High Predictive Performance of Dynamic Neural Network Models for Forecasting Financial Time Series

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***Abstract*—The study presents high predictive performance of dynamic neural network models for noisy time series data; explicitly, forecasting the financial time series from the stock market. Several dynamic neural networks with different architecture models are implemented for forecasting stock market prices and oil prices. A comparative analysis of eight architectures of dynamic neural network models was carried out and presented. The study has explained the techniques used in the study involving the processing of data, management of noisy data, and transformations stationary time series. Experimental testing used in this work includes mean square error, and mean absolute percentage error to evaluate forecast accuracy. The results depicted that the different structures of the dynamic neural network models can be successfully used for the prediction of nonstationary financial signals, which is considered very challenging since the signals suffer from noise and volatility. The nonlinear autoregressive neural network with exogenous inputs (NARX) does considerably better than other network models as the accuracy of the comparative evaluation achieves a better performance in terms of profit return. In non-stationary signals, Long short term memory results are considered the best on mean square error, and mean absolute percentage error.**

Keywords—Dynamic neural network; financial time series; prediction stock market; financial forecasting; deep learning-based technique

I. Introduction

Financial time series such as stock markets are considered one of the most common economic activities across the globe. The fluctuations of the stock market are produced by complex activity and their moves are translated into a blend of gains and losses that are represented in time series [1]. The purpose of stock market forecasting is to predict the future values of company stock price or financial instrument dealt on an exchange. This process will provide essential information about the actual stock price movement and its trends that is beneficial for the investors as it enables them to make the right choice about buying/selling strategies [2]. In addition, the successful prediction of a stock's future price might produce a significant profit. Therefore, there is an increase in the importance of analyzing stock markets in the economic world. However, stock market prediction is considered a challenging task and this is related to the structure of data [3]. The stock market price is based on the random walk hypothesis as proposed by Zhang et al. [4]. Few studies have claimed that the stock market is actually unpredictable; however, others are interested in solving this problem [5, 6].

A number of studies have appeared that focus on trying to find the optimum methodology for stock market forecasting. Each technique has shown a good ability to predict future prices. However, the methods can be divided into conventional prediction techniques, described in detail by Box, Jenkins, and Reinsel [7], and unconventional techniques using AI algorithms such as Artificial Neural Network (ANN). The application of conventional methods such as ARIM and ARIXM for financial time series forecasting have been introduced by few studies [8, 9]. However, in the extensive application of these methods, these models suffer from certain limitations in capturing some types of economic behavior, such as non-stationary or economic performance, at specific periods of time [10, 11]. Hence, various artificial neural network architectures (ANNs) have been used recently to predict future values for finical time series data.

ANNs have proven to be extremely successful for predicting this type of time series such as stock market prices [, 12-18]. Furthermore, studies have also attempted to continue to develop more efficient and accurate ANN architectures for solving forecasting problems [18]. In the similar context, the present study aims to compare forecasting performance of eight neural networks. The neural networks are non-linear autoregressive neural network (Nar), NARX neural network with external input, Elman network, layer recurrent neural network (Layer-RNN), Jordan network, echo recurrent neural network (ESN) ,time delay neural network (TDNN) furthermore the deep learning-based network, long short term memory (LSTM) has been used in this study.

These dynamic neural network architectures have been implemented and their performances have been measured by using statistical and financial measurements. The rationale behind selection of the neural network for predicting the prices of the stock market is based on its ability to understand the nonlinear mapping which prevails between input and output. Moreover, various studies supplement that stock market demonstrates chaos, which is a nonlinear deterministic procedure [19]. As the neural network has the ability to learn about the non-linear process, it can help in improving the financial predictions. The study has used dynamic neural network to forecast stock market prices and oil prices time series. It is important for the investors to maximize their returns at an appropriate time through buying or selling of their investments. It is quite challenging to predict the future price of stock because the data of stock market is highly time-variant and presented in a non-linear pattern.

In this study, the chosen time series involves of three different financial indexes. The first two are a global stock markets which are NASDAQ and Oil prices. NAS DAQ and Oil prices are more delicate to changes in the world economy. The last financial index is one of the popular Saudi stock market in which is Al-rajhi bank prices. It was selected because in the literature, there have been insufficient studies on forecasting the Saudi market. These three indexes were selected in order to test the dynamic neural networks (DNNs) on three various time series. The investigation of stock market data to predict the future of stocks is also a great challenge due to the evolution of information technology and the increase in economic globalization. Therefore, the process of predicting valuable information regarding stock market is important concerning the current status of movements in stock prices. This information is likely to help the customers in taking decisions to finalize whether to sell or buy the shares in a given stock. The comparative assessment is likely to depict the accuracy of recent dynamic neural networks as compared to the traditional models. Furthermore, this study will compare between standard dynamic neural network with deep and layered hierarchical neural network long short term memory (LSTM).Moreover, the results would encourage future studies to use the dynamic neural network to forecast volatility in the financial time series.

II. Literature Review

Recently, a series of studies have been presented in the area of financial data analysis using several ANN architectures for financial time series forecasting. ANN has been proved to offer promising results in terms of stock price forecasting. Dase et al. [20] presented a literature review using ANNs to forecast world stock markets. ANNs have been shown to be extremely successful in predicting non-linear and non-stationary time series. Some existing studies have compared the performances of traditional forecasting models with neural networks [12, 13, 15, 21-25]. Empirical results reported in various studies indicated that the neural networks perform better than linear regression techniques using financial evaluation functions or forecasting error measures [26-29]. Kamruzzaman and Sarker [25] investigated the performance of three ANN models that aimed to forecast foreign exchange rates; they were the standard MLP network trained with the back-propagation learning algorithm, the scaled conjugate gradient network, and Bayesian regression. The experiments attempted to predict six foreign currencies against the Australian dollar. The results also showed that ANNs outperformed ARIMA statistical techniques. Bagherifard et al. [30] confirmed that ANNs give a superior performance than the ARIMA model in financial time series prediction in terms of statistical or financial matrices.

