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A Neural Network Approach to Forecasting Stock Prices of Saudi Companies

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Abstract: Over the past decade, the local Saudi stock market has witnessed a rising interest, which is due mainly to the increase in investment in local stocks. In addition, government's commitment to the privatization of its profitable public utilities (e.g., the communication and electrical services) has encouraged many investors to move their money from overseas to the local market. This paper examines the use of artificial neural networks as an emerging technique for forecasting weekly stock prices. Stock prices of seven different Saudi companies were used in the study to demonstrate the capabilities of this new technology. Several evaluation measures were used to evaluate the performance of neural networks in forecasting stock prices for the selected companies. The results showed superior performance of neural network technology which makes it a valuable tool for decision making in the area of investment.

Introduction

In recent years, there has been an increasing interest in artificial neural networks for solving a wide range of managerial problems. Neural networks try to emulate the behavior of the biological neurons in terms of their ability to adopt in response to their environment and they have the ability to learn complex relations from a set of data [1,2]. Although the area of artificial neural networks appeared a long time ago, their use was limited to some few areas because of the programming requirements to build an artificial neural network. But advances in hardware and software technology have resulted in a number of neural network development tools usually referred to as shells that are easy to use. Such tools helped neural network users to overcome previous difficulties associated with implementing this technology.

In the investment domain, stocks are highly preferable alternative and there has been a great deal of attention devoted to the evaluation of the changes in stock prices.

Well known classical forecasting models used in forecasting include statistical methods and time series analysis models such as smoothing algorithms and regression analysis. Recent years witnessed the emergence of more advanced techniques based on machine learning concepts such as neural networks which are capable of identifying complex nonlinear relationships based on historical data that are difficult to capture using traditional forecasting models [3,4].

The objective of this study is to explore the effectiveness of neural networks in forecasting stock prices and to identify the future trend of these prices during the period of study. Stock prices of seven Saudi companies from different sectors were selected. The data are within the period from June 1990 up to January 1999 and were obtained from the Saudi Arabian Monetary Agency (SAMA). These data were collected and incorporated on a weekly basis.

Artificial Neural Networks

Basic concepts

Neural networks consist of processing units or neurons and connections that are organized in layers. These layers are organized as an input layer, a hidden layer and an output layer. Each neuron receives a number of inputs and produces an output which will be the input to another neuron in the next layer. The connections between different neurons are associated with weights that reflect the strength of the relationships between the connected neurons [5,6].

The neuron or the processing element is the basic unit of the artificial neural network. Figure 1 shows an artificial neuron j which has n inputs $x_1,\ldots,x_i,\ldots,x_n$ and each input is weighted before reaching the neuron j by the connection weights $w_{1j},\ldots,w_{ij},\ldots,w_{nj}$. In addition, it has an activation function that determines the output of the neuron y_j. There are different kinds of activation functions but the sigmoid function which takes values between 0 and 1 is widely used and has the form:

$$y_j = 1/(1+e^{net_j})$$

where y_j is the output of the neuron j and $net_j = \sum_i w_{ij}x_i$ is the weighted sum of the inputs to the neuron. The purpose of the activation function is to ensure that the output of the neuron is bounded.

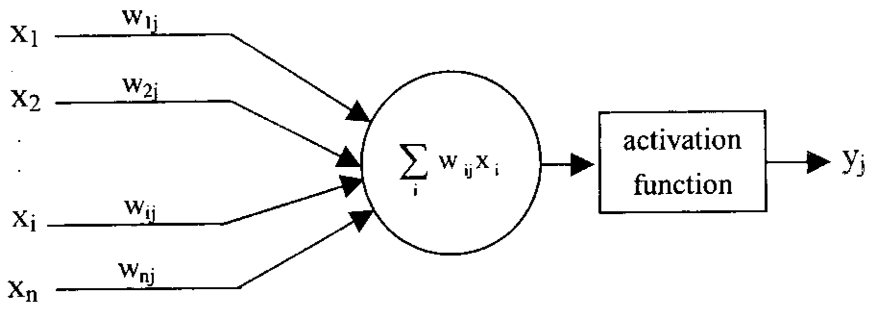

Fig. 1. An artificial neuron.

Each neural network has a specific architecture that defines the number of neurons in the network and the way they are connected. There are different kinds of neural network architectures each used for a specific purpose but the feedforward neural network is a highly popular network and widely used to solve problems in the managerial area [3,5].

Feedforward neural network

The feedforward neural network is divided into an input layer, a hidden layer and an output layer, and each layer can have different number of neurons. Each neuron in the input layer is connected to all neurons in the hidden layer. Similarly, each neuron in the hidden layer is connected to all neurons in the output layer. Figure 2 illustrates a three layer feedforward neural network.

