The Use of Artificial Neural Networks in the Analysis and Prediction of Stock Prices

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***Abstract*—In recent years there has been a significant growth of interest in the incorporation of historical series of variables related to stock prediction into mathematical models or computational algorithms in order to generate predictions or indications about expected price movements. The objective of this study was to utilize artificial neural networks to predict the closing price of the stock PETR4 which is traded on BM&FBOVESPA. Three stages were used to generate the prediction: obtainment of the samples, pre-processing, and prediction. 32 different configurations were created by varying the window size and prediction horizon. The best performance was obtained with 5 days of quotes and a prediction horizon of 1 day where the mean squared error was 0.0129.**

***Index Terms*—Artificial Neural Network, Financial Time Series, Stock, PETR4, Forecasting.**

I. Introduction

Comprehending complex financial markets requires the assimilation and analysis of many variables. To build stock models, two types of prediction have been used: one-step-ahead and multiple-steps-ahead. Zhang, Patuwo and Hu [1] describes two methods reported in the literature of making predictions using multiple step predictions.

The first method is called iterative prediction which is used in the Box-Jenkins model where the prediction values are iteratively used as inputs for subsequent predictions. Considering models based on artificial neural networks (ANN), only one output neuron is necessary.

The second method is called the direct method and consists of placing various outputs in the neural network which correspond to the desired prediction horizons. Zhang, Patuwo and Hu [1] suggests that the predictions of multiple step predictions using the direct method perform better than the iterative method for the following reason: neural networks can be constructed directly for multiple step predictions while the iterative method constructs only one function that is used to predict one point at a time and then repeats this function to predict points in the future.

The discussion and comparison of the performance of traditional methods and methods based on neural networks began in the 1990s [2–12]. According to Palit [13], linear prediction using non-linear mapping of neural networks cannot generate better results than statistical algorithms. Conversely, the use of neural networks, when dealing with non-linear time series data, could obtain better results than traditional statistical algorithms.

The aim of this article is to apply ANN to predict the closing price of stocks traded on the São Paulo Stock Exchange (BM&FBOVESPA) in various standard horizons, and the tendencies of future behavior within these horizons. Time series of historical stock price quotations were used, as well as technical indicators and macroeconomic series, using the stock PETR4 of the company Petróleo Brasileiro S.A (Petrobras) as a case study. Results show that the direct method with horizons of 1, 5, 15, 22, 37, 44, 66 and 110 days of quotes follow the behavior and tendency of the stock.

The study is divided into four sections. Section II describes the proposed method of analysis of the financial market. Application and experimental results are presented in Section III. Finally, Section IV describes the conclusions of the study.

II. Proposed Method

A set of 3 stages (Figure 1) was necessary to predict the behavior and tendencies of the shares: 1) obtainment of the samples; 2) pre-processing of the inputs; 3) the task of prediction itself. The following sections describe each of the stages.

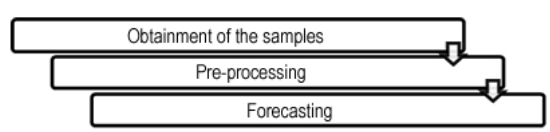

Fig. 1. Stages of the prediction process.

A. Obtainment of the Samples

The sample data set consisted of the series presented in Table I. PETR4 is the ticker symbol of the preference shares of the company Petróleo Brasileiro S.A. (Petrobras). Pre-processing was conducted on the daily quotes for PETR4 in order to include technical indicators which are mathematical calculations applied to the series of prices. The result is a value used to anticipate changes in the stock price [14–16]. These indicators were calculated from samples relating to the period 04/01/2000 to 18/08/2009 which represents a total of 2,384 observations.

TABLE I
SUMMARY OF VARIABLES.

Series Name	Series Description	Category	Variable
Opening	First trading prices	PETR4 quote	Z1
Closing	Last trading prices	PETR4 quote	Y
Highest	Highest trading price	PETR4 quote	Z2
Minimum	Lowest trading price	PETR4 quote	Z3
Volume	Number of stocks traded	PETR4 quote	Z4
Ibovespa	Bovespa index	Index	Z5
Dow Jones	Dow Jones index	Index	Z6
Selic	Over-Selic, Basic interest rate	Macroeconomic series	Z7
CDI	Bank Deposit Certificate	Macroeconomic series	Z8
WTI-Cushing	West Texas Intermediate Dollars per Barrel	Macroeconomic series	Z9
USD-Sell	US Dollar sell-price	Macroeconomic series	Z10
USD-Buy	US Dollar buy-price	Macroeconomic series	Z11
EMA(5)	5-day Exponential Moving Average	Technical Indicator	Z12
EMA(22)	22-day Exponential Moving Average	Technical Indicator	Z13
EMA(200)	200-day Exponential Moving Average	Technical Indicator	Z14
BBLineBottom	Lower Bollinger band	Technical Indicator	Z15
BBLineTop	Top Bollinger band	Technical Indicator	Z16
BBLineMiddle	Middle Bollinger band	Technical Indicator	Z17
MACD	Moving Average Convergence Divergence	Technical Indicator	Z18
AC	Acceleration/Deceleration	Technical Indicator	Z19
AO	Awesome Oscillator (AO)	Technical Indicator	Z20
WilliamsR	Williams %R	Technical Indicator	Z21

