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A Neural Network based approach to support the Market Making strategies in High-Frequency Trading

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***Abstract*—Artificial Neural Networks (ANN) have been frequently applied to reduce risks and maximize the net returns in different types of algorithm trading. Using a real dataset, and aiming to support the Market Making process in High-Frequency Trading, this work investigates the use of a multilayer perceptron (MLP) to predict positive oscillations in short time periods (5, 10 or 15 minutes). The statistical analysis of our results showed that a neural network is more effective in short-term oscillations (5 minutes) when compared with the results obtained in longer periods (10 or 15 minutes). The result is important because it allows to insert a higher quantity of limit orders once they will be placed more frequently, which increases the market liquidity. It contextualizes a new contribution in the High-Frequency Trading field, where this work proposes a new trigger to start a market making process.**

I. INTRODUCTION

Currently, there are several algorithmic traders that use electronic platforms for inserting orders in markets without the human intervention [1]. A particular type of algorithmic trading is High-Frequency Trading (HFT). This category of trading emerged in the last decade and recently has gained attention from academic researches. Studies suggested that HFT firms accounted for 50-75% of all US equity trading volume in the last 3 years [2].

In this new category of trading (HFT), the Artificial Intelligence field has been investigated using Artificial Neural Networks (ANNs) [3] and Fuzzy Systems [4], [5].

Nowadays, one of the most common type of HFT is by performing a process called Market Making [2], [6]. The market markers place buy and sell limit orders (simultaneously or not) with the purpose of making profit through small fluctuations in stock prices. With the objective to maximize the net return, the attempt to forecast if the stock price will go up in the next few minutes can help market makers because limit orders will be inserted following the expected trend. If the forecast trend is confirmed, the market making process can perform trades in the prices suggested at the beginning of execution. Otherwise, losses are usually acquired. This work presents a study using an Artificial Neural Network (ANN) based on a Multilayer Perceptron (MLP) to predict the positive oscillation in the stock price considering short time windows. This method can be used as a support decision for market making process.

In this work, using a real and reliable dataset, five liquid symbols of Brazilian Stock Exchange (BM&F BOVESPA) are investigated. This work performed an experimental analysis, varying the size of the time window (basis to forecast the positive oscillation through a neural network). The results indicate that a neural network is more effective in short-term oscillations (5 minutes) when compared with the results obtained in longer time windows (10 or 15 minutes). This result is also significant for other investors because, if applied, allows the execution of a higher volume of limit orders for market making, which increases the market liquidity.

It is noteworthy that, besides the high-frequency, the methodology proposed in this work can be applied to other types of algorithm trading, e.g., in medium and low frequencies. Moreover, the methodology can be employed to predict negative oscillations of stock prices for market makers.

The remainder of this paper is organized, as follows. The related works are presented in Section II. The Section III decribes the methodology used in this work. The experiments and their analysis are showed in Section IV, followed by the conclusions and future directions (Section V).

II. RELATED WORK

Before the advent of computers, the stock market investors made their negotiations based mainly on intuition. With the growth of investments and stock trading, a continued search for better tools to accurately predict the stock market has become necessary in order to increase profits and reduce losses.

Statistical regression, technical analysis, fundamental analysis, time series analysis, chaos theory are some of the techniques that have been adopted to predict the market trends [7]. However, these techniques are not able to generate consistently a correct prediction of the stock market, generating many doubts among analysts about the use of many of these approaches [8]. Thus, predicting the change of price movement in stock markets and try to make correct investment decisions is one of the main needs and challenges in this context [9].

The concept of artificial neural networks (ANN) was introduced around a half century ago, but only in late eighties it can be seen a significant gain in scientific and technical presentations in this area. In recent years, there have been a large number of research papers on the application of neural networks in economics and finance [10], [11].

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ANN have been used in several works in developing applications to aid in financial decision making. Simple neural networks models could provide a good prediction of price movement of the stock market. This performance increases the complexity of the network architecture and uses more historical data. Different ANN architectures, such as Multilayer Perceptron (MLP), Generalized Feed Forward networks and Radial Basis Functions (RBF) are increasingly being used and tested for accuracy. Many researchers are also investigating the possibility of adding indicators that can help to improve the neural network training and performance with actual datasets, minimizing errors in forecasting [12].

