A Comparison of Artificial Neural Network Models and Time Series Models for Forecasting Turkey's Monthly Aluminium Exports to Iraq

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ABSTRACT

Forecasting is a major branch of statistics with several applications, particularly in econometrics. Many governments utilize it to develop long-term goals and make future decisions. The two main forecasting approaches are examined in this study to discover the best forecasting model for the monthly amount of aluminium products exported from Turkey to Iraq. The Autoregressive Integrated Moving Average (ARIMA) model is used in the first technique, known as Box-Jenkins, while the Artificial Neural Network (ANN) model is used in the second. The data, which comes from the official websites of the UN Comtrade and the Turkish Statistical Institute (TUIK), contains the monthly volume of aluminium products exported between 2010 and 2019. For analysis, three software tools Alyuda NeuroIntelligence, R, and SPSS were used. This comparison also included Akaike Information Criteria (AIC), Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and R^2. According to the results, the Feed Forward Neural Network (FFNN) model fits better than the ARIMA model. Furthermore, the FFNN model exhibits less errors than the ARIMA model and is much better in terms of goodness of fit due to lower MAE, RMSE, and AIC values.

Keywords: Time Series, Artificial Neural Networks, Forecasting, ARIMA, Aluminium Exports.

1. INTRODUCTION

Time series forecasting is one of the most important branch of statistics and is extensively used in forecasting to analyze existing data leading up to a change and create an appropriate model for forecasting the future of the change. Forecasting is used to make the majority of critical administrative choices in both the private and public sectors, whether in economics, finance, agriculture, engineering, or any other profession. Therefore, the key authorities and decision makers are constantly considering the best way to decide the future of their project or organization (Adhikari and Agrawal, 2013). ARIMA is one of the most well-known and commonly utilized time series prediction algorithms, having been employed for over five decades. The essential assumption of this model, as stated by Box and Jenkins (1970), Hipel and McLeod (1994), and Cochrane (2005), is data linearity and normal distribution. Hence, this model is less effective when the data are nonlinear.

Artificial intelligence is one of the earliest and most important fields of computer science, developed at a time when the classical and neuron-classical fields used by researchers and scientists had become impractical. Artificial Neural Networks (ANN) are intelligent technologies that have a relatively new place among modern scientific systems such as "Genetic Algorithms", "Expert Systems", "neural computing", "Fuzzy Systems", "Molecular computing" and "Hybrid systems" (Lingireddy and Brion, 2005). Most of the systems mentioned above can only answer one problem at a time, however Neural Networks (NN), which are algorithms based on natural biological evolution, were designed to adapt to a larger range of issues. NNs are often quite versatile because to their structure and may be applied to a wide range of issues with only minor adjustments. This field requires knowledge of neurophysiology, computer neuroscience, computational methods, pattern recognition, control theory, computer science, artificial intelligence, statistics, mathematics, computer vision, parallel processing, and hardware (digital, analog, optical etc.) (Chatfield, 1997). ANNs are currently attracting a lot of research attention in the machine-learning sector, and they are heavily depended on for predicting in all fields of economics, business, finance, engineering, and so on. ANNs are distinguished by the fact that they are unaffected by a dataset's lack of linearity and normal distribution (Kihoro et al., 2004; Kamruzzaman et al., 2006). Over the previous three decades, several different kinds of ANN models have been produced, each intended at solving a different set of issues. The Feed Forward neural network, which was utilized in this study, has been by far the most extensively and effectively used for predicting.

In other hand, international trade is critical to improving people's living standards, creating jobs, and giving buyers access to a wider range of merchandise. International trade has existed since the birth of civilization, but its importance has expanded in latest years, with exports and imports representing for a larger share of Gross Domestic Product (GDP). In this paper, two of the most frequent and fundamental time series models were used to forecast the quantity of aluminium products transported from Turkey to Iraq between 2010 and 2019. These are the (ARIMA) and modern models (ANN). The data were obtained from the official websites of UN Comtrade and TUIK. Furthermore, these two countries and aluminium products were not chosen at random. Turkey and Iraq have a long history of economic, political, and cultural ties, and every change in one of these countries has an immediate impact on the other. Iraq is Turkey's primary trading partner, mainly in aluminium exports, and vice versa. aluminium products are one of the most commonly imported goods into Iraq from Turkey, and Turkey is a major exporter of these products to Iraq. Iraq and Turkey's relationship has grown rapidly, and Iraq has emerged as Turkey's most major trade partner.

2. Study Area

The study area is critical in any study, and chosen based on the research problem. The study area, as clear from Figure 1, is two independent neighboring countries, with strong economic and political relations with each other throughout history to the present. These two countries are Turkey and Iraq.

Figure 1. Map of Turkey and Iraq

2.1. Turkish export to Iraq

Iraq and Turkey's connection has grown fast, and Iraq is now Turkey's most important commercial partner. According to UN Comtrade, trade volume between Turkey and Iraq is expanding year after year, and during the previous decade, Iraq has been among the ten top importer of Turkish commodities, indicating that the value of Turkish exports to Iraq is increasing year after year. Turkish exports to Iraq were valued $829 million in 2003, accounting for 0.02% of total Turkish worldwide exports. Turkish exports climbed exponentially until they peaked in 2013, when the value of Turkish exports to Iraq reached US $11,949MM, comparable to fourteen times the amount of exports in 2003. Following ISIS's invasion of Iraq in 2014, the value of Turkish exports to Iraq declined from $11,949MM to $10,888MM, a trend that lasted until the end of the ISIS battle in 2016. Turkey's export value began to rise again in 2017, reaching US $10,223MM in 2019, accounting for 6% of Turkey's total worldwide exports. According to the presented data, there is a considerable positive association between the value of Turkey's global exports and the value of Turkey's exports to Iraq. Furthermore, during the past two decades, Iraq has been one of Turkey's top ten trading partners in terms of aluminum exports.

