Improving Time Series' Forecast Errors by Using Recurrent Neural Networks

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ABSTRACT
Elman Neural Network (ENN) is considered one of the most powerful tool in solving various models. This paper suggests the use of ENN in a model free technique to solve time series models of any type. The objective of this paper is to compare between the suggested smart method against the traditional method in solving time series problems. The accuracy of the prediction method measures used in this paper are Root-Mean-Square Error (RMSE) and Mean Absolute Percentage Error (MAPE), thus evaluating the adopted prediction methods. The results show that suggested smart method which uses the ENN is better compared to the traditional method, which uses Autoregressive Integrated Moving Average (ARIMA) model to solve time series forecasting models.

CCS Concepts
• **Computing methodologies→ Neural networks**

Keywords
Elman Neural Network; Recurrent Neural Networks; time series forecasting; ARIMA model.

1. INTRODUCTION
Time series forecasting is an effective tool for decision making. Hence, many researchers have taken interest in this area of research for the past few decades. The Autoregressive Integrated Moving Average (ARIMA) model, which is the result of research efforts by the authors in [1], has been the most popular method in forecasting research, applications and practices. The effort to improve the forecasting accuracy is an ongoing effort; many have contributed in the improvement of forecast process effectiveness. That is due to the fundamental impact of forecast accuracy on many cases of decision making process. Recently, the accumulated research effort has flourished with introduction of new techniques, such as the introduction of Artificial Neural Networks (ANN) in the forecasting process. The main strength of these techniques is their ability of learning and self-adaptation with any model. Therefore, in overcoming the need for assumption on the nature on time series, such assumption is needed in the classical forecasting methods such as Box-Jenkins method.

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Like many other Artificial Intelligence model and techniques, Artificial neural networks are based on human biology and behavior, their structure is based on a biological neural system, thus they represent nonlinear models. A Recurrent Neural Network (RNN) is a subclass of neural networks, the distinctive characteristics of RNN is that its internal state is formed by the directed cycle formed by the connection of the network's units, which allows it to exhibit dynamic temporal behavior. Unlike feed forward neural networks, RNNs can use their internal memory to process arbitrary sequences of inputs. This makes them applicable to tasks such as unsegmented connected handwriting recognition, where they have achieved the most significant results.

Unfortunately, due to the extreme difficulty in training RNN in a proper manner, they were not popular in applications despite being very powerful in sequence models. Nevertheless, the training difficulty can now be overcome with the recent advancement in Hessian-free optimization, thus, enabling their successful application to challenging sequence problems. Although both ARIMA and ANNs have the flexibility in modeling a variety of problems, none of them is the universal best model that can be used indiscriminately in every forecasting situation [2]. Therefore, many researchers tend to combine Autoregressive Moving Average (ARMA) and ANN, this combination results in a hybrid model [3] [4] [5] [6] [7] [8] and [9].

2. METHOD
The main aim of this paper is to compare between the efficiency of the Autoregressive Moving Average (ARMA) models and RNNs in solving time series problems. In order to achieve that, after discussing both models, both models are used in the practical part to perform forecasting on selected dataset. The data selected to apply both models is a well-known set of the real crude oil production data for the United Arab Emirates (UAE). The main reason for choosing this data set, is due to the increase interest in crude oil production forecasting, since crude oil is one of the most important natural resources in the Middle East and the World, this importance originates from its worldwide impact on the economies and industries, as well as the production significant relation with budget.

2.1 Traditional Method
The statistical approach in forecasting involves the construction of stochastic models to predict the value of an observation xt using previous observations. This is often accomplished using linear stochastic difference equation models, with random input. By far, the most important class of such models is the linear Autoregressive Integrate Moving Average (ARIMA) model or

Box–Jenkins models. The ARIMA (p, d, q) model for such time series is represented by [1]:

$$\varphi B \; 1 - B^{d} \; x_t = \theta B \varepsilon_t \qquad \ldots (1)$$

2.2 Artificial Neural Networks

The concept of ANN is to simulate the data in order to generate a model for it, without the need for a pre-proposed model for the data under investigation. Therefore, a considerable amount of attention from researchers has been focused on ANN, due to its flexibility compared to other mathematical tools used in data model learning. The application of ANN covers almost any form of data handling; it is generally used as a powerful tool in classification, analysis and forecasting.

