Fuzzy-neural model with hybrid market indicators for stock forecasting

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Abstract: A number of research had been carried out to forecast stock price based on technical indicators, which rely purely on historical stock price data. Nevertheless, their performance is not always satisfactory. In this paper, the effect of using hybrid market indicators of technical, fundamental indicators and experts opinion for stock price prediction is examined. Input variables extracted from these market hybrid indicators are fed into a fuzzy-neural network for improved accuracy of stock price prediction. The empirical results obtained with published stock data shows that the proposed model can be effective to improve accuracy of stock price prediction.

Keywords: artificial neural networks; fuzzy logic; market indicators; stock prediction; electronic finance; stock index.

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1 Introduction

Stock markets environment are very complicated, dynamic, stochastic and thus difficult to predict (Tsanga et al., 2007). However, finding the best time to buy or sell has remained a very difficult task for investors because there are numerous factors that may influence stock prices (Chang and Liu, 2008; Weckman et al., 2008; Adebiyi et al., 2009). Nevertheless, several research efforts have been carried out to predict the market to make profit using different techniques with different results.

The price variation of stock market is a very dynamic system that has intrigued analysis from a number of disciplines. The common approaches 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 (Chang and Liu, 2008).

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. In this work, we explore the combination of the technical indicators, fundamental indicators and experts opinion for stock market prediction with the objective of attaining improved stock market prediction.

The rest of the paper is organised as follows. Section 2 presents a review of related works. Section 3 describes the proposed hybrid model. Section 4 describes the research methodology used. Section 5 discussed the results obtained. The paper is concluded in Section 6.

2 Related works

A review of previous studies on stock price forecasting shows that the use of technical indicators is prevalent. The technical indicators, such as current stock price, opening

price, closing price, volume, highest price and lowest price, are often used with ANNs model. In recent time, hybrid models have been effectively engaged in stock price prediction. Examples in literature where technical indicators have been used include the following. In Phua et al. (2003) technical indicators with ANNs model was used to forecast stock price and their findings revealed that ANN has average success rate of 60% and the best prediction result is 74%. In Chen et al. (2003) technical indicators with ANN model was used and their finding showed that ANN obtained higher return than other investment strategy. Kunhuang and Yu (2006) used technical indicators with ANN and their 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 could forecast stock index increment and trading volume will lead to modest improvements in stock index performance. Tsanga et al. (2007) technical indicators with ANN was utilised to created trading alert system and their findings showed that ANN can effectively guide investors when to buy or sell stocks. Avci (2007) also used technical indicators with ANN, and his finding demonstrated that ANN could be used effectively to forecast daily and sessional returns of the Ise-100 Index.

Other works that had applied ANN models with technical indexes to stock price predictions with varying findings are Kimoto et al. (1990), Kamijo and Tanigawa (1990), Stansel and Eakins (2004), Chen et al. (2005), Huang et al. (2005), Roh (2007), Giordano et al. (2007), Jain and Kumar (2007), Kyungjoo et al. (2007), George and Kimon (2009), Mohamed (2010), Esmaeil et al. (2010) and Tiffany and Kun-Huang (2010). Wang (2007) proposed hybrid ANN (ANN and GARCH) with technical indicators and his findings showed that ANN combined with other techniques has good forecast ability as good as ARIMA model. Kim and Shin (2007) used hybrid ANN (ANN and Genetic Algorithm) with technical indicators and their findings showed that hybrid model has better forecast ability than single model and ANN has ability to forecast stock market. Yan (2008) used hybrid ANN (ANN and Grey Theory) with technical indicators and his findings showed that hybrid model has better forecasting performance to stock price prediction. Khasel et al. (2009) used hybrid ANN (ANN and Fuzzy Logic) with technical indicators and their finding revealed that hybrid models exhibit effectively improved forecasting accuracy of stock price prediction. 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.

From the above-mentioned literature reviews, it is obvious that technical indicators with ANN model had been widely used, although there are only a few cases of the use of fundamental indicators. This paper contrasts previous approaches by combining technical indicators, fundamental indicators and experts' opinion to improve stock price prediction using fuzzy-neural architecture. 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. Fundamental indicators are the company performance indices such as price per annual earning, return on asset, return on common equity, book value and financial status of the company, whereas the experts opinion are other influential factors such as interest rate, inflation rate, foreign exchange rate, business sector, management calibre, investors confidence, government policy and political factors among others. Hence, the novelty of our approach in this paper stems from the use of hybrid parameters for improving stock market prediction.

