ARTIFICIAL NEURAL NETWORK SYSTEM FOR PREDICTION OF US MARKET INDICES USING MISO AND MIMO APROACHES

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ABSTRACT

Advocates of fundamental analysis depreciate technical analysis as a superficial study of trends and patterns depicted by charts without any conclusive proof of efficacy. However, technical trading is one of the ancient trading techniques and the advancements in technical trading are growing exponentially in the age of superfast computers. Predicting the movements of stock prices precisely using sophisticated techniques needs continuous improvement to capture trends. Technical trading techniques using fuzzy models are gaining prominence in predicting non-linear trends in stock markets because of the capability of extracting meaningful information from a large set of data. Artificial neural network (ANN) integrated models are serving the needs of learning non-linear patterns and helping in making better predictions. This research paper focuses on designing models using the architecture of ANN techniques, specifically Error Back Propagation Network (EBPN) and Radial Basis Function Network (RBFN), from Multi Input Multi Output (MIMO) and Multi Input Single Output (MISO) perspectives. The tests of the models developed in this study were performed using the key variable of open, close, high and low prices of DOW30 and NASDAQ100. We used two measures of predictability: Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Based on the results, we observed that EBPN outperformed RBFN in predicting the future prices. The results of MIMO approach were also precise than MISO for both systems.

***Keywords**: Artificial Neural Network (ANN), Error Back Propagation Network (EBPN), Radial Basis Function (RBFN), Multi Input Single Output (MISO), Multi Input Multi Output (MIMO).*

INTRODUCTION

Volatility has several aspects for trading including predicting the stock market direction for investing. The prediction of the market gives an idea of the direction of the economy. Therefore, volatility of the stock market has implications beyond the stock market. Volatility can be defined for a single stock and its performance relative to industry, sector and the market. However, the volatility of the overall market is an indicator of the direction of the economy. A volatile market presents the uncertainty and risk to the investors whether individuals or institutions. Researchers continue to explore innovative tools and techniques to recognize trends to predict future trends to help investors, financial professionals and fund managers. Recently, researchers have been trying to design models using sophisticated tools to make improved predictions so that investors can manage their portfolios for the maximum possible returns for a given level of risk.

Due to high volatility in the stock market, there is a need to design and develop models that can decipher non-linear trends in the stock market more precisely. The use of Artificial Neural Network (ANN) techniques has taken prominence because of its ability to capture the non-linear trends of stock market data better than traditional techniques. The study of the existing literature reveals that applications of ANNs are more promising alternatives than time series forecasting (Trippi and Turban, 1996). ANN has received the attention of researchers for forecasting market indices because of its trend learning capabilities for non-linear and noisy data, and its massive interconnectivity and parallel processing power (Principe et al., 1999). Researchers are using supervised and unsupervised ANNs for predicting trends in stock index data.

Guresen et al. (2011) conducted a thorough review of ANN models being used in the forecasting of stock market indices. The study revealed a brief description of models developed by using ANN for forecasting of indices data of different countries.White (1988) demonstrated an application of a simple neural network to analyze the daily returns of IBM. Trippi and DeSieno (1992) accomplished technical analysis to demonstrate the effectiveness of an ANN trading system designed for S&P 500 index futures contracts. Lin and Lin (1993) developed a model integrating neural networks to forecast the trends of then Dow Jones Industrial Average (DJIA). Lam (2004) tested the predictability of neural networks for financial performance trendsby combining variables used in fundamental and technical analysis. Ghiassi et al. (2005) compared techniques developed using ANN, ARIMA and DAN2 (Dynamic Architecture of ANN) and established that DAN2 predictions outperformed the other methods. Kumar and Ravi (2007) conducted a review on bank bankruptcy to demonstrate the ability of ANN in financial forecasting. Zhu et al. (2008) developed the model using neural networks to predict the trends of several market indices includes NASDAQ, DJIA and STI. Manjula et al. (2011) integrated a neural network in developing a model for predicting the trends of the daily returns of the Bombay Stock Exchange, SENSEX. They used a multilayer perceptron network to design the architecture of the model and used multiple linear regression (MLR) for training to provide a better option for weight initialization. Qing et al. (2011) scanned the predictive power of several well-established models, including dynamic versions of a single-factor CAPM-based model and Fama and French's three-factor model. They further compared the predictive power of the Multiple Output (MIMO) and Multi Input Single Output (MISO). Sharma and Rababaah (2014) developed a model integrating signal processing with ANN for predicting trends in the US stock market. Further, Rababaah and Sharma (2015) enhanced the predictive power of the model by incorporating two different signal processing techniques with ANN.

