Scientific Research and Essays Vol. 6 (14), pp. 2934-2940, 18 July, 2011
Available online at http://www.academicjournals.org/SRE
DOI: 10.5897/SRE10.1040
ISSN 1992-2248 ©2011 Academic Journals

Full Length Research Paper

Using a weightless neural network to forecast stock prices: A case study of Nigerian stock exchange

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Accepted 19 January, 2011

This research work, proposes forecasting stock prices in the stock market industry in Nigeria using a Weightless Neural Network (WNN). A neural network application used to demonstrate the application of the WNN in the forecasting of stock prices in the market is designed and implemented in Visual Foxpro 6.0. The proposed network is tested with stock data obtained from the Nigeria Stock Exchange. This system is compared with Single Exponential Smoothing (SES) model. The WNN error value is found to be 0.39 while that of SES is 9.78, based on these values, forecasting with the WNN is observed to be more accurate and closer to the real data than those using the SES model.

Key words: Weightless neural network, single exponential smoothing.

INTRODUCTION

There have been several research activities on Artificial Neural Networks (ANNs) over the years (Hwang, 2001; Medeiros and Pedreira, 2001; Zhang, 2001). ANNs have been successfully used for a variety of tasks in many fields of business, industry, and service (Widrow et al., 1994; Lorrentz et al., 2010; Cao et al., 2005) and become an acceptable tool for pattern classification and prediction. Furthermore, ANNs are used for quantitative modeling for researchers and practitioners (Lam, 2004; Lee et al., 2004). The number of published papers related to ANN in diversified field of scientific journals proves the importance and wide acceptability of it (Zhang, 2004).

One of the major characteristics of ANNs is that it serves as a promising alternative tool for forecasters. This is so, because its inherent nonlinear structure is particularly useful for capturing complex underlying relationships which can be found in many real world problems. In addition, ANNs are used today because apart from its versatility as tool for forecasting applications in nonlinear structured problems, they are good for modeling linear processes. These capabilities have been studied and confirmed by a number of researchers (Hwang, 2001; Medeiros and Pedreira, 2001; Zhang, 2001).

A WNN model was proposed by Nontokozo (2006) for forecasting stock prices in the stock market industry in Zimbabwe. The system prototype was designed using Microsoft Visual Basic version 6.0 and it provided the following features: forecast of stock prices in the market using a WNN that uses a ram node, forecast of stock prices in the market using the single exponential smoothing (SES) forecasting model. Nontokozo then made a comparison of the two forecasting tools. Based on the outcome of his comparison, he concluded that forecasts done employing the WNN are closer and accurate to the observed real stock data than those done using the SES model. The present work done in this paper is to further substantiate his claims to forecast stock prices in the Nigeria Stock Exchange using WNN. More specifically, we first develop tools, apply WNN and SES techniques then compare the results of both techniques of forecast.

Related works

To forecast means to make statements about events, whose actual outcomes have not yet been observed. Different forecasting horizon can lead to different results which are one of the drawbacks that affect the performance of the ANNs. Huang et al. (2003) indicated that, for forecasting horizons of 1, 3, 5 days, the ANNs perform

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better (that is, the forecast results are closer to the real data) when compared with the random walk model, while as for 10 and 30 days forecasting horizons, the general performance of ANNs is worse (that is, the forecast results are not closer to the real data) compared with the random walk model. Based on these observations he argued that it was necessary to determine an appropriate forecasting horizon. In parallelism with this, Chun and Kim (2003) proposed the use of Lyapunov exponent in determining the most suitable predictive horizons from the perspective of information loss. This is because from the most suitable forecasting horizon, good forecasts can be generated by the ANNs. Chun and Kim (2003) generalized their findings by saying that ANNs can give effective forecasts for short and medium term forecasting. They defined "short-term" as "one – three step(s)", "medium-term" as "four - eight steps", and "long-term" as "more than eight steps". Here, "step" denotes data frequency, such as days, weeks, months or quarters.

In his view, Walczak (2004) stated that it is problematic to forecast financial time series using ANN. According to him, so many decisions, and each of these decisions affects the performance of the neural network forecasting model. Some of these decisions are which data to use for the ANN and the size of such data and which architecture of the ANN is to be chosen. He said the global nature of financial markets makes it important to categorize global knowledge into ANN instead of using single data from time series to forecast. He also observed that specific markets were partially dependent on other global markets, and said that inclusion of such information can improve ANN performance.

