The Use of Artificial Neural Network for Forecasting of FTSE Bursa Malaysia KLCI Stock Price Index

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Abstract. Stock forecasting has become an issue of interest in financial market. There are many prediction techniques have been reported in stock prediction. Artificial Neural Networks are viewed as one of the more suitable technique for prediction model. In this paper, an experiment on the forecasting of the FTSE Bursa Malaysia Stock Index was conducted to investigate the influence of neural networkĝs architecture on prediction performance by using multilayer perceptron with Levenberg Marquardt training algorithm. The result show FTSE8 and FTSE9 model achieves closer prediction of the actual value than other models.

Keywords: Artificial Neural Network, Stock Price Forecasting

1 Introduction

Forecasting of the future trend in financial market, has become a challenge and attracted many people. For investors, traders, and market participants, prediction of stock price is very important in making buy and sell decision. However, they usually get loss because of unclear investment objective and blind investment. Therefore to create good decision support systems has become an important research problem.

Over the years, linear techniques have been used by researchers and analysts since they are very simple and easy to apply. However, this linear indicator has always worked well on a linear movement but stops helplessly when dealing with nonlinear behavior of the market [1,2].

Artificial neural network (ANN) is widely used in many applications as a prediction technique for its nonlinear structure which is able to deal with even the most complex problems, and that is the reason why ANN becomes a very promising prediction technique and it also provides better performance on forecasting [1, 3-6]. ANNs are able to learn the relationship from the data itself is not like other techniques that construct functional form to represent the relationship of data.

This paper investigate the suitable of ANN architecture for predicting of the next day of FTSE Bursa Malaysia stock price index by using multilayer perceptron with Levenberg Marquardt training algorithm. The rest of this paper is organized as follow. In section 2, the ANN training algorithm, data collection, and performance measure are summarized. The experiment results of the model are described in section 3. Finally, conclusions are given in section 4.

2 Artificial Neural Network Forecasting Model

Neural networks are composed of simple elements operating in parallel. These elements are inspired by biological nervous systems. As in nature, the connections between elements largely determine the network function. A neural network can be trained to perform a particular function by adjusting the values of the connections (weights) between elements.

Multilayer feedforward is the most commonly used neural networks architecture, it consists of one input layer, one output layer, and one or more hidden layer (between input-output layer). Neuron is a processing unit that became the basis of information in the operation of neural networks. All the neurons at each layer are connected to each neuron at the next layer by interconnection value called weights.

Typically, neural networks are adjusted, or trained, so that a particular input leads to a specific target output. Fig. 1 illustrates such a situation. There, the network is adjusted, based on a comparison of the output and the target, until the network output matches the target. Typically, many such input/target pairs are needed to train a network.

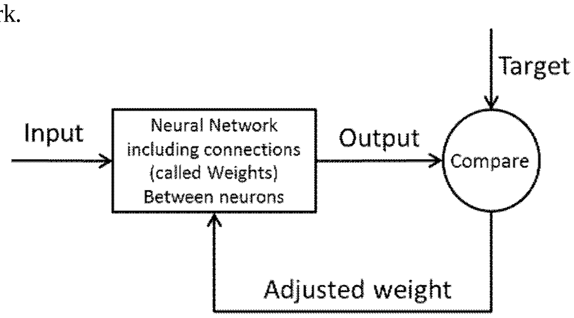


Fig. 1. Neural network training illustrations.

2.1 Levenberg Marquardt Training Algorithms

The Levenberg-Marquardt algorithm was designed to approach second-order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feedforward networks), then the Hessian matrix can be approximated as

$$\mathbf{H} = \mathbf{J}^T \mathbf{J} \tag{1}$$

and the gradient can be computed as

$$\mathbf{g} = \mathbf{J}^{T}\,\mathbf{e} \tag{2}$$

Where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix [7]. The Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like update:

$$\mathbf{xk}_{-1} = \mathbf{x}_{k} - [\mathbf{J}^{T}\,\mathbf{J} + \mu\,\mathbf{I}]^{-1}\,\mathbf{J}^{T}\,\mathbf{e} \tag{3}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible. Thus, μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this way, the performance function is always reduced on each iteration of the algorithm.

