

Stock Market Prediction using PSO Optimized Neural Network

Suhani Jaiswal
suhanijaiswal4@gmail.com

Rishabh Jaiswal
rsj.rishabh@gmail.com

Abstract – This paper proposes a model based on particle swarm optimized neural network for the price prediction of American stock market. Different configurations of neural networks are tested using a six years series (January 2010 to December 2016), where the data from January 2014 to December 2015 is used for training leaving the last year (i.e. 2016) to verify the predictive capacity of the network. Three attributes of dataset; open, high and low values are used to train the neural network. The results show a good behaviour of neural networks with low-performance errors in both learning and prediction.

Keywords – AAPL, Fuzzy Logic, NASDAQ, Neural Network, PSO, etc.

I. INTRODUCTION

Financial markets are those where the deficit and capital surplus entities concur, the former with the objective of obtaining financing and the latter investing their excess resources. Shares on companies are the most commonly traded securities in a stock market, which in turn is a fundamental component of financial markets. The prediction of the share price is therefore of high interest to investors as it will indicate the signs of buying or selling these securities in order to maximize their profits, however, it is not an easy task given the amount of macroeconomic and microeconomic variables that determine its value (Hadavandi et al., 2010).

In the American context, the stock market has taken great importance for its sustained growth during the last nine years given the recovery of investor confidence. This has also allowed the creation of another important market such as derivatives and integration with other exchanges in the so-called AAPL (American Association of Professional Landmen) stock market dataset that groups the stock exchanges of America.

This situation has led to an increasing number of national and foreign companies listed on the AAPL stock exchange and that some of our main shares are traded simultaneously on the American stock

exchange. For this reason, the study of models that make it possible to prediction the behaviour of the traded shares in the AAPL stock market is becoming increasingly relevant so that they constitute a guide that guides the strategy to be followed by the participating investors.

Some of the mathematical techniques used to address the study of the behaviour of financial markets have been multivariate and univariate, but they show deficiencies when it comes to making predictions outside the sample (Meese and Roesse, 1991). Later studies have shown that the presence of nonlinear dynamics could imply the possibility of making more precise predictions than those provided by a linear stochastic model and, in particular, by the random walk model. In this sense, authors such as Fernández and Sosvilla (1998), provide evidence in favour of the non-linear prediction of exchange rates. Other authors have used stochastic methods based on Markov chains in order to face the random states in the behaviour of these markets (Zhang and Zhang, 2009). Despite not delivering a specific prediction value, its advantage is that it allows predicting possible changes in price states in terms of probability of occurrence. Its application to the Chinese financial market showed the usefulness of the method in terms of providing additional criteria to predictions delivered by other time series based methods.

As a risk control strategy and for the valuation of financial derivatives on stocks and indices, other studies have addressed the volatility prediction problem. In this sense, Yalama and Sevil (2008) use different kinds of GARCH models in order to prediction the daily volatility of the main indices of the stock markets in 10 different countries. As a result, it finds a better performance of asymmetric volatility models with respect to historical models. Another work uses the combination of GARCH, EGARCH, random walk and exponential moving averages methods to predict the behaviour of volatility in the stock markets (Jing-rong, 2007). Its application to the index of the Shenzhen Stock

Exchange in China, showed that the proposed model delivered errors lower than that obtained with the predictions of individual models.

Given the non-linear behaviour of this type of economic variables, new methods based on artificial neural networks have been proposed since the 1990s. Its main characteristic of allowing to establish linear and non-linear relationships between the inputs and outputs of a system has made it possible to show its applicability in high volatility markets, whose variables are due to non-linear behaviours in various areas of engineering and in the electricity markets. A first review showing a broad set of successful applications of neural networks to finance is presented in Trippi and Turban (1992). This book highlights the work of analysis of accounting reports, bankruptcy prediction, risk analysis, forex prediction and financial index negotiation strategies among others. In a recent publication, Li and Ma (2010) present an updated review of these applications to predictions in the securities, derivatives, currencies and financial crises markets. These reviews highlight the superiority in the performance of neural networks with respect to econometric methods and other linear models.