Nontokozo (2006) summarised the work of several researchers (Lawrence, 1997; Tradetrek, 2005; Yi-Fan, 2003; Jelsoft, 2005) who used neural network techniques for forecasting stock market prices. Lawrence (1997) analyzed common market analytical techniques, and then proposed efficient market hypothesis. He contrasted efficient market hypothesis chaos theory and neural networks. Chaos theory is a field of study in mathematics, physics, economics, and philosophy studying the behavior of dynamical systems that are highly sensitive to initial conditions. Though Lawrence did not go on to do practical experiments so as to make his theory work in practice there are some software that are developed using the concepts of ANNs that can forecasts stock prices in the market (Nontokozo, 2006). Amongst them we can mention TradetrekTM Neuro-PredictorTM (Tradetrek, 2005), Neuro XL Predictor (Jelsoft, 2005). TradetrekTM Neuro-PredictorTM (Tradetrek, 2005) is essentially an ANN trained for adaptive prediction of stock prices. During the forecasting process, the TradetrekTM Neuro-PredictorTM is used to determine whether a particular stock is predictable with the accuracy required for a statistically significant prediction. Neuro XL predictor is also a neural network forecasting tool and solves forecasting problem by using Microsoft excel. Apart from those works, Yi-Fan (2003) used fuzzy stochastic prediction method for real-time predicting of stock prices. Emulative neural networks tools (Shachmurove, 2008), are other examples, which is widely accepted by economists, mathematicians and statisticians for data analysis. This acceptance of ENN is because they do not necessarily require assumptions about population distribution.

Most of the work that were presented and available for forecasting the stock prices, used weighted neural network, and none of them tried to implement it by weightless neural network except the work of Nontokozo (2006). Although, the use of weightless neural network is not as common as weighted neural network, the researcher applied WNN in variety of tasks. In a recent study Ludermir et al. (2009) proposed a hybrid system using Weightless Neural Networks (WNNs) and finite state automata. They developed rule insertion and extraction algorithms. Finally they observed that the process of rule insertion and rule extraction in WNNs is often more natural than in other neural network models. In another work, Arguelles et al. (2005) used WNN and Steinbuch Lernmatrix for pattern recognition and classification. He exposed a model for pattern recognition by combining the features of WNN, that is, high speed of learning, easy of implementation and flexibility, with the features of Steinbuch Lernmatrix, that is, learning capacity, recovery efficiency, noise immunity and fast processing. They built fundamental pattern sets for model under the learning phase. Different types of noises were applied to the fundamental patterns to check out the response of the model during the recovery phase. Other examples for the application of WNN includes; the face recognition through WNN, (Alberto et al., 2010), an embedded fingerprints classification system based on Weightless Neural Networks(Conti et al., 2009), an FPGA based adaptive weightless neural network hardware (Pierre et al., 2008), weightless neural networks: knowledge-based inference system (Teresa et al., 2008), vergence control in an artificial vision system using WNN (Karin and Alberto, 2003), alpha-beta weightless neural networks (Amadeo et al., 2008), and automated multi-label text categorization with VG-RAM weightless neural networks (Alberto et al., 2009). Ludermir et al. (1999) has also presented the summary of several weightless neural models.

By observing the unique features of WNN, we are also motivated to apply it for forecasting the stock prices in Nigerian Stock Exchange. We are following the approach of Nontokozo (2006) who applied WNN for forecasting stock prices in Zimbabwe.