B. Pre-processing

1) Cleaning: The sample set has no information for certain days due to holidays or days when there was no trading. For example, the *Dow Jones* index series represents the average profitability of a portfolio of stocks on the New York Stock Exchange (NYSE), which, as a result of bank holidays in Brazil, caused missing values for the Brazilian quote series on those days, or vice-versa.

Cleaning the missing data consists of excluding the tuples from the sample set which contain at least one incomplete attribute. In other words, for each date on which there was missing data, that date was removed from the sample set. On one occasion where the quantity of missing data was relatively small (corresponding to 2.3% of the total), the data was eliminated. However, the authors are working on techniques for recuperating missing data for these cases.

2) Data normalization: Since the series of sample sets have different value scales, it was necessary to adjust the scale of each series into the range [0 to 1].

The normalization method chosen was the linear interpolation [17] (1).

$$A' = \frac{(A - MIN)}{(MAX - MIN)} \tag{1}$$

Where:
A' = normalized value;
A = value to be normalized;
MIN = minimum value of the series to be normalized;
MAX = maximum value of the series to be normalized;

C. Prediction

The direct method was used for predicting the stock closing price, which consists of inserting the series $Y_t(h) = (Y(t), Z_1(t), Z_2(t), Z_3(t), ..., Z_21(t))$, where the components denote the sample set which forms the network input vector and obtains $Y_t(h)$ as output, which is the prediction of $Y_t(t+h)$, of origin t and horizon h.

1) Network Architecture: The network model chosen for prediction was the *MLP feedforward* for its efficiency in the time series prediction process, as well as being the model chosen by [3], [18], [19], [20] and [21] for their studies, where the results obtained were satisfactory.

The network structure (Figure 2) is composed of three layers, being one input layer, one hidden layer and one output layer. The number of neurons in the input layer is defined by the window size (period in days) multiplied by the number of sample set series. The number of neurons in the hidden layer, obtained through experimental results, corresponds to the quantity of sample set series, being 22. The number of neurons in the output layer is defined by the size of the prediction horizon. The activation function chosen for use in the network was the log-sigmoidal.

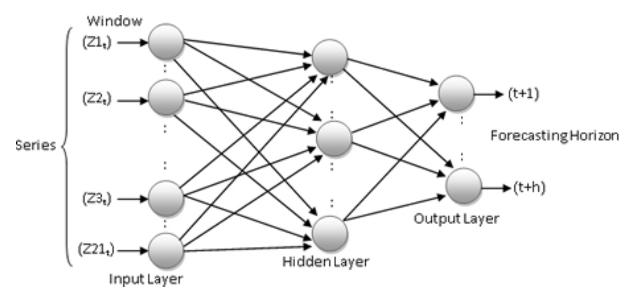

Fig. 2. Proposed network structure.

Table II shows the window sizes and the prediction horizons chosen in this study. For each window size (the number of daily quotes that were used as network inputs), the prediction horizons $\widehat{Y}_t(h)$ = 1, 5, 15, 22, 37, 44, 66 and 110 were tried, corresponding to the number of days that were predicted which represent the typical periodicities of market trading, with long and short trading periods.

TABLE II
WINDOW SIZES AND PREDICTION HORIZONS CHOSEN IN THIS STUDY.

Window sizes	Prediction horizons
5	1; 5; 15; 22; 37; 44; 66; 110.
10	1; 5; 15; 22; 37; 44; 66; 110.
15	1; 5; 15; 22; 37; 44; 66; 110.
22	1; 5; 15; 22; 37; 44; 66; 110.

2) Training process: Learning was conducted through a supervised process in which the inputs and intended outputs were provided to the network. The algorithm chosen for the network training was *resiliente backpropagation* [22], an adaptation of the standard *backpropagation* algorithm [23]. The algorithm aims to eliminate the negative influence of partial derivatives on weighting adjustment. For network convergence, the number of epochs was set at 10,000 and the minimum error rate at 0.001. In other words, the training ended when one of these two conditions was met.