Generally, ANN can be characterized into two types on the basis of the architecture. Both the architectures are different and possess different functions for overcoming a specific problem. One type of ANN is the feed-forward neural network where the inputs (signals) go in one direction to layers until they reach the output layer. This type of neural network has been applied for financial time series analyzing [17, 31]. The other type of ANN is the recurrent neural network (RNN), also called the dynamic neural network, in which the direction of the signal is similar to that in feed-forward networks along with recurrent links from some layers. These links provide RNNs with the capability of having a memory that help the RNNs to exhibit a dynamic behavior in the predicted signals, which means that the neural network learning process is based on previous information in addition to current input data. This information will be stored and then it will be used for better prediction of future time series values. Since the data structure in stock markets is dynamic, learning from historical data is essential where future values depend on historic values. Consequently, feedback links in RNNs will leverage the abilities of neural networks (ANNs) for time series forecasting.

Few of the previous studies have shown the application of the dynamic neural network in different areas [1, 18, 32-35]. These applications show the capability that makes them appropriate for time series forecasting with acceptable forecasting results. Elman RNN [36] and echo-state network (ESN) have been used for financial forecasting [37-40]. Lin et al. [39] investigated the ability of the ESN to forecast future stock prices over the short term by using historical S&P 500 data. The result indicated that ESNs achieved a good result. Another type of dynamical model is the non-linear autoregressive model with exogenous inputs (NARX) that is used for financial forecasting by a number of researchers [41-44]. Cocianu and Grigoryan [43] used NARX to forecast the Bucharest Stock Exchange and compare the result with ARIMA models. In addition, the Time Delay Neural Network (TDNN) is another type of dynamic neural network used by Kim et al. [46] for stock market prediction tasks. The network is generating profits (using the annualized return as a financial measure) for the non-stationary data prediction, which has not been achieved by majority of the benchmarked networks.

Other studies have attempted to design novel dynamic neural networks to perform in financial time series forecasting. Ghazali et al. [1] developed a new dynamic neural network including recurrent links in addition to the feed-forward Dynamic Ridge Polynomial Neural Network (DRPNN). The proposed network achieved a better result on the annualized return for the prediction of the exchange rate signals. This network was also applied to predict Standard & Poor’s (S&P) 500 stock index future signals [1]. Another developed dynamic neural network is called Dynamic Self Organized Neural Network Inspired by the immune system (DSMIA) [18]. This model was designed to model the dynamics of the stock market by using dynamic links. DSMIA architectures are linked with the recurrent network using self-organized immune algorithm layer. DSMIA was effective in predicting accuracy in forecasting, which was proved by the simulation results. Alaskar et al. [18] used DSMIA for financial market forecasting for stationary and non-stationary data and for one and five forecasting horizons. The network is generating profits (using the annualized return as a financial measure) for the non-stationary data prediction, which most benchmarked networks are unsuccessful at doing.

III. Dynamic Neural Networks (DNNs)

The study has implemented eight Dynamic neural networks models to forecast the financial time series. The model of neural network imitates the working of the human brain. It functions by stimulating various interlinked processing units which are in the form of neuron abstract [47]. Such as, the units responsible for processing are arranged in the form of layers, usually in three layers; namely, input layer (input field), hidden layers and an output layer (target field). All these units are connected together through variable strengths or weights, where the information is passed on from one neuron to other. The networks help in investigating the individual record, where continual predictions are based on every record. This is mostly effective in NN for overcoming time series problem where non-linear dynamics are observed [47]. The eight neural networks have been discussed in this section.

A. Non-Linear Autoregressive Neural Network (NAR)

A non-linear autoregressive neural network is recurrent connection network with multiple layers [44] as presented on Fig. 1. It applies to time series prediction, and modelling non-linear function. NAR model can be written as follows:

$$y(t) = f(y(t-1), y(t-2), \ldots, y(t-d)) + e(t) \quad (1)$$

Where; y(t) is the value of a data series n at time t, d shows the number of past values of the series, y(t−1), y(t−2), ..., y(t−n), are called feedback delays.

B. Non-Linear Autoregressive Neural Network with External Input(NARX)

The non-linear autoregressive neural network with exogenous inputs (NARX) uses past values of the time series to the external input series. NARX was proposed by Lin et al. [48]. The structure of this network is illustrated in Fig. 2 below. The NARX predict future values of the time series by using its last outputs and external data [45]. NARX output is computed by the following equation:

$$y(t) = f(y(t-1), \ldots, y(t-d), x(t-1), \ldots, x\left(t-d\right) \quad (2)$$

Where; y(t) is the recent prediction value of the dependent output variable y. x is the externally determined variable that influences y. Therefore, it is able to represent dynamic inputs in historical time series sets. This property will help NARX to deal with continuous and discrete inputs.

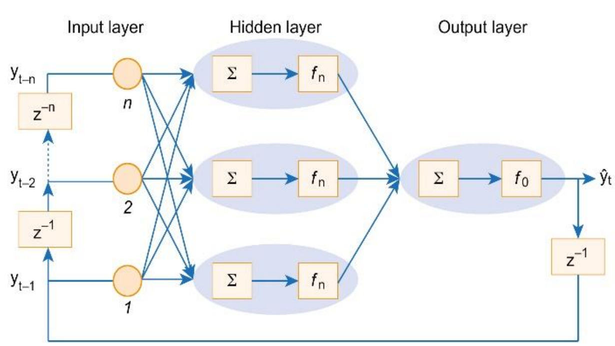

Fig. 1. A Non-Linear Autoregressive Neural Network is Recurrent Connection Network with Multiple Layers.

