# An Improved Stock Price Prediction using Hybrid Market Indicators

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## ABSTRACT
In this paper the effect of hybrid market indicators is examined for an improved stock price prediction. The hybrid market indicators consist of technical, fundamental and expert opinion variables as input to artificial neural networks model. The empirical results obtained with published stock data of Dell and Nokia obtained from New York Stock Exchange shows that the proposed model can be effective to improve accuracy of stock price prediction.

**Keywords**: Neural Network; Market Indicators; Stock Market; Stock Price Prediction; Experts Opinion

## 1. INTRODUCTION

The ability to accurately predict the future is crucial to many decision processes in planning, organizing, scheduling, purchasing, strategy formulation, policy making and supply chains management and so on. Therefore, prediction/forecasting is an area where a lot of research efforts have been invested in the past. Yet, it is still an important and active field of human activity at the present time and will continue to be in the future (Zhang et al., 2004).

Stock price prediction has always been a subject of interest for most investors and financial analysts. Nevertheless, finding the best time to buy or sell has remained a very difficult task for investors because there are other numerous factors that may influence stock prices (Pei-Chan and Chen-Hao, 2008; Weckman, 2008). Stock market prediction has remained an important research topic in business and finance. However, stock markets environment are very complicated, dynamic, stochastic and thus difficult to predict (Wei, 2005; Yang and Wu, 2006; Tsanga et al., 2007; Tae, 2007). Presently, financial forecasting is regarded as one of the most challenging applications of time series forecasting. Financial time series presents complex behavior, resulting from a huge number of factors, which could be economic, political, or psychological. They are inherently noisy, non-stationary, and deterministically chaotic.

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Financial forecasting is of considerable practical interest. The most common approaches to stock price prediction are fundamental and technical analysis. The fundamental analysis is based on financial status and performance of the company. The technical analysis is based on the historical financial time series data (Pei-Chan and Chen-Hao, 2008). The ability of artificial neural networks (ANNs) to mine valuable information from a mass of historical information and be efficiently used in financial areas. The application of ANN to financial forecasting have been very popular over the last few years (Kate and Gupta, 2000; Abu-Mostafa el al., 2001; Defu et al., 2005; Khashei, 2009; Mehdi and Mehdi, 2010).

In this study artificial neural network with hybrid market indicators was used to develop an improved stock price predictive model. However, from literature survey, previous research efforts on stock market prediction had engaged predominantly technical indicators for forecasting of stock prices. The impact of fundamental analysis variables has been largely ignored. This study contrast previous studies by exploring the combination of the technical indicators, fundamental indicators and experts opinion for stock price prediction with the objective of attaining improved stock price prediction.

The rest of the paper is organized as follows. Section 2 presents a review of related works. Section 3 describes the methodology used. Section 4 describes the experimental results obtained. The paper is concluded in section 5.

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**2. Related Works**

A review of previous studies on stock price forecasting shows the prevalent use of technical indicators with artificial neural networks (ANNs) for stock market prediction over the last two decades. What follows are example from the literature of related works that had applied the application of ANNs with technical indicators to stock price prediction. Kunhuang and Yu (2006) used backpropagation neural network with technical indicators to forecast fuzzy time series, the study findings showed that that ANN has better forecast ability than time series model.

Zhu et al., 2007 also used technical indicators with ANN and their findings revealed that ANN can forecast stock index increment and trading volume will lead to modest improvements in stock index performance. Tsanga el al., 2007 used ANN with technical indicators to create trading alert system and their findings showed that ANN can effectively guide investors when to buy or sell stocks. Avci (2007) also used ANN to forecasting daily and sessional returns of the Ise-100 Index and his finding demonstrated that ANN can be used effectively to forecast daily and sessional returns of the Ise-100 Index.

**Table 1: Stock Variables (Technical Indicators)**

| Variable | Description |
|---|---|
| O | Opening price of a stock for a specific trading day |
| C | Closing price of a stock for a specific trading day |
| V | Stock transactions volume (Buy/Sell) |
| H | Highest stock price within a specified time interval (day, month etc.) |
| L | Lowest stock price within a specified time interval (day, month etc.) |

Other works that had applied ANN models with technical indexes to stock price predictions with varying findings to mention a few are as follows: (Kim and Lee, 2004; Stansel and Eakins, 2004; Chen el al., 2005; Lipinski, 2005; De Leone et al., 2006; Roh, 2007; Giordano et al., 2007; Kyungjoo et al., 2007; Al-Qaheri et al., 2008; Bruce and Gavin, 2009; Mitra, 2009; Mohamed, 2010; Esmaeil et al., 2010; Tiffany and Kun-Huang, 2010). Recent research tends to hybridize several artificial intelligence (AI) techniques with technical indicators with the intention to improve the forecasting accuracy, the combination of forecasting approaches has been proposed by many researchers (Rohit and Kumkum, 2008; Khashei el al., 2008). From their studies, they indicated that the integrated forecasting techniques outperformed the individual forecast.

However, O'Connor and Maddem (2006) used fundamental indicators with ANN and their findings revealed that ANN has forecast ability in stock market because it has better return than overall stock market. Other research works that engaged the use of fundamental indicators to forecast stock prices (Atiya el al., 1997; Quah and Srinivasan, 1999; Raposo and Crux, 2002).