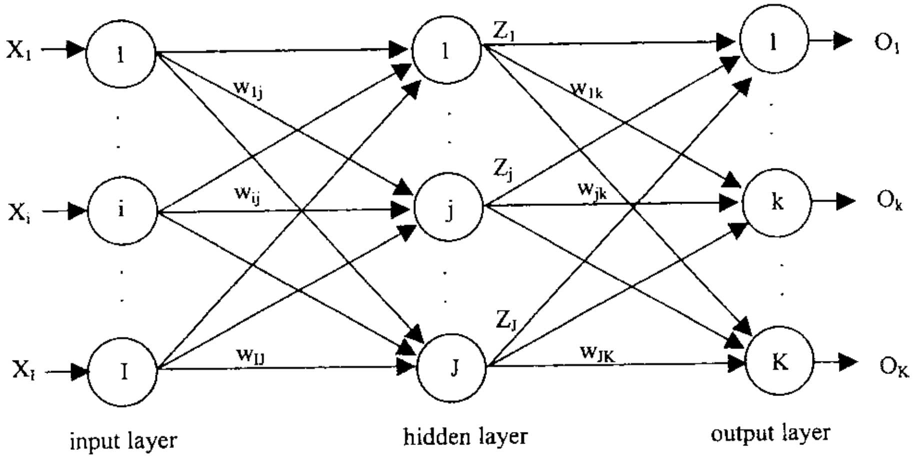

Fig. 2. A three layer feedforward neural network.

This kind of neural networks has only feedforward information paths and does not have backward information paths and the neurons are arranged in layers where the output of a neuron in a particular layer is connected to the input of every neuron in the next layer [7,8]. The number of neurons in the input and output layers is determined by the number of input and output variables in the problem where the neural network is used whereas the hidden layer can have any number of neurons.

Each neuron receives inputs from other neurons through the weighted connections and process these inputs and the results of this processing will be the inputs to neurons in the next layer. The neuron has an activation level which depends on the layer where the neuron is located. The activation level of the neuron in the input layer is determined in response to inputs it receives from the outside. For the neuron in the hidden and output layers, the activation level is a function of the activation levels of the neurons connected to it in previous layer and the associated connection weights.

Learning in Neural Networks

The concept of learning

Learning in artificial neural networks is the process by which the neural network adjusts itself in response to inputs in order to produce the desired outputs [5]. It is a process of knowledge acquisition where the network induces the knowledge from a set of data sample usually referred to as examples. During the process of learning, the network modifies its connection weights based on the inputs received so that its outputs come close to actual or target outputs [5].

There are several learning methods but generally they can be classified into two main categories: supervised and unsupervised [9]. In supervised learning, a set of data that includes input and output values called training data is used to obtain the weights that minimize the deviations between actual and network outputs. In the unsupervised learning, there are no predetermined output values and the network learns from input values only so it can recognize them later.

The backpropagation learning method

The backpropagation learning algorithm is a supervised learning method used to train feedforward neural networks based on a set of data that contains a number of input and output pairs. In this learning method, input data are processed in the network and the resulting outputs are compared with actual outputs and the deviations or errors are used to update connection weights in a way that guarantees minimization of the sum of squared errors [5,6].

The feedforward neural network shown in Fig. 2 is used to illustrate the backpropagation learning method. Given an input vector x_p, $p=1,2,\ldots,N$ and its target output, where N is the size of the training sample, the objective of the learning process is to compute a set of weights w_{ij} and w_{jk} for the neural network connections that map inputs into the corresponding outputs as to minimize the sum of squared errors between target outputs T_k and the outputs produced by the network during the learning process O_k. The objective of the learning process can be stated as:

$$\min \quad E = \sum_k (T_k - O_k)^2$$

The objective of minimizing the error function E is achieved by continually changing the values of the weights w_{ij} and w_{jk} until a set of weights that minimize E has been reached. The backpropagation learning method includes a number of steps (for more details see for example [5,6,10,11,12]):

1. The weights w_{ij} and w_{jk} are randomly initialized.
2. A training vector x_p is presented to the input layer and, by using an activation function (e.g., the sigmoid function), the output of each neuron in the hidden layer is calculated as follows:

$$Z_j = f(\text{net}_j)$$

$$\text{net}_j = \sum_i w_{ij} X_i \qquad i = 1,2,..,I; \quad j = 1,2,..,J$$

The outputs of the neurons in the hidden layer are used to calculate the outputs of the neurons in the output layer which are the outputs of the neural network:

$$O_K = f(\text{net}_k)$$

$$\text{net}_k = \sum_j w_{jk} Z_j \qquad k = 1,2,..,K$$

4. The connection weights of the neural network are adjusted in order to minimize the error calculated at each node in the output layer. This error is the difference between what the neural network actually produces using the weights w_{ij} and w_{jk} and what the network should produce based on actual outputs. The weights connecting the neurons in the hidden layer and in the output layer are adjusted first using the following equation:

$$w_{jk}(t+1) = w_{jk}(t) + \Delta w_{jk}(t)$$

where

$$\Delta w_{jk}(t) = \eta \theta_k Z_j + \alpha w_{jk}(t-1)$$

$$\theta_k = (T_k - O_k) \frac{\partial O_k}{\partial \text{net}_k}$$

The term $w_{jk}(t+1)$ is the set of weights in iteration *t+1* and $w_{jk}(t)$ is the set of weights in iteration *t* of the training process whereas the term $\frac{\partial O_k}{\partial net_k}$ is the derivative of the activation function used in the output layer. If the sigmoid function is used, the derivative will be $O_k(1-O_k)$. The terms and are constants between 0 and 1 used to control and improve the quality of the training process. The constant η is the learning rate whereas α is the learning momentum and will be briefly discussed in the next subsection.