The first significant study on the application of neural network models for prediction of the financial market was published by White [13]. He presented some results, using techniques of modeling and neural network learning to discover and decode nonlinear regularities in stock price movements. The study was focused on the stocks of IBM and with granularity of Daily returns. Having to deal with the main features of economic data, the statistical inference played an important role and technical changes were necessary to the learning process. After this study, several research efforts have been conducted to examine the effectiveness of prediction of neural network models in stock markets [14], [15], [16], [17].

In the work [18], the authors investigated the use of neural networks to predict the future trend of the stock market index. In this work they compared the accuracy of ANN prediction with multiple linear regression analysis, which is a traditional technique. Furthermore, the error probability of the prediction model is calculated using conditional probabilities. This study achieved a probability of 93.3% in predicting the rising market movement and 88.7% in drop movement in the S&P 500 stock market index. The authors concluded that neural networks are able to predict the financial market and, if properly modeled and trained, investors can benefit from the use of this predictive tool.

A new model of ANN to predict the stock price on the Singapore Stock Exchange (SES) using the stocks of Singapore Airlines (SIA) is presented in [19]. The model was built to predict the closing price of the SIA within one week, based on current and historic knowledge of the maximum, minimum and closing prices and, also, the trading volume. The output layer of the neural network has only one node that stores the value of the closing price provided for one week from the current day. The network was trained using supervised learning through the generalized delta rule. They verify that the closing prices provided are very close to real. From the 50 test cases, 47 (94%) presented absolute errors less than 5% and 35 predictions (70%) showed absolute errors lower than 1%. The work [8] reports that the application of neural networks to predict the financial market variables and the use of technical analysis and fundamental analysis is a predominant factor for stock market predicting. The article presents a hybridized approach that combines the use of variables of technical and fundamental analysis as indicators of the stock market to predict future stock prices. The obtained results showed significant improvement compared to using only variables of technical analysis. In another context, the prediction approach was also satisfactorily as a guide for traders and investors in making qualitative decisions.

In [20], they used algorithms for training neural networks to predict Standard&Poors 500 Index and then compared the results using a genetic programming (GP) approach. Feed forward networks were used to predict the index value and the network was trained using a back propagation algorithm. The neural networks were trained to predict the variation of the closing price of S&P 500 for next 1, 2 and 4 weeks. The model performed well using historical data as input. However, as the author mentioned, the future performance of the model is not guaranteed, which demand new researches and strategies to improve the consistency of this kind of approach.

Chen et. al [21] present a survey of the literature on prediction mechanisms, including prediction markets and peer prediction systems. They focus on the design process, highlighting the objectivesand properties that are important in the design of good prediction mechanisms.

In the High-Frequency Trading context, the approach in [3] used artificial neural network model as input popular technical indicators to predict trading signals, which can be useful to perform day trading. The dataset used to build the model is the high frequency ticks of intra-day stocks from some industry sectors in the Indonesia Stock Exchange Market. The authors used a multilayer feedforward perceptron with one hidden layer and training using the backpropagation algorithm. The study compares the performance of the model with naïve buy-and-hold strategy and the maximum profit profile. The experimental results showed that the proposed model performed better than naïve strategy. Thus, the author concluded that the ANN is useful to generate trading signal predictors for intra-day traders from the high frequency dataset.

In [4], a new approach for High-Frequency order execution is proposed using a novel way of momentum analysis which makes use of fuzzy logic reasoning mechanisms. The algorithm proposed order placement algorithm also considers the market's intraday volatility to minimize trading costs. The study reports that find better order execution rates is an intriguing problem and to brokers trading large orders, the effect of size of the order, market's trend and volatility are crucial for order scheduling.

This work presents a new approach to predict the positive oscillations in stock market, which can be applied in strategies for High-Frequency Trading. This methodology also can be used in other trading contexts, like low and medium frequencies strategies.

