A Comparison Of Feed Forward Neural Network Models And Time Series Models For Forecasting Turkey's Monthly Dairy Exports To Iraq

Diyar M. Khalil

Mathematic Department, Faculty of Sciences, Soran University, Kurdistan Region - Iraq

***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 paper to discover the best forecasting model for the monthly amount of dairy 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 Feed Forward Neural Network (FFNN) 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 dairy 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 R2. According to the results, the 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, Feed Forward Neural Networks, Forecasting, ARIMA, Dairy Exports.**

INTRODUCTION

The 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

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Corresponding author’s e-mail: diyar.khalil@soran.edu.iq

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 dairy 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 dairy 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 dairy exports, and vice versa. Dairy 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

3. MATERIAL AND METHODS

The data utilized in this paper to comparing the two models are the amount of monthly dairy exports from Turkey to Iraq from January 1, 2010 to December 31, 2019. The data was obtained from the official websites of UN Comtrade and TUIK. The data was collected using the Harmonized System, a standardized product categorization system that allows member countries to classify traded goods for customs purposes. The data which represented in appendix A, includes the quantity of dairy products, which are edible animal-derived items such as milk, yogurt, and cream. Three statistical software applications were used to analyze the data: Alyuda NeuroIntelligence, R, and SPSS. The ARIMA model was built with R and SPSS, whereas the ANN model was built with Alyuda NeuroIntelligence and R.

4. LITERATURE REVIEWS

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 forecast other time series, like stock prices 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 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 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, 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 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.

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).

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 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 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).

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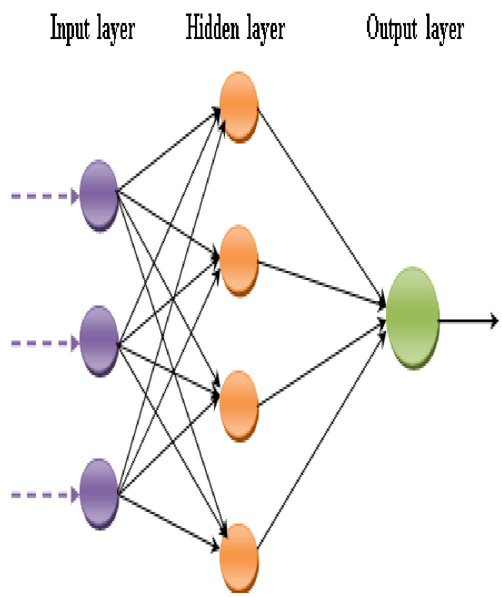

Figure 2. Architecture of NN

7. RESULTS AND DISCUSSION

7.1. Results of using ARIMA for forecasting dairy 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 dairy exports to Iraq from January 2010 to December 2019.

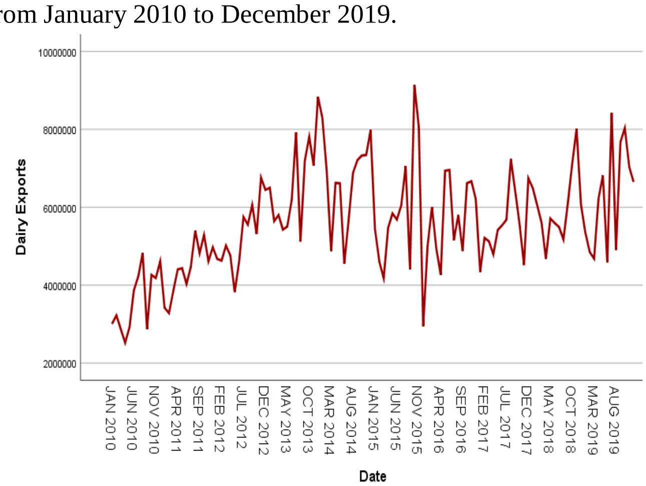

Figure 3. Sequence chart of monthly amount of dairy export from Turkey to Iraq

There are a total of hundred and twenty observations. The highest monthly value of exports was 9137607 US dollars in October 2015, and the lowest monthly amount was in April 2010 (2521880 US dollars). Furthermore, the Kolmogorov-Smirnov p-value is 0.2 (higher than 0.05), confirming that the data are normal, as shown in Table 1. 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 stationary because the ADF value is -3.702 and the P-value is 0.027, which is less than 0.05.

