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Presidential Election's Economic Uncertainty Influence on Narx Neural Networks Ability to Predict Stock Index

[1] Shahryar Haghighifard, [2] Arash Saharkhiz
[1][2] Department of information technology, Mapua University, Makati, Philippines

Abstract: The stochastic nature of the stock market has made it difficult to forecast its performance. Therefore, vigilance is crucial in making the best decisions. Presidential elections have been observed to be a factor that causes uncertainty in stock market's performance. In this article, the researchers aimed to determine Artificial Neural Network's (ANN) capability to forecast stock market index with and without an influence of presidential election uncertainty. Historical data of Philippines stock exchange market for past eight years was obtained and divided into five different datasets based on different time frames leading to the presidential election. The researchers grouped the data into complete data, data without one month before the presidential election, data without six months before the presidential election, data containing only one month before presidential polls and data comprising just six months before presidential elections. A test dataset also collected to measure the performance of each network trained by above datasets. Then a NARX neural network was trained using each dataset. After examining all datasets, the datasets in which the data of six months and one month before elections were eliminated, showed better learning rate comparing to other datasets. This study shows a new way to consider presidential polls as one of the factors to predict the stock market. Although it is not possible to forecast the market by examining a sole consideration, the findings of this research can help market analysts to make better decisions.

Key Words: **Artificial Neural Networks, stock market prediction, NARX, Philippines Stock Exchange.**

I. INTRODUCTION

Many commercial businesses, firms or private investors are counting on the stock market as a means to increase profit. Due to uncertainty and its stochastic nature, the Stock market can be devastating for many investors and on the other hand a gold mine to others. Although there are many approaches to forecast this potentially profitable market, this still is not an easy task to do. This difficulty is usually due to the reason that multifarious factors affect the stock market and handling all these elements to predict the market is a tedious challenge. Many factors affect stock indexes. Some can influence specific market sectors while others play a more substantial role. [1] investigated this by measuring how oil price can impact the stock market. They found out that oil price affects more on oil-related sectors of the market. In another study, [2] identified that liquidity of stock market increases just as positive oil shocks come from the oil-specific demand side. In a paper, [3] examined the influence of fluctuation of foreign currencies against US dollar and its effects on the stock market. They showed that as these currencies' value increases the stock indexes elevate. Machine learning algorithms are appropriate tools to investigate time series data such as stock prices. These algorithms are reliable when it comes to studying the non-linear relations between elements of such [4]. Artificial neural networks as one of these algorithms showed a decent performance in past studies. [5] utilized neural networks to identify failing banks. In another study, [6] applied their version of neural networks, which they call "expectile Regression Neural Network (ERNN)," to predict concrete compressive strength and housing price. This algorithm used widely for economic purposes such as credit risk estimation [7] or bankruptcy prediction [8]. It is proven that presidential elections affect stock market [9], [10], [11], and [12]). The main objective of this research is to investigate the effects of the presidential election as a form of political uncertainty, on the learning ability of an artificial neural network to predict stock market index. The data used to conduct this research yielded from Philippines stock exchange market historical data. The rest of this paper is organized as follows. Section 2 presents some previous related works on the stock market prediction by artificial neural networks. Furthermore, some relevant research that indicates the relation between stock market prices and presidential elections has been presented in this section. Section 3 offers this research's proposed methods. Section 4 illustrates the results of this study. Finally, section 5 is a conclusion of this research's contributions.

II. BACKGROUND OF THE STUDY

Predicting stock prices by using machine learning algorithms is not relatively new. There have been significant researches done to achieve this goal, and it is rational due to different factors that influence the market. Furthermore, many researchers tried to enhance machine learning algorithms to attain better results. Although it is indispensable to consider many aspects to perform a robust prediction [13], however, this study's primary intention is to measure whether or not one of these factors, which is the presidential election as a political uncertainty, influence ANN's learning ability. In a study [14], suggest a fusion model based on multi-diverse base classifiers to deliver a better stock returns. In another research [15], they experiment different machine learning algorithms, based on two monthly and daily time intervals, to forecast Indian stock market. In another paper [4] utilizes Artificial Neural Networks to predict NASDAQ stock exchange daily rate. They used backpropagation algorithm to train their data and compared the algorithm's ability to predict based on a short-term and long-term model. [16] combined disparate online data sources with traditional timeseries and technical indicators and examine the ability of Artificial Neural Networks alongside other learning algorithms such as decision trees and support vector machines, to predict Apple NASDAQ stock one-day ahead. [17] used data mining techniques to predict the daily direction of S&P 500 Index ETF (SPY) return based on 60 financial and economic features. In a paper, [18] examined artificial neural networks (ANN) to predict the Japanese Nikkei 225 index. They stepped further by combining ANN with genetic algorithm (GA) and simulated annealing (SA), and the results showed that this combination could increase the learning algorithm's efficiency significantly. Studies show political events such as presidential elections influence stock market. For instance [19], investigated cointegration and causal relationships between the Iowa and in trade presidential futures markets alongside election polls. Furthermore, they recorded the election predictions of Nate Silver. They found out that market movements and the presidential election have effects on each other. They showed that the increase in policy uncertainty curtails stock returns. In another study [20] examined the influences of political uncertainty on the stock market. They observed that market uncertainty elevates as the possibility of winning increases for the eventual winner

