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Suchira Chaigusin
Edith Cowan University

Chaiyaporn Chirathamjaree
Edith Cowan University

Judith Clayden
Edith Cowan University

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The Use of Neural Networks in the Prediction of the Stock Exchange of Thailand (SET) index

Suchira Chaigusin
School of Computer and Information Science
Edith Cowan University
schaigus@student.ecu.edu.au

Chaiyaporn Chirathamjaree
School of Computer and Information Science
Edith Cowan University
c.chirathamjaree@ecu.edu.au

Judy Clayden
School of Computer and Information Science
Edith Cowan University
j.clayden@ecu.edu.au

Abstract

Prediction of stock prices is an issue of interest to financial markets. Many prediction techniques have been reported in stock forecasting. Neural networks are viewed as one of the more suitable techniques. In this study, an experiment on the forecasting of the Stock Exchange of Thailand (SET) was conducted by using feedforward backpropagation neural networks. In the experiment, many combinations of parameters were investigated to identify the right set of parameters for the neural network models in the forecasting of SET. Several global and local factors influencing the Thai stock market were used in developing the models, including the Dow Jones index, Nikkei index, Hang Seng index, gold prices, Minimum Loan Rate (MLR), and the exchange rates of the Thai Baht and the US dollar. Two years' historical data were used to train and test the models. Three suitable neural network models identified by this research are a three layer, a four layer and a five layer neural network. The Mean Absolute Percentage Error (MAPE) of the predictions of each models were 1.26594, 1.14719 and 1.14578 respectively.

1. Introduction

The ability to predict future trends interests many people. For all stock traders, prediction of stock prices is very important in making buy and sell decisions. Although many economists support the Efficient Market Hypothesis (EMH) which specifies that there is no room for stock forecasting, many researches have been reported which support or reject this hypothesis [6]. While the debate on this issue is ongoing, predictive results from many researches ([5, 7, 8, 9]) encourage the researchers to seek better stock prediction. Techniques of prediction vary greatly according to the availability of information, quality of modeling and the underlying assumptions used [1].

Neural networks are regarded as more suitable for stock prediction than other techniques [6]. Unlike other techniques that construct functional forms to represent relationships of data, neural networks are able to learn patterns or relationships from data itself [6]. The ability of neural networks to deal with non-linear relationships between training input and targeted output pairs makes them suitable for forecasting and modeling nonlinear dynamic and complex systems such as stock markets [6]. In practice, neural networks have been widely used in many areas such as signal processing, pattern recognition, control, speech production, speech recognition and business [10]. Therefore, a variety of neural network models have been created. The backpropagation neural network is a popular neural network model; there are many successful applications for backpropagation neural networks in science, engineering and finance [11].

Generally, stock markets represent countries' economic status. Different stock markets have different characteristics based on the economics of the countries they represent. As the Thai stock market was officially established on April 30, 1975 [13], it is considered as a young stock market and remains in a developing stage.

This study investigated the Thai stock market using feedforward backpropation neural networks. It aimed to find suitable neural network models for the prediction of the next day SET index by applying seven time series, expected to be the factors influencing the stock market, to the models created.

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2. Data Selection and Preprocessing

In developing prediction models for the Thai stock market index forecasting, the choice of selection input data is important. Naturally, the Thai stock market has unique characteristics, so the factors influencing the prices of stocks traded in this market are different from the factors influencing other stock markets. According to Chaigusin, Chirathamjaree, and Clayden (2008), the major indicators driving the Thai stock market include the Dow Jones index, Nikkei index, Hang Seng index, gold prices, Minimum Loan Rate (MLR), and the value of the Thai Baht [2]. In this study, the exchange rates of the Thai Baht and the US dollar were used as the value of the Thai Baht. The data used were historical daily data based on the period of 2003 to 2004. The SET index of this period is shown in Figure 1.