The ANN are Artificial Intelligence (AI) applications; it is a network of interconnected units as the name suggests. It was inspired by the bio-nervous system. The humane neural system consists of a huge number of cells called neurons; each of these has a large number of connections, which connects it to other neurons. Human abilities, skills and habits are closely related to the continuity of the connection between those neurons, therefore, as long as the neurons connectivity for a certain skill is constantly activated, the knowledge of the skill is saved in the bio-neural network. If the connection is not active for a while, like a skill not used for a period of time, then the knowledge might be lost from the network. The same idea is applied to ANN; the constant practice of the connection that represents some data can improve the ability to perform the task.

In this manner, neural networks can be defined as an interconnected group of neurons. The output of a neuron is connected and through weights with other neuron inputs as well as to the neurons themselves. Artificial neural networks can thus be defined as a structure of information that is processed in parallel, of a set of processing element elements linked together by a set of connectors. The processing elements apply an activation function to their inputs for output. Artificial neural networks are used in various fields such as prediction, engineering, medicine, research and optimization research, statistical models, risk management, finance, forecasting and others [5, 10].

2.3 Recurrent Neural Networks

This type of ANN is also referred to as dynamic ANN, nodes, or neurons. Thus, this network interconnects themselves and others in a certain manner, leading to the information flow and signal being multidirectional. In other words, the input of a specific neuron is connected to the output of the same neuron or another neuron from a previous time instance, such as previous iteration. Therefore, the direction of information flow is forward towards the output. On the contrary, the information flow is backward as input to the neuron itself or other neurons for the next iteration [11, 12]. Some of the important examples of this type are Hopfield, Elman and Jordan.

2.4 Elman Neural Networks

Recurrent neural networks, also known as feedback neural networks, can be distinguished from feed-forward neural networks by their significant characteristic, which is the ability to reintegrate the output feedback into the model; this is accomplished by having a loopback connection. The Elman Neural Network, which structure is depicted in Figure 1, is one of the most well-known and widely used RNN. This network would have a single hidden layer supported with delay feedback; technically, it is considered a special case of feed-forward network, supported with additional memory neurons and local feedback. [3, 4, 10].

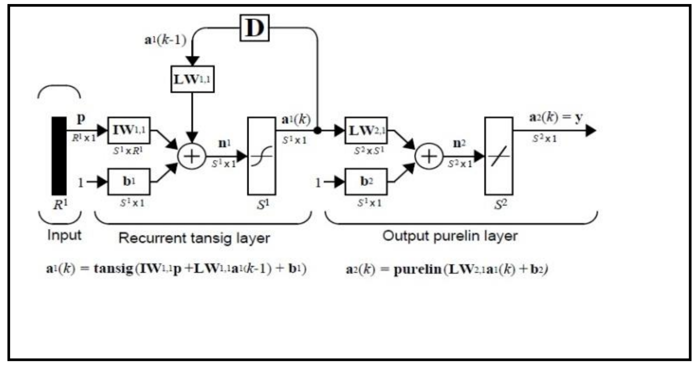

Figure 1. Structure of Elman Neural Network [11]

3. APPLICATION

In this section, the application process is performed, a prediction of future value for oil production to the United Arab Emirates is calculated based on the crude oil production data acquired from United States Energy Information Administration and is illustrated in Figure 2, which shows the time series for crude oil production for the United Arab Emirates for the period between 1980-2012.

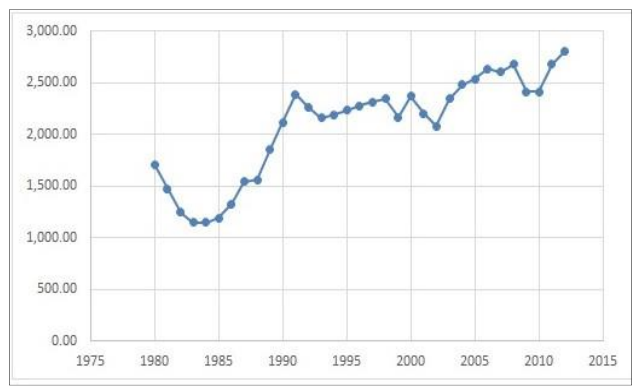

Figure 2. UAE Oil Production Time Series

Forecasting results for both models were calculated. In order to generate the results, MATLAB (Version 8.2) high level programming language is used to estimate neural network forecasting results [12], while Statistica (version 8) program and SPSS (version 21) are used to estimate the ARIMA model [13] [14].

3.1 Traditional Method

The results estimated from using the ARIMA model, which represents the traditional approach are shown in Figure 3, which shows that the behavior of the Autocorrelation Function (ACF) is exponentially and the Partial Autocorrelation Function (PACF) at the first lag.