III. Methodology

The main objective of this work is to model an Artificial Neural Network (ANN) to predict the positive oscillation of stock prices in short term windows. The stocks of the companies discussed in this article include: *Banco Bradesco S. A.* (BBDC4), *Banco do Brasil S. A.* (BBSA3), *Usinas Siderurgicas de Minas Gerais S.A.- USIMINAS* (USIM5), *Petroleo Brasileiro S.A. Petrobras* (PETR4) e *Vale S.A.*(VALE5). These companies are part of a select group of Brazilian symbols (BM&F Bovespa), called Bovespa Index. The Bovespa Index is the result of a theoretical portfolio of assets prepared in accordance with the criteria established in its methodology[1]. The companies that participates of Bovespa Index have greater marketability and representativeness of the Brazilian Stock Exchange. Thus, the chosen stocks for our experiments can be considered liquid and very important in the Brazilian Stock Exchange.

The data of stock prices of these five companies were acquired through the real-time data gathering (data feed), received directly from a brazilian licensed vendor[2]. Initially, the system processes the raw data (tick by tick), to synthesize it in a larger granularity, called candlestick. A candlestick represents the price variability of a certain asset in a time unit (e.g., 15 minutes), as shown in Figure 1. It represents:

- Open - the first trade price in the period;
- Close - the last trade price in the period;
- High - the higher trade price in the period;
- Low- the lower trade price in the period.

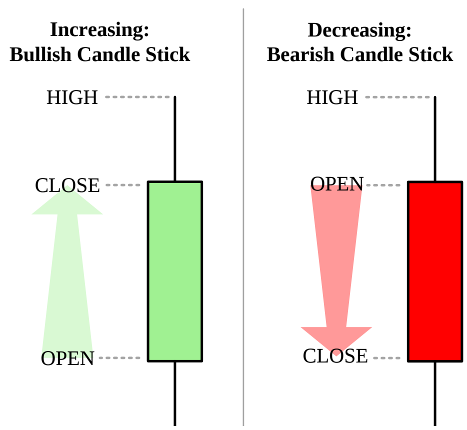


Fig. 1. Representation of a candlestick.

The time interval depends on the analysis to be performed, which may be minutes, days, weeks, or months. In this work the proposed system uses the candlesticks of 5, 10 and 15 minutes of time intervals. The goal is to evaluate the influence of temporal granularity in predicting fluctuations in the price of an asset.

A. General Overview

For generation of the patterns used in the prediction model, this work used the candlesticks on the equivalent of one day negotiation sequence. The candlesticks were used to generate the technical analysis indicators [22], considering its importance in terms of price variation. These indicators are presented in Section III-B.

The pattern generation of the neural network follows the methodology illustrated in Figure 2. As this paper attempts to predict stock price oscillation for a given time interval, this interval was defined as Time Window. From the point of view of the stock market, the Time Window is equivalent to the period of the operation of a particular strategy, that is, the difference between the start time of an operation and its finalization. For example, if the system can predict that a stock will have a positive oscillation of R$0.07 at an interval of at most 15 minutes, the Time Window will be 15 minutes. Then, the proposed system inserts a new limit order to try to buy this stock in the best bid price and inserts another one to try to sell using the best bid price plus 7 cents. In this case, the execution can obtain a profit of R$0.07 in this time window per share.

In this context, this work check if the stock price presented an expected oscillation in the Time Window, checking in the future to identify the occurrence or not of this variation. Using the Time Window of *Checking Oscillation* shown in Figure 2 as an example, if the system execution is in time t_4 and the Time Window is of 5 units of time, the system needs to check all candlesticks until t_9 to identify if the desired variation has occurred. Such verification is performed as follows:

$$var = Max(t_i, t_j) - OpenPrice(t_i) \tag{1}$$

where t_i is the instant of time where the operation is started, t_j is the instant of time equivalent to the size of $t_i + TimeWindow$, $Max(t_i, t_j)$ is the highest price achieved by the stock between t_i and t_j. Finally, $OpenPrice(t_i)$ is the starting price of the candlestick at time t_i.

The output of the neural network is taken as follows: it takes the value 1 if the stock presents the defined positive oscillation within Time Window; and 0 if it has not presented such variation.