3. MATERIAL AND METHODS

The data used to compare the two models in this research are the monthly aluminum exports from Turkey to Iraq from January 1, 2010 to December 31, 2020. The information was collected from the UN Comtrade and TUIK official websites. The information was gathered depending on the Harmonized System, a standardized product classification system that allows member countries to classify traded commodities for customs purposes. Appendix A contains data on the quantity of aluminum products (which are aluminum and articles thereof) exported from Turkey to Iraq. The data was analyzed using three statistical software applications: Alyuda NeuroIntelligence, R and SPSS. The ARIMA model was created using R and SPSS, whereas the ANN model was created using Alyuda NeuroIntelligence and R.

4. LITERATURE REVIEW

The development of ANN was a crucial achievement in the history of data analysis. This technique has benefited researchers from all over the world and in all sectors, including economics, trade, medicine, statistics, engineering, physics, chemistry, geology, and so on. Several studies comparing ANNs approach with time series model will be provided in this area.

Kohzadi et al. (1996) compared ARIMA and the price prediction performance of neural networks. Monthly prices for live wheat and cattle from 1950 to 1990 were used as data. According to empirical results, neural network models were able to identify a significant number of turning points for cows and wheat. The ARIMA model could only do this for wheat, but it could be applied to other time series prediction such as stock and financial prices. To identify an appropriate model for forecasting seasonal time series, Hamzaçebi (2008) compared the Seasonal Artificial Neural Network (SANN) with the seasonal autoregressive integrated moving average (SARIMA). He applied both models to four real-world data sets from around the world: data set of air travelers in Taiwan, seasonal sales time series, soft drinks data set, and total machinery production in Taiwan. His results revealed that the ANN model has a lower forecast error than the SARIMA model, and that when the seasonality in the data set is high, the ANN model is best suited. Jalaee et al. (2011) used an ANN model and an econometric model to forecast Iranian agricultural product exports from 1965 to 2001. The results showed that the ANN model outperformed traditional econometric models in terms of performance, accuracy, and error in predicting Iranian agricultural product exports. Aliahmadi et al. (2013) were using the ANN and linear regression models to predict the export of raw petroleum in Iran from 1976 to 2005 in order to identify the best forecasting model. According to the findings, the NN outperformed the linear regression model in forecasting crude oil exports in Iran. Sebri (2013) compared ANN to the traditional time series technique used by the SARIMA model to predict household water consumption in Tunisia. Their data set consists of 122 records dating from the first quarter of 1983 to the end of 2010. Their findings reveal that the SARIMA model beats the ANNs in regards of forecasting accuracy on raw, non-seasonal, or non-trended data. Safi (2013) forecasted monthly electricity usage in Gaza using the ARIMA model and ANN from January 2000 to December 2011. The results show that the ANN model is superior the ARIMA model in predicting consumption of electricity. Adebiyi et al.

(2014) examined the performance of ANNs and the ARIMA model forecasting with reported stock market data from the New York Stock Exchange. According to the empirical results, the ANN model outperforms the ARIMA model. The results resolve and clarify the literature's contradictory opinions on the superiority of the ARIMA model over NNs, and vice versa. Dhini et al. (2015) compared three prediction models for predicting weekly consumer products demand in Indonesia: ARMA, ANN, and hybrid model that combines the ANN and ARIMA models. The experimental result showed that the ANN model was so much more accurate. Safi (2016) forecasted the Palestine Gross Domestic Product (GDP) quarterly values using ARIMA, ANNs and regression; the results showed that the ANNs outperformed the ARMA and regression models in predicting Palestine GDP. Chuentawat et al. (2016) used the ANN and traditional time series models to forecast residential electricity demand in Thailand's Bangkok metropolitan region. Their data was collected on a monthly basis, beginning in January 2000 and ending in May 2000. They also measured each model's performance using the rooted mean square error (RMSE) and the mean absolute percentage error (MAPE). Their findings revealed that the ANN model performs better than the ARIMA model in predicting electricity usage. Bozkurt et al. (2017) compared the seasonal autoregressive integrated moving average (SARIMA) and ANN models to pick the most suitable model for forecasting power load in the Turkish electricity market for hourly periods ranging from first of January of 2013 to end of December 2014. According to their empirical findings, the ANN model suits the Turkish market better than SARIMA. Furthermore, SARIMA outperforms ANN in post-holiday forecasts. Mishra et al. (2018) applied time series models and ANN to forecast rainfall; the results demonstrate that the ANN model gives optimistic predictions for both forecast models and that the one-month forecast model performs better than the two-month forecast mode. Rhanoui et al. (2019) wanted to identify the most reliable model for predicting budget data, so they compared the ARIMA model with the Recurrent Neural Network (RNN). Their results revealed that the NN model is more accurate and has a lower prediction error than the ARIMA model. Abraham et al. (2020) showed that the artificial neural network is better than the classic time series methods for predicting the Brazilian soybean production, yield, and harvest region from January 1961 to December 2016, where they compared the artificial neural network with classical time series model to predict the Brazilian soybean production, yield and harvest region. However, their results indicated that the ANN is suitable tools to predicting the agriculture time series. Khalil (2022) compared the ARIMA model with FFNN model to discover the best forecasting model for the monthly amount of dairy products exported from Turkey to Iraq. The results showed that FFNN model is more accurate than the ARIMA model. Additionally, due to lower MAE, RMSE, and AIC values, the FFNN model has less errors than the ARIMA model and is considerably superior in terms of goodness of fit.

