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Analysis of US Stock Market Post Presidential Election Performance using ANN Techniques

Dinesh K. Sharma
University of Maryland Eastern Shore
dksharma@umes.edu

H.S. Hota
Bilaspur University
proffhota@gmail.com

Richa Handa
Dr. C. V. Raman University
richihanda@yahoo.com

ABSTRACT

This research paper focuses on the analysis of a political event, which has taken place in the USA due to the 2016 presidential election. The impact of the event on trends in the stock market was analyzed using two intelligent techniques: Radial Basis Function Network and Error Back Propagation Network regarding N-days ahead prediction. Experimental results obtained through USA stock data DOW30 and NASDAQ100 reveals that USA stock market is almost stable during the presidential election.

KEYWORDS: Event Analysis, Radial Basis Function Network, Error Back Propagation Network.

INTRODUCTION

Prediction of stock market prices (Wang et al., 2011) is very challenging due to its chaotic data series. Stock market analysis based on various events is also a very crucial task due to drastic ups and down in stock trading (Lahmiri, 2016) and more error prone especially for next day ahead prediction. Stock prices are influenced by several factors and events, some of which impact stock prices directly and others that do so indirectly. Stock prices of different companies can be affected by two different types of events: expected and unexpected events. Expected events are those which are almost known to everyone, such as a presidential election. On the other hand, an unexpected event occurs suddenly and without warnings, such as natural disasters, wars, demonetization and other political activities.

This paper explores two Artificial Neural Network (ANN) techniques: Radial Basis Function Network (RBFN) and Error Back Propagation Network (EBPN) for stock data prediction with a particular reference to event analysis. The primary motive of the proposed research work is to check the robustness and efficiency of ANN (Navi, 2011; Leonel, 2015) based models, developed from historical stock data before occurring events and validated through stock data after the events. The empirical results show that models are able to adjust to the stock trading changes during the event and are robust enough to incorporate sudden fluctuations of the stock market with a high value of Mean Absolute Percentage Error (MAPE).

LITERATURE REVIEW

Researchers are focusing on developing prediction models based on different preprocessing and ANN techniques. Authors have also analyzed various events using many statistical techniques. Many authors have investigated the effect of the different events on the stock market of different countries. However, very few papers related to event analysis using ANN techniques were found. Very few papers are available in which intelligent techniques were used to analyze the effect of events. These are tabulated in Table 1 as below:

Table 1: Summary of Literature Review

YEAR	REFERENCES	JOURNAL
2017	Jens	Journal of Financial Economics
2017	Obradovic & Tomic	Ekonomska Istrazivanja
2016	Gunay	Borsa Istanbul Review
2016	Sharma et al.	Academy of Accounting and Financial Studies Journal
2016	Mo et al.	Expert Systems with Applications
2015	Savita & Ramesh	Procedia - Social and Behavioral Sciences
2015	Sharma et al.	International Research Journal of Finance and Economics
2014	Chien et al.	Journal of Business & Economics Research
2013	Goodell & Vahamaa	Journal of Banking & Finance
2012	Gan et al.	Applied Mathematical Modelling
2012	Manjunatha et al.	Indian Journal of Science & Technology
2011	Wang et al.	Expert Systems with Applications
2009	Wong & McAleer	Mathematics and Computers in Simulation

STOCK DATA AND METHODS

For this event analysis, about six years' time series data from January 2011 to March 2017 of the DOW30 and the NASDAQ100 are collected from the financial site: www.yahoofinance.com. These data also contains data for presidential elections in the USA in 2012 and 2016. Data are normalized by dividing each sample with the highest stock price to achieve smooth convergence during learning through nonlinear time series data.

To check the robustness and efficiency of the developed models, these stock data are divided into three parts: training, testing, and validation. The stock data before the event is divided into training (80%) and testing (20%) to develop prediction models and data after the event is considered for model validation as shown in Table 2.