3 The proposed hybrid model

In this paper, a hybrid predictive model based on technical, fundamental indicators and experts' opinion using fuzzy neural 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 (1)

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

where p is the stock price, x and y are the other influence factors such as daily highest price, daily lowest price and experts opinion. In the first phase, fuzzy logic is used to convert the input qualitative data of experts opinion linguistic variables into fuzzy values express in the range of [0, 1] using linear membership function. The four linguistic properties that were used are low, normal, high and very high. The dependent variable criterions are based on [1, 10]. Fuzzy set *low* ranges from 0 to 2, fuzzy set *normal* ranges from 3 to 5, fuzzy set *high* ranges from 6 to 8 and fuzzy set *very high* ranges from 9 to 10 and their membership expression are shown in equations (2)–(5), respectively.

$$\mu_{\text{low}}(x) = \frac{1}{2}x \tag{2}$$

$$\mu_{\text{normal}}(x) = \frac{1}{2}x - \frac{3}{2} \tag{3}$$

$$\mu_{\text{high}}(x) = \frac{1}{2}x - 3 \tag{4}$$

$$\mu_{\text{veryhigh}}(x) = x - 9. \tag{5}$$

In second phase, an artificial neural network is used to model the nonlinear data. Thus,

$$y_t = w_0 + \sum_{j=1}^{q} w_j \cdot g\left(w_{0j} + \sum_{i=1}^{p} w_{ij} \cdot y_{t-1}\right) + \varepsilon_t \tag{6}$$

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 1 depicts the fuzzy-neural architecture used in this study.

In this paper, three different models for the empirical investigation and validation of the proposed model were used as indicated in Table 1. The first model used ANN only. The inputs to the ANN model are purely technical analysis variables of historical stock data. The second and third models are hybrid models that combined artificial neural networks and fuzzy logic. The inputs of second model are only technical and fundamental analysis variables, whereas 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 P/E, ROA and 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. The experts opinion consist of inflation rate (I), management quality (M), investors confidence (F), government policy (G) and political factor (T) etc. For the hybridised approach, 21 input variables were identified and used to train the network comprising both technical, fundamental variables and experts' opinion variables as indicated in model 3 of Table 1. Table 2 is description of input variables used in this study.

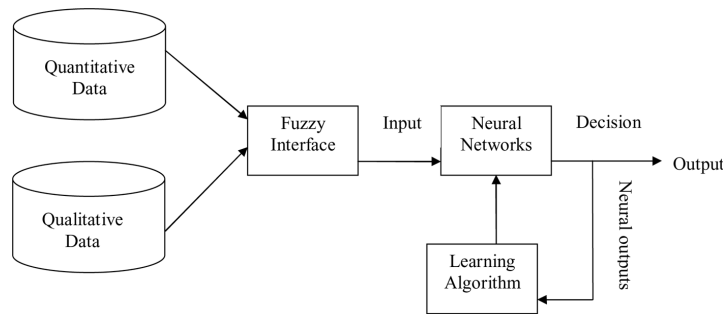**Figure 1** Proposed fuzzy-neural architecture for stock prediction

Table 1   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	FL + ANN	$O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}, P_{i-1}, P_{i-2}, R_{i-1}, R_{i-2}, E_{i-1}, E_{i-2}$	$y(t+1)$
3	FL + ANN	$O_{i-1}, O_{i-2}, H_{i-1}, H_{i-2}, L_{i-1}, L_{i-2}, C_{i-1}, C_{i-2}, V_{i-1}, V_{i-2}, P_{i-1}, P_{i-2}, R_{i-1}, R_{i-2}, E_{i-1}, E_{i-2}, M_{i-1}, F_{i-1}, I_{i-1}, G_{i-1}, T_{i-1}$	$y(t+1)$

Table 2   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 $i-2$	P_{i-2}	The price per annual earning of year $i-2$
H_{i-1}	The daily high price of day $i-1$	R_{i-1}	Return on asset of trading year $i-1$
H_{i-2}	The daily high price of day $i-2$	R_{i-2}	Return on asset of trading year $i-2$
L_{i-1}	The daily low price of day $i-1$	E_{i-1}	Return on equity of trading year $i-1$
L_{i-2}	The daily low price of day $i-2$	E_{i-2}	Return on equity of trading year $i-2$
C_{i-1}	The closing price of day $i-1$	M_{i-1}	Management quality as at trading day $i-1$
C_{i-1}	The closing price of day $i-2$	F_{i-1}	Investors confidence as at trading day $i-1$
V_{i-1}	The trading volume of day $i-1$	I_{i-1}	Inflation rate as at trading day $i-1$
V_{i-2}	The trading volume of day $i-2$	T_{i-1}	Political factor as at trading day $i-1$
		G_{i-1}	Government policy as at trading day $i-1$

4 Methodology

The central objective of this paper is to improve the accuracy of stock price prediction by the combination of technical indicators (quantitative data), fundamental indicators and market experts' opinion (qualitative data) using fuzzy neural architecture. To achieve this aim, the following steps were carried out as described in the subsection below.