It is possible to conclude from the literature and references mentioned that modern methods, such as ANNs, outperform traditional time series models, such as ARIMA, for forecasting future values in all sectors of life.

5. Time Series Definition

A time series is a set of data points that are recorded over time. A time series is defined mathematically as a set of vectors x(t), t=0, 1, 2, …, where t reflects the duration of time that elapsed and the variable x(t) considered a random variable (Hipel et al., 1994; Raicharoen et al.; 2003; Cochrane, 2005). There are two types of time series: discrete and continuous. Discrete time series can be represented by a city's population, a company's revenue, or the currency exchange between two currencies. A continuous time series, on the other hand, collects observations at every point in time, whereas a discrete time series takes observations at certain points in time. Continuous time series can be used to record temperature measurements, flow of the river, chemical production activity, and so on. A discrete time series records successive observations at regular intervals such as hourly, daily, weekly, monthly, or yearly. A discrete time series variable is assumed to be evaluated as a continuous variable on a real number scale, as mentioned in (Hipel, 1994).

5.1. The Autoregressive Moving Average (ARMA)

The ARMA model is the outcome of merging the Autoregressive (AR) and Moving Average (MA) models. Because it incorporates auto-regressive and moving-average terms, the ARMA model can represent complex time series with fewer parameters than an equivalent AR model (Montgomery et al., 2015; Adhikari and Agrawal, 2013). The following is an ARMA (p, q) model:

$$Z_t = C + \varphi_1 Z_{t-1} + \varphi_2 Z_{t-2} + \cdots + \varphi_p Z_{t-p} + e_t - \theta_1 e_{t-1} - \theta_2 e_{t-2} - \cdots - \theta_q e_{t-q} \qquad (1)$$

5.2. Autoregressive Integrated Moving Average (ARIMA)

In their natural form, most time series are not stationary. If the time series indicates a trend, the trend must be removed by differentiating. If the differentiated model is stationary, the original non-stationary model can be replaced with an ARMA model. This is an auto-regressive integrated moving average (ARIMA) model, also known as a Box-Jenkins model. The term "integrated" relates to the fact that a stationary model fitted with differentiated data must be summed (or "integrated") in order to obtain a model for the data in its original form. A single difference is frequently enough to establish a stationary series. ARIMA (p,d,q) is the notation for an ARIMA process with order p for the AR part, order q for the MA part, and differences d (Weisang and Awazu, 2008; Montgomery et al., 2015).

6. Artificial Neural Networks (ANN)

Artificial neural networks (ANNs), also known as "Neural Networks," are a type of computing tool that mimics the organic processes of the human brain. A neural network is a set of simple operations that are linked together. Each unit has a little amount of local memory. These neurons are linked together via channels of communication (connections) that carry numerical data. Two of the most common applications of ANNs are classification or categorization and predicting. Most ANN applications employ supervised learning, which implies that training data should include input as well as the desired outcome, or "Target Value." Following the successful training, input data without an output value can be sent to the ANN, and the ANN will compute an output value (Gurney, 2018; Graupe, 2013).

A network, often known as an ANN model, is made up of three layers: an input layer, one or more "hidden" layers, and an output layer. Each layer can have an unrestricted number of nodes or "neurons," with each node in each layer generally connected to each node in the next layer via a weighted connection. The data is delivered into the NN through the input layer. The nodes of the hidden layer process the input data they receive as the sum of the weighted outputs of the input layer. The nodes of the output layer process the input data they receive as the sum of the weighted outputs of the hidden layers' units and generate the system output (Mishra et al., 2007; Mehlig, 2019). This network can be represented as shown in (Figure 2).

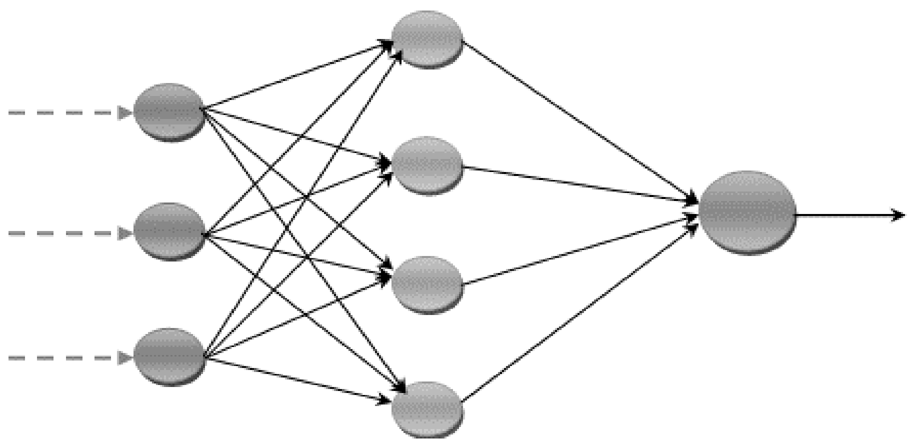

Figure 1. Structure of neural network

7. RESULTS AND DISCUSSION

7.1. Results of Using ARIMA for Forecasting Aluminium Exports Time Series:

The initial stage in building ARIMA modeling was to describe the features of the data in this study. Figure 3 displays the dynamic attitude of monthly Turkish aluminium exports to Iraq from January 2010 to December 2020.