From the above literature review, technical indicators with ANN model had been widely used, while there are only few cases of the use of fundamental indicators. This research work contrasts Previous approaches by combining technical indicators, fundamental indicators and experts' opinion to improve stock price prediction using ANN model. The technical analysis variables are the core stock market indices such as current stock price, opening price, closing price, volume, highest price and lowest price etc. Fundamental indicators are the company performance indices such as price per annual earning, return on asset, return on common equity, book value, financial status of the company, etc. while the experts opinion are other influential factors such as interest rate, inflation rate, foreign exchange rate, business sector, management caliber, investors confidence, government policy and political factors among others. Hence, the novelty of our approach in this research work stems from the use of hybrid parameters for improving stock market prediction.

**3. Methodology**

**3.1 Multi-layer Perceptron Model**

This study utilised three-layer (one hidden layer) multilayer perceptron models (feedforward neural network models), as these models are mathematically proved to be universal approximator for any function. Multi-layer perceptron model was chosen in this study because it is the most common network architecture used for financial neural networks.

**3.2 Input Variables**

The basic input data includes: raw data such as the daily open, high, low and close prices, and trading volumes which formed the technical variables in table 1. Table 2 consists of fundamental variables while the market expert opinion variables are listed in table 3. The form in which the expert's opinions were captured on stock indices is described in figure 1.

**Table 2: Stock Variables (Fundamental Indicators)**

| Variable | Description |
|---|---|
| P/E | Price per annual earning |
| ROA | Return on Asset |
| ROE | Return on Common Equity |

**Table 3: Possible Stock Price Influence Factors (Experts Opinion)**

| Variable | Description |
|---|---|
| M | Management Quality |
| F | Investors Confidence |
| I | Inflation Rate |
| B | Business Sector Growth |
| G | Government Policy |

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| | |
|---|---|
| Management Quality (MQ): | 0-2 = Poor, 3-5 = Normal, 6-8 = Good, 9-10 = Very Good |
| Investor Confidence (IC): | 0-2 = Low, 3-5 = Normal, 6-8 = High, 9-10 = Very High |
| Inflation Rate (IR): | 0-2 = Low, 3-5 = Normal, 6-8 = High, 9-10 = Very High |
| Business Sector Growth (BSG): | 0-2 = Low, 3-5 = Normal, 6-8 = High, 9-10 = Very High |
| Government Policy (GP): | 0-2 = Bad, 3-5 = Normal, 6-8 = Good, 9-10 = Very Good |

Figure 1: Format for capturing expert's opinion

### 3.3 Data Preprocessing

Data selection and pre-processing are crucial step in any modeling effort. In order to generalize the new predictive model. The stock data are divided into two sets: the training and testing data which are scaled to the range of (0, 1) using min-max normalization equation (1).

$$x_{ni} = \frac{x_i - x_{\min}}{x_{\max} - x_{\min}} \qquad (1)$$

where $x_i$ is the real-world stock value, $x_{ni}$ is the scaled input value of the real-world stock value $x_i$, $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the unscaled dataset. The network predicted values, which are in the range (0, 1) are transformed to real-world values with the following equation:

$$x_i = x_{ni}(x_{\max} - x_{\min}) + x_{\min} \qquad (2)$$

### 3.4 The Proposed Predictive Model

In this research work, a predictive model based on technical and fundamental indicators, and experts' opinions using neural network architecture is proposed. The aim is to yield more accurate results in stock price prediction. Based on the idea behind technical analysis of investment trading, it is assumed that the behaviour of stock market in the future could be predicted with previous information given in the history (Li, 2005). Therefore, there exists a function in equation (3)

$$p(t+1) = f(p_{t-k},\ldots, p_t; x_{t-1},\ldots, x_t; y_{t-m},\ldots, y_t;\ldots) \qquad (3)$$

where $p$ is the stock price, $x$ and $y$ are the other influence factors such as daily highest price, daily lowest price, experts opinion etc. Artificial neural network is used in order to model the nonlinear data. Thus,

$$y_t = w_0 + \sum_{j=1}^{q} w_j . g\left( w_{0j} + \sum_{i=1}^{p} w_{ij} . y_{t-1} \right) + \varepsilon_t \qquad (4)$$

where, $w_{ij}(i = 0,1,2,\ldots, p,\ j = 1,2,\ldots,q)$ and $w_j(j = 0,1,2,\ldots,q)$ are model parameter often called connection weights; $p$ is the number of input nodes; and $q$ is the number hidden nodes.

The study used three-layer (one hidden layer) multilayer perceptron models (a feedforward neural network model) trained with backpropagation algorithm. The activation function that was used is sigmoid function. Figure 2 depicts the neural network architecture used in this study.

In this study, three different models for the empirical investigation and validation of the proposed model were used as indicated in table 4. The models were created with ANN. The inputs to the first model contained purely technical analysis variables of historical stock data. The second and third models contained hybrid of market indicators. The inputs to the second model consist of technical and fundamental analysis variables while the inputs to the third model combined both the technical and fundamental variables with the market experts' opinion variables.