5. After all the weights connecting neurons in the hidden layer and the output layer have been adjusted, the weights connecting the neurons in the input and hidden layers have to be adjusted as follows:

$$w_{ij}(t+1) = w_{ij}(t) + \Delta w_{ij}(t)$$

where

$$\Delta w_{ij}(t) = \eta \theta_j X_i + \alpha w_{ij}(t-1)$$

$$\theta_j = \frac{\partial Z_j}{\partial net_j} \sum_k \theta_k w_{jk}$$

The term $\frac{\partial Z_j}{\partial net_j}$ is the derivative of the activation function for the nodes in the hidden layer and for the sigmoid function it will be $Z_j(1-Z_j)$.

There are two main activities performed in this learning method: forward pass and backward pass. In the forward pass stage, inputs to the network are received through the neurons in the input layer and based on these inputs, the outputs of the neurons in the hidden layer are determined. Similarly, the outputs of the neurons in the hidden layer are used as inputs to the neurons in the output layer and by using an activation function, the outputs of the neurons in the output layer of the network are determined [10,11].

In the reverse pass stage, deviations between target and network outputs are calculated and backpropagated to update the weights where the weights connecting hidden and output layers are updated first then the weights connecting input and hidden layers. Forward and reverse passes in the backpropagation learning method are repeated continuously for each data pair until the weights that minimize the deviations between the outputs produced by the network and target outputs are obtained [10,11].

Specification of learning parameters

The size of the neural network impacts the learning process since lager neural networks require longer time to learn. In addition, the ability of the learning process to reach a minimum error is influenced by two learning parameters: the learning rate and the learning momentum [5,13]. When the decrease in the error function is slow, it is better to choose a larger value for to hasten the learning process. On the other hand, when the decrease is fast, a smaller value for is preferred to guarantee that a minimum value of the error will be reached [5,6].

It should be noticed, however, that there is a critical relationship between the learning rate and the time required to train the network. A smaller value of η guarantees arriving at a minimum error value but this requires a longer time to train the network whereas a larger value for η results in a shorter time to train the network but there is no guarantee that a minimum error will be attained [5]. The learning momentum is another parameter that can be used to control the speed of the learning process. A larger value for α can considerably speed up the learning process and this is recommended in cases where the convergence to a minimum error occurs too slowly [5,6].

Neural Networks for Financial Forecasting

In rapidly evolving financial markets, the development of accurate financial forecasts has been the focus of research in the area of finance since investment decisions rely heavily on the quality of these forecasts. Artificial neural networks are emerging as a key technology capable of improving forecasting abilities of decision makers in this area because they have the ability to approximate complex functional forms with a reasonable level of accuracy [14,15,16]. Therefore, artificial neural networks can be used to model any functional relationship between a set of input and output variables including the functional forms encountered in time series forecasting models [14,15].

A time series consists of a number of observations $y_1, y_2, \ldots, y_T$ where the index refers to time points. In time series analysis, it is assumed that there is an underlying process from which data are generated and the future value of a time series can be forecasted using past observations [3]. Neural networks can capture the underlying process within a time series even in highly irregular data samples [3,4,10]. Although many neural network models are available, the feedforward multilayer network is widely used in the area of forecasting. The inputs of the network are the past, lagged observations, of the time series and the outputs are the future values. The forecasting function takes the following form:

$$y_{t+1} = f(y_t, y_{t-1}, \ldots, y_{t-m})$$

where y_t is the observation at time t and m is the number of past observations used to forecast the future value.

In a time series y_t with T observations, we can use an artificial neural network with m input nodes and one output node to forecast future values after training the network with T-m observations [3]. The first training pattern consists of $y_1, y_2, \ldots, y_m$ as the inputs and y_{m+1} as the target output. The second training pattern consists of $y_2, y_3, \ldots, y_{m+1}$ for the inputs and y_{m+2} for the desired output. The last training pattern is $y_{T-m}, y_{T-m+1}, \ldots, y_{T-1}$ for the inputs and y_T for the target output [3]. The objective of the training process is to find the set of weights that minimize the sum of squared errors between estimated and actual outputs.

Application and Results

Artificial neural networks were used to forecast weekly stock prices for seven Saudi companies selected from different sectors. These companies are NADEC, Food Products Co., GACO, Jazira Bank, Makkah Construction Co., SABIC and The SAVOLA CO. Each neural network has two input nodes, five hidden layer nodes and one output node which indicates that the data from weeks t and $t-1$ were used to predict one week ahead $t+1$.