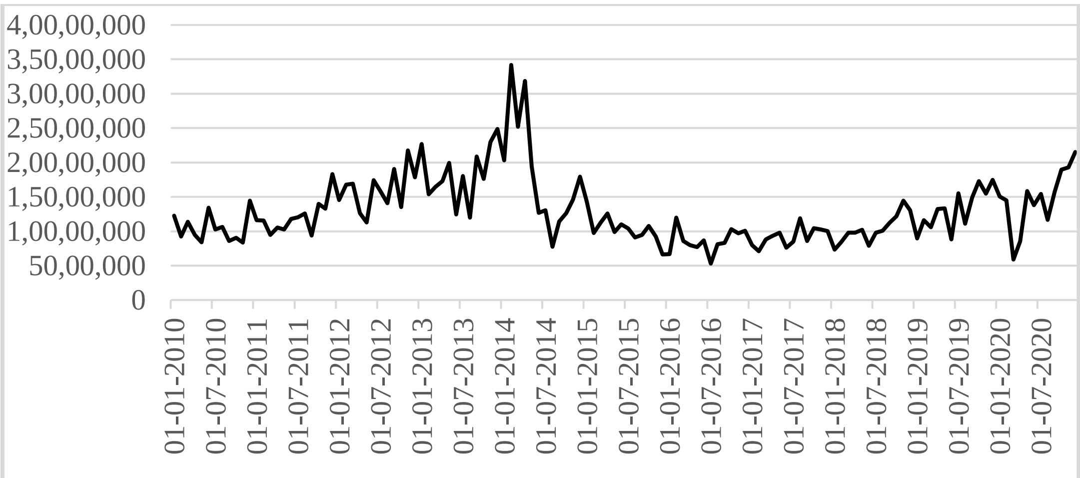

Figure 3. Sequence chart monthly amount of aluminium export from Turkey to Iraq

There are a total of 132 observations. The average of monthly exports of aluminium from Turkey to Iraq was 12886029 US dollars, where the lowest monthly value of exports was 5300992 US dollars in July 2016, and the highest monthly amount was in February 2014 34184003 US dollars. Furthermore, the Augmented Dickey - Fuller (ADF) test is used to assess the time series' stationarity; the results of the ADF test demonstrate that the series is not stationary because the ADF value is -2.222 and the P-value is 0.484, which is more than 0.05, and indicated that the data is not stationary. So it is necessary to do one difference on the dataset to make it stationary.

Box and Jenkins developed a method for fitting interactive autoregressive moving average models to time series. It is based on the stationary behavior of time series around the mean and variance. There are 182 models fitted to the data, and a lower AIC value suggests a best model. Other criteria, statistically significance of parameters, also the most essential of which is the randomness of residuals must be met by the model. Thus, ARIMA (0,1,3) was preferred because it has the minimum AIC and its parameter is highly significant. as shown in Tables 2 and 3 The estimated model is statistically significant, and the parameters are also significant.

7.1.1. Choosing an Appropriate Model

Table 2: ARIMA(0,1,3) model parameters.

	Estimate	SE	T-test	P-value
MA1	-0.5225	0.086	5.974	0.000
MA2	0.207	0.092	-2.984	0.039
MA3	-0.308	0.077	3.396	0.001

Table 3. ARIMA(0,1,3) model Statistics

RMSE	MAE	AIC	R^2	MAPE
3232838.305	2342358.922	4302.47	0.631	18.329

7.1.2. Checking the Model

Following the identification and estimation of the candidate ARIMA (0,1,3) model, the model's fit to the data had to be evaluated. This stage of the model diagnostic checking procedure comprises parameter and residual analysis. The residuals for the ARIMA (0,1,3) model were diagnostically tested using autocorrelation function (ACF) and partial autocorrelation function (PACF) plots for residuals, as displayed in Figure 4, all ACF and PACF residuals values were statistically significant at the 95% confidence level. This suggests that the residuals are random white noise and that the model fits the data.