The fundamental variables consist of financial ratios such as price per annual earning (P/E), return on asset (ROA), and return on equity (ROE). P/E is equal to the market price per share of stock divided by the earning per share. The ROA measures a firm's performance in using the asset to generate income. ROE measures the rate of return earned on the common stockholders' investment. Both the ROA and ROE are used to determined management effectiveness of a firm. The experts opinion consist of inflation rate (I), management quality (M), investors confidence(F), government policy (G) and Business sector growth (B) etc. For the hybridized approach 18 input variables was identified and used to train the network comprising both technical, fundamental variables, and experts' opinion variables as indicated in model 3 of table 4. Table 5 gives the description of input variable used in this study.

**Table 4: The Input and Output Parameters of the Models used in this Study**

| Model | Technique | Input | Output |
|---|---|---|---|
| 1 | ANN | $O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}$ | y(t+1) |
| 2 | ANN | $O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}, P_{i-1}, R_{i-1}, E_{i-1}$ | y(t+1) |
| 3 | ANN | $O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}, P_{i-1}, R_{i-1}, E_{i-1}$, $M_{i-1}$, $F_{i-1}$, $I_{i-1}$, $G_{i-1}$, $B_{i-1}$ | y(t+1) |

**Table 5: Description of Input Variables used in this study**

| Technical Analysis Variables | | Fundamental and Expert Opinion Variables | |
|---|---|---|---|
| $O_{i-1}$ | the opening price of day *i-1* | $P_{i-1}$ | the price per annual earning of year *i-1* |
| $O_{i-2}$ | the opening price of day *i-2* | $R_{i-1}$ | return on asset of trading year *i-1* |
| $H_{i-1}$ | the daily high price of day *i-1* | $E_{i-1}$ | return on equity of trading year *i-1* |
| $H_{i-2}$ | the daily high price of day *i-2* | $M_{i-1}$ | management quality as at trading day *i-1* |
| $L_{i-1}$ | the daily low price of day *i-1* | $F_{i-1}$ | investors confidence as at trading day *i-1* |
| $L_{i-2}$ | the daily low price of day *i-2* | $I_{i-1}$ | inflation rate as at trading day *i-1* |
| $C_{i-1}$ | the closing price of day *i-1* | $B_{i-1}$ | business sector growth as at trading day *i-1* |
| $C_{i-1}$ | the closing price of day *i-2* | $G_{i-1}$ | government policy as at trading day *i-1* |
| $V_{i-1}$ | the trading volume of day *i-1* | | |
| $V_{i-2}$ | the trading volume of day *i-2* | | |

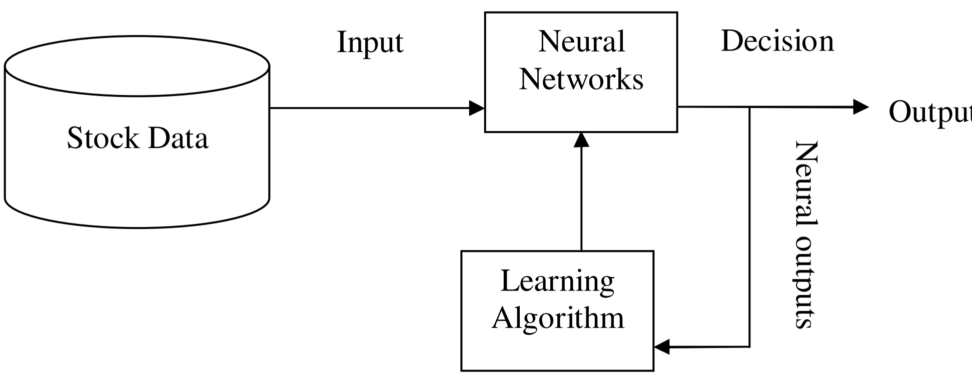


**Figure 2: Neural Network Architecture for Stock Prediction**

We experimented with the different neural network model configurations to determine the best performance in each of the models using Matlab Neural Network Tools Box version 7. The algorithm of the ANN experiment used in this study is shown in figure 3 below. Training data and testing data was carefully selected. In training the network models, the test data were not used. Each model with the different network structures was trained with 1000 epochs, 2000 epochs and 5000 epochs respectively. The mean squared error (MSE) returned for each training session of the different network structure models was noted and recorded.

(1) Define the output
(2) Choose the appropriate network architecture and algorithm. Multi-layer perceptron model trained with backpropagation algorithm was primarily chosen.
(3) Determine the input data and preprocess if necessary.
(4) Choose appropriate learning function.
(5) Choose the appropriate network structure.
(6) Perform the training and testing for each cycle.
(7) If the network produced acceptable results for all cycles, perform step 8 else perform step 5 to try other appropriate network structures else perform step 4 to try with other learning algorithm else perform step 3 to add or remove from input set. Otherwise, go back to step 2 to try different neural network architecture.
(8) Finish - record the results.

**Figure 3: Algorithm for ANN predictive model.**

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## 4. EXPERIMENTAL RESULTS AND DISCUSSION

After several experiments with different network architectures, the network predictive model that gave the most accurate daily stock price prediction in model 1, model 2 and model 3 are presented in a graphical form and also in a table that compares the prediction accuracies of the different models developed. The input neurons of model 1 consist of ten technical analysis variables. The inputs neurons of Model 2 consist of thirteen neurons of combined technical and fundamental analysis variables. The proposed model (model 3), consists of eighteen neurons of combined technical, fundamental and experts' opinion variables respectively. The results of each of the stock index used are presented in following subsections.