Table 1. Normality test of dairy exports time series.

Kolmogorov-Smirnova			Shapiro-Wilk		
Statistic	df	Sig.	Statistic	df	Sig.
0.058	120	0.200*	0.988	120	0.407

I. 7.1.1. Choosing an Appropriate Model

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 one hundred and ninety-two 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, SARIMA (0,1,2)(0,0,1)(12) 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.

Table 2: SARIMA(0,1,2)(0,0,1)(12) model parameters.

	Estimate	SE	T-test	P-value
MR1	-0.688	0.102	7.436	0.000
MR2	-0.166	0.099	6.349	0.000
SMA1	0.201	0.100	2.916	0.004

Table 3. SARIMA(0,1,2)(0,0,1)(12) model Statistics

RMSE	MAE	AIC	R2
1068970	793978.60	3654.28	0.38

7.1.2. Checking the Model

Following the identification and estimation of the candidate SARIMA (0,1,2) (0,0,1) (12) 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 SARIMA(0,1,2)(0,0,1)(12) 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.

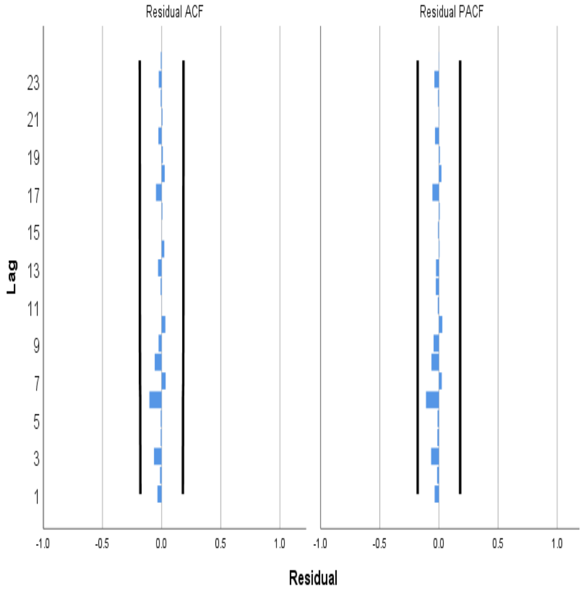

Figure 4. Residual's ACF and PACF for SARIMA(0,1,2)(0,0,1)(12)

As well as, the Box-Pierce test was used to check the correct user model in the final step of model performance verification, and the residual autocorrelation test was performed to evaluate if there was any autocorrelation. According to the Box-Pierce results, the P-value for this model is 0.791, which is considerably greater than 0.05, implying that there is no significant autocorrelation in residuals and are hence white noise. As a result, the SARIMA(0,1,2)(0,0,1)(12) is the best fit for the dairy 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.

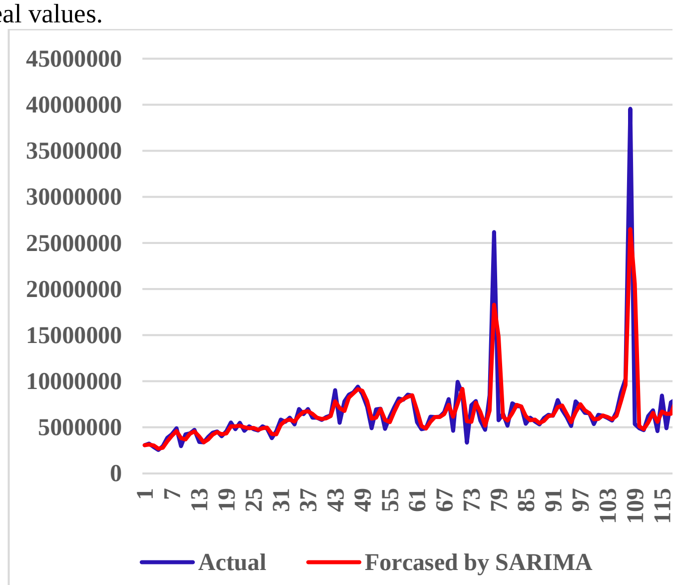

Figure 5. Predicted and actual values

After identifying the fitting models and choosing the best one, the final stage in time series analysis was forward forecasting. The monthly value of Turkish dairy exports to Iraq in 2020 was predicted based on both actual data and the estimated model, as shown in Table 4.