Table 2: Data Partition

Partition Name	Data Range	
	DOW30	NASDAQ100
Training	11-Jan-2011 to 10-Nov-2015	11-Jan-2011 to 10-Nov-2015
Testing	11-Nov-2015 to 08-Nov-2016	11-Nov-2015 to 08-Nov-2016
Validation	09-Nov-2016 to 15-Mar-2017	09-Nov-2016 to 15-Mar-2017

Two machine learning techniques: Radial Basis Function Network (RBFN) and Error Back Propagation Network (EBPN) were used to develop stock market prediction models and validate models with event related data. RBFN uses radial basis functions as activation functions. It is a good alternative to multilayer perceptron (Manjunatha et al., 2012) with its single hidden layer. RBFN is three layers architecture; the first layer called the input layer where source node is given, the second layer is called the hidden layer in which each neuron computes its output using a radial basis function, and this output is sent to the third layer called the output layer.

EBPN is another popular method of ANN (Mo et al., 2016), in which input is given to the input layer, and is propagated forward to the network until it reaches the output layer. The output is compared with actual output to produce the error value, which is propagated back to the network and updates the weight. This process is repeated until it approaches the desired output.

RESULT ANALYSIS

Experimental work is carried out with self-written MATLAB code for RBFN and EBPN under the Window 10 environment. A predefined function of RBFN in MATLAB as newrb() is used to create basic RBFN architecture by adding neurons to the hidden layer and also simulates RBFN until it meets the specified mean squared error (MSE) goal by feeding input and target vectors as parameters of the function. Similarly, EBPN was also constructed with MATLAB function newff() and was simulated with its default parameters like learning rate, momentum, etc.

Normalized training and testing samples were presented to RBFN and EBPN to train and test the models; further validation data were used for N-days ahead prediction for 1-Day, 3-Days, 5-Days, and 7-Days. Predicted values for both indices, DOW30 and NASDAQ100, are compared with actual next-day-close prices regarding Mean Absolute Percentage Error (MAPE) as shown in equation 1. Results are presented in Tables 3 and 4 respectively for DOW30 and NASDAQ100. Results are also analyzed deeply to check the overall performance of the models in three different viewpoints as below:

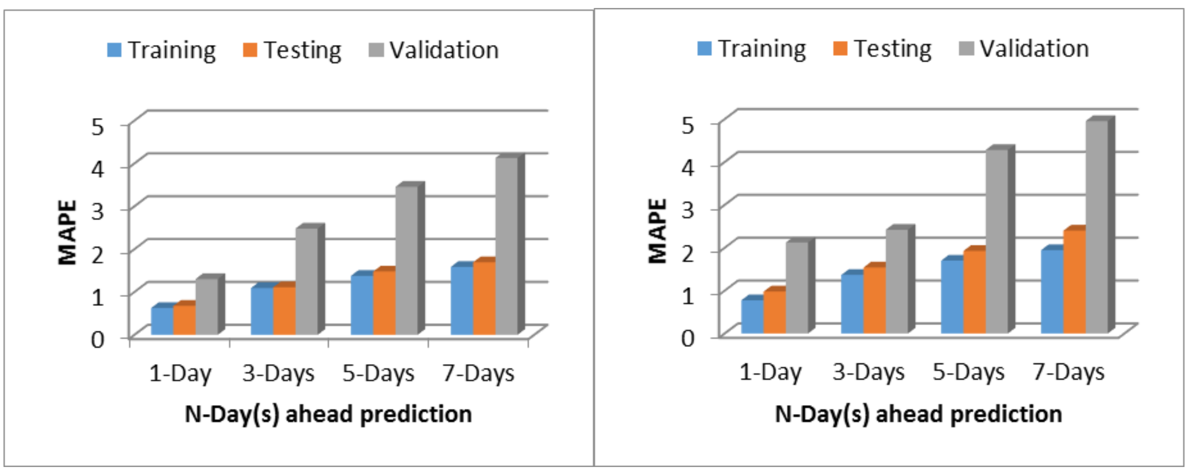
$$\mathrm{MAPE} = \frac{\sum_{i=0}^{n} |Y_{a,i} - Y_{p,i}|}{n} \quad (1)$$

Table 3: Comparative MAPE on training, testing and validation samples for DOW30 Index data with N-days ahead prediction.