### 4.1 Results of ANN Model for Dell Stock Price Prediction

The network structure that returns the smallest mean squared error (MSE) was noted to give the best forecasting accuracy with the test data. Table 6 contained the results of the mean square errors recorded in the course of the experiment. In this case, the network predictive model that gave the most accurate daily price prediction in model 1 was 10-17-1 (ten input neurons, seventeen hidden neurons and one output neuron). Similarly, for model 2, the network predictive model that returns smallest MSE was 13-19-1 (thirteen input neurons, nineteen hidden neurons, one output). The best-fitted network that gave the best forecasting accuracy with test data composed of eighteen inputs, twenty-six hidden neurons and one output neuron 18-26-1. The results presented in table 7 were the findings from testing period (out of sample test data) over the three different models. Also, figure 4 - 6 illustrates the correlation of the level accuracy among different models.

From the empirical results, the forecasting accuracy level of model 1 compared with model 2 are quite impressive. However, the performance of model 2 was better than model 1 in the level of accuracy on many occasions from the different test data. From the figure 6, it is obvious that model 3 is the best of all the three predictive models. There is a great improvement in terms of forecasting accuracy in comparison to results of model 1 and 2. The stock price prediction accuracy of the proposed model that combined technical, fundamental indicators and experts' opinion to create a predictive model was the best with average of 74% accuracy as shown in table 8.

Hence, the proposed predictive model can be used successfully as decision-support in real-life trading in a way that will enhance the profit margin of investors or traders in daily trading.

**Table 6: Statistical performance of Mode 1-3 of Dell Stock index**

| | MSE | | | |
|---|---|---|---|---|
| | **Network Structure** | **1000 Epochs** | **2000 Epochs** | **5000 Epochs** |
| **Model 1** | 10-10-1 | 0.129054 | 0.112363 | 0.093539 |
| | 10-11-1 | 0.144086 | 0.108245 | 0.090521 |
| | 10-12-1 | 0.125668 | 0.099301 | 0.088157 |
| | 10-13-1 | 0.148646 | 0.115732 | 0.092649 |
| | 10-14-1 | 0.141474 | 0.099241 | 0.085206 |
| | 10-15-1 | 0.118226 | 0.096651 | 0.083664 |
| | 10-16-1 | 0.116773 | 0.099222 | 0.080534 |
| | 10-17-1 | **0.097826** | **0.085111** | **0.071589** |
| | 10-18-1 | 0.119719 | 0.093576 | 0.079150 |
| **Model 2** | 13-13-1 | 0.123184 | 0.107412 | 0.090236 |
| | 13-14-1 | 0.130018 | 0.095150 | 0.075755 |
| | 13-15-1 | 0.179753 | 0.121711 | 0.090089 |
| | 13-16-1 | 0.118892 | 0.093771 | 0.076748 |
| | 13-17-1 | 0.128121 | 0.103660 | 0.087496 |
| | 13-18-1 | 0.123907 | 0.097827 | 0.079230 |
| | 13-19-1 | 0.115329 | **0.093167** | **0.067901** |
| | 13-20-1 | 0.118568 | 0.101955 | 0.085272 |
| | 13-21-1 | **0.113894** | 0.094207 | 0.077037 |
| **Model 3** | 18-18-1 | 0.125340 | 0.101465 | 0.083380 |
| | 18-19-1 | 0.153357 | 0.143036 | 0.144930 |
| | 18-20-1 | 0.125132 | 0.121522 | 0.131991 |
| | 18-21-1 | 0.110519 | 0.090850 | 0.072907 |
| | 18-22-1 | 0.115685 | 0.093702 | 0.069479 |
| | 18-23-1 | **0.106685** | 0.090579 | 0.070017 |
| | 18-24-1 | 0.129842 | 0.107310 | 0.078529 |
| | 18-25-1 | 0.112151 | 0.090779 | 0.070529 |
| | 18-26-1 | 0.112049 | **0.088974** | **0.061821** |