In recent years, neural networks are forming a list together with diffuse logic and genetic algorithms. Bekiros and Georgoutsos (2007) compared the performance of a Neuro-diffuse network with respect to a neural network in the task of predicting the direction of the market for the NASDAQ and NIKKEI indices. It was found that a negotiation strategy based on the indication of both models is superior with respect to a strategy of buying and maintaining the index. Additionally, the results of the Neuro-diffuse model were superior to the neuronal model since they had greater success in predicting their direction.

A review of 100 scientific publications dedicated to price prediction in the stock markets of different parts of the world using neural networks and Neuro-diffuse networks is presented by Atsalakis and Valavanis (2009). All these works demonstrate the superiority of these intelligent computing techniques with respect to conventional models in terms of better prediction accuracy. However, they write down the difficulty in the definition in the structure of the model, since in most cases it was done by trial and error. However, Chen et al. (2011) compared the performance of models based on time series and fuzzy logic with an algorithm also based on time series but modifying the inputs to the price variation

and the trend sign. In its application to the Taiwan stock market index, it was found that the proposed model far exceeded the prediction with AR, ARMA and fuzzy logic models.

In the scientific literature there are also models that combine neural networks with genetic algorithms. Hao (2010) proposes a neuro-genetic network to prediction the price of shares in the short term in the stock exchange of Shenzhen (China), which combines the ability to search for genetic algorithms in order to determine the neural network optimal weights. The proposed model yielded very good results in the prognosis of the following four days, however, the error was greater by increasing the number of days or when trying to address the problem with weekly data.

A hybrid model using genetic algorithms, fuzzy logic and neural networks is proposed by Hadavandi et al. (2010). Its application to the price prediction of two technological stocks and two airlines showed a better performance in the model when compared with similar works that used neural networks or diffuse logic individually.

Since the majority of references consulted have focused on the price prediction in mature financial markets located in developed countries and that in previous work of our research group a better performance of artificial intelligence models has been found in the price prediction in the electricity and currency markets; This paper proposes a model based on PSO optimized neural networks for the price prediction of the American stock market. The proposed model is applied to the study of the price of the shares of AAPL inc. taking into account that it trades in the American stock exchange at New York. Different neural network structures are tested using the price series and the six-year US dollar index, where the two years data are used for training leaving the last year for prediction. The results demonstrate the applicability and good behaviour of neural networks in emerging markets such as America, obtaining low performance errors both inside and outside the sample.

II. ARTIFICIAL NEURAL NETWORKS

A neural network is a system that allows establishing a linear or non-linear relationship between outputs and inputs. Its characteristics are inspired by the nervous system which gives them several advantages such as their adaptive learning capacity, are self-organizing, can operate in parallel in real time and offer fault tolerance for redundant coding of information.

From the point of view of solving problems, neural networks are different from conventional computers that use sequential algorithms, while neural networks act like the human brain, processing information in parallel, and can also learn and generalize to situations not included in the training process. Neural networks can process information faster than conventional computers, but they have the disadvantage that we cannot follow their response step by step as you can do when running a conventional program on a computer so it is not easy to detect errors.

Artificial neural networks are very effective in solving complicated classification and pattern recognition problems. The most used is the forward propagation call. Figure 1 shows a forward propagation network with two hidden layers. The number of inputs is directly dependent on the information available to be classified while the number of output neurons is equal to the number of classes to be separated. The units of one layer are connected unidirectionally with those of the next, in general all with all, subjecting their outputs to multiplication by a weight that is different for each of the connections.