III. METHODOLOGY

This research has utilized NARX or Nonlinear Autoregressive with exogenous (external) input model to predict stock index of Philippines stock market and investigates the effect of elimination of short time (one month) and longtime (six months) data of before election on neural network's prediction performance

3.1 Dataset and data collection

The dataset used for this research is collected from historical data of Philippines stock exchange market between the penultimate election until one year after the last election, which is from Jun-2009 to Jun2017. In a study, [9] investigated 27 OECD (Organization for Economic Cooperation and Development) countries and revealed that factors that can affect market during the presidential election. It is found that the country-specific component of index return variance can easily double during the week around an election. The results of this study show higher uncertainty in the stock market in short time before an election. We hypothesized that elimination of data in such high uncertain periods could increase ANN's ability to forecast market index. To investigate the short-term effect of highly uncertain times, we removed the data of one month before elections from our dataset. Furthermore, we decide to eliminate the data of six months before elections to examine the long-term effect of uncertain periods. Although [11] and [20] used one poll as the sample to investigate the influence of presidential election on the stock market, the collected data in this research has prices of the stock market during two elections, and this may increase the accuracy of the predictive model. This hypothesis has tested, and its result presented in the discussions section. The data used in this research (historical prices of Philippines stock exchange index) have collected from wall street journal database [21]. This data had to be cleaned; this way different datasets which each represents information with different time interval related to presidential elections is available to train by the NARX artificial Neural Network. Then the performance of the model regarding each dataset measured and compared with each other. The dataset cleaned into five different sets. First is the dataset which consists of all data in the mentioned time interval, second, the dataset in which the data of six months before elections are eliminated to investigate the long-term effect of election. Thirdly, the dataset is that in which the data of one month before votes are excluded. This dataset is to review the short-term impact of the presidential elections. Fourthly, the datasets which are eliminated time intervals

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for each case. These datasets are used to examine if training the predictive model with data prone to uncertainty can enhance its forecasting ability. Fifth, a test set which does not having any data from any of the above time intervals. The last dataset is the historical data of one month (July-2017) and used as a test set to evaluate the performance of networks trained by other datasets.

3.2 Artificial Neural Network

This algorithm has inspired from biological systems in which neurons are the signal processing elements. ANNs are non-linear statistical data modeling tools, and they model the affiliation between inputs and outputs in the dataset, and this leads them to be able to learn relations between data attributes. Accordingly, by determining the patterns of data, this algorithm can predict future events. [4] used ANN to predict values of NASDAQ exchange rates and the results showed better results when OSS training method and TANGSIG transfer function in a network with 20-40-20 neurons in three hidden layers used. Therefore, in this research, this network structure will be used to be trained and predict the dataset, and at the end, the performance of the networks will be measured by comparing each network's ability to predict the test dataset. Additionally, the predictability of each network will be observed by their R2 value.

3.3 NARX

NARX or nonlinear autoregressive network with exogenous inputs is a recurrent dynamic network which is based on the linear ARX model (a frequently used model for time-series modeling). Figure 1 shows the NARX network model from a broader view. The box in the middle is layers of ANN that approximate the network's function (f). Figure 2 is a more detailed structure of the network, as you can see there are 2 layers of Feedforward neural network that make this approximation and as NARX use the ARX model, input and output may be multidimensional.