*Bold characters indicate the best results for each of epoch session*

**Table 7: Sample of Empirical Results of ANN Models of Dell Stock Index**

| Sample Period | Actual Value | Predicted Values | | |
|---|---|---|---|---|
| | | Model 1 | Model 2 | Model 3 |
| 3/31/2010 | 15.02 | 14.97 | 14.93 | 15.03 |
| 3/30/2010 | 14.97 | 15.05 | 14.96 | 15.11 |
| 3/29/2010 | 14.96 | 14.59 | 14.69 | 14.63 |
| 3/26/2010 | 14.99 | 14.50 | 14.66 | 14.62 |
| 3/25/2010 | 14.87 | 14.96 | 15.19 | 15.52 |
| 3/24/2010 | 14.99 | 14.66 | 15.23 | 14.96 |
| 3/23/2010 | 15.22 | 14.23 | 14.30 | 14.57 |
| 3/22/2010 | 14.62 | 13.67 | 13.98 | 14.02 |
| 3/19/2010 | 14.41 | 13.85 | 14.37 | 14.05 |
| 3/18/2010 | 14.55 | 14.25 | 14.36 | 14.51 |
| 3/17/2010 | 14.59 | 14.00 | 13.88 | 14.19 |
| 3/16/2010 | 14.30 | 13.89 | 13.76 | 14.11 |
| 3/15/2010 | 14.26 | 13.96 | 13.91 | 14.13 |
| 3/12/2010 | 14.26 | 13.59 | 13.60 | 13.76 |
| 3/11/2010 | 14.21 | 14.18 | 14.33 | 14.40 |
| 3/10/2010 | 14.31 | 13.85 | 13.92 | 14.24 |
| 3/09/2010 | 14.18 | 13.92 | 13.95 | 14.26 |
| 3/08/2010 | 14.01 | 13.57 | 13.66 | 13.90 |
| 3/05/2010 | 13.88 | 13.33 | 13.39 | 13.53 |
| 3/04/2010 | 13.67 | 13.09 | 13.25 | 13.17 |
| 3/03/2010 | 13.71 | 13.70 | 13.76 | 13.89 |
| 3/02/2010 | 13.68 | 13.55 | 13.69 | 13.94 |
| 3/01/2010 | 13.57 | 13.16 | 13.19 | 13.31 |

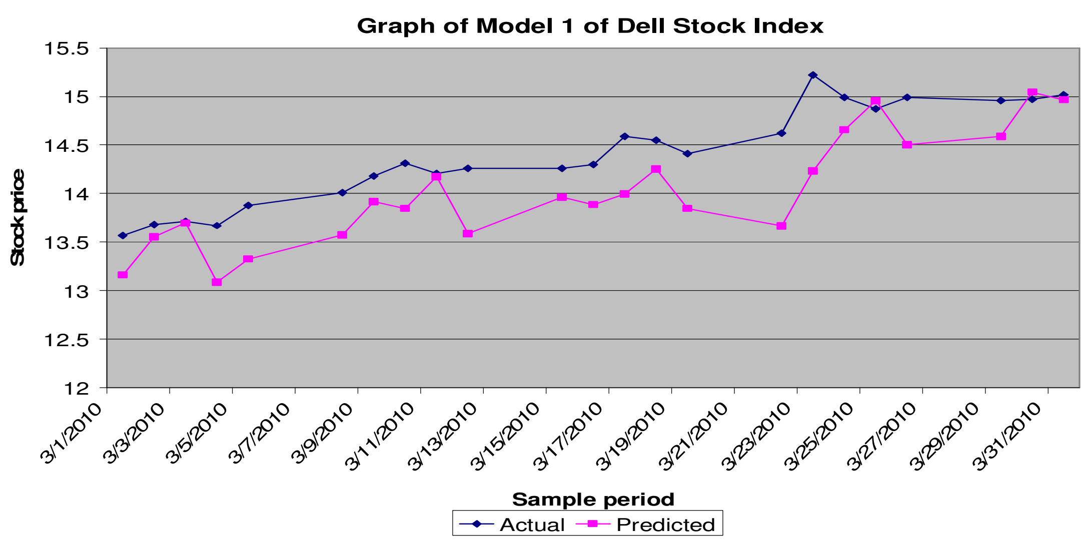


Figure 4: Graph of Actual Stock Price vs Predicted values of Model 1 of Dell Index

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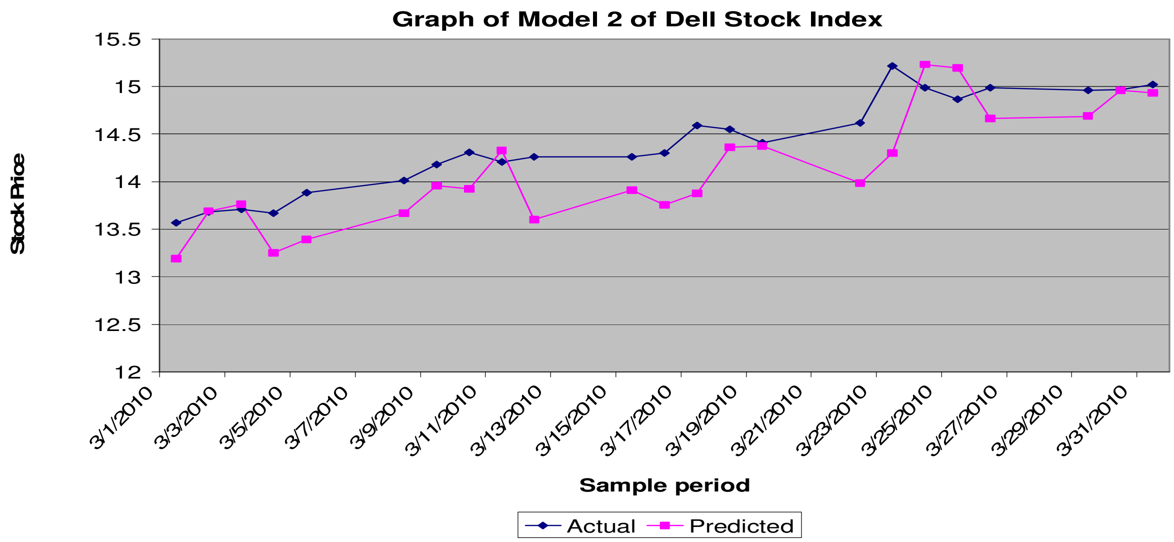