Hence, the best ARIMA model for this time series is ARIMA (1,0,0). The results of this method are shown in Table 1. The table clearly depicts that the parameters of the model are significant.

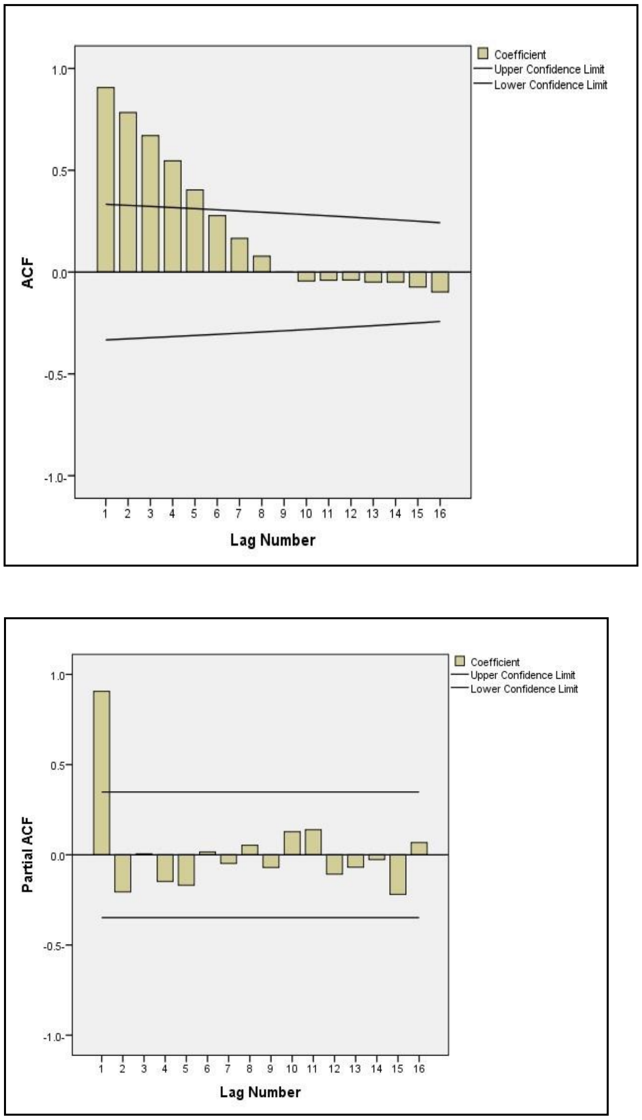

Figure 3. ACF and PACF for UAE Oil Production

Table 1. Parameter Estimation of ARIMA Model

Estimation Parameters		Asympt. Std. Err.	Asympt. t(32)	p-value
ϕ	0.97251	0.006420	151.4605	0.000

3.2 Modern Method

In time series forecasting, the inputs in neural networks are typically the past observations of the data series based on ARIMA models and output is the future value. The main lag-structures are used to determine the number of input units of the corresponding neural networks. Since the best ARIMA is (1,0,0), hence the input nodes for this time series is observation at lags 1, past observations at t_{-1}, i.e. X_{t-1} and the output is X_t , and the best number of nodes in hidden layer is 15 nodes, with one layer, after multiple trials. The Structure of Elman Neural Network is illustrated in Figure 4. On the other hand the performance results of the network are shown in Figure 5.