2.2 Data Collection

The data sets consist of the OHLC (open, high, low, and close) prices of FTSE Bursa Malaysia Stock Index and composed of daily rates from January 2000 to December 2012. The data sets are divided into three sets, training, testing and validation datasets by 70/15/15 principle where 70% of the data are used as a training datasets and other 15% of the data are used as testing and validation datasets respectively. Figure 2 show the historical data of FTSE Bursa Malaysia KLCI plotted by finance.yahoo.com that will be used in this paper.

Data normalization is one of the most important steps in the use of an ANN. Inputs could have different ranges, the input data has to be normalized in order to ensure that none of the transfer function in the neurons becomes saturated due to a large input value.

Fig. 2. The historical data of FTSE Bursa Malaysia KLCI

2.3 Performance Measurement

In order to evaluate the performance of the prediction model, this study use statistical analysis involving the Mean Squared Error (MSE), Root Mean Squared Error (RMSE), and Mean Absolute Percentage Error (MAPE). MSE is the average squared difference between output and target. Lower values are better and zero means no error. The RMSE is a relevant performance measurement when the aim of the prediction is to minimize the size of the squared error without taking into consideration the direction of the error. The MAPE is a measure of accuracy of a method for constructing fitted time series values especially trend estimator. If the MAPE value of the model < 20%, performance of the model is good, If the MAPE value of the model < 10%, performance of the model is excellent the formula is defined as:

$$MSE = \frac{1}{n} \sum_{i=1}^{n} (F_i - A_i)^2 \quad (4)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (A_i - F_i)^2}{n}} \quad (5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{A_i - F_i}{A_i} \right| \quad (6)$$

where A_i is the actual value and F_i is the forecast value.

3 Experiment Result

The ANN forecasting model was trained with four inputs representing daily open, high, low, close (OHLC) prices, one hidden layer, and one output neuron to predict FTSE Bursa Malaysia KLCI stock price index. The performance of the forecasting model depends on a number of parameters, e.g., initial weight which chosen on training process, different training parameter and algorithm, and the number of neuron in hidden layer.

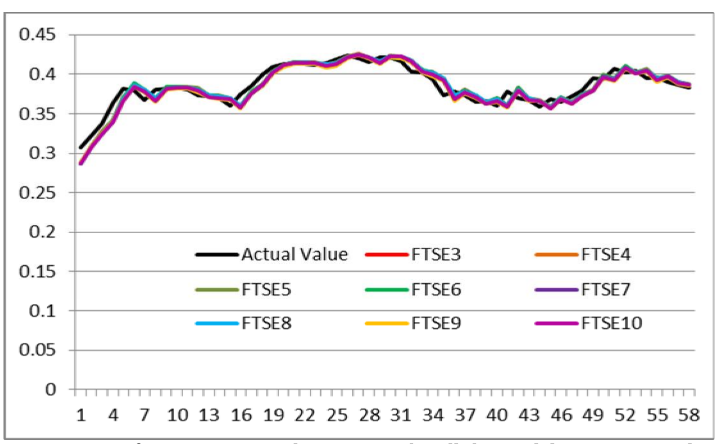
In this study, the model was trained with Levenberg-Marquardt training algorithm with different initial weight and architecture. The number of hidden neuron was varied 3-10 in order to investigate the influence of ANN architecture in forecasting performance. The architecture denoted by ‘*input-hidden-output*’, *input* indicating the number of neuron in input layer, *hidden* indicating the number of neuron in hidden layer, and *output* indicating the number of neuron in output layer. In this section, the forecasting model that yielded the best result is presented.

The models were trained with different number of hidden neuron to predict FTSE Bursa Malaysia KLCI. The prediction performance of the best experiment is reported in table 1. This study use MSE, RMSE, and MAPE in order to investigate how well the performance of the forecasting model. Table 1 show that all models generally perform better. In scale of MAPE, the best performance is achieved by FTSE8 with architecture 4-8-1 and MAPE value is 1.222853%, its quite low than other models.

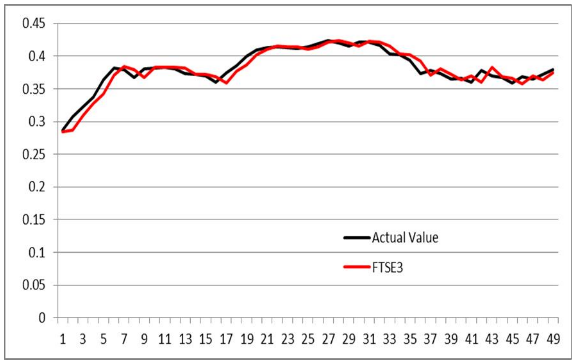
Table 1. The prediction performance of FTSE Bursa Malaysia KLCI by using different ANN architectures.