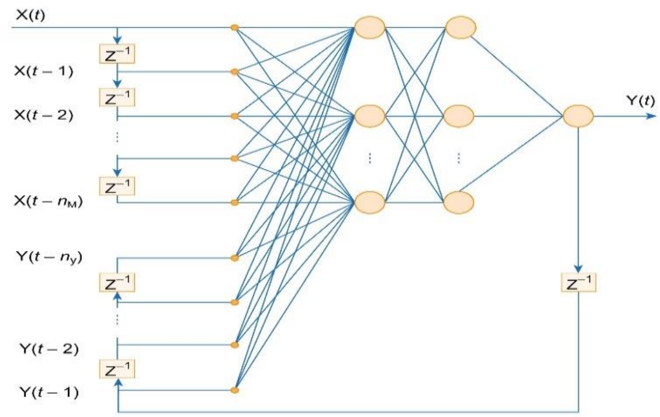

Fig. 2. A Non-Linear Autoregressive Neural Network with External Input.

C. Elman Network

Elman Recurrent Artificial Neural Network (ELMAN) was designed by Jeffrey Elman in 1990. Its first application was to discover patterns in natural languages [49]. The ERNN architecture is similar to the feed-forward neural network, in addition to some context units. The concept of unit context is regarded as the units which store delayed hidden layer of values and represent these in the form of additional network inputs. Such as these context units store the past activation outputs from the hidden layer. Therefore, the feedback links in the ERNN are transformed from the hidden to the input layer through the context-switching nodes, as illustrated in Fig. 3.

The dynamic equations of the ELMAN networks are as follows:

$$u_i(t) = \sum_{j=1}^{n} w_{i,j}^{u}(t) u_j(t-1) + w_i^{x}(k-1) x(t) \quad (3)$$

$$y(t) = \sum_{i=1}^{h} w_i^{y} u_i(t) \quad (4)$$

where n number of output units, w^u refer to the weight connected to context units. Where $u_j(t-1)$ is the context output at time t. h represent number of hidden units. And $u_j(0) = 0$.

D. Layer Recurrent Neural Network (RNNLayers)

This network is similar to the ELMAN network, except that it involves many layers, each of which has a feedback loop from the last layer. Furthermore, it uses arbitrary number of layers and arbitrary transfer functions in each layer.

E. The Jordan Network

The Jordan neural network is similar to the feed-forward network, except that there are feedback links from the output layer to a set of context units. This network was established by Jordan [50], who used the network to learn sequential tasks in language processing. The main aim of designing the Jordan network was to make a neural network that is capable of showing temporal variations and temporal context dependence [50]. In this network, the recurrent links are presented from the output layer to the input layer, in which the input units hold a copy of the values of the external inputs. The context units hold a copy of the values of the feedback link from the previous output units, in addition to self-feedback connections from the context units to themselves Fig. 4.

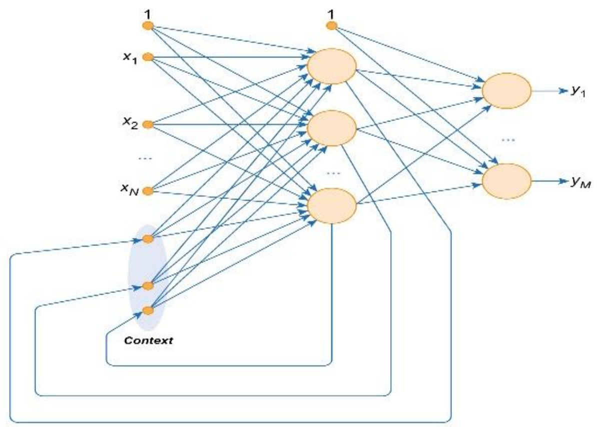

Fig. 3. ELMAN Neural Network.

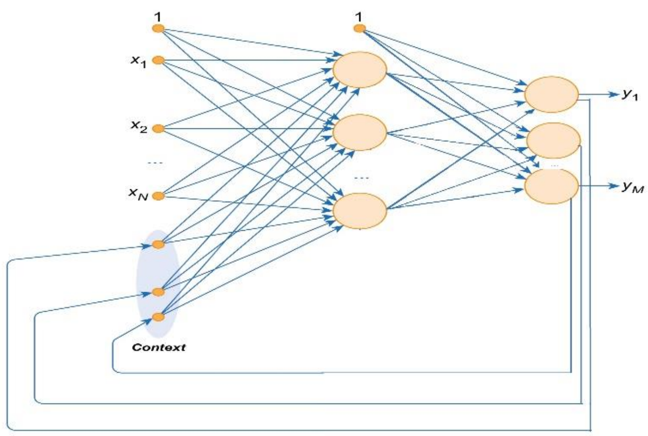

Fig. 4. A Jordan Neural Network.

The dynamic equations of the Jordan neural network can be determined as follows:

$$Z_i(t) = \sum_{j=1}^{n} w_{i,j}^{u}(t) y_j(t-1) + w_i^{x}(k-1)x(t) \quad (5)$$

$$y(t) = \sum_{i=1}^{h} w_i^{y} Z_i(t) \quad (6)$$

Where, Z(t) represents the context unit.

F. *Echo Recurrent Neural Network (ESN)*

The recurrent network of an echo-state network involves an 'echo-state' characteristic [51] that is utilized as a fading memory. Jaeger et al. [52] introduced the echo-state network; however, this network is considered as part of reservoir computing methods based on the recurrent neural network [51]. It involves two parts [52, 53];

- Dynamic reservoir - A recurrent network with a number of units and weights that connect the units with each other.
- Output units - Connected to the neurons of the dynamic reservoir.

The input units are applied to the dynamic reservoir as shown in Fig. 5. The reservoir in the network performs as a fading memory, which is where the echo state name comes from [50].