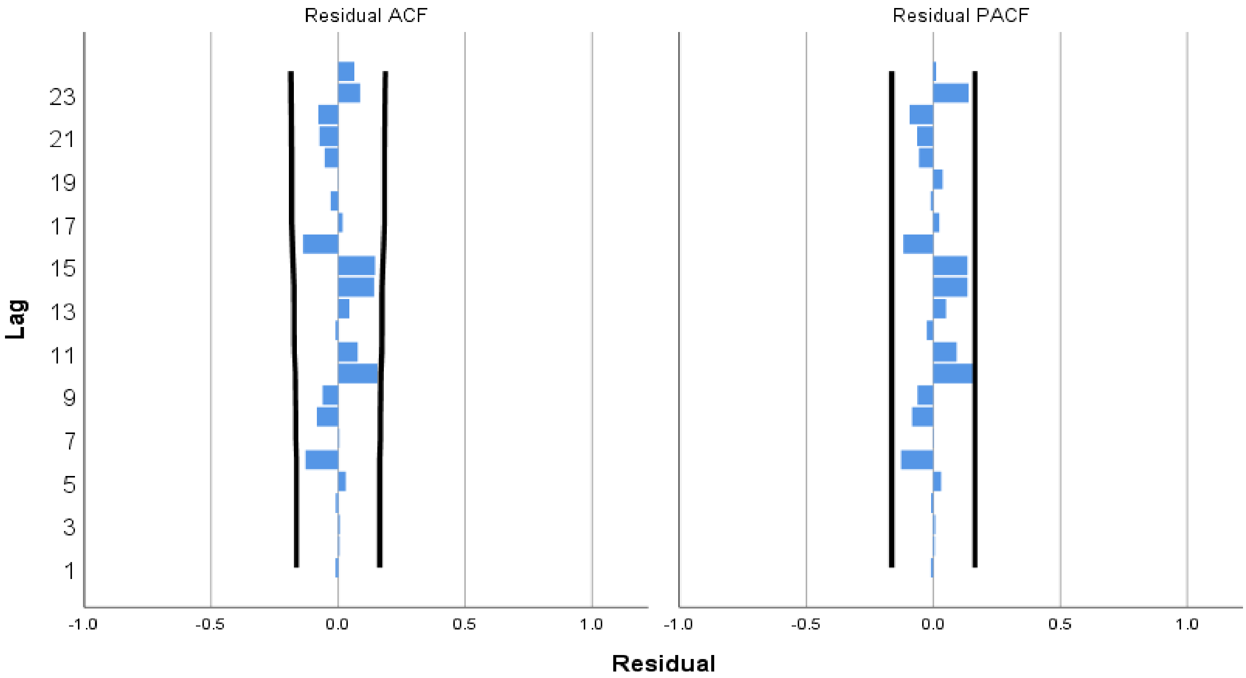

Figure 4. Residual's ACF and PACF for ARIMA(0,1,3)

In addition, the Box-Pierce test was used to verify that the correct user model was utilized in the last step of model performance verification, and the residual autocorrelation test was used to determine whether there was any autocorrelation. According to the results, the P-value for this test is 0.202, which is considerably greater than 0.05, showing that the residuals have no significant autocorrelation and are hence white noise. As a result, the ARIMA(0,1,3) is the best fit for the aluminium export data, having passed model construction diagnostic tests. As shown in Figure 5, the predicted values behave like the actual values, i.e., they converge to the series of real values.

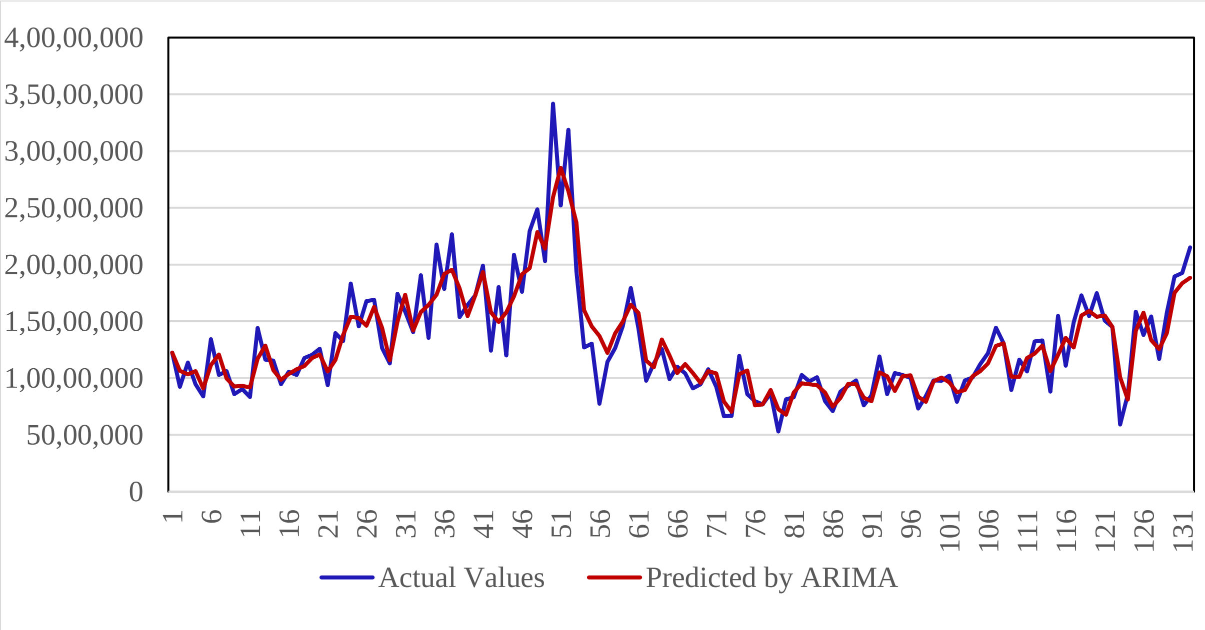

Figure 5. Predicted and actual values

The final stage of time series analysis was forward forecasting, which was done after identifying the best fitting models and selecting the best one. Table 4 shows the predicted monthly value of Turkish aluminum exports to Iraq in 2021 based on real data.

Table 4. Actual and forecasted value of monthly aluminium exports from Turkey to Iraq in 2021

No.	Date	Actual	Forecast
1	Jan-21	17874721	18421221
2	Feb-21	17710845	16999520
3	Mar-21	21164574	19251234
4	Apr-21	20953718	21038137
5	May-21	17108465	18179195
6	Jun-21	17607180	16722866
7	Jul-21	16168994	17453734
8	Aug-21	24366681	21001913
9	Sep-21	25374437	24570587
10	Oct-21	23247445	22715820
11	Nov-21	23079365	21432543
12	Dec-21	27398059	26620981

8.1. Application of artificial neural networks on aluminium time series

The application of neural networks on time series does not necessitate phased processing. The structure of a multilayer feed forward neural network model must contain the number of input layer nodes, the number of hidden layers and hidden nodes, the number of output nodes, and the activation functions for hidden and output nodes. According to Tang et al., (1991); Sharda and Patil (1992), the total number of input neurons required in this model must be 12 because the data is monthly and there is no seasonality in the data. There is only one output unit needed, and it displays monthly aluminium export estimates from Turkey to Iraq. As mentioned previously trial and error is the most effective method for determining the ideal amount of concealed units. Here, 80% of the data was used for training, 10% for validation, and 10% for testing. The logistic activation function was used in both the output and hidden layers. The network was trained using the conjugate gradient descent approach to determine the best neural network design. After training the network numerous times and testing 399 various neural networks, the optimum neural network has two hidden layers, with the first layer containing 7 nodes and the second layer consisting 13 nodes. Figure 6 displays the desired network's architecture.