This paper emphasized the architectural design of ANN as MISO and MIMO (MIMO1 and MIMO2), based on various important predictors, where investors can select a suitable model based on their requirements or trading needs. For example, some investors may be interested in the Next-Day-Close price while others are interested in both Next-Day-Close price and the Next-Day-Open price and so on. It was assumed that ANN will map an input pattern with its corresponding output pattern in a more associative manner with a higher number of predictors. Three designed architectures of ANN were trained using two stock indices data: DOW30 and NASDAQ100. Simulated results were analyzed in terms of MAPE and found that the performance of predictors were better in the case of MIMO2 as compared to others (MISO and MIMO1). It was also noted that EBPN produces more consistent results than RBFN at both training and testing stages and was always higher in case of testing rather than training.

EXPERIMENTAL SETUP

Data Description: Index data for the DOW30 and NASDAQ100 indices were downloaded from the online source Yahoo Finance (http://finance.yahoo.com) from January 1, 2000 to January 31, 2012 and used in this research work. A total of 3000 samples were collected for both indices, out of which latest 600 samples (20%) were used to test the ANN models and remaining 2400 samples (80%) were used to train the models. Data were normalized using simple normalization method by dividing each sample with maximum value of the data. This is required due to the non-linear nature of time series data with different magnitudes, where larger magnitude variables may dominate the smaller variables (Bashah et al., 2015).

Performance Measures: The predictive model was verified with using two well-known measures: Mean Absolute Error (MAE) and Mean Absolute Percentage Error (MAPE). Equations 1 and 2 were written based on actual index price Y(t) and predicted index price Y'(t) with T as total number of samples. A lower value of these measures indicates that the model is more accurate. When results of measures are not consistent, we can consider MAPE suggested by Makridakis (1993) as the benchmark which provides relatively more stable value than other measures.

$$\text{MAE} = \sum_{t=1}^{T} |Y(t) - Y'(t)| / \text{T} \quad (1)$$

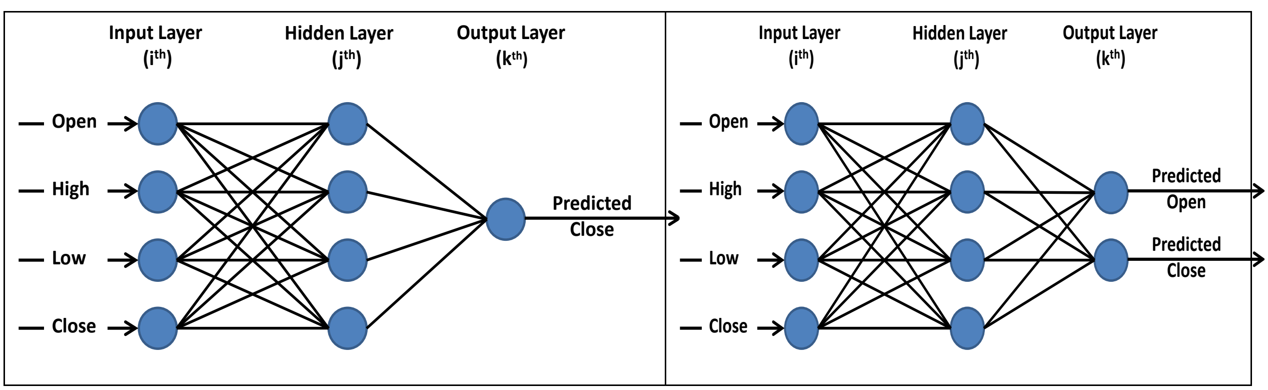
$$MAPE = \sum_{t=1}^{T} |Y(t) - Y'(t)/Y(t)| / T \quad (2)$$

ANN Techniques: In the past two decades ANN techniques have been attracting researchers for time series data forecasting due to their ability to learn non-linear patterns. The following two ANN techniques were used in the current research work for forecasting US stock price index data.