There are seven time series, one for each company. Each sample was split into two parts: a training sample and a holdback sample. The training sample is used to train the network during the learning process in order to reach the set of connection weights that best describe the relationship between inputs to the network and its outputs. The holdback sample was not used in the learning process but it was processed by the network after it has finished training in order to evaluate the predictive capability of the network.

The neural networks were trained with a commercially available software package, NeuroShell®2 [17]. This package automatically normalizes all the inputs and outputs between 0 and 1 using the highest and lowest values in the training set. Normalization is needed so the data lies within the limit values of the sigmoid function. The package allows the user to easily input the data, define the structure of the network and specify learning parameters through a friendly user interface. In addition, the package enables the user to view the behavior of the artificial neural network during the learning process and interrupt the learning process when the network reaches a steady state.

There are several measures that can be used to assess a forecasting technique. The neural network software package produces several measures that can be used to evaluate the neural network for both the training sample and the holdback sample. These evaluation measures are listed as follows:

$$\text{R squared}\,(R^2) = 1 - \frac{SSE}{SS_{yy}} = \frac{\Sigma(y-\hat{y})^2}{\Sigma(y-\bar{y})^2}$$

$$\text{Mean squared error (MSE)} = \frac{\Sigma(y-\hat{y})^2}{T}$$

$$\text{Mean absolute error (MAE)} = \frac{\Sigma|y - \hat{y}|}{T}$$

$$\text{Correlation coefficient (r)} = \frac{SS_{y\hat{y}}}{\sqrt{SS_{yy}SS_{\hat{y}\hat{y}}}}$$

where y is the target observation and $\hat{y}$ is the predicted value and T is the number of observations.

In all the stock price samples for the seven companies, neural networks showed superior performance. Figures 1 and 2 show detailed values for the evaluation measures for the training sample and the holdback sample for one company included in the study, NADEC. The results for the training sample show the fitting capability of the neural network where an R^2 value of over 99 percent has been achieved between actual and predicted values of the company stock prices. The evaluation results for the holdback sample also show that the neural network achieved R^2 value of over 99 percent. This reflects the ability of the neural network to generalize the results obtained from the training sample during the learning process to any other data sample. A summary of the evaluation results for the training samples for all the companies is given in Table 1 whereas Table 2 summarizes the evaluation results for the holdback samples.

Forecasting results also can be obtained in graphical forms. Figures 5 through 18 show the results obtained from the networks for the training and holdback samples of the stock prices for each company. Each graph has three different lines, one for actual values and another for predicted values and a third line representing the prediction error. The graphs show that the lines for actual and predicted stock prices almost overlap with each other whereas the error line is close to zero. These results demonstrate the ability of artificial neural networks to predict stock prices to a high level of accuracy even with the existence of some irregular patterns in the time series which makes them a valuable alternative to be used for forecasting in the area of finance and in forecasting problems in general.

Table 1. Evaluation results for the training sample

Company name	R^2	MSE	MAE	r
NADEC	0.991	15.19	2.76	0.996
FOOD Products Co.	0.985	26.4	3.25	0.992
GACO	0.991	3.27	1.15	0.995
Jazira Bank	0.975	760.77	13.39	0.987
Makkah Construction Co.	0.983	272.91	9.32	0.992
SABIC	0.955	364.08	7.47	0.977
The Savola Co.	0.972	872.81	15.04	0.986

Table 2. Evaluation results for the holdback sample

Company Name	R^2	MSE	MAE	r
NADEC	0.992	12.77	3.02	0.997
Food Products Co.	0.986	27.17	3.27	0.993
GACO	0.996	1.65	0.99	0.998
Jazira Bank	0.987	447.54	12.75	0.994
Makkah Construction Co.	0.987	238.82	9.34	0.993
SABIC	0.944	361.20	9.67	0.972
The Savola Co.	0.994	133.64	8.47	0.997

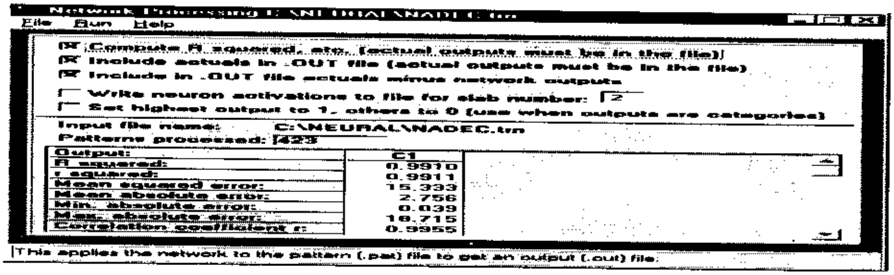

Fig. 3. Detailed evaluation results for the training sample – NADEC.