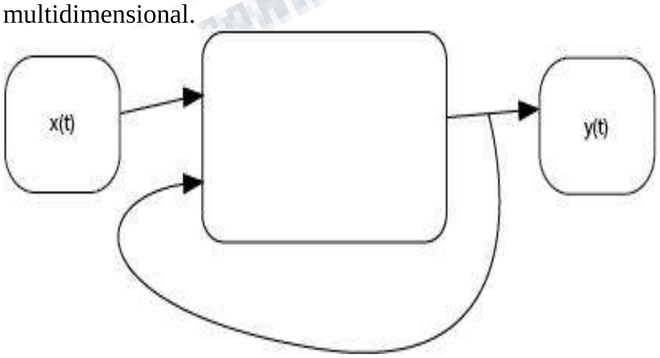

fig 1 - Typical NARX network structure

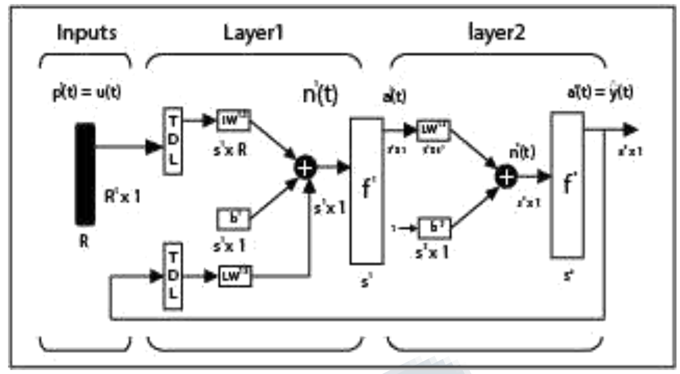

fig 2 - Detailed structure in which we can see the Feedforward ANN

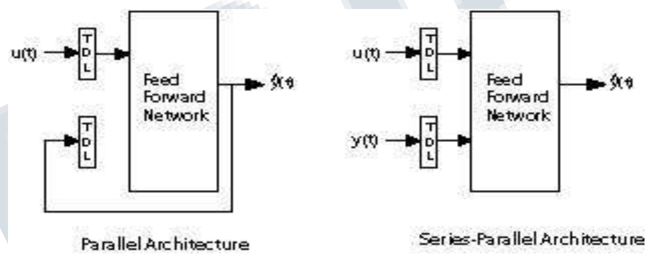

Fig 3 - a comparison of parallel and series-Parallel Architectures

( ) = ((− 1), … , (−), (− 1), … , (−) (1)

As we can see in figure 2 and formula 1, when an input enters the network, it goes through different layers of feedforward ANN. In a feedforward ANN, the network's output is fed back to the input. As an essential characteristic of NARX network the output that is feeding back to the network in a NARX structure, is the real output, as it is available during training, not the estimated network's output. This arrangement called series-parallel architecture and has two benefits for the network's performance. First of all, it results in a more precise input for feedforward network, Furthermore, at the same time the network has a feedforward architecture, and training can be done with static backpropagation. As it is evident in figure 3, in a Series-Parallel architecture, real output data (y(t)) will be fed to network's input instead of its estimated value (̂( )). All that has to be done is to initiate different random weight trials for each input data. The network starts with this value and adjusting them throughout the training. The network stops its iterations if

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its estimated value does not change in 6 iterations. In [22] you can learn more about this network.

3.4 Performance measurement

performance of the network was measured by two different methods. First, by determination coefficient (R2) which calculated as showed at equation (2).

$$) = 1 - \frac{\sum(/0123/2405)^7}{\sum(/0123/8)^7} \quad (2)$$

secondly, the performance measured by mean square error(MSE) of the output as demonstrated by equation (3)

$$\frac{\sum(/24053/012)^7}{} \quad (3)$$

$$= \qquad <$$

y(exp) represents experimental values while y(pred) is the representation of predicted values and M serves as total number of data.

IV. RESULT AND DISCUSSIONS

A NARX network had trained by each indicated dataset, and its performance measured. Each dataset randomly divided into three portions, 70 percent for training, 15 percent for validation and 15 percent for testing. The trained dataset's performance tested again by the test dataset. This test is essential because it is a way to scale the learning ability of each network by the same measure. Each dataset has trained three times with three different training algorithms. The first algorithm is Levenberg-Marquardt, which is faster than others, however, employs more memory. The second algorithm is Bayesian-Regularization, which is slower but can give better results. The last algorithm is Scaled Conjugate Gradient which is using less memory. The performance of each trained network on every three datasets shown in table 1 through 3 and the performance of the network for eliminated data of each dataset presented in table 4 and 5.

Training algorithm	R2	MSE
levenberg-Marquardt	0.677801	2,738.89282
Bayesian- Regularization	0.694017	2611.678995
Scaled Conjugate Gradient	0.273199	12552.32212

Table 1 - performance of NARX network trained by the dataset of all data

Training algorithm	R2	MSE
levenberg-Marquardt	0.732139	2578.18445
Bayesian- Regularization	0.723893	2404.26964
Scaled Conjugate Gradient	0.554445	11737.96887

Table 2 - performance of NARX network trained by the dataset in which the data of one month before elections had eliminated

Training algorithm	R2	MSE
levenberg-Marquardt	0.690205	2806.70741
Bayesian- Regularization	0.730727	2380.16446
Scaled Conjugate Gradient	0.618455	39417.23568

Table 3 - performance of NARX network trained by the dataset in which the data of six months before elections had eliminated