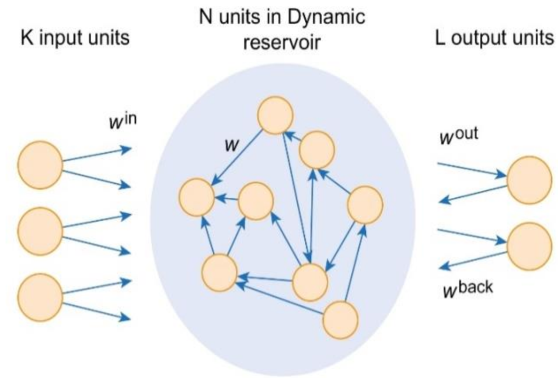

Fig. 5. Echo Recurrent Neural Network.

The activation of the internal units is computed as:

$$u(t) = f(w^{in}x(t) + wu(t-1) + w^{back}y(t-1)) \quad (7)$$

$$y(t) = f(w^{out})(x(t), u(t), y(t-1)) \quad (8)$$

Where; w^{in} is the weight that connects the input units, w^{out} is the weight that connects the output units w^{back}, is the weight connected the output units to internal units ,and fare the transfer function. The output units are y(t). The weights in the dynamic reservoir are trainable by back-propagation algorithm. However, the recurrent weights on the ESN network do not adjust during training.

G. *Time Delay Neural Network (TDNN)*

The TDNN model design is modular as well as incremental, which forms a larger network using its subcomponents. The TDNN has been illustrated in Fig. 6. The network was designed in 1987, when it was used for speech recognition [54].

It provides an effective way of forming proactive predictions in univariate time series. All input and output variables are scaled between upper and lower boundaries of the network transfer function.

$$\{x(t), x(t-\Delta), x(t-2\Delta), \ldots, x(t-m\Delta)\} \quad (9)$$

This network has been shown to be effective in modelling long-range temporal dependencies [54]. According to Junior et al. [55] the TDNN model will eventually behave as a kind of RNN architecture, since a global loop is needed to feed back the current estimated value into the input regressor.

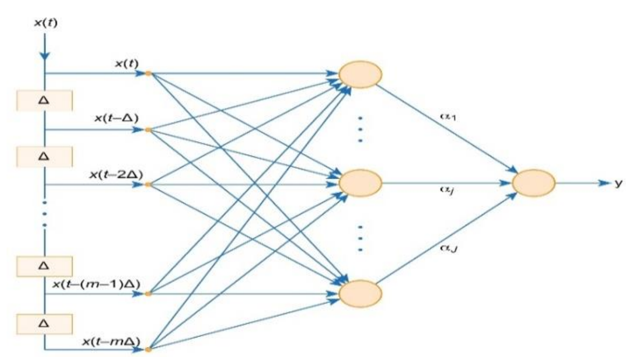

Fig. 6. Time Delay Neural Network (TDNN).

H. Long Short-Term Memory (LSTM) Network

LSTM is a recurrent Neural Network (RNN) with the capability of remembering the values from earlier stages for the purpose of future use. Long Short-Term Memory (LSTM) was first developed by Hochreiter & Schmidhuber (1997) as a variant of Recurrent Neural Network (RNN) [48]. LSTM has been implemented in stock forecasting [46, 48, 58]. LSTM has showed a good performance when compared with traditional-based algorithms such as ARIMA model [58]. LSTM are considered as type of deep learning network. The usual hidden layers are changed with LSTM cells. The LSTM architecture is illustrated below Fig. 7.

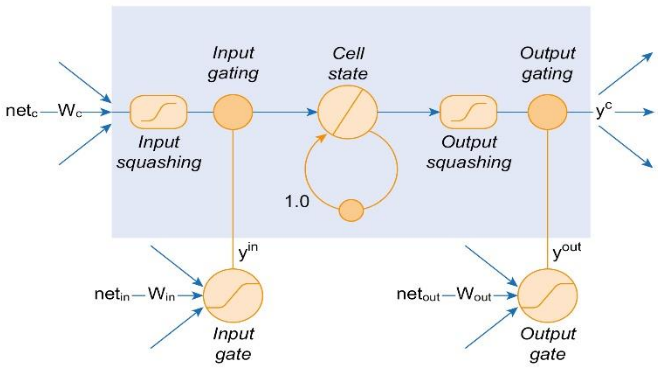

Fig. 7. Long Short-Term Memory (LSTM) Network.

The main aspect of LSTM is having memory block holds memory cells with self-connections storage the temporal state of the network in addition to forget, input gate, and output gate in each LSTM layer [58] has been represented in Fig.7. Gates are able to control the flow of information. The gates and their main functions are as follows:

- Input gate: Input gate contains of the input.
- Cell State: activated through the entire network and its function is to add or eliminate information.
- Forget gate layer: Decides which part of information to be allowed.
- Output gate: It contains of the output produced by the LSTM.
- Sigmoid layer creates numbers between zero and one.
- Tanh layer generates a new vector, which will be added to the state.

IV. Methodology

A. Dataset Description

The experiments conducted in this study are implemented in a MATLAB environment. The performance of the eight neural networks has been evaluated using different time series data. Three noisy financial time series have been studied and used to evaluate the performance of the eight neural network architectures. The data was collected from different resources. The day-by-day stock price of NASDAQ and Al-rajhi has been used as data series. For these companies, the stock movement price for seven years, 2010 to 2017. The historical data consists of daily closing price, opening price, the source of the data can be found at https://finance.yahoo.com. The crude oil price (West Texas Intermediate (WTI) was used in this study. Oil time series was monthly data involving the period between 1st January 1986 and 1st December 2016, with a total of 389 trading months. The source of the data can be found at https://fred.stlouisfed.org/series/DCOILWTICO.