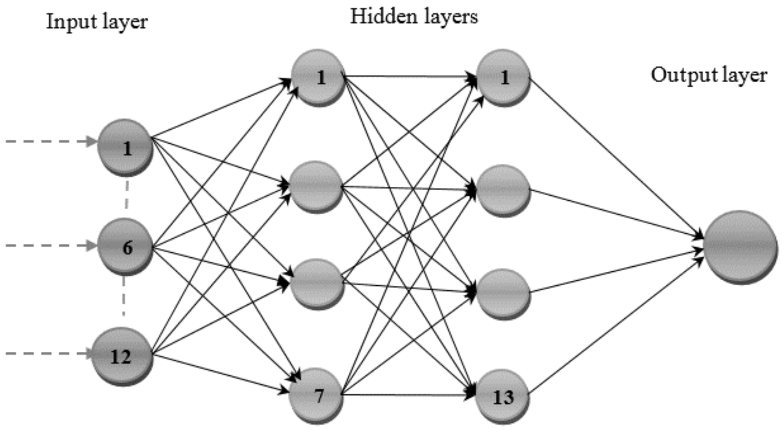

Figure 6. Architecture of FFNN (12:7:13:1)

The statistical measurements of FFNN (12:7:13:1) are represented in Table 5.

Table 5. Statistical measurements for FFNN (12:7:13:1)

RMSE	MAE	AIC	R^2	MAPE
1836794.629	1575698.923	1308.286	0.831	14.331

Furthermore, as illustrated in Figure 7, forecasted aluminium export values are closely related to real values, implying that the predicted values converge with the actual value series.

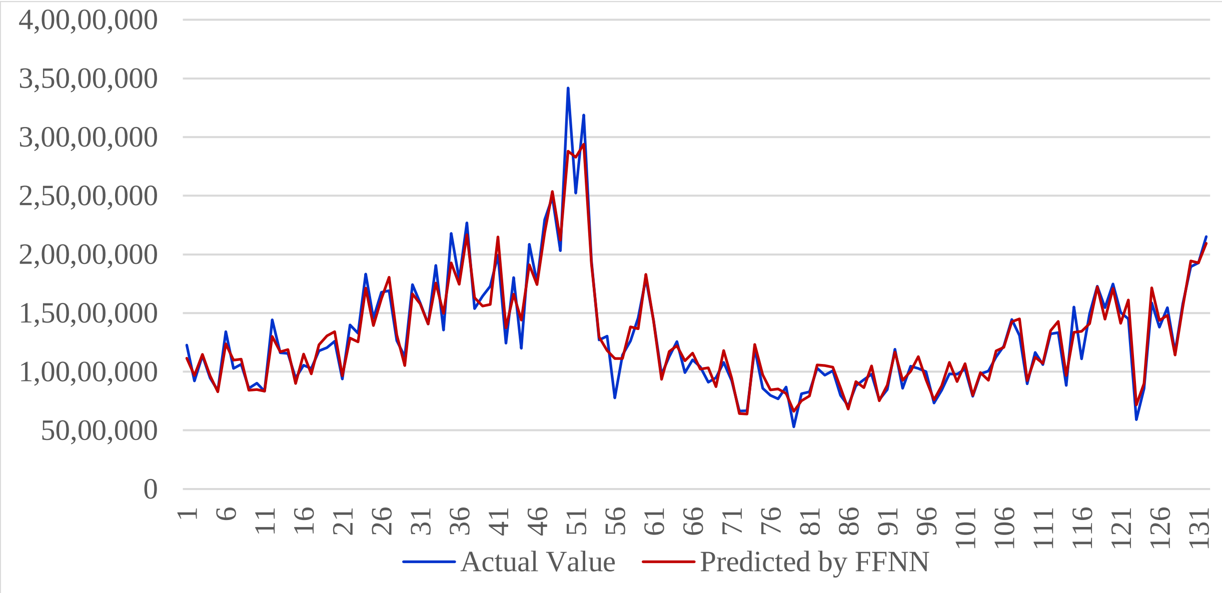

Figure 7. Forecasted and real values of aluminium exports time series by using FFNN (12:7:13:1).

The real data and forecasted values of Turkish aluminium exports to Iraq in 2021, according to FFNN (12:7:13:1) are shown in the (Table 6).