4.1 Data collection and pre-processing

Data selection and pre-processing are crucial step in any modelling effort. To generalise the new predictive model, different data set of historical stock prices from different companies were collected from Nigeria Stock Exchange (NSE) except the financial indices, which are obtained from published annual report, and expert's opinion, which are obtained from the stock market experts. 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 normalisation equation (7).

$$x_{ni} = \frac{x_i - x_{min}}{x_{max} - x_{min}} \tag{7}$$

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

$$x_i = x_{ni}(x_{max} - x_{min}) + x_{min}. \tag{8}$$

4.2 Input variables

The basic input data includes raw data such as the daily open, high, low and close prices and trading volumes of NSE, which formed the technical variables in Table 3. Table 4 consists of fundamental variables while the market expert opinion variables are listed in Table 5. The form in which the expert's opinions were captured on stock indices is described in Figure 2 and the sample data of expert's opinion that are fed into fuzzy-neural predictive model is shown in Table 6.

Table 3 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.)

Table 4   Stock variables (fundamental indicators)

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

Table 5   Possible stock price influence factors (experts opinion)

Variable	Description
M	Management quality
F	Investors confidence
I	Inflation rate
T	Political factor
G	Government policy

Figure 2   Format for capturing expert's opinion

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

Table 6   Sample data of experts' opinion

Company name	MQ	IC	IR	BSG	GP
AfriBank Nig. plc.	7	4	4	5	6
UTC Nigeria plc	5	5	4	5	8
Flour mill nig. plc	8	6	4	7	6
Dangote flour mill plc	7	7	4	8	6

4.3   Implementation

For the implementation of the different models, we experimented with the different neural network model configurations to determine the best performance in each of the model using Matlab Neural Network Tools Box version 7. The algorithm of the ANN experiment is shown in Figure 3. Training data and testing data were carefully selected, and various outcomes of different network structure models were implemented with Matlab Neural Network Tools Box version 7. In training the network model, the test data were not used. It was trained for 3000 epochs for each training set. The output of neural network model was analysed by comparing the predicted values with the actual values over a sample period. For the output of the proposed model to be considered useful for trading decision support, overall hit rate of level of accuracy should be considerably high enough to be acceptable. The empirical results are presented in Section 5.

Figure 3   Algorithm for ANN predictive model

(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 produce 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.

5   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 was 10-17-1. This model was created with artificial neural networks. The data used were purely technical analysis variables, which were quantitative in nature. The input variables to the model consist of 10 technical variables. Model 2 was created with fuzzy neural approach. The inputs to model 2 consist of technical and fundamental analysis variables. The network predictive model that gave the best accurate daily stock price prediction was 16-22-1. The proposed hybrid model (model 3), which combined the quantitative and qualitative data of technical, fundamental and experts' opinion using fuzzy neural approach. The best-fitted network that gave the best forecasting accuracy with test data is composed of 21 inputs, 26 hidden and one output neurons 21-26-1. The results presented in Table 7 were the findings from testing period (of sample test data) over different models. Similarly, Figures 4–6 illustrate the correlation of the level accuracy among different models.

Figure 4   Model 1 (see online version for colours)
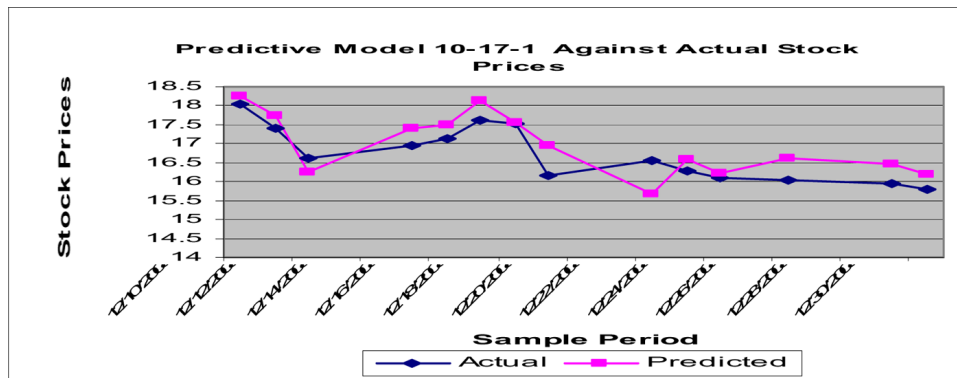
From the empirical results, the forecasting accuracy level of model 1 compared with model 2 is quite impressive. However, the performance of model 2 was better than model 1 in the level of accuracy on many occasions from the different test data. From Figure 6, it is obvious that model 3 is the best of 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 80% accuracy. Hence, the proposed predictive model can be used successfully as decision support in real-life trading in a way that will enhance the profiting of investors or traders for daily trading.