N-Day(s) ahead prediction	RBFN			EBPN		
	Training	Testing	Validation	Training	Testing	Validation
1-Day	0.6261	0.6749	1.302	0.6255	0.6451	1.2799
3-Days	1.0922	1.1118	2.4769	1.0845	1.1177	2.825
5-Days	1.3765	1.4784	3.4536	1.377	1.6583	4.2183
7-Days	1.5857	1.6943	4.1264	1.5651	1.8005	4.7647

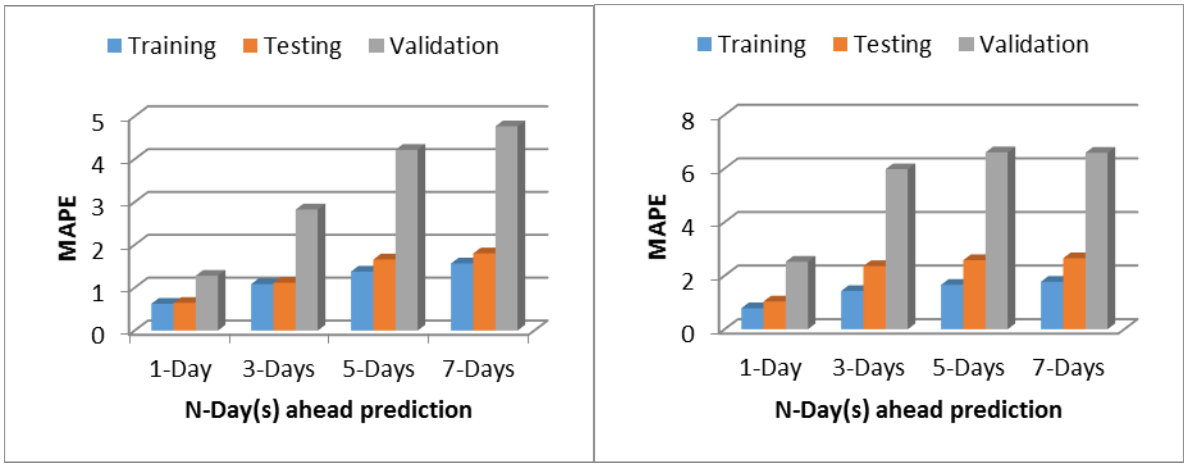
Table 4: Comparative MAPE on training, testing and validation samples for NASDAQ100 Index data with N-days ahead prediction.						
N-Day(s) ahead prediction	RBFN			EBPN		
	Training	Testing	Validation	Training	Testing	Validation
1-Day	0.7750	0.9782	2.1227	0.7817	1.0361	2.5175
3-Days	1.3666	1.5393	2.4172	1.4269	2.3579	5.9719
5-Days	1.6989	1.9243	4.2791	1.6555	2.5778	6.6005
7-Days	1.9446	2.3984	4.9531	1.7721	2.6497	6.5868

Case 1: **Comparative analysis in terms of data partitions-** Typically performance of the models varies at different stages of training, testing, and validation. The performance of the models in the case of known target samples (Training stage) is always higher than the models with unseen samples (Testing and validation stage). The performance of the models decreases for the higher value of N in the case of N-Days prediction. Comparative graphs as shown in Figures 1 and 2 reflects these facts where training MAPE is lower than testing MAPE followed by validation MAPE for both the indices using both the techniques. On the other hand, MAPE is continuously increasing while the value of N is increasing.



(a) (b)

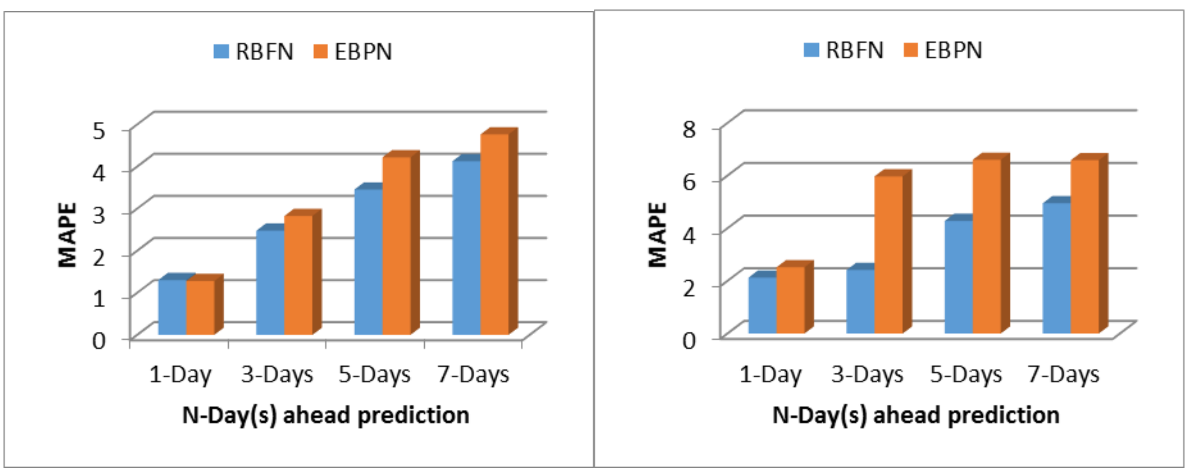
Figure 1: Comparative analysis in terms of data partition using RBFN for (a) DOW30 (b) NASDAQ100.