The sample set passed through a "windowing" process in accordance with the window size chosen and the prediction horizon (as shown in Figure 3). Subsequently, the sample set was divided into two sub-sets which were randomly selected without replacement for better network generalization. One was a training set consisting of 2/3 of the samples and the other was for validation and testing consisting of 1/3 of the samples.

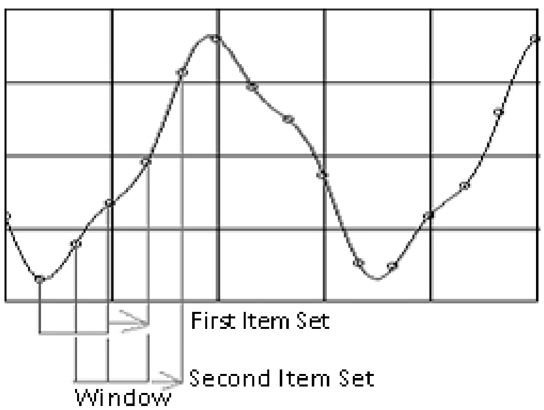

Fig. 3. Windowing technique.

3) Results validation: After the network training process was complete, the validation and test set was used to validate and measure the network performance. The methods used for measuring the performance of the neural network are presented in 2 and 3.

Root Mean Square Error - RMS, (2)

$$RMS = \sqrt{\frac{1}{n}\sum (predicted_i - current_i)^2} \qquad (2)$$

Mean Percentage Error - MRPE, (3)

$$MRPE = \frac{1}{n}\sum |predicted_i - current_i| * 100\% \qquad (3)$$

III. Results and Discussion

Experiments were performed to predict the PETR4 stock price for 32 configurations (4 window sizes x 8 prediction horizons) in order to obtain the best possible configuration, as shown in Table II. The objective of the tests was to analyze the influence of window size on the prediction horizon (Table III). A total of 2,384 observations were used in the experiments which related to the period from 04/01/2000 to 18/08/2009 and which passed through the "windowing" process described above.

It can be observed from Table III that the variance increases as the prediction horizon increases, reflecting the increased uncertainty of the predictions for $\widehat{Y}_t(h)$ multiple step predictions.

TABLE III
Prediction of Error as a Function of Window Size.

Prediction horizons	RMS				MRPE			
	5	10	15	22	5	10	15	22
1	0.0129	0.0161	0.0179	0.0168	0.79%	0.84%	0.92%	0.92%
5	0.0184	0.0191	0.0168	0.0203	1.07%	1.14%	1.01%	1.14%
15	0.0241	0.0224	0.0217	0.0214	1.52%	1.34%	1.31%	1.28%
22	0.0248	0.0233	0.0189	0.0188	1.60%	1.47%	1.21%	1.16%
37	0.0292	0.0228	0.0204	0.0201	1.80%	1.40%	1.29%	1.29%
44	0.0292	0.0240	0.0208	0.0223	1.80%	1.49%	1.31%	1.39%
66	0.0297	0.0263	0.0224	0.0206	1.85%	1.62%	1.44%	1.31%
110	0.0329	0.0278	0.0249	0.0219	2.02%	1.75%	1.62%	1.40%

For prediction horizons h = 1 and h = 5, the performance indicators (RMS and MRPE) worsened as the input window and $\widehat{Y}_t(h)$ increased. Indicating that the closing price for these horizons are determined by smaller window sizes. In future studies, heuristics will be used to determine the appropriate window size in relation to the horizon. In the present experiments, the configuration of window size of 5 days and prediction horizon of h=1 generated the best results for the indicators RMS and MRPE.

The performance indicators (RMS and MRPE) for prediction horizons h=15 to h=110 were improving as the input window increased. This is due to the fact that all the information needed to predict $\widehat{Y}_t(h)$ can not be contained in smaller windows.

Figures 4, 5, 6 and 7 shows comparative graphs for the real data and the data obtained by the neural network for the test set with windows of 5, 10, 15 and 22 and a prediction horizon of 1 day.