Proposed application: Weightless neural network to forecast stock prices

Weightless neural network has several advantages over

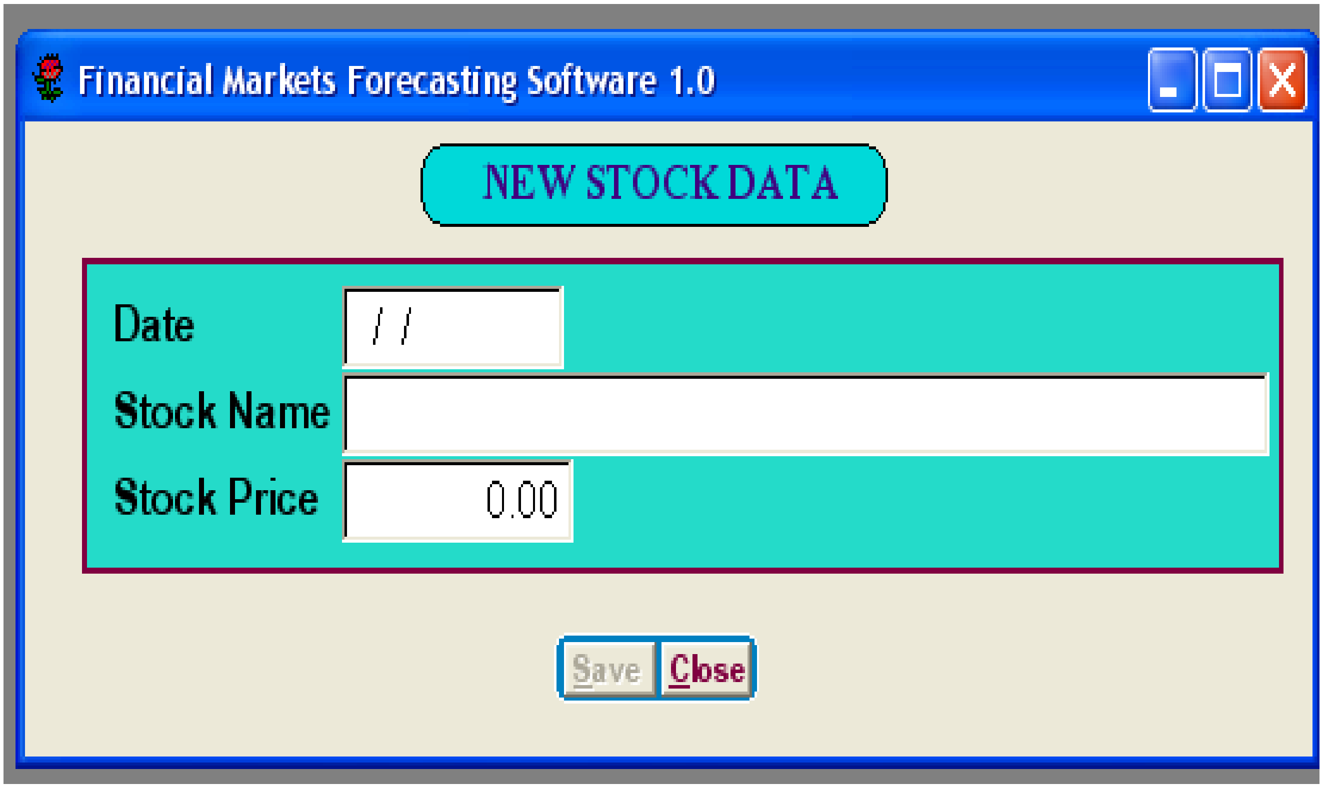


Figure 1. The input component.

weighted neural network. There are several one-shot learning algorithms for WNN where training takes only one epoch. Another advantage of WNN is that instead of adjusting the weights, learning on WNNs generally consists of changing the contents of the look-up table entries, which results in highly flexible and fast learning algorithms. The high speed of learning process in WNNs is also an advantageous feature. By considering theses features, we are also developing a tool using weightless network for forecasting the stock prices in Nigerian Stock Exchange.

Design of tool

We design a weightless neural network tool by using "short-term forecast horizon". Our tool is designed to provide both one point and an m-point forecast of the financial markets (m being a variable ranging from 2 days to 60 days). Our tool has also a constraint that it accepts the collected original data, that is, closing stock prices in multiples of x (where x is the forecast length). The raw closing stock prices are stored in the database of Microsoft Visual Foxprox 6.0.

The normalized data is then converted to n patterns (n representing the number of past months). To make a forecast, we input the number of days or weeks or months, into the system, the system does the forecast, generates a pattern and then checks if such a pattern existed in the past. After identifying the pattern, the data lying at the position m is then produced as the forecasted stock price.

Some of the WNN components are shown in Figures 1 to 3. Figure 1 is for accepting input data; the stock date stock type and closing price. Figure 2 is the report on the stock closing prices while Figure 3 is the forecasting component.