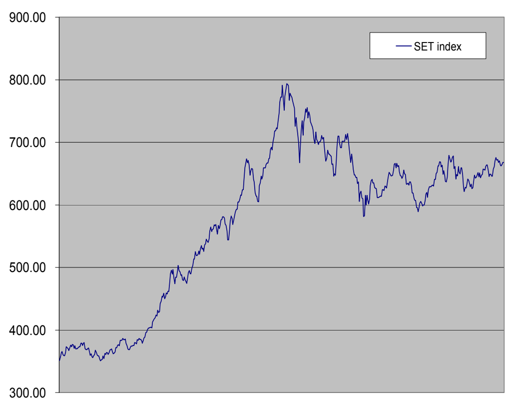

Figure 1 The graph of the SET index, 2003-2004

The raw data were collected from reliable sources including the Stock Exchange of Thailand, the Bank of Thailand and the Gold Traders Association of Thailand. Some raw data used are based on different stock markets, which have different holidays or non trading days, so some data was missing. The assumption underlying this study was that missing data was not significantly different, so gaps were filled by the previous days' data.

Theoretically, feedforward neural networks, considered as universal nonlinear approximation techniques, can deal with data without any data preprocessing process [14]. Practically, data preprocessing is one of critical issues to successful predictions of neural networks [3, 15, 16]. According to Kaastra and Boyd (1996), raw data are at least generally scaled into ranges of transfer functions [3]. Subsequently, the value of output will fall into a range that the neural networks can efficiently handle [16]. In this study, the differences of data between successive days were used and scaled into [-1,1].

3. Neural Network Model Construction

In constructing neural network models, there are many combinations of choices which include number of layers, number of nodes in each layer and training functions. This study applied multilayer feedforward backpropagation neural networks. Backpropagation is a gradient descent algorithm generalized from the Windrow-Hoff learning rule [12]. Training algorithms are the gradient descent backpropagation and the gradient descent with adaptive learning rate. Matlab was used in implementing the neural network models.

In terms of network topology, there are some guidelines for creating neural networks. Yao, Tan and Poh (1999) described how, in the Neural Network News Group's discussions, there were two equations for finding the appropriate number of nodes in hidden layers [4]. These equations follow:

$$HN = \sqrt{N * M} \tag{3.1}$$

$$HN\_layer_i = \ln(HN\_layer_{i-1}) \tag{3.2}$$

where, HN is the number of hidden nodes.
N is the number of input nodes.
M is the number of output nodes.
HN_layer_i is the number of nodes in layer i^{th}.
HN_layer_{i-1} is the number of nodes in layer i^{th} -1.

In addition, Yao, Tan and Poh (1999) and Tsang et al. (2007) described how Freisleben (1992) suggested a formula for finding the suitable number of hidden nodes [4, 5]. This formula is:

$$HN = (j*N) - 1 \tag{3.3}$$

where, j = 1, 2, 3, …

To guarantee accuracy, the Mean Absolute Percentage Error (MAPE) was used to measure the performance of the neural network models. Suppose (a_1, a_2, a_3, … , a_n) are actual values according with predicted values, (p_1, p_2, p_3, … , p_n), the MAPE can be calculated from equation 3.4.

$$MAPE = 100 * \frac{1}{n} \sum \left| \frac{a_i - p_i}{a_i} \right| \tag{3.4}$$

In practice, there are no definite guidelines for constructing neural network models. The process of finding suitable neural network models for the prediction of the SET index was based on trial and error. Accordingly, this study began with 3 layered neural networks, one input layer, one hidden layer and one output layer. After the networks were created, they were tested. When initial predictions were inaccurate, a number of nodes were added to the hidden layer or the number of hidden layers was increased.

To train the neural network models, daily data from 2003 were used. For testing, daily data in 2004, previously unseen in the creation of the neural network models, were used. Based on [2], the following sets of time series data were used for both creation and testing of the foregoing models:

- the SET index
- the Dow Jones index
- the Nikkei index
- the Hang Seng index
- the gold prices
- the Minimum Loan Rate (MLR)
- the exchange rates of the Thai Baht and the US dollar

The underlying assumption of the study is that the six time series data are feasibly related to the movements of the SET index and appropriate to identify the trends of the SET index [2]. Thus, different neural network models were constructed by using the same seven input nodes in an input layer. Some models are shown in Table1, where the first number is the number of nodes in the input layer, the second number is the number of nodes in the first hidden layer, and the third number is the number of nodes in the second hidden layer and so on. The last number is the node of the output layer, which is 1.