In order to generate the set of entries of the neural network, the proposed system sets a time period called *Generating Indicators*, as shown in Figure 2. In this period, the system used a set of candlesticks in the past considering the specified length of Time Window. For example, if the proposed system is in time t_4, it needs go back to the time t_0 for generation the set of inputs, considering the Time Window equals to 5 units of time. The system works with candlesticks being generated each minute. In the experiments, the system varies the Time Window to analyze which would be the best granularity in predicting the stock price oscillation. Details can be seen in Section IV.

Considering a trading session, the system trained the neural network up to a specific time point. And applies the remainder negotiation time as a test dataset. Thus, the proposed system divided the data for each trading day into two parts: the first part contains the training data and the other one, the test data.

B. Technical Analysis Indicators

The proposed methodology in this work considers the characterization and analysis of various technical analysis indicators. An indicator can be defined as a series of data points, which are derived from the price information of stocks applied to a mathematical formula. The data set of price attributes of each stock is a combination of the price of opening, closing, maximum and minimum over a period of time [23].

[1] Ibovespa index:
http://www.bmfbovespa.com.br/indices/ResumoIndice.aspx?Indice=Ibovespa&Idioma=en-us

[2] Current licensed vendors of BM&F BOVESPA market data:
http://www.bmfbovespa.com.br/en-us/services/market-data/authorized-vendors.aspx?idioma=en-us

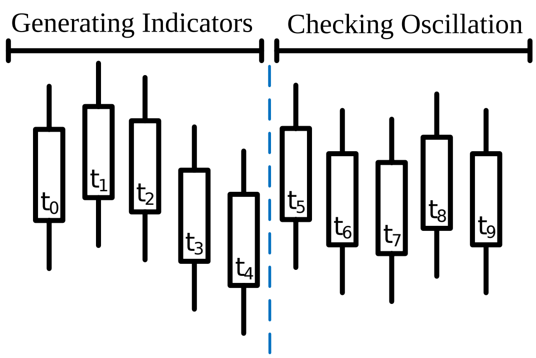


Fig. 2. Building the prediction model

Market analysts generally use one or more indicators for their analysis [23]. These indicators are usually chosen by evaluating the accuracy of the model. Most often, many indicators are omitted and a good model can never be discovered for a particular stock, that is, the more information you have, the better will be the outcome of the model. If the input data are not relevant to the desired output, probably the model will not learn well the associations between the data input and output. Thus, the first step is to use a set of indicators commonly used in traditional technical analysis. Another approach is to perform a correlation analysis, which is useful to search linear relationships between the desired output and the proposed set of inputs. More specifically, a correlation analysis determines whether an input and its desired output vary in the same direction with similar values. Using inputs with high correlation values with the output tend to generate good models [12]. In order to specify the attributes or indicators to adopt in the experiment, this paper previously performed a general characterization of them, observing the typical behavior of each analyzed attribute and the historical stock oscillation, trying to infer which of them has potential to be used in our model.

Next, this paper briefly describes each indicator used as input in our model [3].

1) Relative Strength Index (RSI): RSI is an indicator that measures the speed and change of price movements. It is calculated using the amount of change in the rising and falling prices over a specified period of time. The formula for computing the RSI is as follows:

$$RSI = 100 - \left(\frac{100}{1 + RS}\right) \tag{2}$$

where RS is the average of the high periods divided by the average of the low periods.

2) Moving Average: Moving averages smooth the price to form a trend indicator. They do not predict the direction of price, but define the direction late. It is useful for eliminating noise in raw data, producing a overview of trends.

$$MA = \frac{\sum_{k=1}^{n} ClosingPrice_k}{n} \tag{3}$$

3) Exponentail Moving Average: Exponential moving averages reduce the lag by applying more weight to recent prices. The weighting applied to the most recent price depends on the number of periods in the moving average. There are three steps to calculating an exponential moving average. First, calculate the simple moving average. An exponential moving average (EMA) has to start somewhere so a simple moving average is used as the previous (PRS) period's EMA in the first calculation. Second, calculate the weighting multiplier (MTL). Third, calculate the exponential moving average.

