ \xi_i^+ \geq 0, \xi_i^- \geq 0 \end{cases} \tag{6}$$

In constraints function, y_i represents real Output variable, $\mathcal{E}$ represents accepted fault tolerance (Cai et al, 2023).

2.4. *Metrics*

The metrics used to evaluate model performance play a critical role in determining the reliability and applicability of the obtained results (Engin & İlter Fakhouri, 2024). In addition, various evaluation metrics such as MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Squared Error) have been used to assess the models' performance during training, testing, and cross-validation.

$$RMSE = \sqrt{\frac{1}{ntest}\sum_{t=1}^{ntest}(x_t - \hat{x}_t)^2} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{t-1}^{n}\left|\frac{A_t - F_t}{A_t}\right| * 100 \tag{8}$$

3. Case Study: Forecasting Erdemir's Stock Closing Prices Using SMNM-ANN Method

The iron and steel sector is a significant contributor to Turkey's economy, accounting for 12.6% of the country's total exports. In January 2025, the export of iron and non-ferrous metals saw a 7.8% increase, reaching 1 billion dollars, while the steel sector experienced a 12.4% growth, totaling 1.3 billion dollars. During the same month, Turkey's crude steel production reached 3.2 million tons, positioning the country among the world's largest producers. This achievement enabled Turkey to surpass Germany, whose steel production declined by 8.8% to 2.8 million tons, thus elevating Turkey to the seventh position in global rankings. Moreover, the removal of the 25% tariff exemptions imposed by the U.S. on countries such as Canada, Mexico, the EU, the UK, Brazil, Japan, and South Korea have increased expectations for a competitive environment in the U.S. market, allowing the Turkish steel sector to compete on equal footing with these nations (Türkiye Çelik Üreticileri Derneği, 2025).

Erdemir Ereğli Demir Çelik A.Ş. holds historical importance in the steel industry, having been established by the Turkish government in 1960 and later privatized in 2006 when it was transferred to OYAK. The company's roots trace back to 1959, when a delegation from the Ministry of Industry collaborated with Koppers Company in the United States to explore the feasibility of a flat steel production facility. Founding members included Koppers Associates SA, İş Bankası A.Ş., the General Directorate of Iron and Steel Enterprises, and the Ankara Chamber of Commerce and Industry. A protocol signed by these organizations led to the creation of an entrepreneurial committee tasked with drafting essential documents such as the bill of law, Founders' Agreement, and Company Articles of Association. The Founders' Agreement was executed on February 12, 1960, marking the establishment of Turkey's first flat steel production facility. This was followed by Law No. 7462, enacted on February 28, 1960, which sanctioned the formation of a joint-stock company named Ereğli Demir ve Çelik Fabrikaları T.A.Ş. (Erdemir). The company was officially registered on May 11, 1960, through legislation designed to bolster existing industries and promote the growth of new industrial sectors during Turkey's rapid industrialization phase (Erdemir Kurumsal Tarihçe, 2025).

In this study, I will utilize the SMNM-ANN method to forecast the stock closing prices of Erdemir, focusing on its pivotal role within the Turkish steel industry and the broader economic context.

3.1. Data Set

The study utilizes daily data from January 28, 2015, to May 30, 2025. The data was obtained from investing.com. There is a total of 1,101 daily stock closing price. The table shows the first 10 and the last 10 values of the dataset.

Table 1. Data Set

Time	**Stock Closing Price (TL)**
28 Jan 2015	5,643
29 Jan 2015	5,586
30 Jan 2015	5,582
02 Feb 2015	5,723
03 Feb 2015	5,643
04 Feb 2015	5,765
05 Feb 2015	5,849
06 Feb 2015	5,773
09 Feb 2015	5,792
10 Feb 2015	6,082
…	…
16 May 2025	24,8
20 May 2025	24,86
21 May 2025	24,24
22 May 2025	23,88
23 May 2025	23,54
26 May 2025	23,52
27 May 2025	23,8
28 May 2025	23,86
29 May 2025	23,82
30 May 2025	23,56

The descriptive statistics of the dataset used in the study are presented in Table 2.