(i) Error Back Propagation Network (EBPN): EBPN (Shivanandam et al., 2011) is probably the most popularly used MLP for financial time series data forecasting in which the logistic or tangent hyperbolic function are used as the activation function in the hidden layer and output layer and which performs the training process in a supervised manner using an error back propagation algorithm in two different stages. (i) Forward pass: In which input is received by the neurons of hidden layer and output is calculated. These outputs are forwarded to outer layer neuron to produce the final output of the model based on the activation function in the outer layer. The actual index value is compared with predicted index value in order to calculate the error. (ii) Backward pass: In which the error calculated in first stage is sent back to previous layer (hidden layer) to adjust synaptic weights. There is a significant amount of literature available which concentrates either EBPN as individual model or as a combination with other techniques like fuzzy logic, genetic algorithm and wavelet transforms.

(ii) Radial Basis Function Network (RBFN): Radial basis function (RBF) networks (Shivanandam et al., 2011) are feed-forward networks trained using a supervised training algorithm. These have a single hidden layer generally with a special type of activation functions known as basis functions. A suitable basis function could be radial basis, polynomial and sigmoid and linear basis function determined by the data pattern. These are also known as kernel type and can be changed to tune the network. In comparison to back propagation in many respects, radial basis function networks have several advantages. They usually train much faster than back propagation networks. They are less susceptible to problems with non-stationary inputs because of the behavior of the radial basis function in hidden units. Also, the set-up of RBFN topology is very simple and straight forward. Many researchers are using RBF network for the prediction and classification problem and it has proven to be a useful neural network architecture. In RBFN, each unit of hidden layers acts as a locally tuned processor that computes a score for the match between the input vector and its connection weights or centers. In effect, the basis units are highly specialized pattern detectors.

ANN Model Development: An ANN model learns from the relationship of input and output, where each input is mapped with output (Bashah et al., 2015). A suitable architecture is always expected from the network designer for predicting more accurate results. The architecture of model is a network between input, hidden and output layer (Bashah et al., 2015). Neurons at the input layer and output layer depend upon elements in the input and output vector respectively. The number of neurons at the hidden layer may be decided using trial and error methods or other methods. Forming a suitable set of input and output pattern based on available input and output may improve the performance of model. Performance of ANNs may vary by mapping the input pattern with a single output and mapping input patterns with multiple outputs. It is to be assumed that the mapping of the input pattern with more than one output may improve the overall performance of the ANN. Keeping this in mind three ANN architectures were designed as Multi Input Single Output (MISO) and Multi Input Multi Output (MIMO1 and MIMO2) as shown in Figure 1 (a) and (b) with Error Back Propagation Network (EBPN) and Radial Basis Function Network (RBFN). MISO produces one output while MIMO1 and MIMO2 produce two and three outputs respectively with four inputs and four neurons at the hidden layer. These form 4X4X1, 4X4X2 and 4X4X3 architectures of ANN for MISO, MIMO1 and MIMO2. One predictor as Next-Day-Close is considered for MISO, two predictors as Next-Day-Close, Next-Day-Open are considered for MIMO1 while three predictors as Next-Day-Close, Next-Day-Open and Next-Day-High are considered for MIMO2, keeping in mind that these predictors are important for investors and fund managers (Sharma et. al, 2013).



(a) (b)

Figure 1: Three layer MLP-ANN MIMO architecture for Stock Index Forecasting (a) MISO (b) MIMO

SIMULATION WORK AND RESULT ANALYSIS

Simulation work was done using Clementine Data Mining software by creating a stream and by feeding Stock Price Index data through MS-Excel files. As stated above, data were splits as training and testing samples. The Clementine stream produced predicted output which were compared against the expected output in terms of MAE and MAPE using equations 1 and 2 and are shown in Table 1 and Table 2 respectively. For most of the predictors MAE and MAPE at the testing stage were always higher than MAE and MAPE at training stage for both the ANN models, especially for DOW30 data set and partially for NASDAQ100 data set. Results of EBPN were more consistent than that of RBFN at both training and testing stages.

A comparative result analysis of the work as per data presented in Tables 1 and 2 can be explained in two different viewpoints as follows:

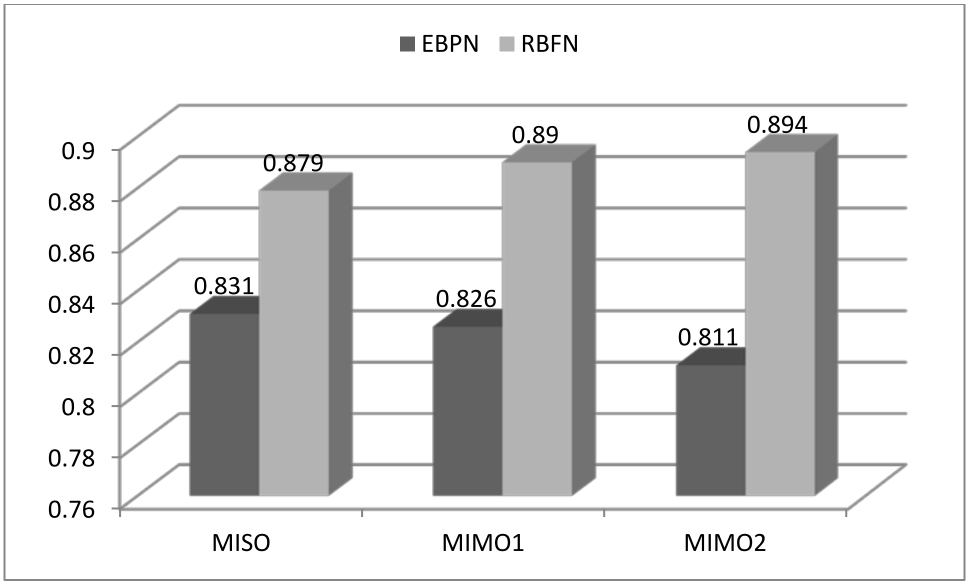
Table1: A Comparative Results ShowingMAE of MISO and MIMO

Dataset	Architecture Type	Predictor	EBPN		RBFN	
			Training	Testing	Training	Testing
DOW30	MISO	Next-Day-Close	95.145	92.680	99.690	97.890
	MIMO1	Next-Day-Close	94.730	92.234	99.664	99.011
		Next-Day-Open	30.355	26.399	45.140	46.020
	MIMO2	Next-Day-Close	92.417	90.331	23.246	99.698
		Next-Day-Open	23.467	17.534	17.290	45.175
		Next-Day-High	64.759	65.534	15.482	71.152
NASDAQ100	MISO	Next-Day-Close	31.640	26.834	36.720	44.540
	MIMO1	Next-Day-Close	31.107	24.145	36.505	47.518
		Next-Day-Open	18.131	19.073	25.783	26.129
	MIMO2	Next-Day-Close	29.763	23.246	35.581	25.638
		Next-Day-Open	16.290	17.290	25.138	19.196
		Next-Day-High	20.876	15.482	26.579	21.843

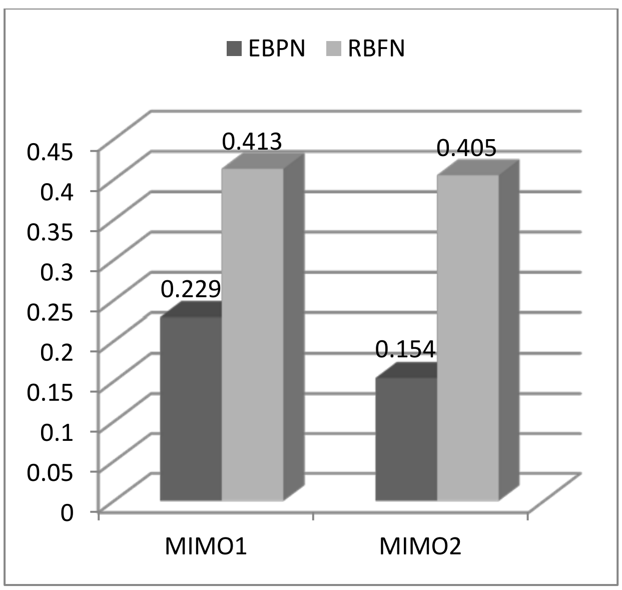
Table 2: A Comparative Results ShowingMAPE of MISO and MIMO