Data used

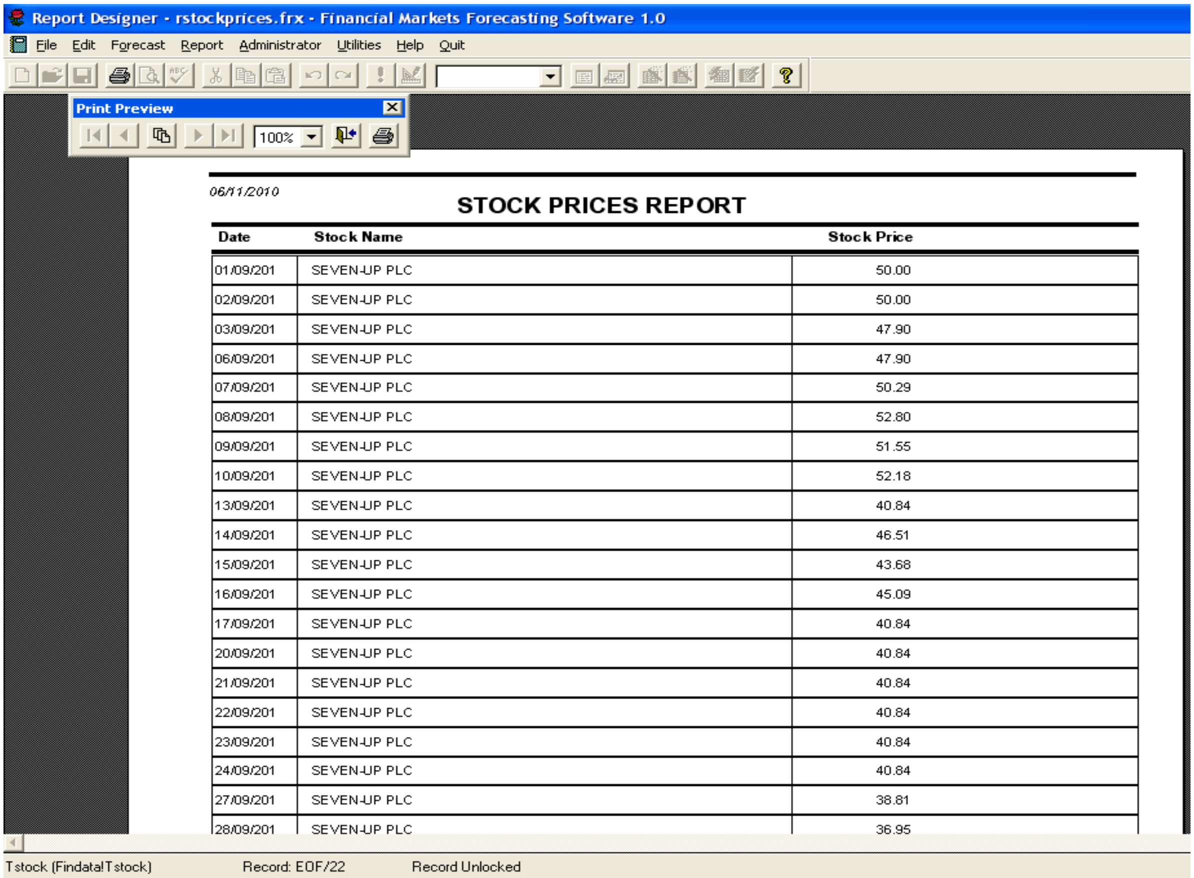
Our tool is designed for forecasting the stock price in Nigerian Stock Exchange. We collected the real data from the Nigerian Stock Exchange. Basically two inputs are required for our model namely:

1. Name of company.
2. Daily stock closing prices.

RESULTS

We have applied our tool on the raw data (closing stock prices) collected from the Nigerian Stock Exchange. To prove the worth of our tool, we also analyze the data, through Single Exponential Smoothing (SES) model. Obviously, for this comparison we have also developed a tool for analyzing the data through SES model. The process of forecasting through SES model is simple and as follows:

First, the data (closing stock prices) is stored in MS excel and accessed from the same place in multiples of x, where x is the forecast length. After smoothening the data, it is subtracted, squared and then find out the mean



Date	Stock Name	Stock Price
01/09/201	SEVEN-UP PLC	50.00
02/09/201	SEVEN-UP PLC	50.00
03/09/201	SEVEN-UP PLC	47.90
06/09/201	SEVEN-UP PLC	47.90
07/09/201	SEVEN-UP PLC	50.29
08/09/201	SEVEN-UP PLC	52.80
09/09/201	SEVEN-UP PLC	51.55
10/09/201	SEVEN-UP PLC	52.18
13/09/201	SEVEN-UP PLC	40.84
14/09/201	SEVEN-UP PLC	46.51
15/09/201	SEVEN-UP PLC	43.68
16/09/201	SEVEN-UP PLC	45.09
17/09/201	SEVEN-UP PLC	40.84
20/09/201	SEVEN-UP PLC	40.84
21/09/201	SEVEN-UP PLC	40.84
22/09/201	SEVEN-UP PLC	40.84
23/09/201	SEVEN-UP PLC	40.84
24/09/201	SEVEN-UP PLC	40.84
27/09/201	SEVEN-UP PLC	38.81
28/09/201	SEVEN-UP PLC	36.95

Figure 2. Stock closing prices report.