B. Data Processing

The first step before financial forecasting was to select a forecasting horizon. From a trading principle, Cao and Tay [56] declared that a chosen long forecasting horizon might evade over-trading resulting in great transaction rates. However, complexity of the forecasting procedure could increase if the forecasting horizon is very long. In contrast, analysts have claimed that the forecast horizon needs to be small as the persistence of financial time series is for a limited period [1]. This experiment applies one-day ahead predictions from the trading and prediction point of view.

The second step was choosing the pre-processing method, since financial time series are suffering from non-stationary signal [18, 57]. It is also important to transform the data before sending it to the neural network. The transformation technique used is Relative Difference in Percentage of price (RDP) [59], which is used by a number of researchers in this field [1, 18, 57]. It creates a five-day measure of the relative difference in price data. Table I shows the calculations of the data transformation into stationary series.

TABLE. I. THE PRE-PROCESSED DATA TRANSFORMED INTO STATIONARY SERIES

	Indicator	Calculations
Input variables	EMA15	$P(i) - EMA_{15}(i)$ $EMA_n(i) = \frac{a^0 p_i + a^1 p_{i-1} + a^2 p_{1-2} + \cdots + a^{n-1} p_{i-n+1}}{a^0 + a^1 + a^3 + \cdots + a^{n-1}}$
	RDP-5	$\frac{p(i) - p(i-5)}{p(i-5) * 100}$
	RDP-10	$\frac{p(i) - p(i-10)}{p(i-10) * 100}$
	RDP-15	$\frac{p(i) - p(i-15)}{p(i-15) * 100}$
	RDP-20	$\frac{p(i) - p(i-20)}{p(i-20) * 100}$
Output variable	RDP + k	$\frac{p(i+k) - p(i)}{p(i) * 100}$ $p(i) = EMA_e(i)$

where α is the weight factor which is experimentally selected in these experiments as 0.85 as recommended on [18], P(i) is the values of signal for the ith day, and k is a horizon of one or five step ahead prediction. Once this process is completed, the signal will be more symmetrical and it will track normal distribution as represented on Fig. 8. RDP helps in reducing the influence of trends on financial time series and smooth the data to reduce noise, which can improve the prediction process [1, 56]. The input variables are calculated from four lagged RDP values based on five-day periods (RDP-

5, RDP-10, RDP-15 and RDP-20) and one transformed signal exponential moving average (EMA15). The main reason for applying (EMA 15) is to keep useful information contained in the original signal, which might be eliminated by the RDP method [18].

Another pre-processing method applied to the data is scaling. This method is implemented to decrease the variances in the data and to reduce the computational time. All input and output variables are scaled between [0.1 0.9]. The procedure steps of this study are represented in Fig. 9.

C. DNNs

The DNNs parameters are 1000 epochs with one unit for input and output layer. The learning algorithm for each DNNs was backpropagation. Table II below represents the different parameters for each DNN.

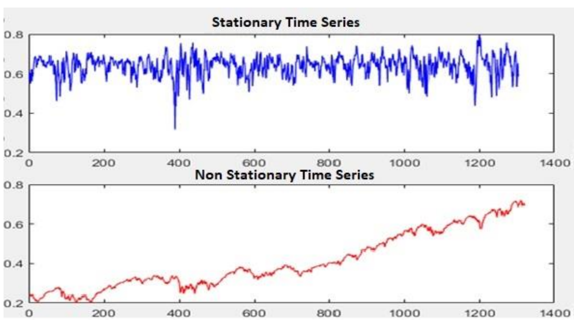

Fig. 8. The Stationary and Non-Stationary Time Series.

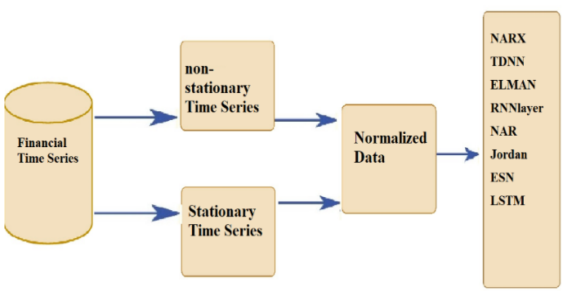

Fig. 9. The Procedure Steps of this Study.

TABLE II. THE PARAMETERS FOR EACH DNN

	Learning rate	mu	Hidden layer
NARX	0.01	0.001	1
TDNN	0.01	0.001	1
ELMAN	0.01	0.9	1
RNNlayers	0.01	0.001	1
NAR	0.01	0.001	1
Jordan	0.01	0.001	1
ESN	0.01	0	100 hidden units
LSTM	0.01	0.001	1. Sequence input with 1 dimensions 2. LSTM with 200 hidden units 3. 50 fully connected layer 4. Dropout layer 5. 1 fully connected layer 6. Regression Output (MSE)

D. Modelling Performance Criterions

There are different evaluation functions that are applied to estimate the network prediction performance; some of them are related to financial criteria and some of them are statistical criteria. The statistical criteria have been used to evaluate the performance of the neural network prediction model, which includes the functions listed below:

- Mean Square Error (MSE) computes the square of the error between the target and forecasted values:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y}_i)^2 \qquad (10)$$

Where; $\hat{y}_i$ is the predicted value, y_i is the actual value and N is the number of data.