Architecture of forecasting model	MSE	RMSE	MAPE
FTSE3 (4-3-1)	7.35409E-05	0.008576	1.224402
FTSE4 (4-4-1)	7.30288E-05	0.008546	1.229448
FTSE5 (4-5-1)	7.37532E-05	0.008588	1.255798
FTSE6 (4-6-1)	7.45234E-05	0.008633	1.234733
FTSE7 (4-7-1)	7.34923E-05	0.008573	1.227778
FTSE8 (4-8-1)	7.33632E-05	0.008565	1.222853
FTSE9 (4-9-1)	7.28078E-05	0.008533	1.234135
FTSE10 (4-10-1)	7.28882E-05	0.008537	1.228351

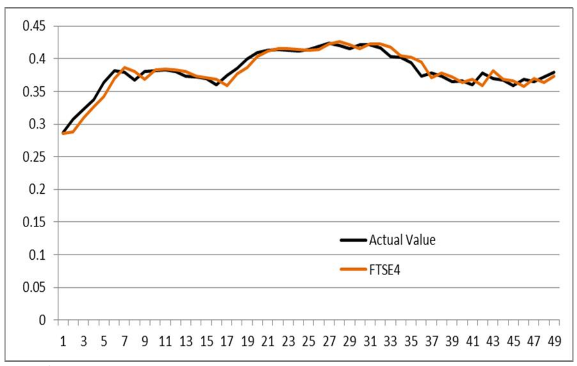
In term of MSE and RMSE, the best performance is achieved by FTSE9 with architecture 4-9-1, MSE and RMSE value is 7.28078E-5, 0.008533 respectively. The comparative diagrams showing the output forecast by ANN model against actual value series for all models are shown in Fig. 3(a)-(i). Fig. 3(a) shows the forecasting of FTSE Bursa Malaysia KLCI by all the models. The plots show that the FTSE8 and FTSE9 forecasting model more closely follows the actual rate. Both forecasting models attain significantly high rate of predicting correct directional change (± 97%).



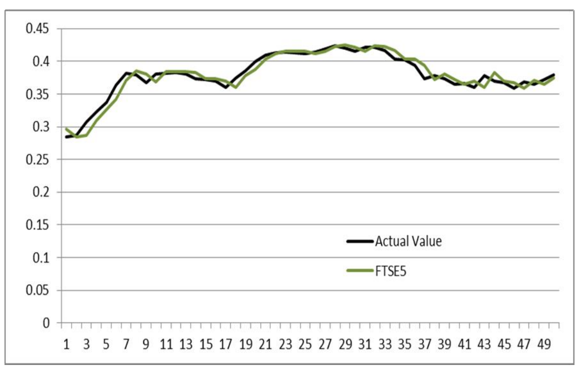
(a). Forecasting of FTSE Bursa Malaysia KLCI by all the models against actual value



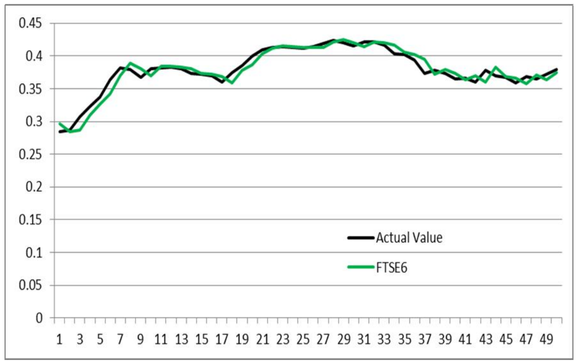
(b). Forecasting of FTSE Bursa Malaysia KLCI by FTSE3 model against actual value