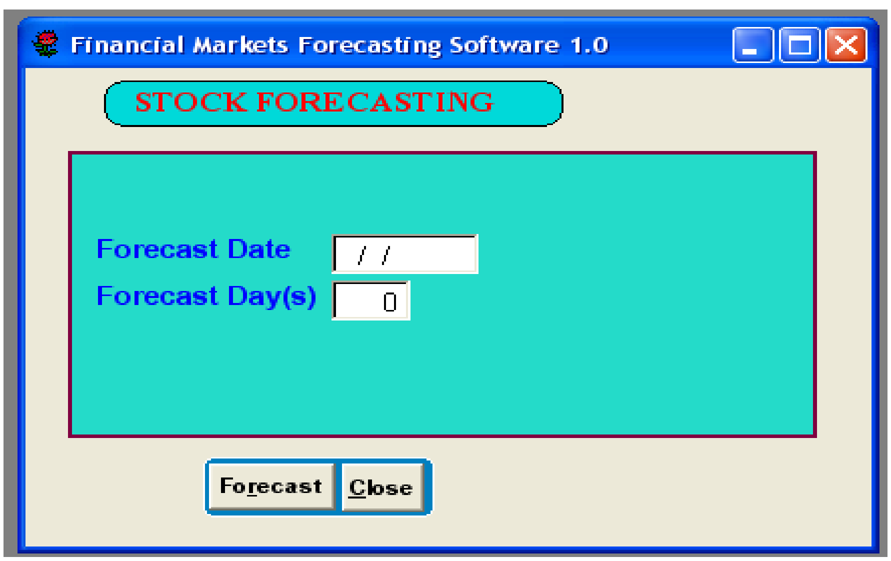


Figure 3. Forecasting components.

squared error.

Secondly, we use the least mean square to forecast. After storing the original past data in MS Excel, we applied it on both tools (for WNN and SES). We compute the mean squared error of each tool as given by Equation 1. Some of the data observed are shown in

Table 1. WNN forecast with 0.39 mean squared errors.

Period	Data	WNN	Error	$(\text{Error})^2$
1	50.00			
2	50.00	50.00	0.00	0
3	47.90	50.00	-1.05	1.1025
4	47.90	47.90	0.00	0
5	50.29	50.00	-0.91	0.819025
6	52.80	52.80	-1.26	1.575025
7	51.55	52.18	-0.01	2.5E-05
8	52.18	52.18	-0.32	0.099225
9	40.84	46.51	0.00	0
10	46.51	43.68	-0.01	2.5E-05
11	43.68	46.51	-1.42	2.002225
12	45.09	45.09	-0.70	0.497025
13	40.84	43.68	-0.71	0.511225
14	40.84	40.84	0.00	0
15	40.84	40.84	0.00	0
16	40.84	40.84	0.00	0
17	40.84	40.84	0.00	0
18	40.84	40.84	0.00	0
19	38.81	40.84	-1.02	1.030225
20	36.95	38.81	-0.93	0.8649
21	36.95	36.95	0.00	0
22	36.95	36.95	0.00	0
				0.39

Tables 1 and 2. The forecasting tool with the least mean squared error is the best tool as it deviates very slightly from the original data. From Table 1, the second period of the error for WNN is 0.00 whereas that of SES is -5 as shown in Table 2. The third period the error for WNN is -1.05 from Table 1 and that of SES is -1.39 from Table 2. As shown in Table 1, the errors of WNN are less than that of SES model in Table 2. There are several periods where the forecast values are accurate as the real data in WNN, these periods are 2, 4, 14, 15, 16, 17, 18, 21 and 22. While in SES periods 16, 17 and 18 are the only accurate ones.

$$MSE = D^2/N \quad (1)$$

Where
MSE = Mean Squared Error.
D = difference between the data and the tool i.e WNN or SES.
N = Number of data.

Figure 4 shows the graphical comparison of the WNN and SES, the vertical-axis represents the stock closing prices while the horizontal-axis represents the period of forecast. From the graph, it can be easily observed that WNN is closer to the real stock closing prices than SES. The SES has the higher values at some points in the graph.