4) Moving Average Convergence/Divergence (MACD): $MACD$ is a specific example of an oscillator in price and is mainly used on the closing prices of an asset to detect price trends, showing the relationship between two moving averages. Basically consists of 2 elements: line $MACD$ and the line signal. The line $MACD$ formed by the difference between two exponential moving averages (EMA), one short and one long, generally containing 12 and 26 periods, respectively.

$$MACD = EMA[12] - EMA[26] \tag{4}$$

The signal or $TRIGGER$ is formed by the exponential moving average of 9 periods ($EMA[9]$) the $MACD$ line itself.

$$TRIGGER = MME[9, MACD] \tag{5}$$

5) Average Directional Movement Index (ADX): The Average Directional Movement Index (ADX) indicator describes when a market is trending or not trending, that is, the strength of a trend. When combined with *Plus Directional Indicator* ($+DI$) and *Minus Directional Indicator* ($-DI$), defines the trend direction. The main purpose of the ADX is to determine whether a stock is trending or is in a trading range.

6) Aroon Indicator: A technical indicator used for identifying trends in an underlying security and the likelihood that the trends will reverse. It is made up of two lines: one line is called $Aroonup$, which measures the strength of the uptrend, and the other line is called $Aroondown$, which measures the downtrend. They are defined as:

$$AroonUp = \frac{N - MAX}{N} * 100 \tag{6}$$

$$AroonDown = \frac{N - MIN}{N} * 100 \tag{7}$$

, where N is the number of periods, MAX is the number of periods since the maximum of N periods, MIN is the number of periods since the minimum of N periods. The *Aroon Indicator* is calculated as $AroonUP - AroonDown$.

The indicator reports the time it is taking for the price to reach, from a starting point, the highest and lowest points over

[3] http://www.stockcharts.com

a given time period, each reported as a percentage of total time.

7) Bollinger Bands: Bollinger Bands are volatility bands placed above and below a moving average. Volatility is based on the standard deviation, which changes as volatility increases and decreases. The bands automatically widen when volatility increases and narrow when volatility decreases.

They are calculated as follows:

$$UpperBand = SMA[20] + 2 * SD[20] \tag{8}$$

$$MiddleBand = SMA[20] \tag{9}$$

$$LowerBand = SMA[20] - 2 * SD[20], \tag{10}$$

where SMA is the *Simple Moving Average* around the 20 periods, and SD is the *Standard Deviation*.

8) Commodity Channel Index (CCI): The Commodity Channel Index (CCI) is a versatile indicator that can be used to identify a new trend or warn of extreme conditions. In general, CCI measures the current price level relative to an average price level over a given period of time. CCI is relatively high when prices are far above their average. CCI is relatively low when prices are far below their average. In this manner, CCI can be used to identify overbought and oversold levels. It is calculated as:

$$CCI = \frac{TP - SMA(PT)}{0.015 * SD(TP)} \tag{11}$$

where TP is calculated using $(high + low + close)/3$.

9) Chande Momentum Oscillator (CMO): It is created by calculating the difference between the sum of all recent gains and the sum of all recent losses and then dividing the result by the sum of all price movement over the period. This oscillator is similar to other momentum indicators such as the Relative Strength Index and the Stochastic Oscillator because it is range bounded (+100 and -100). The formula for the indicator is:

$$CMO = 100 * \frac{Up - Down}{Up + Down}, \tag{12}$$

where Up is the sum of the momentum of up days in the period under analysis and $Down$S is the sum of the momentum of down days in the period under analysis. The default period is the last 9 days.

10Rate of Change (ROC): The Rate-of-Change (ROC) indicator, which is also referred to as simply Momentum, is a pure momentum oscillator that measures the percent change in price from one period to the next. It is a simple technique indicator that show the percentual difference between actual price and the *Closing Price* of N previous periods.

$$ROC = \frac{CP - CPA}{CPA} * 100, \tag{13}$$

where CP is the *Closing Price* and CPA is the *Closing Price* of N previous periods. ROC is classed as a price momentum indicator or a velocity indicator because it measures the rate of change or the strength of momentum of change.