Table 6. Actual and predicted values of FFNN (12:7:13:1) for aluminium exports value from Turkey to Iraq in 2021

Date	Actual	Forecast
Jan-21	17874721	18237009
Feb-21	17710845	18869467
Mar-21	21164574	21368870
Apr-21	20953718	20827756
May-21	17108465	17997403
Jun-21	17607180	18562381
Jul-21	16168994	17279197
Aug-21	24366681	23312123
Sep-21	25374437	24816293
Oct-21	23247445	24305927
Nov-21	23079365	23790123
Dec-21	27398059	26887191

9. Comparison of FFNN and ARIMA Results

Following the application of the FFNN and ARIMA models to forecast the monthly amount of aluminum exports from Turkey to Iraq, the results were compared to identify which model was better. Since the AIC values of the FFNN models are far lower than that of the ARIMA models, the FFNN models are much more efficient in terms of goodness of fit than the ARIMA models. This suggests that FFNN model is superior ARIMA models. Moreover, because the RMSE value of the FFNN models in this research is lower than that of the ARIMA models, it is clear that the FFNN models have less error than the ARIMA models. Additionally, when the MAE values of the two models are compared, the FFNN models fit better than the ARIMA models. Another measurement used to evaluate the FFNN and ARIMA models is R^2. According to the results, the FFNN models have a higher R^2 value than the ARIMA models. As seen in tables 7 and 8, when both models are used for prediction, the FFNN models are substantially more accurate and have fewer errors than the ARIMA models.

Table 7. Comparison of the FFNN and ARIMA

Model	MAPE	RMSE	MAE	AIC	R^2
ARIMA(0,1,3)	18.329	3232838.305	2342358.922	4302.47	0.631
FFNN(12:7:13:1)	14.331	1836794.629	1575698.923	1308.286	0.831

Table 8. Real and Forecasted values of aluminium exports from Turkey to Iraq in 2021

Date	Actual data	Forecast by FFNN (12:7:13:1)	Forecast by ARIMA (0,1,3)
Jan-21	17874721	18237009	18421221
Feb-21	17710845	18869467	16999520
Mar-21	21164574	21368870	19251234
Apr-21	20953718	20827756	21038137
May-21	17108465	17997403	18179195
Jun-21	17607180	18562381	16722866
Jul-21	16168994	17279197	17453734
Aug-21	24366681	23312123	21001913
Sep-21	25374437	24816293	24570587
Oct-21	23247445	24305927	22715820
Nov-21	23079365	23790123	21432543
Dec-21	27398059	26887191	26620981

Figure 8 shows that predicted values produced by both approaches closely match the actual values, but the FFNN model values appear to outperform the ARIMA models in terms of forecasting performance, supporting accuracy of the FFNN models' for forecasting.

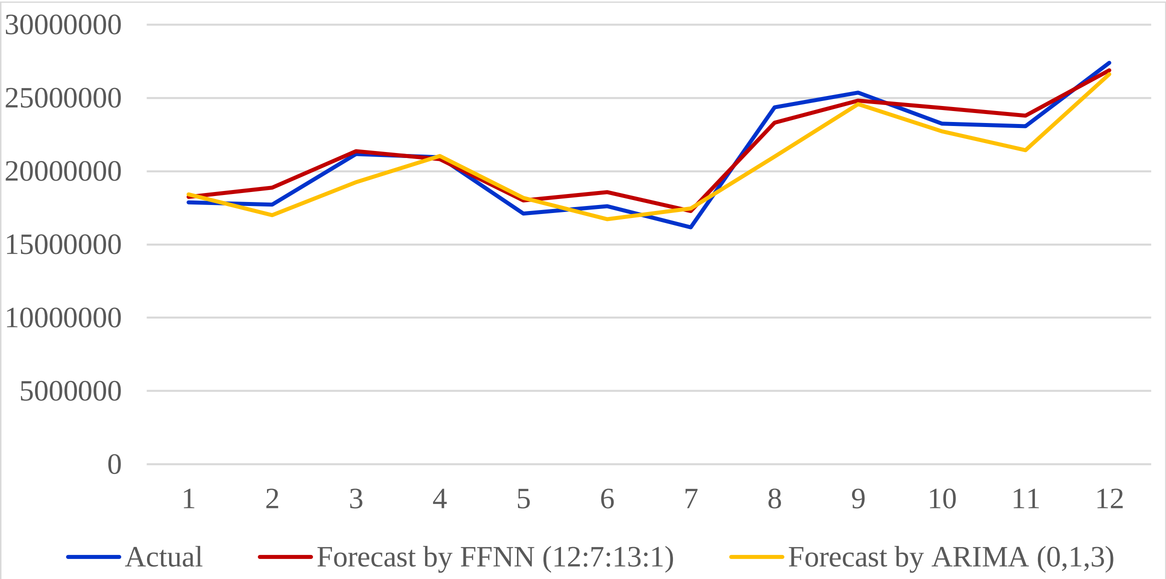

Figure 8. Actual and forecasted values in 2021 using ARIMA and FFNN models.

10. Conclusions

According to the findings, it is clear that the FFNN models are more accurate and have less error than the ARIMA models. Furthermore, forecast values generated by FFNN models seem to have better forecasting ability and behaved more like actual values than those generated by the ARIMA model. Also the FFNN models are significantly better in terms of goodness of fit than the ARIMA models. In regards to the network's architecture, and also the optimal network learning algorithm. it was determined that two hidden layers are the most appropriate for this networks. Moreover, conjugate gradient descent surpasses other learning algorithms when it comes to training neural networks. The logistic function looks to be better than other functions in terms of activation function. Furthermore, no systematic methodologies exist for deciding which network topology can best replicate the function by mapping inputs to outputs. As a result, time-consuming experiments and trial-and-error processes are commonly used.

Recommendations

Because neural network models have a lower error value and are more accurate than traditional time series models, they are recommended for predicting the amount of agricultural product exports.

When designing the architecture of a network, the number of hidden layers should not exceed two. Having more than two hidden layers reduces the accuracy of a network's results.

The conjugate gradient decent algorithm is recommended for training networks. Furthermore, in terms of forecasting the value of agricultural product exports, the logistic function is highly suggested as an activation function.