Figure 5: Graph of Actual Stock Price vs Predicted values of Model 2 of Dell Index

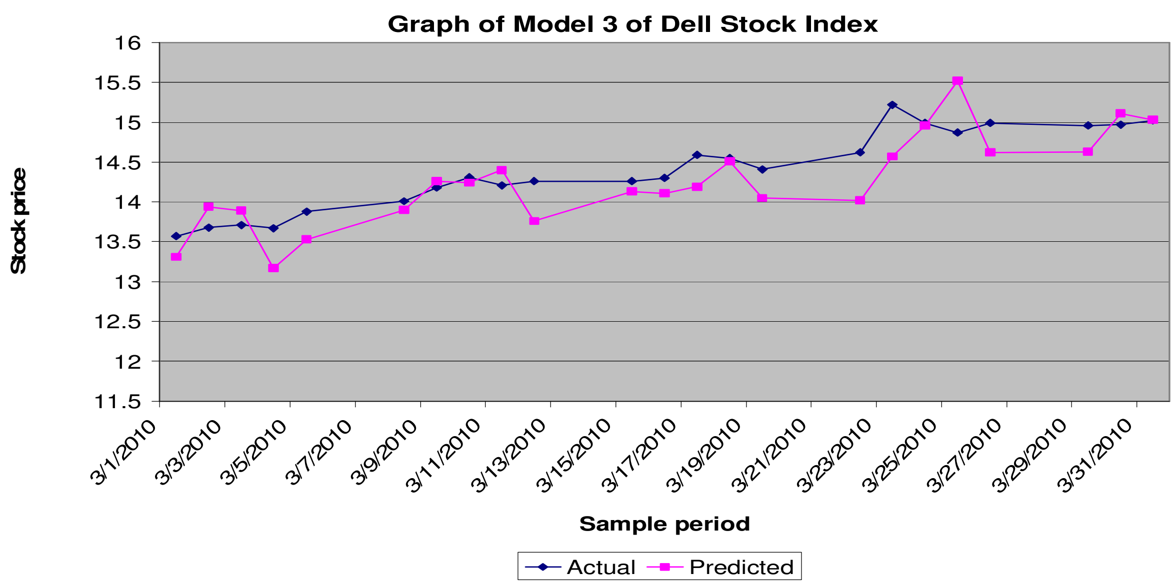


Figure 6: Graph of Actual Stock Price vs Predicted values of Model 3 of Dell Index

**Table 8: Confusion matrix of predicted result of ANN model for Dell index**

| | | Predicted | |
|---|---|---|---|
| | | Up | Down |
| Actual | Up | 13 | 3 |
| | Down | 5 | 4 |

AC = 74%

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### 4.2 Results of ANN Model for Nokia Stock Price Prediction

In table 9, the highlighted values indicate the ANN structure that returns smallest mean square errors which are noted to give best performance over other structures. For model 1, we have 10-14-1 (ten input neurons, fourteen hidden neurons and one output neuron). For model 2, we have 13-14-1 (thirteen input neurons, fourteen hidden neurons, one output) and for model 3, we have 18-21-1 (eighteen inputs, twenty-one hidden neurons and one output neuron).

However, model 3 is noted to give the best prediction over the other two models. The results presented in table 10 are the predicted values of each of the model earlier mentioned. Also, figures 7 - 9 illustrate the correlation of the level accuracy among different models. From the figure 9, it is obvious that model 3 is the best of all the three stock price predictive models with average of 70% accuracy as shown in table 11.

**Table 9: Statistical performance of Mode 1-3 of Nokia Stock index**

| | MSE | | | |
|---|---|---|---|---|
| | **Network Structure** | **1000 Epochs** | **2000 Epochs** | **5000 Epochs** |
| **Model 1** | 10-10-1 | 0.131413 | 0.085673 | 0.065958 |
| | 10-11-1 | 0.130266 | 0.100147 | 0.074376 |
| | 10-12-1 | **0.104179** | **0.076013** | 0.055319 |
| | 10-13-1 | 0.148378 | 0.123140 | 0.094993 |
| | 10-14-1 | 0.113599 | 0.077468 | **0.052256** |
| | 10-15-1 | 0.120586 | 0.094881 | 0.063535 |
| | 10-16-1 | 0.112569 | 0.087723 | 0.590738 |
| | 10-17-1 | 0.121481 | 0.099204 | 0.064114 |
| | 10-18-1 | 0.129727 | 0.088369 | 0.074229 |
| **Model 2** | 13-13-1 | 0.142468 | 0.111148 | 0.083957 |
| | 13-14-1 | 0.125704 | 0.085771 | **0.048449** |
| | 13-15-1 | 0.130336 | 0.092512 | 0.063329 |
| | 13-16-1 | 0.120522 | **0.070893** | 0.051680 |
| | 13-17-1 | 2.328160 | 0.092799 | 0.053544 |
| | 13-18-1 | 0.132760 | 0.109483 | 0.068056 |
| | 13-19-1 | **0.110694** | 0.081275 | 0.053134 |
| | 13-20-1 | 4.077420 | 0.110826 | 0.067431 |
| | 13-21-1 | 0.145350 | 0.100590 | 0.052527 |
| **Model 3** | 18-18-1 | 0.109847 | **0.048198** | 0.041309 |
| | 18-19-1 | 0.131226 | 0.102727 | 0.066412 |
| | 18-20-1 | **0.109616** | 0.073874 | 0.052122 |
| | 18-21-1 | 0.136433 | 0.070053 | **0.038898** |
| | 18-22-1 | 0.130056 | 0.096053 | 0.054354 |
| | 18-23-1 | 0.118424 | 0.083801 | 0.049239 |
| | 18-24-1 | 0.170919 | 0.083517 | 0.050821 |
| | 18-25-1 | 4.497720 | 4.374340 | 4.347050 |
| | 18-26-1 | 0.222150 | 0.202463 | 0.062659 |