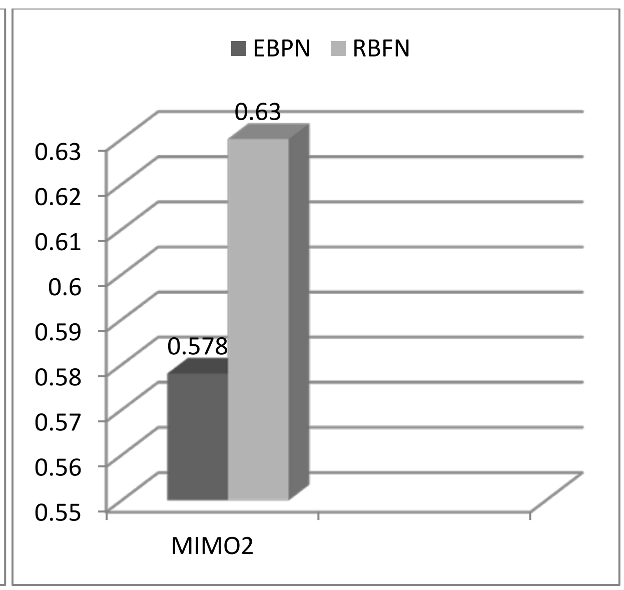
Dataset	Architecture Type	Predictor	EBPN		RBFN	
			Training	Testing	Training	Testing
DOW30	MISO	Next-Day-Close	0.939	0.831	0.989	0.879
	MIMO1	Next-Day-Close	0.937	0.826	0.987	0.890
		Next-Day-Open	0.293	0.229	0.439	0.413
	MIMO2	Next-Day-Close	0.917	0.811	1.103	0.894
		Next-Day-Open	0.225	0.154	0.809	0.405
		Next-Day-High	0.627	0.578	0.731	0.630
NASDAQ100	MISO	Next-Day-Close	1.801	1.256	1.942	2.048
	MIMO1	Next-Day-Close	1.777	1.140	1.926	2.161
		Next-Day-Open	1.118	0.883	1.406	1.199
	MIMO2	Next-Day-Close	1.670	1.103	2.043	1.221
		Next-Day-Open	0.982	0.809	1.488	0.898
		Next-Day-High	1.197	0.731	1.465	1.018

(a) **Comparative Analysis of two ANN Techniques:** Out of the two ANN techniques considered in this piece of research work, EBPN outperformed RBFN in terms of MAE and MAPE as shown in Table 1-2 and Figure 1-2. MAPE of EBPN was always less than that of RBFN for all the ANN architectures for both the indices in the case of training and testing for predictors: Next-Day-Close (Figure 1(a) and 2(a)), Next-Day-Open (Figure 1(b) and 2(b)) and Next-Day-High (Figure 1(c) and 2(c)). For example, Next-Day-Close price in case of MISO, MIMO1 and MIMO2 (Figure 1(a)) are 0.831,0.826 and 0.811 respectively using EBPN and are 0.879, 0.890 and 0.894 respectively using RBFN for DOW30 Index data. Similarly, the results of EBPN were better than RBFN for NASDAQ100 Index data. These results also showed that EBPN produced more consistent results than RBFN, demonstrating that EBPN is more reliable than RBFN.



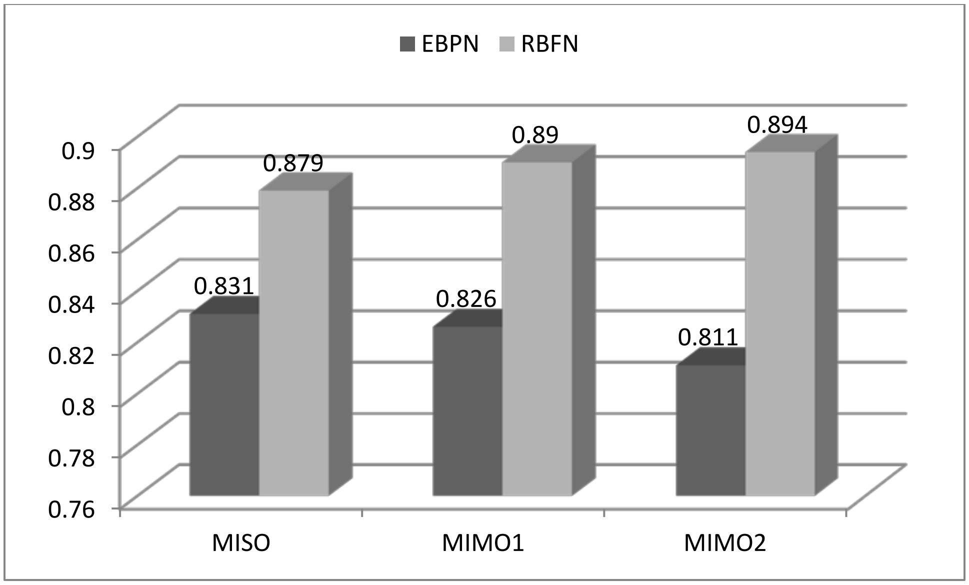
(a)