Future Studies

Research should be done on the export of other products from Turkey to abroad, particularly electrical goods and furniture. It is necessary to use other forecasting methods, like Bayesian, to find the appropriate method of predicting the value of Turkish exports to Iraq and globally.

Declarations

Availability of data and materials

The data were represented in **appendix A**, in the end of paper. The ARIMA model was constructed using R, while the ANN model was created using Alyuda NeuroIntelligence and R.

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Appendix A: Monthly value of Aluminium exports from Turkey to Iraq (UN Comtrade)

Year	Month	Commercial Value (US$)
2010	Jan-10	12,263,267
2010	Feb-10	9,225,613
2010	Mar-10	11,374,022
2010	Apr-10	9,452,110
2010	May-10	8,392,190
2010	Jun-10	13,422,794

2010	Jul-10	10,281,589
2010	Aug-10	10,631,862
2010	Sep-10	8,592,885
2010	Oct-10	9,034,431
2010	Nov-10	8,336,035
2010	Dec-10	14,432,849
2011	Jan-11	11,620,763
2011	Feb-11	11,546,940
2011	Mar-11	9,458,490
2011	Apr-11	10,563,477
2011	May-11	10,278,216
2011	Jun-11	11,778,279
2011	Jul-11	12,050,728
2011	Aug-11	12,599,558
2011	Sep-11	9,378,473
2011	Oct-11	13,980,634
2011	Nov-11	13,276,177
2011	Dec-11	18,324,605
2012	Jan-12	14,560,723
2012	Feb-12	16,781,449
2012	Mar-12	16,909,469
2012	Apr-12	12,656,465
2012	May-12	11,295,752
2012	Jun-12	17,426,447
2012	Jul-12	15,869,459
2012	Aug-12	14,066,372
2012	Sep-12	19,059,789
2012	Oct-12	13,540,006
2012	Nov-12	21,776,516
2012	Dec-12	17,864,180

2013	Jan-13	22,688,102
2013	Feb-13	15,370,327
2013	Mar-13	16,436,802
2013	Apr-13	17,293,831
2013	May-13	19,921,625
2013	Jun-13	12,432,444
2013	Jul-13	18,013,092
2013	Aug-13	11,985,094
2013	Sep-13	20,866,670
2013	Oct-13	17,610,980
2013	Nov-13	22,949,069
2013	Dec-13	24,870,902
2014	Jan-14	20,305,523
2014	Feb-14	34,184,003
2014	Mar-14	25,218,276
2014	Apr-14	31,874,304
2014	May-14	19,432,882
2014	Jun-14	12,707,485
2014	Jul-14	13,042,001
2014	Aug-14	7,755,665
2014	Sep-14	11,426,420
2014	Oct-14	12,633,133
2014	Nov-14	14,595,239
2014	Dec-14	17,932,873
2015	Jan-15	14,378,766
2015	Feb-15	9,761,624
2015	Mar-15	11,287,043
2015	Apr-15	12,570,872
2015	May-15	9,913,423
2015	Jun-15	11,012,571
2015	Jul-15	10,413,500

2015	Aug-15	9,095,153
2015	Sep-15	9,475,656
2015	Oct-15	10,786,453
2015	Nov-15	9,236,336
2015	Dec-15	6,650,488
2016	Jan-16	6,663,434
2016	Feb-16	11,971,392
2016	Mar-16	8,577,884
2016	Apr-16	7,978,636
2016	May-16	7,697,140
2016	Jun-16	8,684,583
2016	Jul-16	5,300,992
2016	Aug-16	8,126,248
2016	Sep-16	8,296,358
2016	Oct-16	10,293,271
2016	Nov-16	9,717,657
2016	Dec-16	10,072,785
2017	Jan-17	7,973,292
2017	Feb-17	7,092,850
2017	Mar-17	8,808,828
2017	Apr-17	9,328,205
2017	May-17	9,791,670
2017	Jun-17	7,604,128
2017	Jul-17	8,487,563
2017	Aug-17	11,908,062
2017	Sep-17	8,598,519
2017	Oct-17	10,459,739
2017	Nov-17	10,268,684
2017	Dec-17	10,017,834
2018	Jan-18	7,329,545

2018	Feb-18	8,428,153
2018	Mar-18	9,814,997
2018	Apr-18	9,776,592
2018	May-18	10,230,650
2018	Jun-18	7,910,397
2018	Jul-18	9,809,922
2018	Aug-18	10,062,411
2018	Sep-18	11,249,699
2018	Oct-18	12,184,933
2018	Nov-18	14,444,026
2018	Dec-18	13,075,206
2019	Jan-19	8,965,838
2019	Feb-19	11,636,775
2019	Mar-19	10,591,007
2019	Apr-19	13,223,959
2019	May-19	13,327,800
2019	Jun-19	8,819,248
2019	Jul-19	15,504,627
2019	Aug-19	11,087,464
2019	Sep-19	14,938,765
2019	Oct-19	17,281,522
2019	Nov-19	15,463,079
2019	Dec-19	17,485,159
2020	Jan-20	15,062,675
2020	Feb-20	14,508,940
2020	Mar-20	5,910,921
2020	Apr-20	8,556,394
2020	May-20	15,870,647
2020	Jun-20	13,792,090
2020	Jul-20	15,448,299
2020	Aug-20	11,679,410

2020	Sep-20	15,775,144
2020	Oct-20	18,963,768
2020	Nov-20	19,269,224
2020	Dec-20	21,525,602