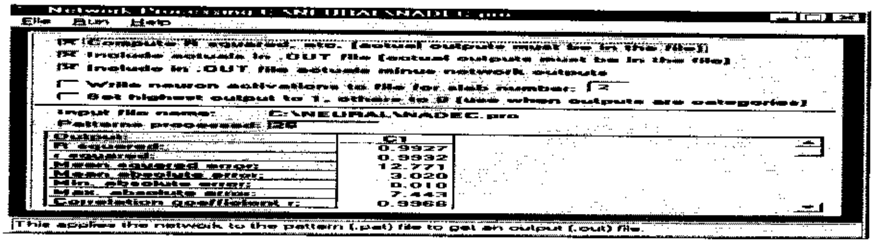

Fig. 4. Detailed evaluation results for the holdback sample – NADEC.

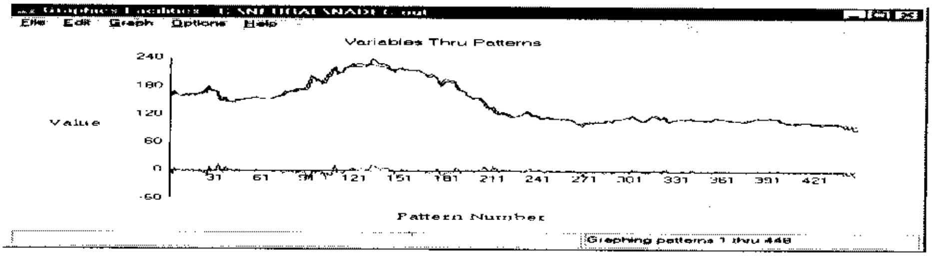

Fig. 5. Forecasting results for the training sample – NADEC.

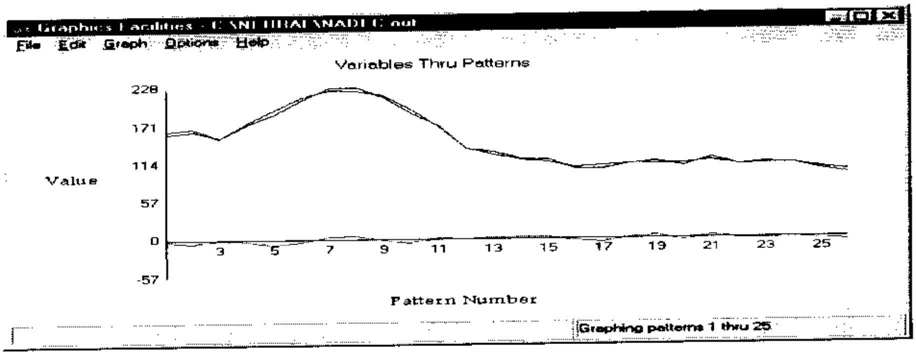

Fig. 6. Forecasting results for the holdback sample – NADEC.

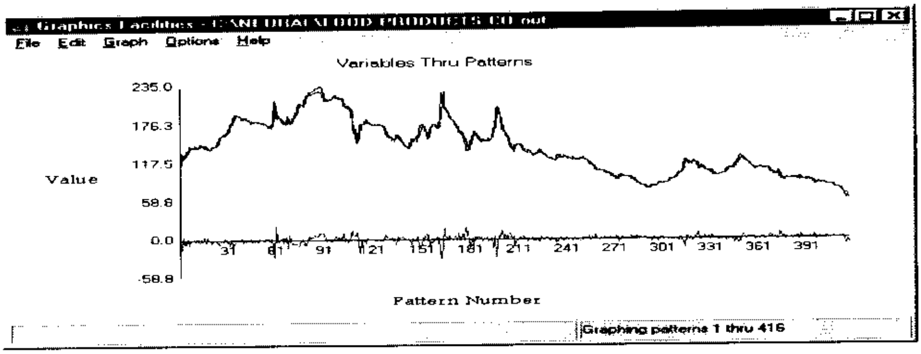

Fig. 7. Forecasting results for the training sample – FOOD PRODUCTS CO.

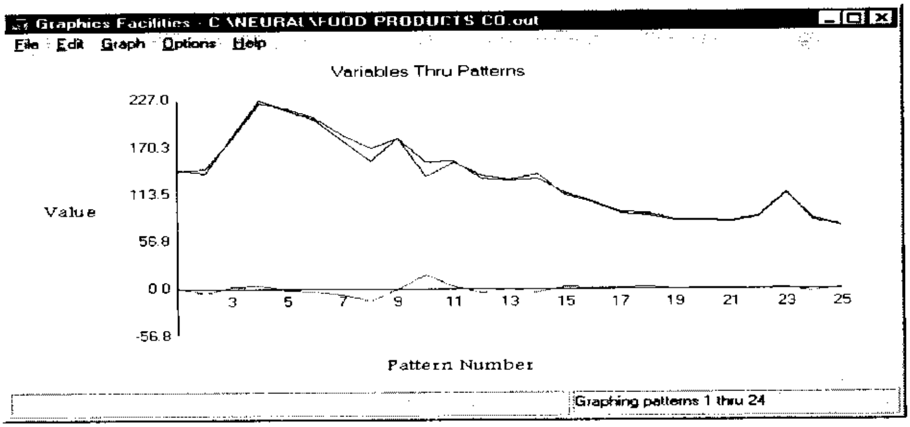

Fig. 8. Forecasting results for the holdback sample – FOOD PRODUCTS CO.