Table 2. Descriptive Statistics

Data Set	SD	Mean	Minimum	Maximum
	6,25	17,27	5,45	29,7

Figure 3 shows the time series graph of the dataset used in the study.

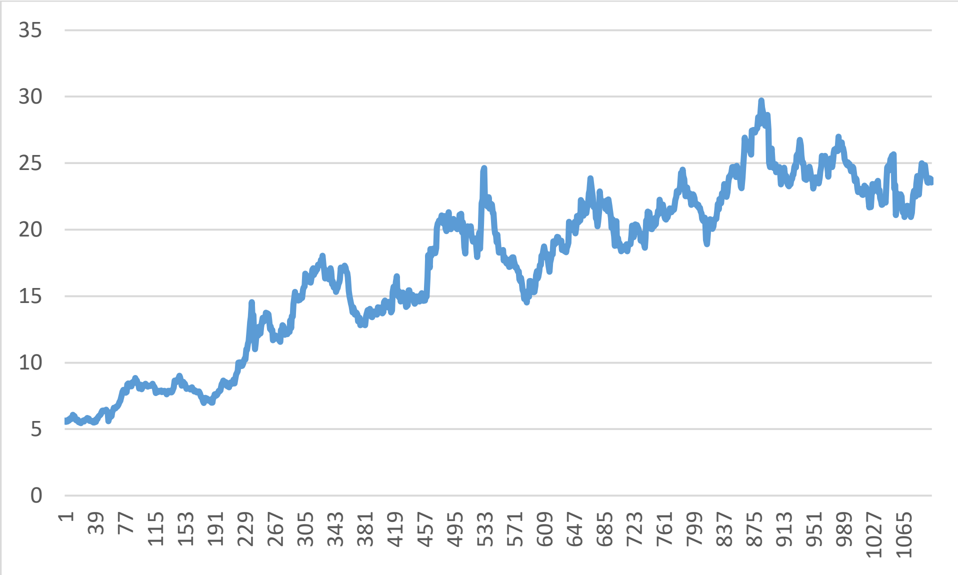

Figure 3. Time Series Graph

3.2. Results

In the SMNM-ANN AFM method, the input of the model, which consists of lagged variables, is determined based on hypothesis tests. Additionally, SMN-ANN is a single-neuron model, so there is no need for hyperparameter selection in the method. In the SMNM-ANN AFM method, all available data is evaluated as training data, and the method provides multi-step predictions. The overfitting problem is addressed through the early stopping conditions and restart strategies used in the particle swarm optimization-based training algorithm for SMN-ANN. As a result of the application of the method, predictions are obtained for 10 steps ahead, meaning forecasts are made for up to 10 days from today. The performance of multi-step predictions is investigated with real data. Therefore, predictions beyond 10 steps have not been considered. It is clear that prediction errors for 100 steps ahead will be very large, and taking the test data in proportion to the training data makes sense when obtaining a one-step prediction. However, since this study focuses on multi-step predictions, the test data has been kept short.

The prediction results obtained with SMNM-ANN AFM are shown in the table. The table contains test values and forecasting values. The dataset is structured in a block format due to its time series nature. The last 10 values of the dataset have been separated for testing purposes.

Table 3. Forecasting Results

Test Data	**SMNM-ANN-AFM**
24,8000	24,0906
24,8600	24,1110
24,2400	24,1297
23,8800	24,1483
23,5400	24,1669
23,5200	24,1855
23,8000	24,2041
23,8600	24,2226
23,8200	24,2412
23,5600	24,2598

The forecast values of other machine learning algorithms used for comparison are also shown in Table 4.

3.3. Comparison Analysis

The forecasting performance using the SMNM-ANN method is compared with machine learning methods. The SVM method, boosted tree, and decision trees methods were compared with the results. The performance of the methods was compared using various metrics.

Table 4. Comparison Analysis

Metric	SMNM-ANN	Boosted Tree	Decision Tree	SVM(Gaussian)
RMSE	0,6983	1,184643569	0,739846125	0,736238007
MAPE	2,5138	4,512706504	2,521974243	2,639225477

When the results were examined, it was observed that the proposed SMNM-ANN-AFM method had better forecasting performance compared to other machine learning methods. Figure 4 shows the forecasting results of the methods.