(a) (b)

Figure 2: Comparative analysis in terms of data partition using EBPN for (a) DOW30 (b) NASDAQ100.

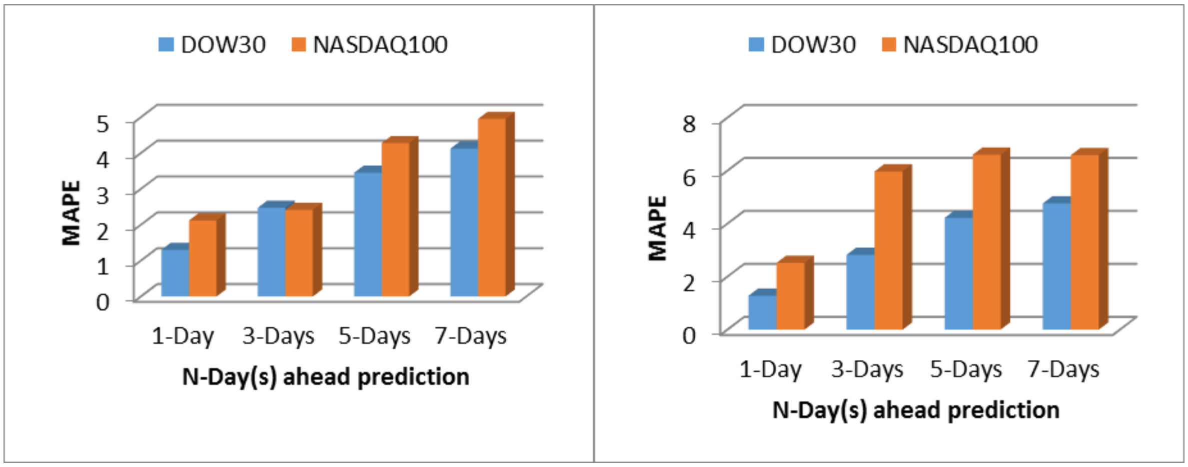
Case 2: Comparative analysis of two techniques RBFN and EBPN- Comparative MAPE regarding N-days ahead prediction for event related data (Validation Data) is shown in Figure 3 which reflects that the RBFN is performing better to incorporate event related changes in the stock market than EBPN. It has been observed in many cases that EBPN sometimes perform better than RBFN and it all depends upon the nonlinear trends of stock data.



(a) (b)

Figure 3: Comparative graph in between RBFN and EBPN for (a) DOW30 (b) NASDAQ100.

Case 3: Comparative analysis of DOW30 and NASDAQ100 stock trends during event- This section analyzes how the developed models are self-sustainable and capable during any expected or unexpected events. As shown in Figure 4, the models are performing better in the case of DOW30 Index data for both RBFN and EBPN as compare to NASDAQ100 for N-days ahead prediction but in both the cases models are capable of adjusting to sudden fluctuations of the stock market.



(a) (b)

Figure 4: Comparative graph of stock data of DOW30 and NASDAQ100 for (a) RBFN (b) and EBPN

CONCLUSION

Sudden fluctuations in the stock market always need to be incorporated by stock price prediction models. The traditional statistical models can't adapt or incorporate these variations. On the other hand, machine learning techniques like ANNs are self-capable to adjust these fluctuations and able to produce comparatively better outputs. This paper analyzes how machine learning based models are robust when events related data are presented. Comparative analyses were done with two US-based stock indices (DOW30 and NASDAQ100) for the presidential election held in the USA in 2016. The event has been studied for N-days ahead prediction. The empirical results show that RBFN performs better than EBPN. The two models are shown to adjust to the sudden changes of the stock market with less MAPE due to any event.

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