Table 4. Actual and forecasted value of monthly dairy exports from Turkey to Iraq in 2020

No.	Date	Actual	Forecast
1	Jan-20	11121442	7298200
2	Feb-20	8873174	6636228
3	Mar-20	6767136	6913408
4	Apr-20	10855890	7174719
5	May-20	8910783	6491870
6	Jun-20	7591878	6429840
7	Jul-20	8435663	7221536
8	Aug-20	8637065	6810063
9	Sep-20	8465773	6999261
10	Oct-20	8622053	7041272
11	Nov-20	7634299	6439596
12	Dec-20	9183348	6497694

8.1. Application of artificial neural networks on dairy time series

The use of neural networks on time series does not need staged processing. 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 must all be included in the structure of multilayer feed forward neural network model. Because of the seasonality of the data, this model requires a total of four input neurons. There is only one output unit needed, and it displays monthly dairy export estimates from Turkey to Iraq. As previously stated, there is no simple way to identify the optimal number of hidden units without training and testing. Trial and error is the most effective method for determining the acceptable number of hidden units. In this paper, 80% of the data was utilized for training, 10% for validation, and 10% for testing. In both output and hidden layers, the logistical activation function was utilized. To discover the optimum design of neural network, the network was trained using the conjugate gradient descent algorithm. After training the network several times and testing three hundred and eighty different networks, the ideal neural network is one that has two hidden layers, with the first layer having 12 nodes and the second layer containing 8 nodes. Figure 6 depicts the architecture of the desired network.

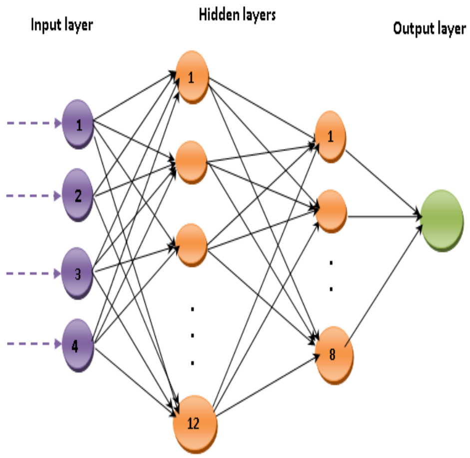

Figure 6. Architecture of best FFNN

The statistical measurements of FFNN (4-12-8-1) are represented in Table 5.

Table 5. Statistical measurements for FFNN (4-12-8-1)

RMSE	MAE	AIC	R2
650105.14	448732.99	1222.48	0.77

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

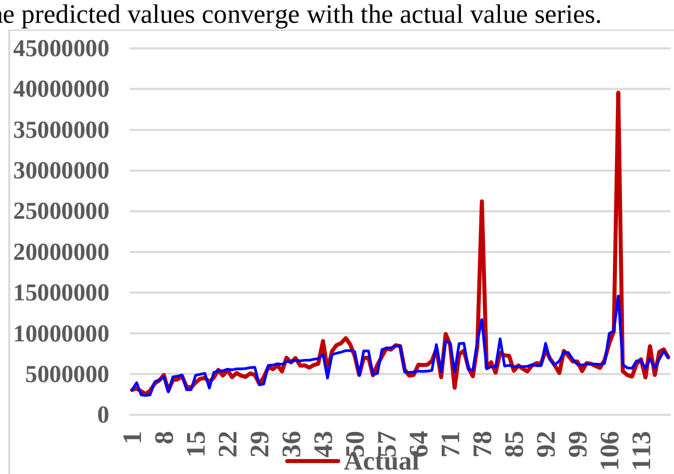

Figure 7. Forecasted and real values of dairy exports time series by using FFNN (4-12-8-1).

The real data and forecasted values of Turkish dairy exports to Iraq in 2020, according to FFNN (4-12-8-1) are shown in the (Table 6).