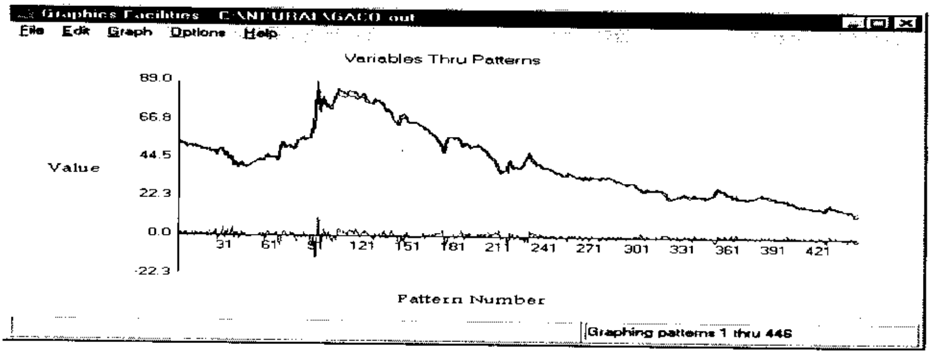

Fig. 9. Forecasting results for the training sample – GACO.

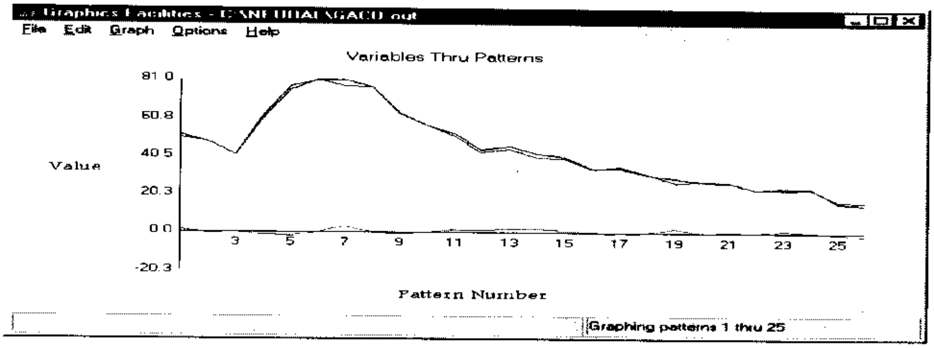

Fig. 10. Forecasting results for the holdback sample – GACO.

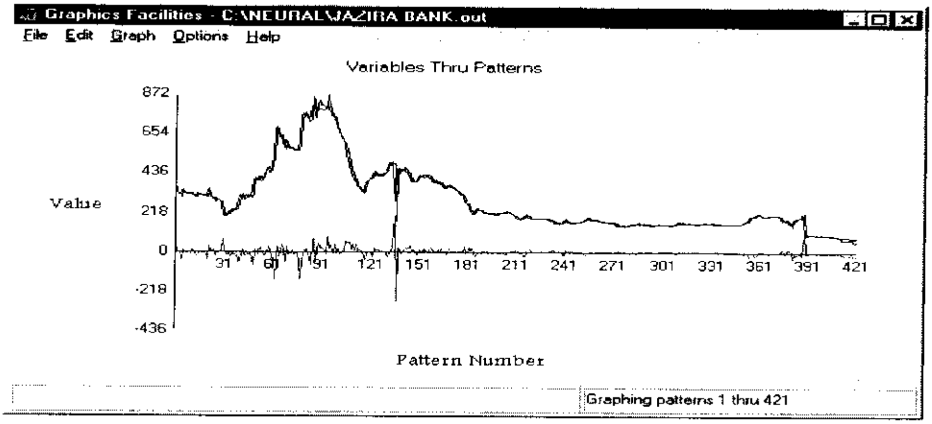

Fig. 11. Forecasting results for the training sample – JAZIRA BANK.

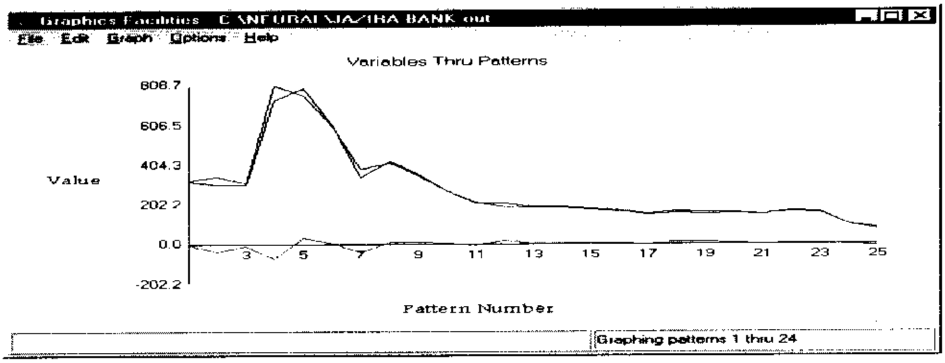

Fig. 12. Forecasting results for the holdback sample- JAZIRA BANK.