*Bold characters indicate the best results for each of epoch session*

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**Table 10: Sample of Empirical Results of ANN Models of Nokia Stock Index**

| Sample Period | Actual Value | Predicted Values | | |
|---|---|---|---|---|
| | | Model 1 | Model 2 | Model 3 |
| 3/31/2010 | 15.54 | 15.42 | 15.46 | 15.34 |
| 3/30/2010 | 15.41 | 15.43 | 15.44 | 15.44 |
| 3/29/2010 | 15.42 | 15.32 | 15.39 | 15.31 |
| 3/26/2010 | 15.46 | 15.15 | 15.31 | 15.07 |
| 3/25/2010 | 15.2 | 15.19 | 15.26 | 15.16 |
| 3/24/2010 | 15.07 | 15.21 | 15.33 | 15.16 |
| 3/23/2010 | 15.26 | 15.13 | 15.23 | 15.20 |
| 3/22/2010 | 15.11 | 15.17 | 15.24 | 15.13 |
| 3/19/2010 | 15.07 | 15.43 | 15.40 | 15.47 |
| 3/18/2010 | 15.28 | 15.21 | 15.16 | 15.07 |
| 3/17/2010 | 15.42 | 14.99 | 15.14 | 14.79 |
| 3/16/2010 | 15.14 | 15.05 | 15.27 | 15.04 |
| 3/15/2010 | 14.81 | 14.91 | 15.21 | 14.68 |
| 3/12/2010 | 14.84 | 14.52 | 14.89 | 14.75 |
| 3/11/2010 | 14.49 | 13.81 | 14.33 | 14.45 |
| 3/10/2010 | 14.56 | 13.98 | 14.40 | 14.62 |
| 3/09/2010 | 14.12 | 14.31 | 14.89 | 14.40 |
| 3/08/2010 | 14.17 | 13.94 | 14.58 | 13.92 |
| 3/05/2010 | 14.13 | 13.79 | 14.67 | 14.19 |
| 3/04/2010 | 13.78 | 13.47 | 14.16 | 13.71 |
| 3/03/2010 | 13.86 | 13.47 | 14.13 | 13.82 |
| 3/02/2010 | 13.51 | 13.39 | 13.79 | 13.50 |
| 3/01/2010 | 13.28 | 13.02 | 13.59 | 13.10 |