Table 1 the neural network models constructed.

3-layer networks	4-layer networks	5-layer networks
7-3-1	7-3-3-1	7-5-3-3-1
7-6-1	7-7-3-1	7-7-5-3-1
7-9-1	7-7-7-1	7-13-7-3-1
7-13-1	7-9-3-1	7-9-5-3-1

4. Experimental Results

The best model for three layered neural networks was 7-3-1 and its training algorithm was the gradient descent with adaptive learning rate. Its performance of predictions demonstrated a MAPE of 1.26594. The prediction graph is shown in Figure 2.

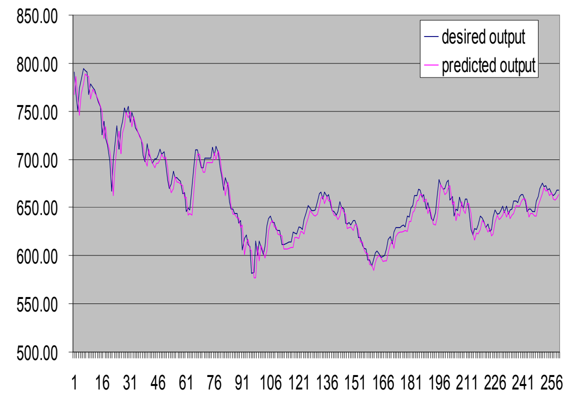

Figure 2 Predicted output of 7-3-1 model against desired output over Jan-Dec 2004 (260 trading days).

The most suitable two models were found to be 7-7-3-1 and 7-13-7-3-1. Their training algorithm is the gradient descent backpropagation. The MAPE for the first and second models are 1.14719 and 1.14578 respectively. The predicted results against actual output of the first and second models are shown in Figure 3 and 4 respectively.

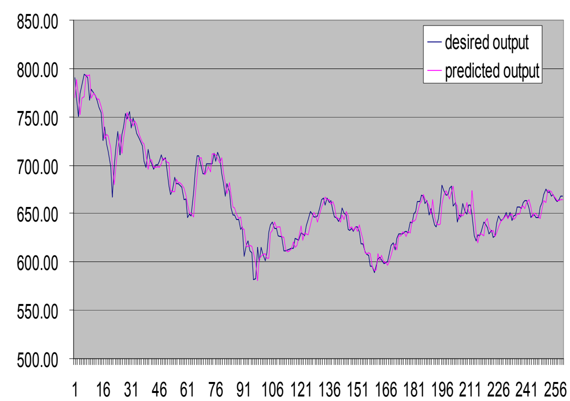

Figure 3 Predicted output of 7-7-3-1 model against desired output over Jan-Dec 2004 (260 trading days).

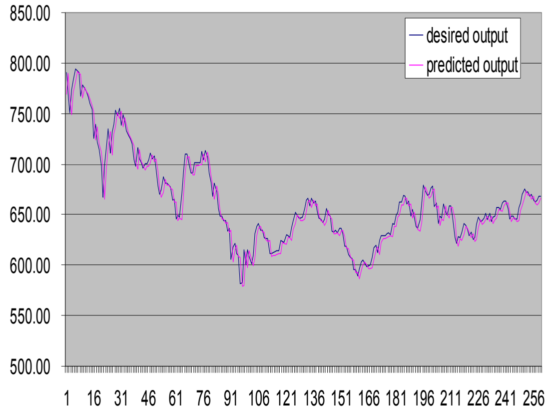

Figure 4 Predicted output of 7-13-7-3-1 model against desired output over Jan-Dec 2004 (260 trading days).

5. Conclusions

The study has presented the prediction of the SET index using multilayer feedforward backpropagation neural networks. The three suitable neural network models for the SET index prediction were found to be 7-3-1, 7-7-3-1, 7-13-7-3-1 and their prediction performance, measured by MAPE, were 1.26594, 1.14719 and 1.14578 respectively. This study therefore supports the assumption that the movements of the SET index were sensitive to the Dow Jones index, Nikkei index, Hang Seng index, gold prices, MLR and exchange rates of the Thai Baht and the US dollar.

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