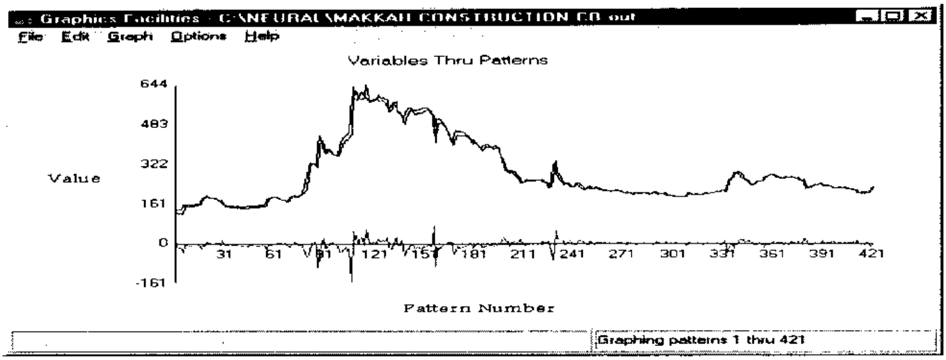

Fig. 13. Forecasting results for the training sample – MAKKAH CONSTRUCTION CO.

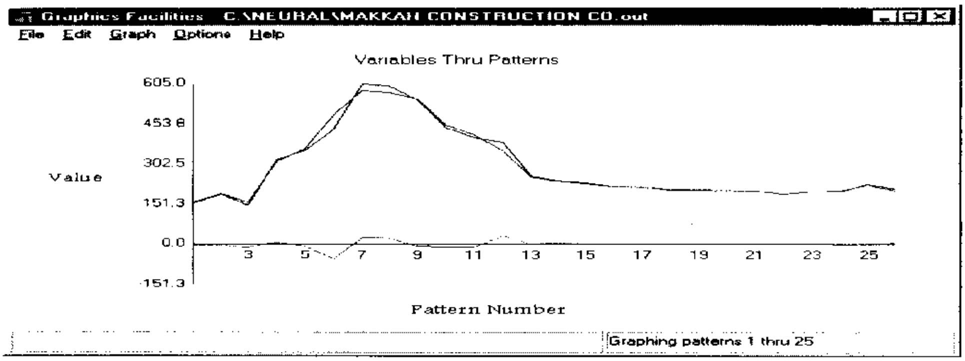

Fig. 14. Forecasting results for holdback sample – MAKKAH CONSTRUCTION CO.

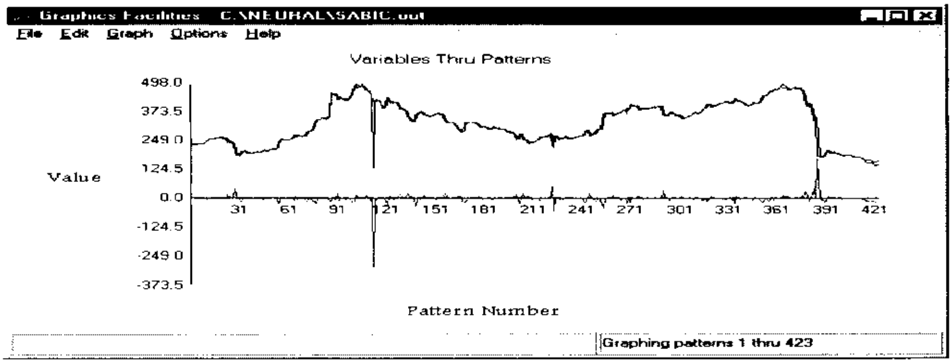

Fig. 15. Forecasting results for the training sample – SABIC.

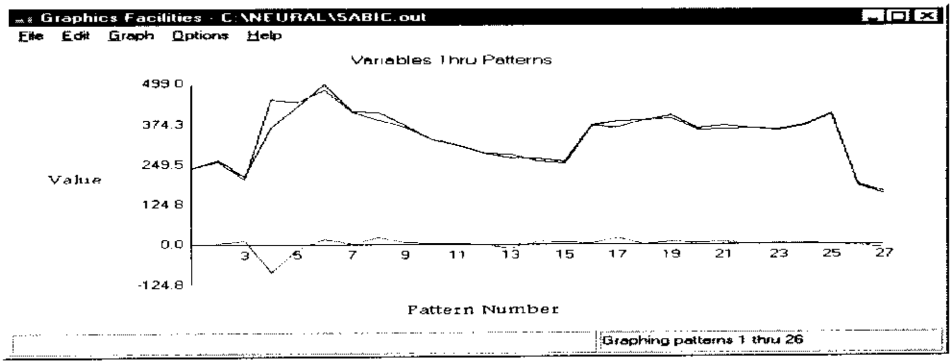

Fig. 16. Forecasting results for the holdback sample – SABIC.