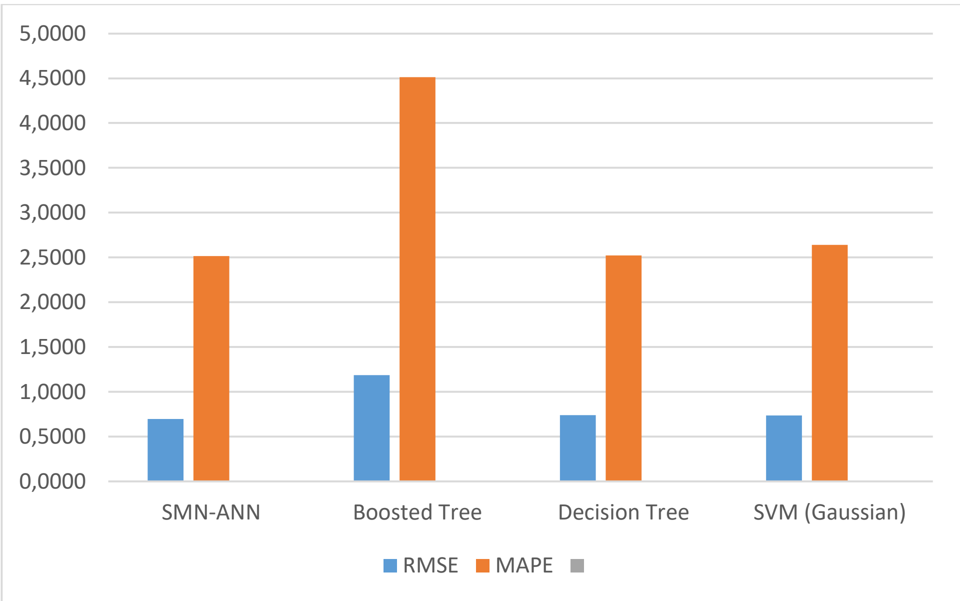

Figure 4. Comparison of Method Results

4. Conclusion

Predicting stock prices is crucial for both businesses and investors, particularly in the steel sector, where market dynamics can significantly influence financial outcomes. In this study, the effectiveness of the SMNM-ANN method for forecasting Ereğli Demir Çelik's stock closing prices was evaluated by comparing it with various machine learning methods.

The results indicate that the SMNM-ANN model provides higher accuracy and reliability compared to traditional forecasting techniques. The RMSE values demonstrate that the predictions made by the SMNM-ANN method exhibit less error relative to other methods, with the lowest RMSE signifying a closer alignment of the model's predictions to actual values. The MAPE values express the accuracy of predictions in percentage terms, with SMNM-ANN achieving the lowest MAPE, highlighting the reliability of its forecasts.

In summary, the SMNM-ANN method outperforms other techniques across various performance metrics such as RMSE and MAPE. This indicates that its predictive capability is superior compared to other machine learning methods, making it particularly advantageous for applications like time series forecasting in the steel industry.

The findings suggest that the SMNM-ANN method could be especially beneficial for predicting stock prices in the steel sector, where accurate forecasts can aid in strategic decision-making and resource allocation. The results are specific to a particular company, sector, and time period. Therefore, future studies that test with broader universes and different forecasting methods will enhance the contribution. Future research could focus on further enhancing this method and exploring its applications in different sectors, including integrating larger datasets and new learning algorithms to improve the model's performance.

Contribution Rate and Conflict of Interest Statement

All stages of the study were designed by the author(s) and contributed equally. There is no conflict of interest in this article.

Ethics Statement and Financial Support

Ethics committee principles were followed in the study. Ethics Committee Report is not required in the study. There has been no situation requiring permission within the framework of intellectual property and copyrights.

Use of Generative Artificial Intelligence and AI-Assisted Technologies in the Writing Process

The author(s) did not use any AI tools during the preparation of this study. The author(s) assume full responsibility for the content of the publication under the AI tool usage declaration.

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