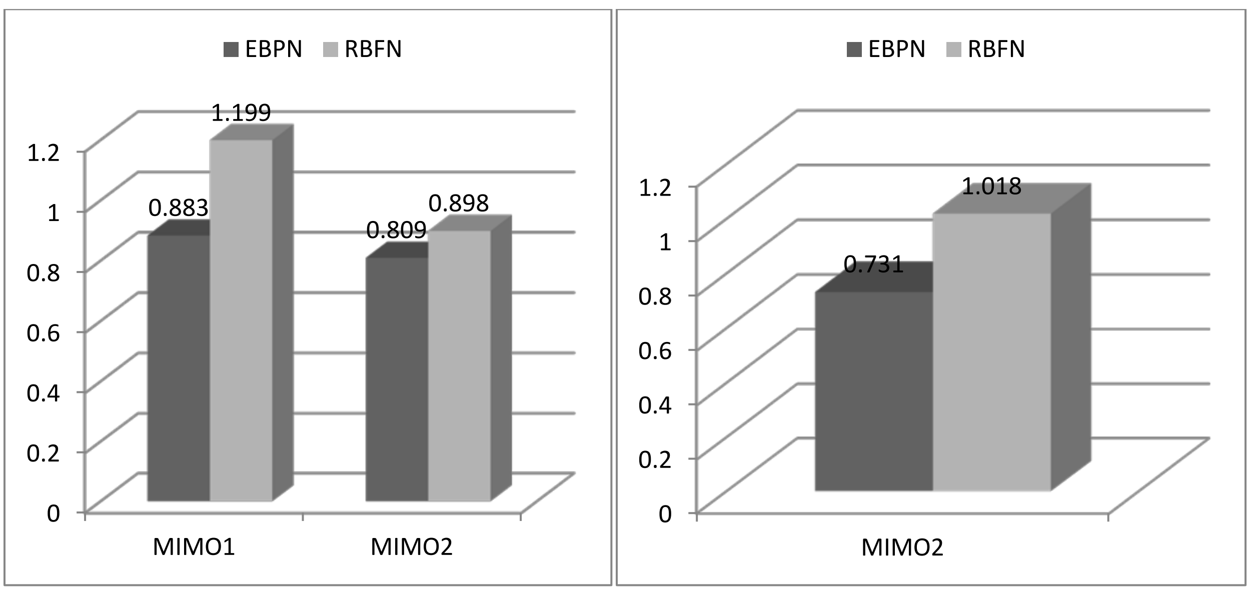


(b) (c)

Figure 1: Comparative MAPE of different ANN techniques simulated for DOW30 Stock Index Data based on various architectures of ANN (At testing stage) for predictor (a) Next-Day-Close (b) Next-Day-Open (c) Next-Day-High.



(a)

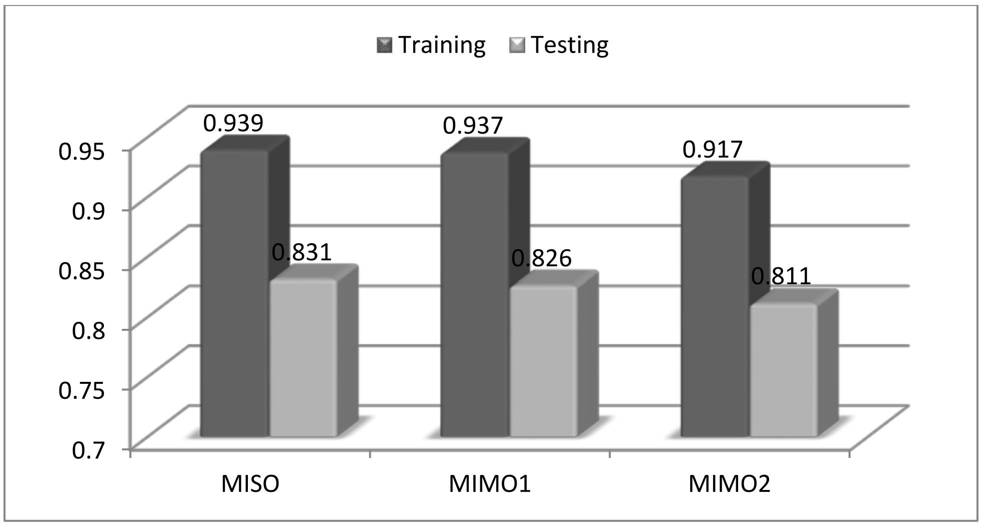


(b) (c)