- Mean Absolute Percentage Error (MAPE). The MAPE is defined as follows:

$$MAPE = \frac{100}{N}\sum_{i=1}^{N}\left|\frac{y_i - \hat{y}_i}{y_i}\right|^2 \qquad (11)$$

- Correct Directional Change (CDC) CDC defines the ability of a prediction model to forecast accurately the successive actual change of a forecasting variable.

$$CDC = \frac{1}{N}\sum_{i=1}^{N} d_i \qquad (12)$$

Where $d_i = \begin{cases} 1 \; if \; (y_i - y_{i-1})(\hat{y}_i - \widehat{y_{i-1}}) \geq 0, \\ \quad 0 \; otherwise \end{cases}$

The financial criterion is likely to be used to determine the quality of the forecasts [13]. These measurements are listed below:

- Annualized Return (AR) computes the ability of forecasting tools to be used as traders. It is a scaled calculation of the observed change in time series value. The better prediction model gains the higher value of AR.

$$AR = \frac{profit}{All\ profit} * 100 \qquad (13)$$

$$Profit = \frac{252}{n} * CR, C\ R = \sum_{i=1}^{n} R_i$$

$$R_i = \begin{cases} +|y_i| \; if \; (y_i)(\hat{y}_i) \geq 0, \\ \; -|y_i| \; otherwise \end{cases} \qquad (14)$$

$$All\ profit = \frac{252}{n} * \sum_{i=1}^{n} abs\,(R_i) \qquad (15)$$

- The last financial criterion is annualised volatility (AV), which is the function that estimates the investment risk and profit possibilities; thus, a small value of volatility is considered to be a better result.

$$AV = \sqrt{252} * \sqrt{\frac{1}{n-1}\sum_{n-1}^{n}(R_i - \bar{R})^2} \qquad (16)$$

V. SIMULATION RESULTS AND DISCUSSION

A. Experimental Results

The simulation results using eight DNNs have been presented in Tables III to VII and Fig. 10 to 13. In this study, the networks are tested in two different sets of signals that are stationary and non-stationary. One-step ahead predictions of financial time series were utilized. In the case of the non-stationary signal, all the data is passed directly to the neural network. On the other hand, for the stationary signal, the original signals have been transformed using RDP.

TABLE. III. THE RESULT OF MSE FOR ONE-STEP AHEAD PREDICTION

	DNNs	Open NASDAQ	Close NASDAQ	Open Al-rajhi	Close Al-rajhi	Oil Prices
Stationary	NARX	0.0001	0.0001	0.000	0.000	0.001
	TDNN	0.0008	0.0010	0.002	0.001	0.003
	ELMAN	0.0310	0.0552	0.022	0.002	0.055
	RNNlayers	0.0139	0.0051	0.092	0.108	0.027
	NAR	0.0002	0.0005	0.001	0.000	0.001
	Jordan	0.0088	0.0067	0.041	0.006	0.014
	ESN	0.0130	0.0096	0.061	0.058	0.115
	LSTM	0.0083	0.0350	0.014	0.022	0.058
Non- Stationary	Narxnet	0.0000	0.00187	0.000	0.000	0.001
	TDNN	0.0006	0.00213	0.001	0.002	0.003
	ELMAN	0.0092	0.01960	0.032	0.015	0.066
	RNNlayers	0.0051	0.0363	0.084	0.717	2.238
	NAR	0.0002	0.00209	0.001	0.001	0.001
	Jordan	0.0028	0.00639	0.001	0.009	0.0261
	ESN	0.0205	0.00024	0.063	0.061	0.086
	LSTM	0.0019	0.00769	0.018	0.818	0.007

TABLE. IV. THE RESULT OF MAPE FOR ONE-STEP AHEAD PREDICTION

	DNNs	Open NASDAQ	Close NASDAQ	Open Al-rajhi	Close Al-rajhi	Oil Prices
Stationary	NARX	4.9638	3.0174	5.8014	8.1437	9.619
	TDNN	6.1601	6.3957	9.8492	10.308	15.52
	ELMAN	12.210	44.518	29.683	26.122	15.68
	RNNlayers	5.3706	14.115	41.355	14.786	33.83
	NAR	4.7291	4.7398	6.8975	8.2749	8.7829
	Jordan	7.3757	21.156	32.222	11.777	19.276
	ESN	8.5551	8.6843	29.6449	14.261	46.569
	LSTM	4.3118	17.281	1.15271	10.218	0.203
Non- Stationary	NARX	1.3911	1.4547	6.14878	5.2597	5.2236
	TDNN	2.5589	3.1934	10.1737	9.2199	9.1529
	ELMAN	13.357	21.752	33.054	10.954	31.655
	RNNlayers	9.2253	17.092	26.929	58.215	159.00
	NAR	1.8488	1.8395	5.14755	6.0778	5.5762
	Jordan	7.6586	9.6192	14.606	14.331	17.823
	ESN	2.3437	2.8355	29.1189	26.861	29.907
	LSTM	2.7303	7.7828	30.6037	1.7817	8.0623

TABLE. V. THE RESULT OF CDC FOR ONE-STEP AHEAD PREDICTION

	DNNs	Open NASDAQ	Close NASDAQ	Open Al-rajhi	Close Al-rajhi	Oil Prices
Stationary	NARX	50.80	50.06	58.24	58.27	48.37
	TDNN	52.62	48.33	63.18	57.66	47.98
	ELMAN	52.89	51.05	59.31	55.77	49.06
	RNNlayers	51.11	48.65	56.65	53.27	48.99
	NAR	54.24	50.84	57.01	58.70	49.26
	Jordan	53.81	50	63.12	61.35	50.22
	ESN	52.43	49.63	57.09	53.67	49.68
	LSTM	45.01	54.03	65.85	63.41	57.60
Non- Stationary	NARX	54.63	59.81	58.53	58.24	55.44
	TDNN	50.18	49.86	63.96	58.21	49.33
	ELMAN	53.35	50.13	57.37	56.29	51.44
	RNNlayers	51.32	53.97	57.20	54.31	51.33
	NAR	57.21	59.26	57.82	58.73	57.44
	Jordan	53.68	50.81	63.19	61.03	53.04
	ESN	50.54	52.52	58.09	54.80	57.93
	LSTM	95.68	88.70	65.04	62.60	72.82