Training algorithm	R2	MSE
levenberg-Marquardt	0.044726	1007465.05297
Bayesian- Regularization	0.201869	1183894.41650
Scaled Conjugate Gradient	0.0073608	1664059.73534

Table 4 - performance of NARX network trained by the dataset in which only data of one month before elections provided

Training algorithm	R2	MSE
levenberg-Marquardt	0.486198	391482.48198
Bayesian- Regularization	0.713221	34531.24173
Scaled Conjugate Gradient	0.193685	77871.93925

Table 5 - performance of NARX network trained by the dataset in which the data of six months before elections had

As it can be seen in above tables the highest R2 value belongs to the network which trained by the levenberg-Marquardt algorithm and its dataset is the network in which the data of one month before elections had eliminated and it is 0.732139. Furthermore, the lowest R2 value belongs to the network which trained by Scaled Conjugate Gradient algorithm, and its dataset is the one in which the only data of one month before elections provided and it is 0.0073608. The average R2 value among all networks shows Bayesian-Regularization algorithm performs better with the average R2 value of 0.6127454(the average R2 value for the levenberg-Marquardt algorithm and Scaled Conjugate Gradient algorithm is respectively 0.5262138 and 0.32942896). Highest R2 value for networks that trained with levenberg-Marquardt algorithm belongs to the network that its training dataset is the one in which the data of one month before the election eliminated. This is also true for the highest value of R2 for networks that trained by

Bayesian-Regularization algorithm, and both have rates near to each other (0.732139 for levenberg-Marquardt and 0.730727 for Bayesian-Regularization). Scaled Conjugate Gradient algorithm showed a lower highest value of R2 compared to other two which is 0.618455, and it belongs to the dataset in which the data of six months before elections had eliminated.

The networks that trained by training dataset of all data showed the average R2 value of 0.548339, the networks that trained by training dataset in which the data of one month before elections had eliminated showed the average R2 value of 0.670159. The networks that trained by training the dataset in which the data of six months before elections had eliminated showed the average R2 value of 0.679795667, the networks that trained by training dataset in which the data of only one month before elections exists showed the average R2 value of 0.084651933. And the networks that trained by training dataset in which the data of only six months before elections exists showed the average R2 value of 0.464368. As can be inferred from above numbers the best performance among networks trained with datasets belongs to the network that trained by the dataset in which the data of six months before elections had eliminated. It is also worth to mention that this number is very

close to the average of the R2 value of the networks that trained by training dataset in which the data of one month before elections had eliminated. It is evident in the results above that although levenberg-Marquardt algorithm showed the highest R2 value; however, Bayesian-Regularization algorithm showed a better performance in average. The results also showed that the networks that trained by datasets in which the data of one month and six months before elections had eliminated had better performance and this proves our hypothesis that elimination of data before the election can increase the ability of the network to forecast markets index. The results showed that the networks that trained by datasets in which the data of one month before elections had eliminated had better performance among all other networks, which means short time elimination of data shows a better result comparing to long-term (six months). This finding could explain that the uncertainty in the market is higher one month before the election.

V. CONCLUSION

Historical data of Philippines stock exchange market in the time interval of one year before the penultimate election until one year after the last election used to conduct this research. The data grouped into complete data, data without one month before the presidential election, data without six months before the presidential election, data containing only one month before presidential polls and data comprising just six months before presidential elections and a test dataset. We hypothesized that elimination of high volatile (uncertain) time intervals such as before presidential elections, can influence the learning ability of Artificial Neural Networks to forecast the stock market index. NARX (nonlinear autoregressive network with exogenous inputs) neural network, which is an appropriate network for time series, used to conduct this research. A NARX network trained with each dataset three times by three different training algorithms (levenberg-Marquardt, Bayesian-Regularization, and Scaled Conjugate Gradient). The results showed the performance of neural network increased when it trained by datasets in which the data of one month and six months before elections had eliminated. The highest R2 value of the network that trained by all data belongs to the network that trained by Bayesian-Regularization training algorithm and is 0.694017. However, the highest R2 value belongs to the network which trained by levenberg-Marquardt training algorithm, and its dataset is the one in which the data of one month before the election eliminated and it is 0.732139. These findings show that by reducing the high volatile time intervals from training data, such as presidential elections, we can achieve better results in forecasting stock index. This research also revealed that levenberg-Marquardt and Bayesian-Regularization training algorithms ability to predict is very close, however, Scaled Conjugate Gradient training algorithm showed a lower result with all datasets.

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Authors' background

Your Name	Title*	Research Field	Personal website
Shahryar Haghighifard	Master student	Machine learning and data processing	Shahryar-hf.com
Arash, sabarkhiz	Professor	Artificial intelligent	

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