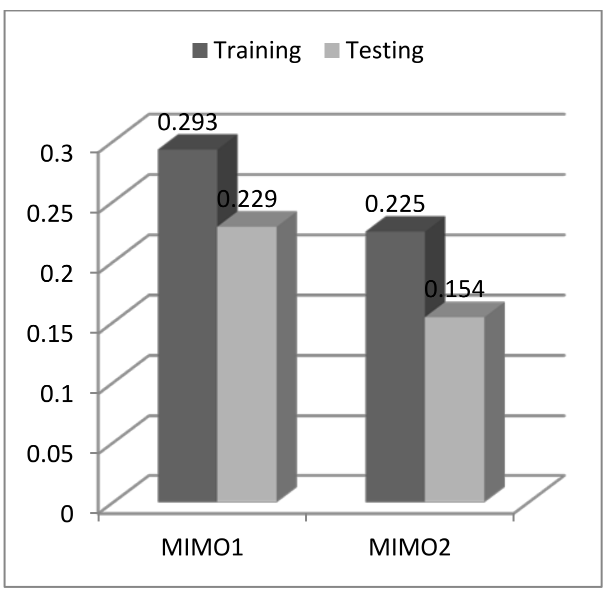
Figure 2: Comparative MAPE of different ANN techniques simulated for NASDAQ100 Stock Index Data based on various architectures of ANN (At testing stage) for predictor (a) Next-Day-Close (b) Next-Day-Open (c) Next-Day-High.

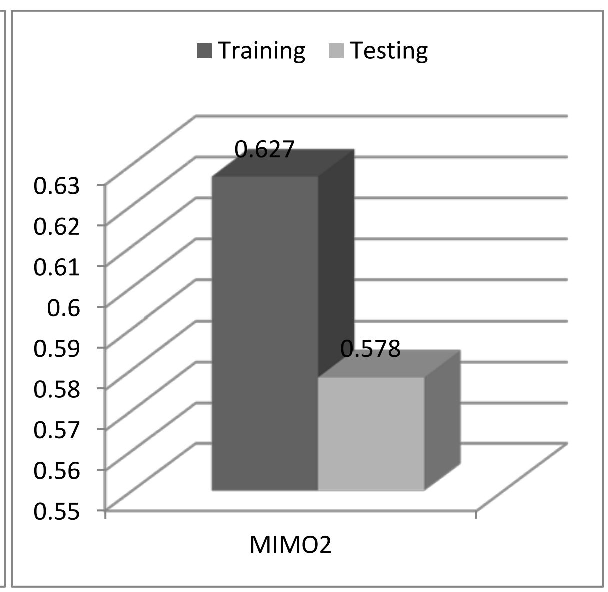
(b) Comparative Analysis of different predictors in case of EBPN: Having demonstrated that EBPN was the better prediction model for Stock Price Index forecasting, the predicted MAPE values were analyzed to compare MISO and MIMO results, i.e., to analyze whether the results improved with an increasing number of predictors. The hypothesis was that MAPE should decrease as the number of predictors was increased. This comparative analysis is shown in

Figure 3 and 4 in form of bar chart at both training and testing stages. Figures 3 and 4 clearly reflect that MAPE of predictors Next-Day-High, Next-Day-Open, Next-Day-Close were continuously decreasing in the case of MISO, MIMO1 and MIMO2 respectively. For example, Next-Day-Close price (Figure 3(c)) in case of MISO is 0.831 while it is 0.826 and 0.811 respectively for MIMO1 and MIMO2 for DOW30 while these are (Figure 4(c)) 1.256, 1.140, 1.103 for NASDAQ 100. Results for other predictors are also promising and consistent (See Figures 3 (a), (b) and 4 (a), (b)).



(a)





(b) (c)

Figure 3: A Comparative MAPE In Case of different ANN architectures simulated for DOW30 Index data Using EBPN for predictor (a) Next-Day-Close, (b) Next-Day-Open, (c) Next-Day-High.