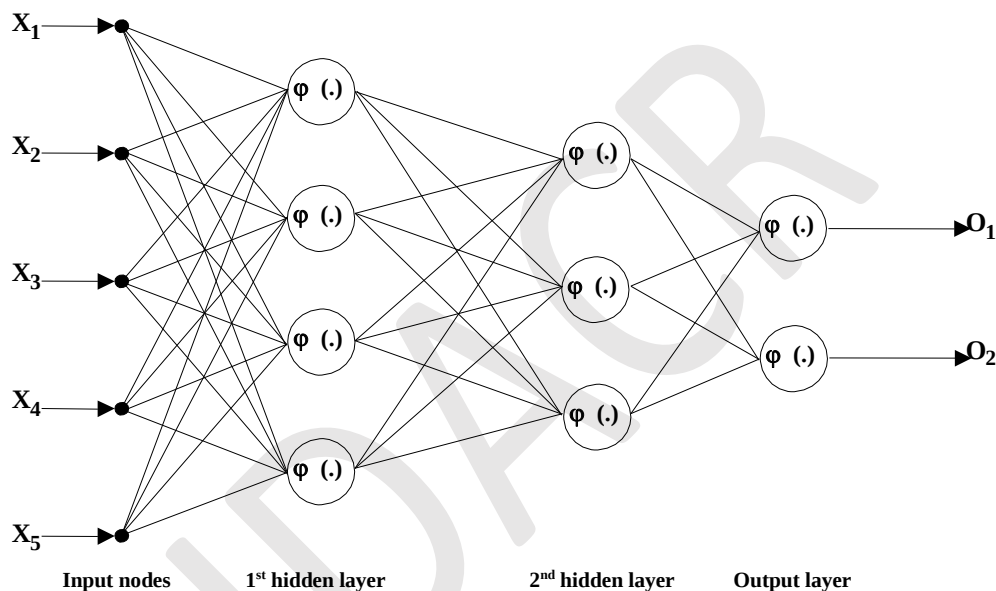


Figure 1: Feed-forward neural network

Artificial Neural Networks have been used to solve numerous problems. Among these are the economic and financial ones, highlighting to a large extent their application in the prediction of time series and their ability to detect and exploit the non-linearity existing in the data, even in conditions where there are incomplete data or the presence of noise; They also stand out for their performance in solving complex problems, where the recognition of models or behaviours is important.

III. PSO OPTIMIZED NEURAL NETWORKS AND PREDICTION OF THE PRICE OF SHARES

For the development of the model, historical data on the price of shares of AAPL inc. were collected, which are simultaneously traded on the Nasdaq stock exchanges. This information was obtained

from the website of the American stock exchange (<https://www.nasdaq.com/>). The input variables correspond to the daily closing prices in United States Dollar (USD) and as a single output you have the price to prediction for the next day.

The network that was used was the multilayer perceptron with forward connections, because within the framework of neuron networks, the perceptron has been shown to be one of the most useful architectures in solving these types of problems. This is due, fundamentally, to its ability as a universal approximator. The architecture of this network is characterized because it has its neurons grouped in layers of different levels. Each of the layers is formed by a set of neurons and three different types of layers are distinguished: the input layer, the output layer and the hidden layer. Each neuron has its respective threshold level and the

transfer function used in all neurons was the hyperbolic tangent.

A. Learning Algorithm

The learning rule or algorithm is the mechanism by which all network parameters are adapted and modified. In the case of the multilayer perceptron it is a supervised learning algorithm; that is, the modification of the parameters is made so that the network output is as close as possible to the output provided by the supervisor or desired output. Therefore, the network learning process is equivalent to finding a minimum of the error function. The learning algorithm used was of the conjugate gradient type because in general it has shown to have a faster convergence, that is, it requires fewer iterations to reach the specified error level.

B. Learning Process

The objective of the learning or training of the network is to adjust the parameters of the network, weights and thresholds, so that the inputs presented produce the desired outputs, that is, in order to minimize the error function. Regarding the number of layers and neurons per layer, there is no method or rule that determines the optimal number of hidden neurons to solve a given problem, they are usually determined by trial and error, that is, starting from an already trained architecture, changes are made by increasing and decreasing the number of hidden neurons and the number of layers until the architecture that fits the problem is achieved. The selection of the best structure in this work was determined by means of the traditional prediction evaluation measures inside and outside the sample, described in the next section.

C. Prediction Model with Neural Networks

In this work, different structures of neural networks with a hidden layer were tested, starting from a number of neurons equal to the average between the number of inputs and the number of outputs. Then the number of neurons in said layer was gradually increased until obtaining the most recommended structure for prediction the price of the shares studied. The selection of the best network structure is made considering the following evaluation measures inside and outside the sample: RMSE (Root Mean Square Error) and the MAPE (Mean Absolute Percentage Error), calculated using equations 1 and 2.

$$RMSE = \sqrt{\frac{1}{n} \sum_{t=1}^n (y'_t - y_t)^2} \quad (1)$$

$$MAPE = \frac{100}{n} \sum_{t=1}^n \left| \frac{y'_t - y_t}{y_t} \right| \quad (2)$$

Where n is the number of observations considered, and t is the real price and y'_t is the price estimated by the model.