Table 7   Sample of empirical results of daily stock price prediction using different model

Sample period	Actual value	Predicted values		
		Model 1	Model 2	Model 3
12/10/2008	18.03	18.25	18.21	18.12
12/11/2008	17.4	17.73	17.56	17.59
12/12/2008	16.6	16.25	16.36	16.62
12/15/2008	16.95	17.41	16.45	17.12
12/16/2008	17.13	17.49	17.27	17.37
12/17/2008	17.62	18.13	17.47	17.49
12/18/2008	17.54	17.54	17.47	17.63
12/19/2008	16.16	16.94	16.47	15.62
12/22/2008	16.56	15.68	16.69	16.65
12/23/2008	16.27	16.58	16.66	16.30
12/24/2008	16.1	16.23	16.25	16.27
12/26/2008	16.05	16.60	15.69	16.47
12/29/2008	15.95	16.45	15.86	15.90
12/30/2008	15.8	16.19	15.86	16.02

Figure 5   Model 2 (see online version for colours)
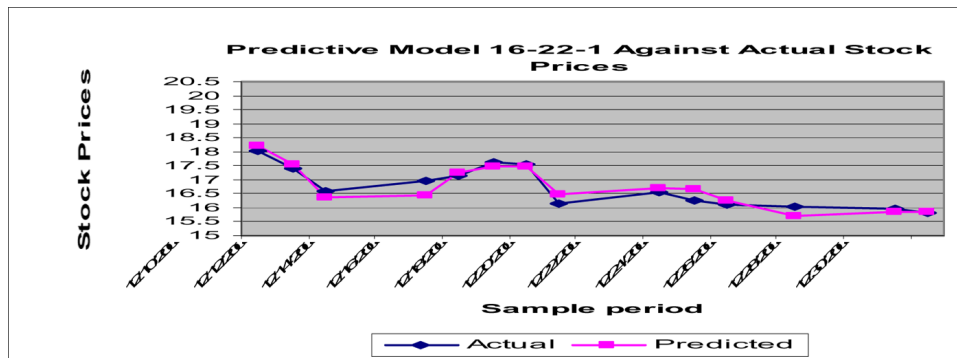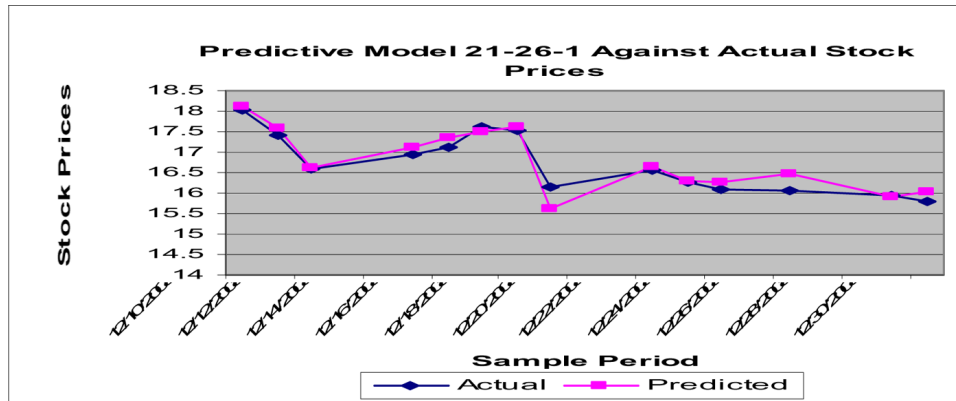
Figure 6 Model 3 (see online version for colours)

6   Conclusion

Technical indices had been widely used in forecasting stock prices with artificial neural networks. Nevertheless, their performance is not always satisfactory. Moreover, in recent times, hybrid models that combine ANNs and other intelligent techniques with technical indices had been engaged 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 fuzzy-neural architecture is presented. 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. Full implementation of the model online and on mobile platform would no doubt contribute to the development of electronic finance. In future work, the critical impact of specific experts' opinion variables on quality of stock price prediction will be examined.

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