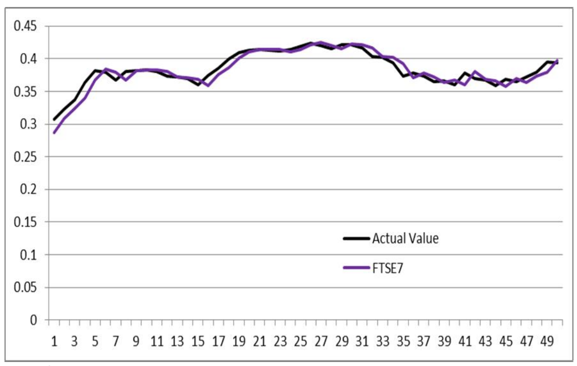
(c). Forecasting of FTSE Bursa Malaysia KLCI by FTSE4 model against actual value



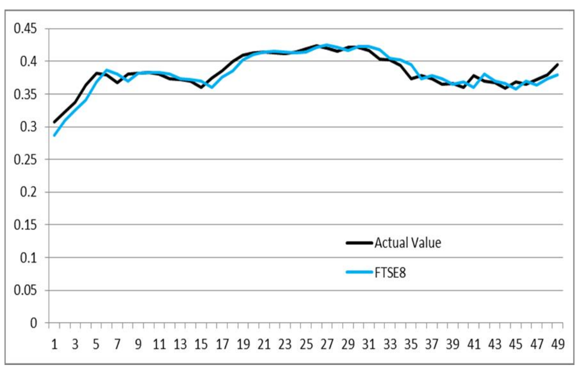
(d). Forecasting of FTSE Bursa Malaysia KLCI by FTSE5 model against actual value



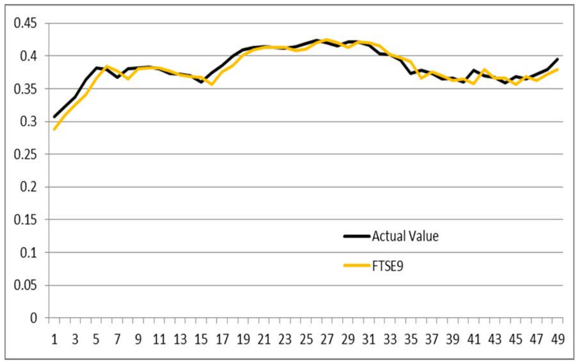
(e). Forecasting of FTSE Bursa Malaysia KLCI by FTSE6 model against actual value



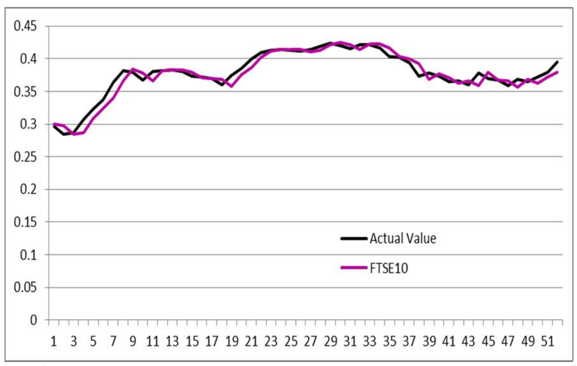
(f). Forecasting of FTSE Bursa Malaysia KLCI by FTSE7 model against actual value



(g). Forecasting of FTSE Bursa Malaysia KLCI by FTSE8 model against actual value



(h). Forecasting of FTSE Bursa Malaysia KLCI by FTSE9 model against actual value



(i). Forecasting of FTSE Bursa Malaysia KLCI by FTSE10 model against actual value

Fig. 3(a)-(i). Forecasting of different architecture of neural network model

4 Conclusions

This study has presented the prediction of FTSE Bursa Malaysia KLCI stock price index by using multilayer feed forward neural networks. FTSE8 and FTSE9 model achieves closer prediction of the actual value than other models.

In scale of MAPE, the best performance is achieved by FTSE8 with architecture 4-8-1 and MAPE value is 1.222853%. In term of MSE and RMSE, the best performance is achieved by FTSE9 with architecture 4-9-1, MSE and RMSE value is 7.28078E-5, 0.008533 respectively.

Results in this study show that generally adding number of neuron can raise the performance accuracy, but deciding the number of neurons in the hidden layer is a very important part of ANN architecture since there is no exact number of the hidden neuron. Using too few neurons in the hidden layer will result in under-fitting and over-fitting will occur when using too many neurons in the hidden layer. Therefore, this problem depends on experimental method to find the optimal number of neuron.

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