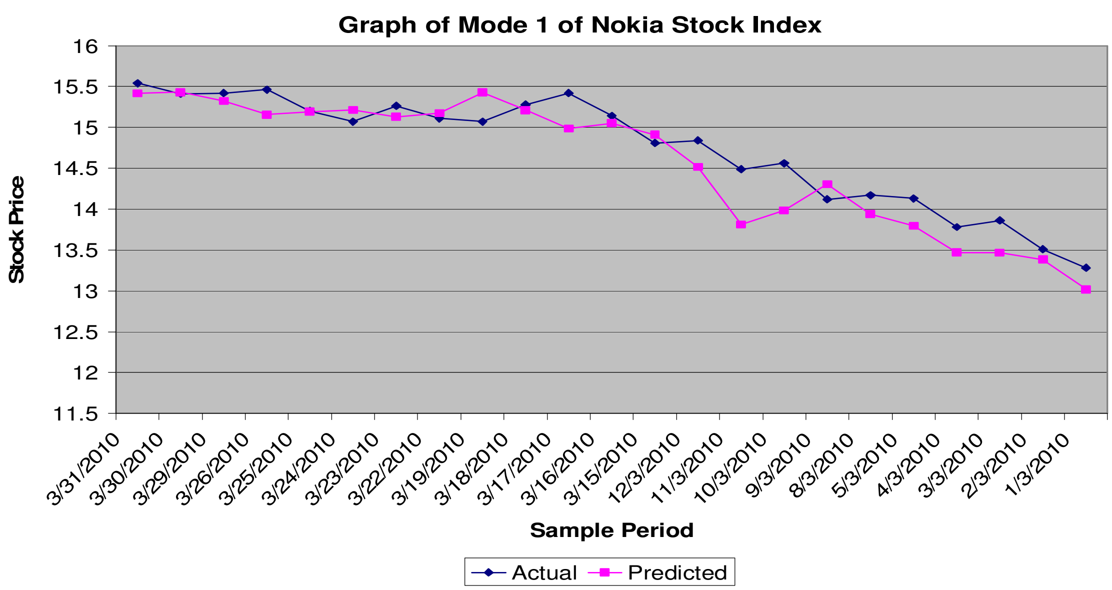


**Figure 7: Graph of Actual Stock Price vs Predicted values of Model 1 of Nokia Index**

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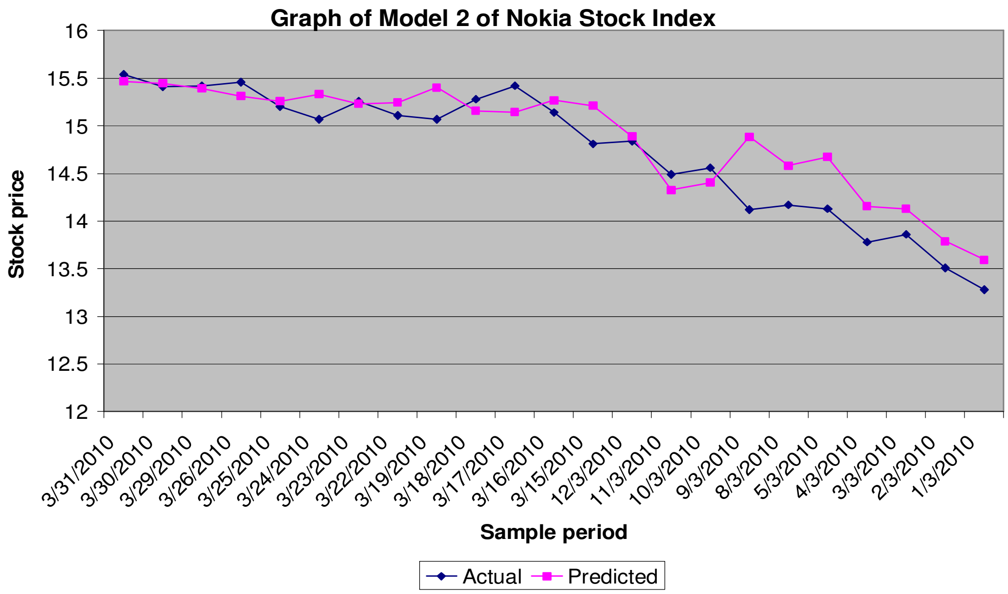


**Figure 8: Graph of Actual Stock Price vs Predicted values of Model 2 of Nokia Index**

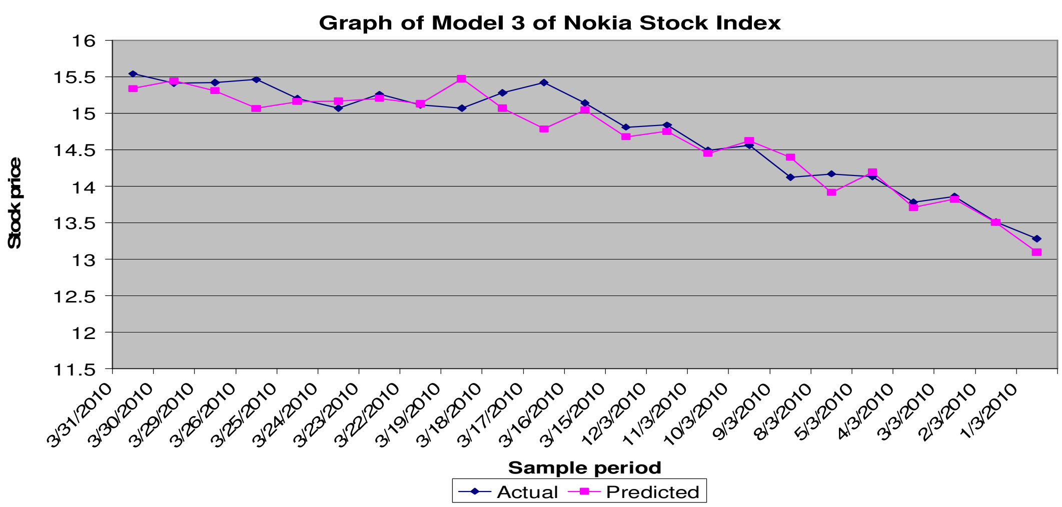


**Figure 9: Graph of Actual Stock Price vs Predicted values of Model 3 of Nokia Index**

**Table 11: Confusion matrix of predicted result of ANN model for Nokia index**

| | | Predicted | |
|---|---|---|---|
| | | Up | Down |
| Actual | Up | 9 | 4 |
| | Down | 3 | 7 |

AC = 70%

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## 5. CONCLUSION

Technical indicators had been widely used in forecasting stock prices with artificial neural networks. Nevertheless, their performance is not always satisfactory. Also, in recent times, hybrid models that combine ANNs and other intelligent techniques with technical indices had been engaged in order to improve accuracy level of stock price prediction with varying results. In this paper, an improved predictive model for stock price prediction based on experts' opinion with technical and fundamental indices using artificial neural network model is presented. What distinguishes this research work from earlier work is that it combined different market indicators to evolve stock price predictive model. In particular, it introduced a new parameter called expert's opinion. The empirical results confirmed superior performance of the proposed model to improve forecasting accuracy of stock price over the conventional approach of using ANN model with technical indicators. Therefore, the proposed predictive model has the potential to enhance the quality of decision making of investors in the stock market by offering more accurate stock prediction. In future work, the critical impact of specific experts' opinion variables on quality of stock price prediction will be examined.

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