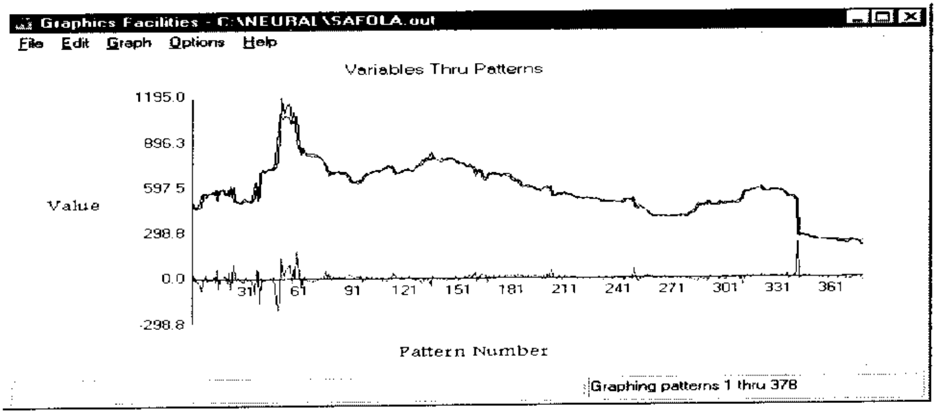

Fig. 17.Forecasting results for the training sample – The SAVOLA CO.

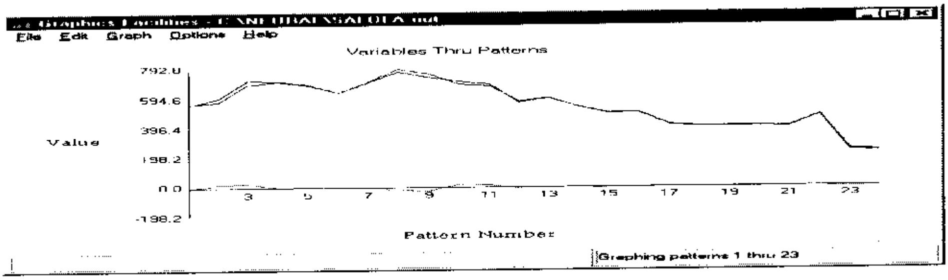

Fig. 18. Forecasting results for the holdback sample – The SAVOLA CO.

Conclusion

Stock prices forecasting using neural networks have recently received much attention. In this study, artificial neural networks have been applied to forecast weekly stock prices of some Saudi companies. Each network has two neurons in the input layer, five neurons in the hidden layer and one neuron in the output layer. Stock prices of seven different Saudi companies were used to demonstrate the forecasting capabilities of neural networks.

Each sample was divided into training and holdback samples. The training sample was used to train the network and to assess its fitting ability whereas the holdback sample was used to evaluate the predictive capability of the neural network. Different measures were used to evaluate the results which are R^2, *MSE*, *MAE* and *r*. The neural network results demonstrate the effectiveness of this approach in forecasting stock prices which result in better investment decisions.

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منهج الشبكات العصبية الصناعية للتنبؤ في أسعار الأسهم للشركات السعودية

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قسم الاقتصاد، كلية الاقتصاد والإدارة، جامعة الملك سعود، فرع القصيم

(قدم للنشر في ١٩/١/١٤٢٠هـ وقبل للنشر في ١٩/١١/١٤٢١هـ)

ملخص البحث. شهد العقد الماضي اهتماما متزايدا في سوق الأسهم بالمملكة العربية السعودية، ويعود ذلك إلى زيادة الاستثمارات في الأسهم المحلية. كما أن قيام الحكومة السعودية بتخصيص بعض القطاعات الحكومية السهامة مثل قطاع الكهرباء والاتصالات شجع العديد من المستثمرين على توجيه استثماراتهم محليا. وسيتم في هذا البحث استخدام الشبكات العصبية الصناعية للتنبؤ بأسعار الأسهم الأسبوعية. وقد تم استخدام أسعار الأسهم لسبع شركات سعودية لإظهار الإمكانات العالية للشبكات العصبية الصناعية. كما تم استخدام عدد من المعايير لتقييم أداء تكنولوجيا الشبكات العصبية الصناعية في التنبؤ بأسعار الأسهم، وأوضحت النتائج الأداء المتميز لتكنولوجيا الشبكات العصبية الصناعية في هذا المجال مما يجعلها أداة مميزة لعملية اتخاذ القرار في مجال الاستثمار.