TABLE. VI. THE RESULT OF AR FOR ONE-STEP AHEAD PREDICTION

	DNNs	Open NASDAQ	Close NASDAQ	Open Al-rajhi	Close Al-rajhi	Oil Prices
Stationary	NARX	100	100	100	100	100
	TDNN	100	100	100	100	100
	ELMAN	100	100	94.67	100	100
	RNNlayers	97.70	97.701	98.51	83.56	95.4
	NAR	100	100	100	100	100
	Jordan	100	100	100	100	100
	ESN	99.32	98.614	88.84	90.94	100
	LSTM	100	100	100	100	100
Non- Stationary	NARX	15.62	15.07	4.89	9.15	13.58
	TDNN	12.19	5.20	9.01	3.71	0.31
	ELMAN	5.47	0.49	1.07	2.86	5.15
	RNNlayers	7.55	3.83	0.95	-2.61	1.49
	NAR	13.05	16.86	0.64	6.04	9.82
	Jordan	8.57	8.07	-4.23	-0.06	6.70
	ESN	-1.35	2.17	1.40	-7.85	11.01
	LSTM	0.56	6.2603	-11.48	1.705	8.298

The neural networks achievement of profitability value is the main interest in these experiments; consequently, the network that generates the highest percentage of Annualized Return (AR) is the best model. In contrast, for the Annualized Volatility (AV), a small value of volatility is a better result. The purpose of using the financial criteria to assess the predicting models is that, from a trading point of view, the models must be producing profit. Therefore, it is meaningful for the predicting model to predict the correct direction change of signals. In addition, annualized volatility is the measure of the changeability in asset returns, which exhibit least preferable volatility. The variance in a stock price is demonstrated through annualized volatility and; therefore, it is utilized as a predictor of profit possibilities and investment risk. When predicting investment risk in real trading, the volatility is one of the best measurements for financial analyst to provide information.

The standard deviation is the statistic used for calculating the portfolio price return over a working year. The neural networks results are obtained with the benefits that this network exhibits over the other systems investigated. Tables III to VII have summarized the average result of 10 simulations gained from testing data sets.

From Table III, it can be observed that the NARX model achieved the smallest MSE compared to the other dynamic neural networks on stationary signals and non-stationary signals except Close NASDAQ non stationary signals, ESN has obtained the best result. In term of financial criteria, it can be observed from Table VI that all the neural networks have achieved 100 in AR, except the ESN network ELMAN, and RNNLayers in some signals. Fig. 10 to 13 have summarized the results achieved from all the neural networks on AR and MSE criteria for the stationary and non-stationary data. The annualized return has been used to evaluate the competence of the networks used in this study. It is an actual trading measurement, which it utilized for investigating the potential monetary benefits and for measuring the entire profitability in a year by using the sell and buy signals.

TABLE. VII. THE RESULT OF AV FOR ONE-STEP AHEAD PREDICTION

	DNNs	Open NASDAQ	Close NASDAQ	Open Al-rajhi	Close Al-rajhi	Oil Prices
Stationary	NARX	0.7228	0.6876	1.3226	1.3052	0.700
	TDNN	0.61884	0.6876	1.3226	1.3052	0.700
	ELMAN	0.61886	0.7418	1.7439	1.3052	0.700
	RNNlayers	0.83902	0.6876	1.5354	2.6592	1.087
	NAR	0.61884	0.6876	1.3226	1.3052	0.700
	Jordan	0.61759	0.6862	1.3410	1.3190	0.70
	ESN	0.89579	1.6634	3.0682	2.8541	0.70
	LSTM	0.62310	3.6716	8.5200	8.4516	1.72
Non- Stationary	Narxnet	0.2191	0.20735	6.2688	5.4067	1.28
	TDNN	0.2196	0.20851	9.2093	9.1975	1.302
	ELMAN	0.2204	0.20875	38.537	23.830	1.329
	RNNlayers	0.2201	0.20858	43.135	105.61	1.301
	NAR	0.2194	0.20695	7.3505	6.0990	1.296
	Jordan	0.2205	0.20982	8.6564	16.095	1.290
	ESN	0.2211	0.21084	31.414	31.068	1.322
	LSTM	41.42	0.1376	12.665	1.1388	1.361

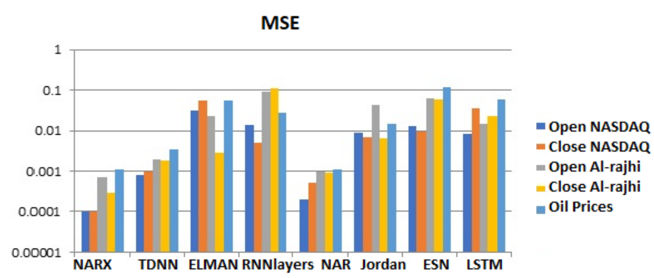

Fig. 10. The Result of MSE using Stationary Signals.

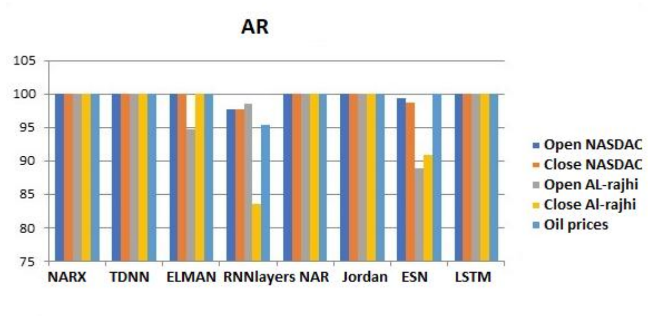

Fig. 11. The Result of AR using Stationary Signals.