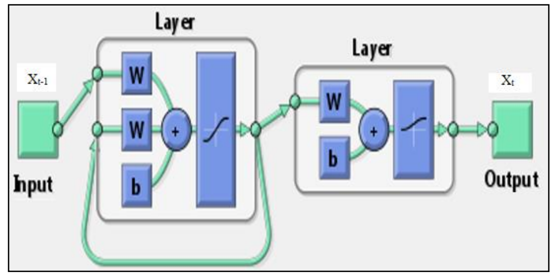

Figure 4. Structure of Neural Network

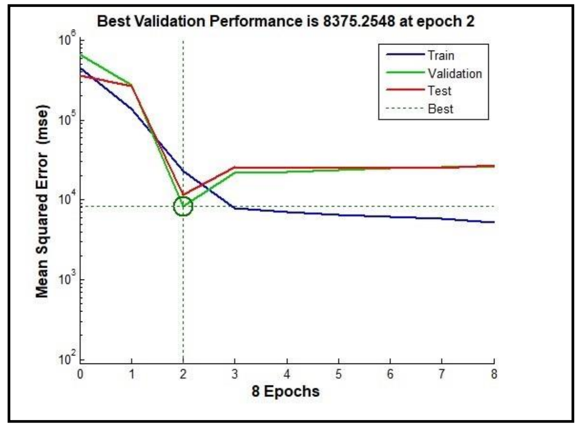

Figure 5. ENN Performance

4. RESULTS AND ANALYSIS

In evaluating the results, two typical indicators Root Mean Squared Error (RMSE) and Mean Absolute Percentage Error (MAPE) are used to compare the predicted and actual values to validate each forecasting method. The error can be estimated by RMSE and MAPE as defined by a number of researchers [1] [2] [8]:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} e_t^2}{n}} \quad \ldots (2)$$

$$MAPE = \frac{\sum_{i=1}^{n} \left|\frac{e_t}{y_t}\right|}{n} \quad \ldots (3)$$

Where:

e_t= actual data-prediction data

y_t is actual data

The results of the methods were used in this paper are shown in Table 2. In the mean time, the Curve fitting for ARIMA models is shown in Figure 6.

Table 2. Results of ANN &BJ(ARIMA)

Method	RMSE	MAPE
ENN	0.46	0.02
BJ	23	8.3

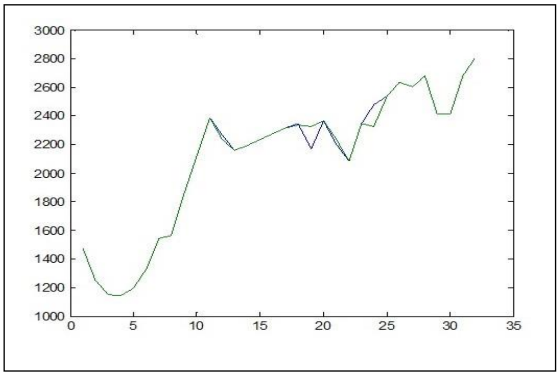

Figure 6. Curve Fitting of UAE Oil Production

The application results indicate that the best method, which satisfies the minimization of error, is Elman neural network (ENN). In addition, RMSE can be represented graphically through histogram as in Figure 7.

Those results show clearly that the use of ANN in general and RNN in specific, improves the prediction results and accuracy of the forecast for time series, by reducing the errors. This is due to the learning and training ability of the network, as well as its adaptability with almost any model unlike traditional methods. Moreover, those results are consistent with other cases of using self-learning artificial neural networks (ANN) and comparing its forecast results with other traditional methods.

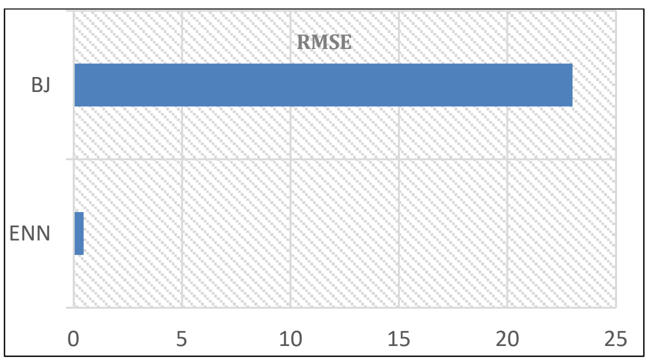

Figure 7. Histogram of RMSE

5. CONCLUSION

The result error analysis clearly shows the improvement in prediction ability and forecast accuracy for the application of Elman neural network compared to ARIMA method in solving time series forecast, this improvement is the result of the dynamic capability of the suggested method, the use of the neurons' output as an input to the next iteration. Moreover, the neural network method flexibility in solving any time series model is also visible; this flexibility is due to the property of training and self-learning.

The results have proven that the best ARIMA model applied for UAE oil production time series is ARIMA (1,0,0). It also demonstrated the suitability of using Elman neural networks as a predictor in the model of oil production to the UAE. The results concluded that the improvement ratio of error is 98% for Elman neural network representing the modern method as compared with the traditional method to solve any time series models represented by the ARIMA method.

This research clearly reaches the conclusion that the adoption of RNN in predicting time series with irregular behavior as an alternative to conventional methods mainly because these networks enable learning, training, and self-adaptation for any model. On the contrary, traditional models assume a set of conditions or assumptions such as the relation being leaner, the stability in time periods and errors being distributed according to a certain particular pattern, although they are not distributed in such pattern originally.

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