Table 6. Actual and predicted values of FFNN (4:12:8:1) for dairy exports value from Turkey to Iraq in 2020

Date	Actual	Forecast
Jan-20	11121442	8976786
Feb-20	8873174	8162560
Mar-20	6767136	6083799
Apr-20	10855890	8824904
May-20	8910783	7985000
Jun-20	7591878	7715808
Jul-20	8435663	8882489
Aug-20	8637065	8376377
Sep-20	8465773	8609091
Oct-20	8622053	8660765
Nov-20	7634299	7920703
Dec-20	9183348	8382025

9. Comparison of FFNN and SARIMA Results

Following the use of the FFNN and ARIMA models to predict the amount of monthly dairy exports from Turkey to Iraq, the results were compared to determine which model was best. Because the AIC values of the FFNN models are far lower than those of the ARIMA models, the FFNN models are significantly better in terms of goodness of fit than the ARIMA models. This indicates that FFNN models outperform ARIMA models. Furthermore, because the RMSE value of the FFNN models in this study is lower than that of the ARIMA models, it is clear that the FFNN models have less error than the ARIMA models. When the MAE values of the two models are examined, the FFNN models fit better than the ARIMA models. R^2 is also another measurement used to compare the FFNN and ARIMA models. Form the results it is clear that that the FFNN models have a higher R^2 value than the ARIMA models. The result indicated that when both models are employed for prediction, the FFNN models are much more accurate and have fewer error than the ARIMA models, as seen in the table 7 and table 8.

Table 7. Comparison of the FFNN and ARIMA

Model	RMSE	MAE	AIC	R2
FFNN(4:12:8:1)	650105.14	448732.99	1222.48	0.77
SARIMA(0,1,2)(0,0,1)[12]	1068970	793978.60	3654.28	0.38

Table 8. Real and Forecasted values of dairy exports from Turkey to Iraq in 2020

Date	Actual	Forecast by FFNN (4:12:8:1)	Forecast by SARIMA (0,1,2)(0,0,1)[12]
Jan-20	11121442	8976786	7298200
Feb-20	8873174	8162560	6636228
Mar-20	6767136	6083799	6913408
Apr-20	10855890	8824904	7174719
May-20	8910783	7985000	6491870
Jun-20	7591878	7715808	6429840

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Jul-20	8435663	8882489	7221536
Aug-20	8637065	8376377	6810063
Sep-20	8465773	8609091	6999261
Oct-20	8622053	8660765	7041272
Nov-20	7634299	7920703	6439596
Dec-20	9183348	8382025	6497694

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.

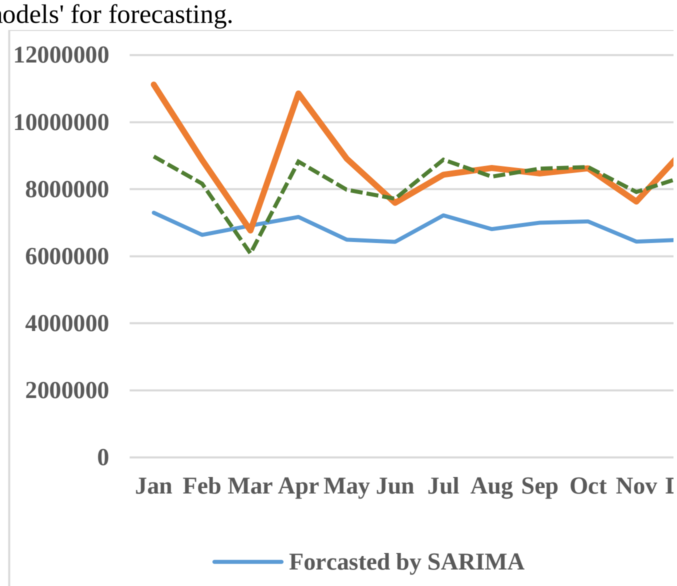

Figure 8. Actual and forecasted values in 2020 using SARIMA and FFNN models.

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, there are no systematic methods for determining which network topology can optimally duplicate the function by connecting inputs to outputs. As a result, time-consuming experiments and trial-and-error methods are frequently employed.