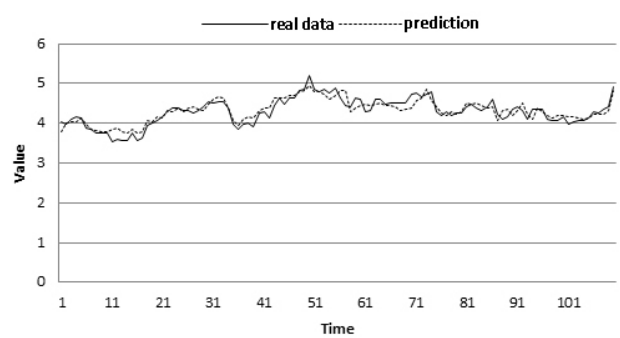

Fig. 4. Prediction chart of the 5-day window test set and 1-day prediction horizon.

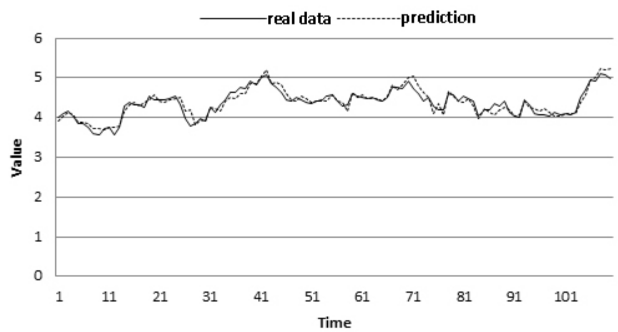

Fig. 5. Prediction chart of the 10-day window test set and 1-day prediction horizon.

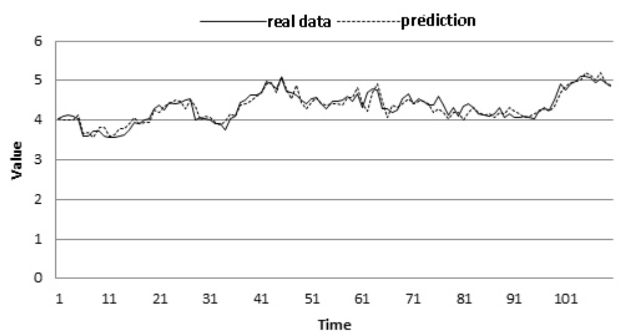

Fig. 6. Prediction chart of the 15-day window test set and 1-day prediction horizon.

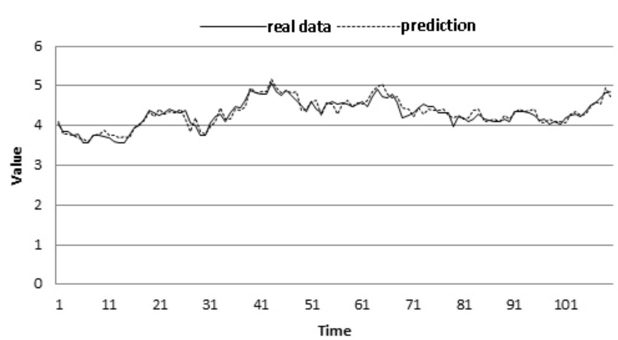

Fig. 7. Prediction chart of the 22-day window test set and 1-day prediction horizon.

IV. Conclusion

This study used artificial neural networks to predict the closing price of the stock PETR4, traded on BM&FBOVESPA. 32 different configurations of window size and prediction horizon were created to make it possible to analyze the influence of the window size on the performance of the network, with the aim of obtaining the best possible configuration.

An analysis of the experiments and table of performance measures presented in this study reveals that increasing the window size and prediction horizon causes the performance measures to worsen. A possible explanation for this is the fact that the distribution of Z changes between t+1 and the following period. This change can be explained economically.

In the experiments conducted in this study, the best performance was obtained with 5 days of quotes and a prediction horizon of 1 day, with RMS of 0.0129. The graphs of the predicted values versus the real values show that the predicted series follows the real series. Prediction horizons larger than 1 day would have great practical application in the market since knowing what the price will be tomorrow, next week or next month, in accordance with the chosen horizon, would allow n trading strategies in the market. One application would be in the stock market where the shareholder has the right to buy or sell shares in the future for a determined price.

In general, the results were satisfactory as they successfully achieved the objective of the study to predict the closing price of the stock PETR4, following its behavior and tendency.

In conclusion, the use of ANN to predict the behavior and tendencies of stocks has demonstrated itself to be a viable alternative to existing conventional techniques, demonstrating the average behavior of the market in the chosen prediction horizon. This gives the investor privileged information and can be used in conjunction with other techniques.

V. Acknowledgment

The authors acknowledge the financial support received from the Foundation for Research Support of Minas Gerais State, FAPEMIG, through Project CEX PPMIII 67/09, and the National Council for Scientific and Technological Development, CNPq, Brazil.

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