In previous phase, Neural Network is trained using back-propagation algorithm to find weight and bias values. The proposed PSO-NN approach uses particle swarm optimization to find weight and bias values. In this method, the value of weight and bias are random and to correct these values a fitness function is employed for PSO.

Fitness Function: The fitness function is a function of weight and bias with the objective of minimizing the mean square error between the predicted and target classes of the training data.

$$\min F(w, v) = \sum_{t=1}^q [c_t - (wx_t + v)]^2 \quad (3)$$

Where, x_t is input and c_t is target output.

Fitness function in equation (3) is minimized using PSO to optimized weight and bias values.

D. Particle Swarm Optimization

James Kennedy and Russell C. Eberhart proposed a PSO approach in 1995. This approach is a heuristic method [14]. The evaluation of candidate solution of current search space is done on the basis of iteration process (as shown in Figure 2). The minima and maxima of objective function is determined by the candidate's solution as it fits the task's requirements. Since PSO algorithm do not accept the objective function data as its inputs, therefore the solution is randomly away from minimum and maximum (locally/ globally) and also unknown to the user. The speed and position of candidate's solution is maintained and at each level, fitness value is also updated. The best value of fitness is recorded by PSO for an individual record. The other individuals reaching this value are taken as the individual best position and solution for given problem. The individuals reaching this value are known as global best candidate solution with global best position. The up gradation of global and individual best fitness value is carried out and if there is a requirement then global and local best fitness values are even replaced. For PSO's optimization capability, the updation of speed and position is necessary. Each particle's velocity is updated with the help of subsequent formula:

$$v_i(t+1) = wv_i(t) + c_1r_1[\hat{x}_i(t) - x_i(t)] + c_2r_2[g(t) - x_i(t)] \quad (4)$$

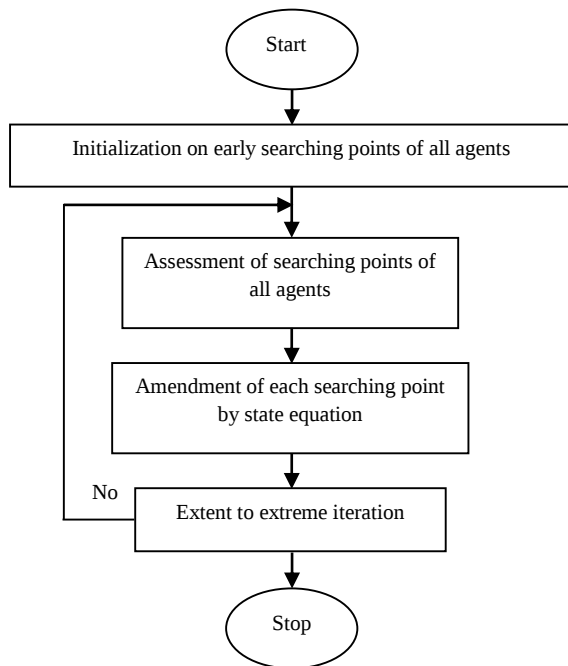


Figure 2: Flow chart of PSO algorithm

This work is aimed at the needs of a swing trader operating in the American stock exchange, whose main objective is to have an idea of the future value of an action in the coming days; in this way a prediction horizon of one year was chosen for which it was found that the PSO optimized neural network was adequately trained with the data of the previous two years.

IV. SIMULATION AND RESULTS

The performance of proposed algorithms has been studied by means of MATLAB simulation.