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

Year	Month	Commercial Value (US$)
2010	Jan-10	3061771
2010	Feb-10	3224587
2010	Mar-10	2874585
2010	Apr-10	2548770
2010	May-10	2971149
2010	Jun-10	3871464
2010	Jul-10	4237404
2010	Aug-10	4902531
2010	Sep-10	2975030
2010	Oct-10	4262337
2010	Nov-10	4337696
2010	Dec-10	4728199
2011	Jan-11	3420314
2011	Feb-11	3368311
2011	Mar-11	3953975
2011	Apr-11	4405207
2011	May-11	4543197
2011	Jun-11	4027188
2011	Jul-11	4590219
2011	Aug-11	5514048
2011	Sep-11	4816802
2011	Oct-11	5493727
2011	Nov-11	4612620
2011	Dec-11	5127130
2012	Jan-12	4800977
2012	Feb-12	4669577
2012	Mar-12	5110550
2012	Apr-12	4878736

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2012	May-12	3822067	2014	Dec-14	8450638
2012	Jun-12	4603201	2015	Jan-15	5563664
2012	Jul-12	5854295	2015	Feb-15	4809165
2012	Aug-12	5589061	2015	Mar-15	4889822
2012	Sep-12	6061932	2015	Apr-15	6147538
2012	Oct-12	5312384	2015	May-15	6123713
2012	Nov-12	7000807	2015	Jun-15	6138952
2012	Dec-12	6446748	2015	Jul-15	6643186
2013	Jan-13	6976319	2015	Aug-15	8074497
2013	Feb-13	6038567	2015	Sep-15	4633584
2013	Mar-13	6065767	2015	Oct-15	9925517
2013	Apr-13	5807619	2015	Nov-15	8593387
2013	May-13	6107273	2015	Dec-15	3335287
2013	Jun-13	6288113	2016	Jan-16	7419805
2013	Jul-13	9048827	2016	Feb-16	7866590
2013	Aug-13	5512088	2016	Mar-16	5743748
2013	Sep-13	7818574	2016	Apr-16	4738367
2013	Oct-13	8563145	2016	May-16	8492093
2013	Nov-13	8784292	2016	Jun-16	26193649
2013	Dec-13	9423810	2016	Jul-16	5790410
2014	Jan-14	8616894	2016	Aug-16	6453106
2014	Feb-14	7219555	2016	Sep-16	5179176
2014	Mar-14	4905386	2016	Oct-16	7599890
2014	Apr-14	6960336	2016	Nov-16	7296709
2014	May-14	7006315	2016	Dec-16	7253545
2014	Jun-14	4845533	2017	Jan-17	5392026
2014	Jul-14	6152726	2017	Feb-17	6055439
2014	Aug-14	7180183	2017	Mar-17	5644727
2014	Sep-14	8150921	2017	Apr-17	5321440
2014	Oct-14	8005257	2017	May-17	6029514
2014	Nov-14	8557097	2017	Jun-17	6354688

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2017	Jul-17	6276694
2017	Aug-17	7959833
2017	Sep-17	6896846
2017	Oct-17	6117672
2017	Nov-17	5133776
2017	Dec-17	7829834
2018	Jan-18	7240104
2018	Feb-18	6554836
2018	Mar-18	6545351
2018	Apr-18	5361815
2018	May-18	6366594
2018	Jun-18	6255524
2018	Jul-18	6015627
2018	Aug-18	5750722
2018	Sep-18	6685501
2018	Oct-18	8783493
2018	Nov-18	10243894
2018	Dec-18	39566678
2019	Jan-19	5361151
2019	Feb-19	4908174
2019	Mar-19	4696420
2019	Apr-19	6224103
2019	May-19	6836325
2019	Jun-19	4585023
2019	Jul-19	8432460
2019	Aug-19	4901054
2019	Sep-19	7726511
2019	Oct-19	8034828
2019	Nov-19	7039546
2019	Dec-19	6651387
2020	Jan-20	11121442
2020	Feb-20	8873174
2020	Mar-20	6767136
2020	Apr-20	10855890
2020	May-20	8910783
2020	Jun-20	7591878
2020	Jul-20	8435663
2020	Aug-20	8637065
2020	Sep-20	8465773
2020	Oct-20	8622053
2020	Nov-20	7634299
2020	Dec-20	9183348

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