DISCUSSION

One can very easily observe that for several periods WNN forecast exactly the same value with the real data and for others its values are very close to the real data. On the other hand, one cannot get the same results from SES. The number of exact predictions through SES is too less than the WNN. Furthermore, there are some periods, where error values of the two tools are closer as shown in serial number 4, 15, 21, and 22 in Tables 1 and 2 respectively. This means that the differences between the two tools are not much from those values. These observations show that, although the SES is capable to forecast the prices but its values for majority of periods are not as realistic as of WNN.

Conclusion and future work

The WNN is used as a tool for forecasting stock prices in the Nigerian market. When compared with SES model, the WNN forecasting tool proved to be more accurate than the SES as it had a smaller mean squared error of 0.39 as compared to the mean squared error of the SES

Table 2. Singe Exponential Smoothing forecast with 9.78 mean squared error.

Period	Data	SES	Error	$(Error)^2$
1	50.00	0.00		
2	50.00	55.00	-5.00	25.00
3	47.90	49.29	-1.39	1.93
4	47.90	47.76	0.14	0.02
5	50.29	48.15	2.14	4.57
6	52.80	50.75	2.05	4.18
7	51.55	52.88	-1.33	1.77
8	52.18	51.48	0.70	0.49
9	40.84	51.12	-10.28	105.60
10	46.51	40.38	6.13	37.58
11	43.68	46.84	-3.16	9.99
12	45.09	43.50	1.59	2.51
13	40.84	44.82	-3.98	15.87
14	40.84	40.44	0.40	0.16
15	40.84	40.88	-0.04	0.00
16	40.84	40.84	0.00	0.00
17	40.84	40.84	0.00	0.00
18	40.84	40.84	0.00	0.00
19	38.81	40.64	-1.83	3.34
20	36.95	38.44	-1.49	2.22
21	36.95	36.80	0.15	0.02
22	36.95	36.96	-0.01	0.00
				9.78

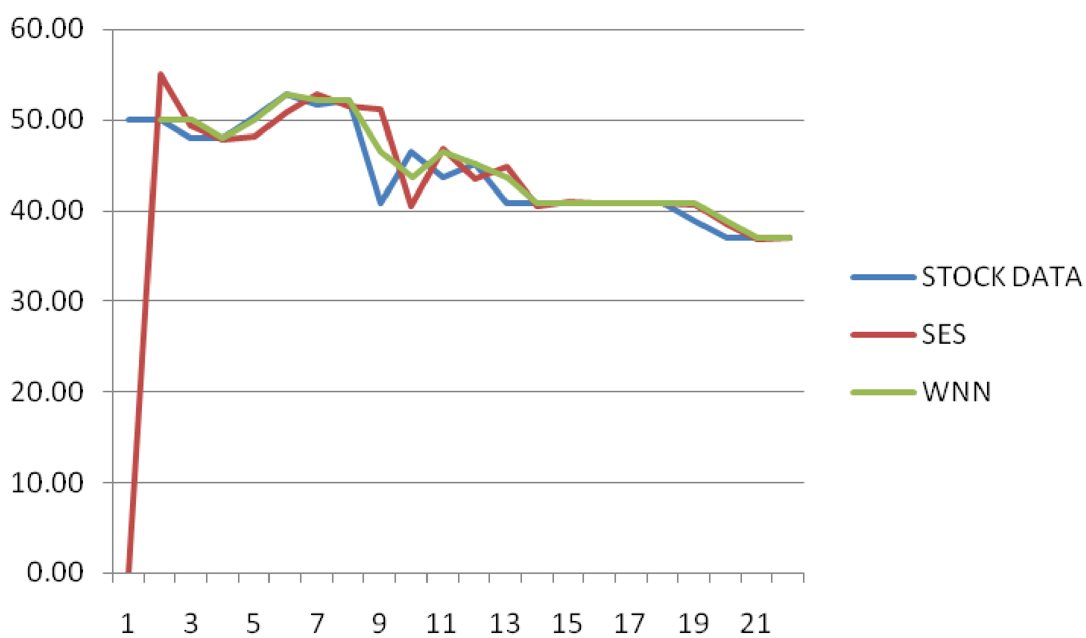


Figure 4. Graph of WNN and SES forecasting.

which was 9.78. The WNN model can be employed and used in the stock market industry and its practical usage may help in forecasting stock prices. The weightless neural network method seems to be one of the most promising tools for forecasting stock prices in the market.

Further research work can be done in future with other statistical forecasting tools in comparison with WNN in order to know the best tool. We also recommend that the performance of the forecasting tool be evaluated after every forecast using some statistical approach so as to tell how good the forecast is.

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