Figure 3: AAPL stock price from January 2010 to December 2016

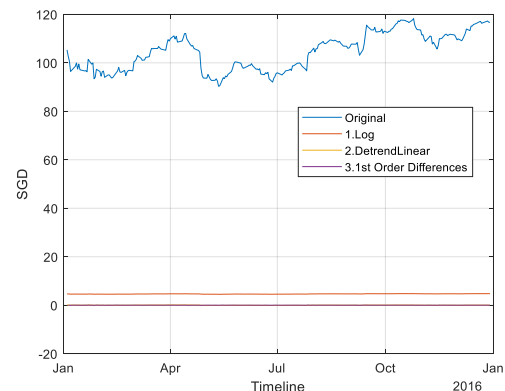


Figure 4: AAPL stock price in year 2016

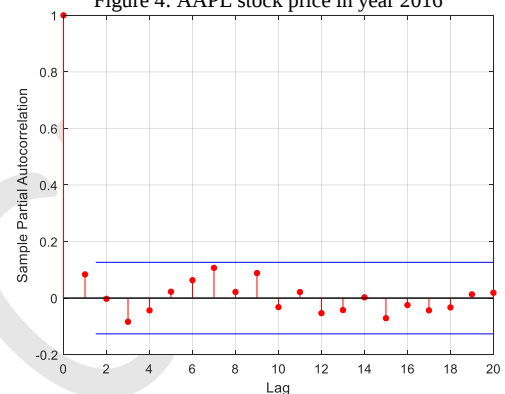


Figure 5: Sample partial autocorrelation function



Figure 6: AAPL stock price in year 2015 using neural network

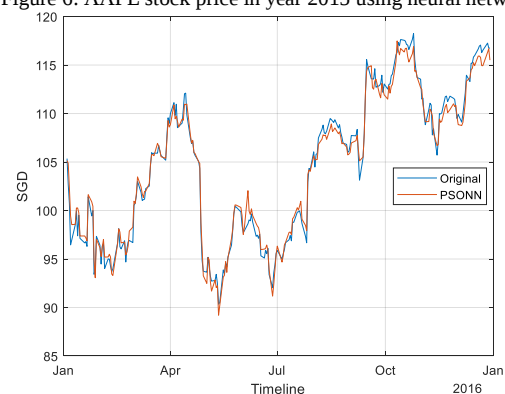


Figure 7: AAPL stock price in year 2015 using PSO optimized neural network

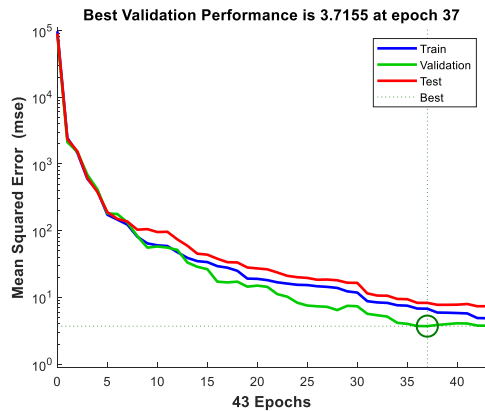


Figure 8: Mean squared error graph

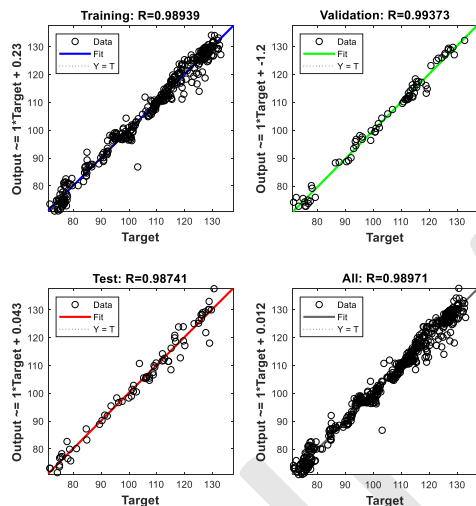


Figure 9: Output

V. CONCLUSION

The successful use of PSO optimized artificial neural networks to prediction the price of the American stock exchange demonstrates their applicability in emerging markets. The advantages of neural networks are concluded as they are simpler models to implement and allow to obtain low prediction errors both inside and outside the sample. The effect of including the particle swarm optimization improved the performance of the neural network. Although the applications shown were in actions of different economic sectors (energy and financial), it was found that practically the same PSO optimized neural network structure using only the price series, can reliably represent the actions used.

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