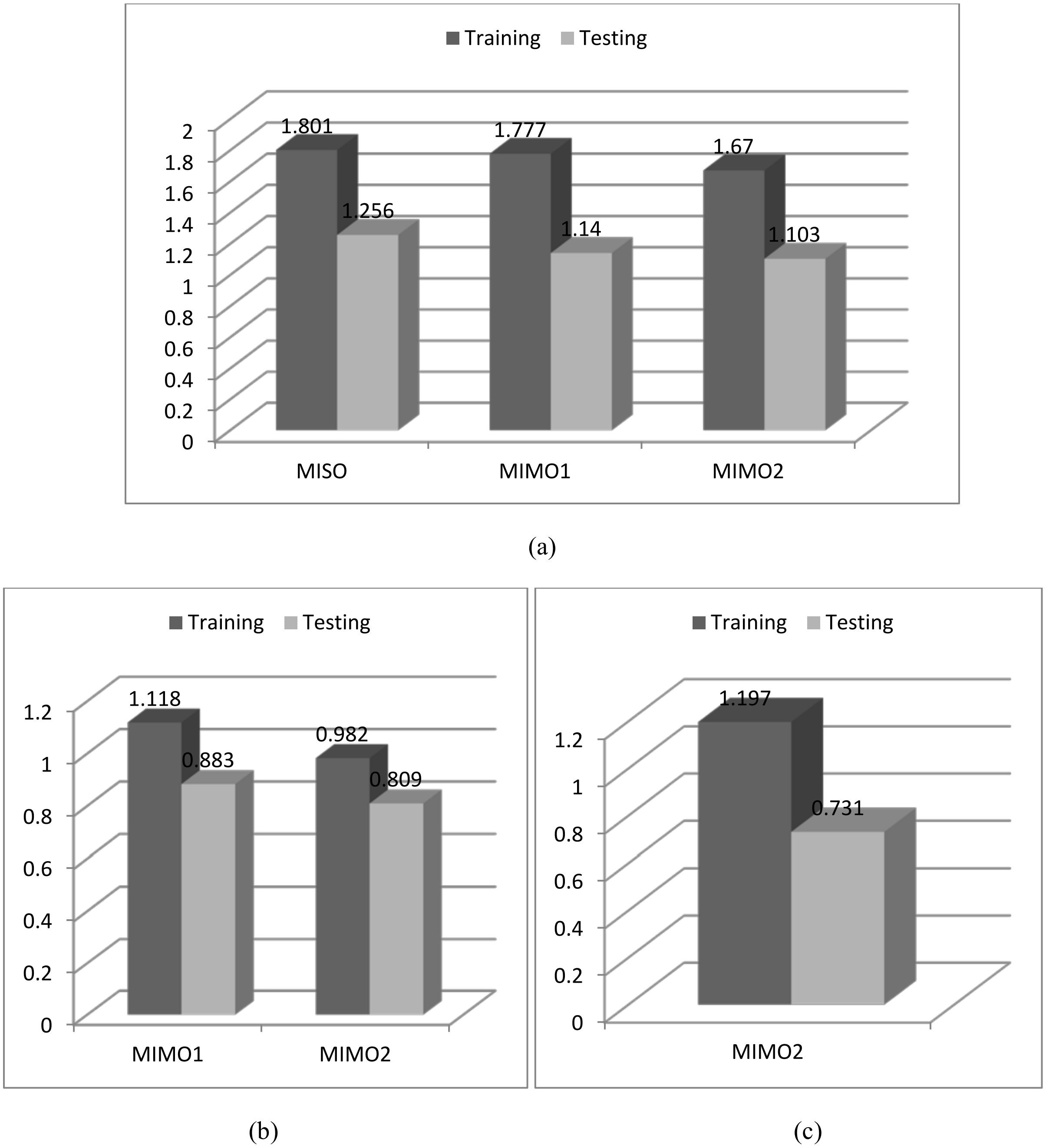


Figure 4: A Comparative MAPE in case of different ANN architectures simulated for NASDAQ100 Index Data Using EBPN for predictor (a) Next-Day-Close, (b) Predictor Next-Day-Open, (c) Predictor Next-Day-High.

CONCLUSION

Artificial Neural Network (ANN) is a widely used technique for financial data forecasting specifically for technical trading perspectives. This study has used a three layer feed forward neural network: Radial Basis Function Network (RBFN) and Error Back Propagation Network (EBPN) for forecasting of two US stock indices, DOW30 and NASDAQ100, based on the architectural design of ANN. We concluded that the results of EBPN technique were better than RBFN. The results showed that predicted values were better in the case of MIMO2 followed by MIMO1 and MISO. Hence, an EBPN based MIMO2 model may be considered better than one of MIMO1 and MISO for predicting trends in US stock market.

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