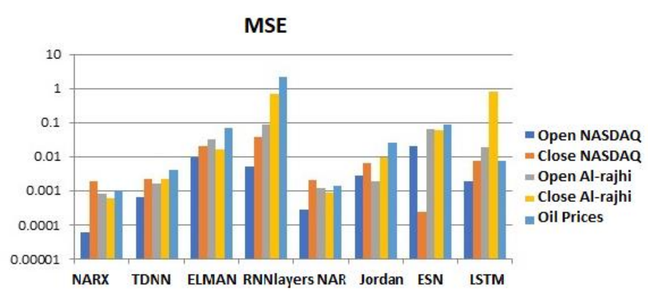

Fig. 12. The Result of MSE using Non-Stationary Signals.

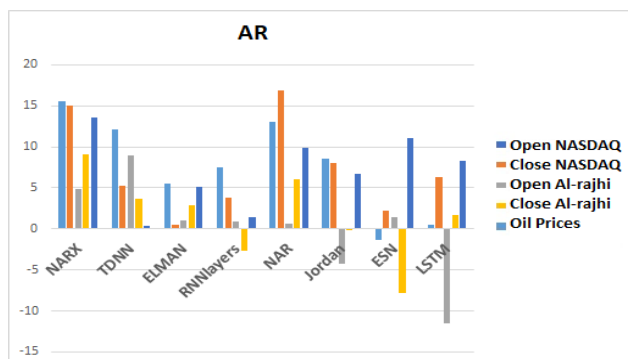

Fig. 13. The Result of AR using Non-Stationary Signals.

It is usually used as the most significant economic parameter for a particular market [18]. This is a scaled calculation of the proposed changes in the time series value where the sign of the change is accurately forecasted. The result of the annualized returns showed that the NARX obtained the best profit return compared to all the other models in the time series data, namely NASDAQ close prices. The NARX has consistently shown the best results with a large margin. Thereby, the NARX has been illustrated as highly favorable performer for this important indicator. From the stationary signals experiment, it can be concluded that the NARX performs better compared to the rest of the dynamic neural networks in most of the financial and statistical measurements. In contrast, the performance of the dynamic neural networks in non-stationary signals varies in five signals. As shown in Fig. 12 to 13, each neural network has achieved a different performance in each signal. In Table VI, the performance of dynamic neural networks is unconsenting, the NARX achieved higher AR in NASDAQ open prices, Al-rajhi close prices, and Oil prices signals. The NAR achieved a higher AR in NASDAQ close prices signals. However, the TDNN showed a good result in Al-rajhi open prices. On the other hand, Mean Absolut percentage Error (MAPE) has exhibited overall standard deviations between measured and predicted values. It is a beneficial parameter for indicating the correct identifying patterns if a system has a low MAPE. In term of stationary signals, LSTM has the best MAPE for the NASDAQ open, Al-rajhi open prices, and Oil prices as can be observed from Table IV. NARX has the best MAPE for the NASDAQ close prices, and Al-rajhi close prices. In term of non-stationary signals, NARX has the best MAPE for NASDAQ open and close prices in addition to Oil prices. However, NAR achieved the lowest values on Al-rajhi open prices whereas LSTM obtained the best result on Al-rajhi close process. The results are clearly represented in Table IV.

B. Discussion

Among the eight networks, as shown from Fig. 10 and 13, the NARX is the best dynamic neural network. The NARX is considered to be a recurrent neural network with inserted memory. Memory allows the NARX to memories the output of the perceptions produced in any layer by unfolding the dependencies of the predicted series far longer than a simplest recurrent neural network. This shows an impact when forecasting nonlinear, aperiodic, and unknown datasets. The NAR is considered to be a good alternative model relating to its simplicity, despite of the NARXs exibility to model exogenous input to help increase performance by modelling external dependencies.

Predicting the stock market future prices has become important because of the successful prediction of stock prices promises attractive benefits. The results for the stock market prediction are validated through evaluation metrics. Specifically, mean square error, and mean absolute percentage error are used to estimate the forecasting accuracy in the stock market. The comparative analysis was carried out on eight dynamic neural network architectures. The first model was non-linear autoregressive neural network (NAR). The second was non-linear autoregressive network with exogenous inputs (NARX), which use external information, caused great improvement in time series forecasting performance.

Also, the deep and layered hierarch neural network LSTM was selected in the comparative analysis in this paper. Despite the success applications of deep layers neural network, deep layered dynamic neural network (LSTM) has filed to achieve the best performance in some signals. In addition, the simplest recurrent neural networks such as Elman, Jordan and ESN network are implemented in this paper. The obtained results show that the performance of each dynamic neural network was different in both stationary and non-stationary predictions. This is related to the non-stationary signals is very difficult since the signals are affected from noise and volatility.

VI. Conclusion

The study has applied dynamic neural network models to forecast high predictive performance of financial time series using stationary and non-stationary data to exploiting the temporal attributes of the neural models in a correct approach. The Elman and Jordan neural networks have been adopted in the neural network models to encode the information for preserving its temporal aspects. From the research experiments, the simulation results showed that the prediction of non-stationary financial signals is very challenging since the signals are suffering from noise and volatility. These unstable behaviours make the signals move and fall sharply at some point during the network training. During the training, the dynamic neural networks are attempting to learn the price values of the non-stationary signals; however, their responses are not sufficient. This is related to the fact that the behaviour of price values was not stable. The extensive experiments of this research confirmed that NARX, NAR and TDNN achieved the best profit values compared to the other networks; although, the prediction for the non-stationary signals usually presents inconsistent results. This study has described the potential of neural networks model for performing more effectively and the applicability of a specific type of neural network models in stationary and non-stationary environments. The improved ways of the neural networks should be explored by the future studies for mapping the data onto the neural networks models and the modification of the grading and classification of candidate solutions for parallel architectures. Thereby, decompositions of the search space of candidate solutions can be used to solve the different parts of the problems.

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