The next section presents the experimental evaluation of the work, where this methodology is applied to actual data from some important Brazilian stock market symbols.

IV. Experiments

To understand the application of neural networks in this work, is necessary to understand the concept of Intraday Trading. Day Trading or Intraday Trading is one method used in trading on stock exchange, which aims to obtain profit from price moves of financial assets throughout the day. Unlike other approaches that use neural networks for prediction stock exchange, our approach considers that the price oscilation tendency that exists between the beginning of the trading day and up to a schedule in the middle of the day can extend until stock market closing time. Thus, the proposed system trains the neural network until certain schedule and apply the test in the remainder of the day. If this hypothesis is true, there will be a significant hit rate about the prediction of movement market during the remaining of the day. The system uses the period from the beginning of the trading day until 2 p.m. for the generation dataset used as input to the neural network training. After 2 p.m. until the end of trading session the system generates the data to be applied as the test set.

A. Architecture of the neural network

This research used a multilayer perceptron (MLP) neural network trained with backpropagation algorithm. The network has three layers, where one of them is a hidden layer. The dataset used for training and testing of the neural network are described in Section IV-B. The learning function or the activation function used was a sigmoid function, as follows:

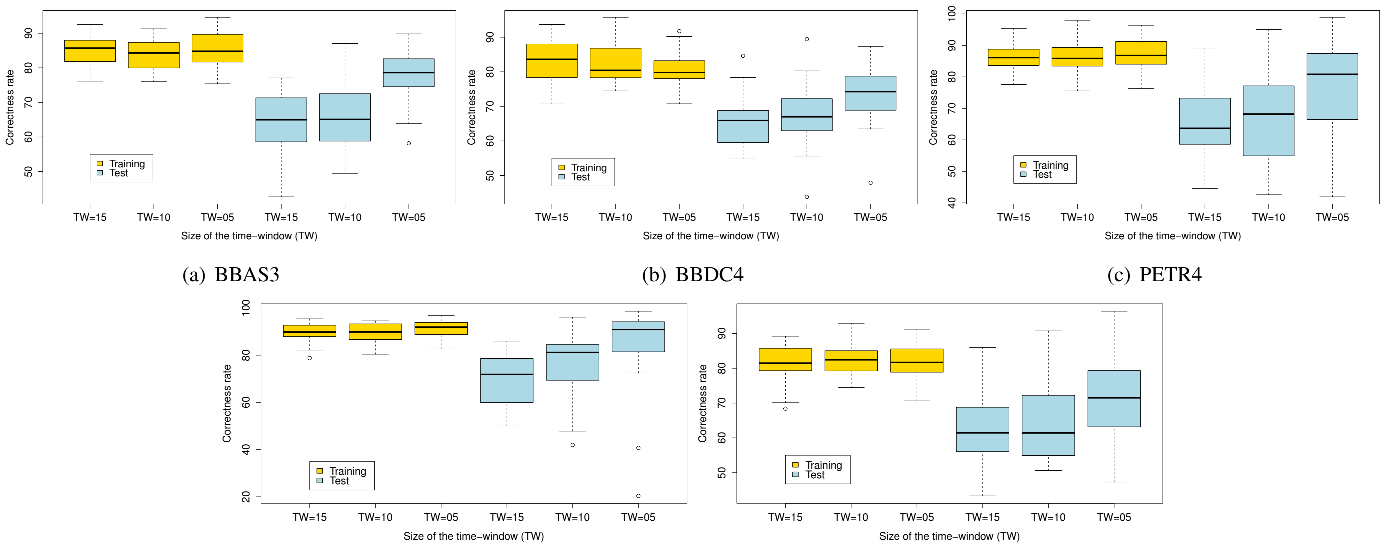
$$f(x) = \frac{1}{(1 + e^{-\beta x})} \tag{14}$$

This function was used because, according to the literature, the sigmoid function is the most widely used and perform better than other functions for our problem domain, such as Unit Step function, Piecewise linear function, and Binary Transfer function [24].

The architecture of the neural network used in this work consists of an input layer composed by N units (x_i ($i = 1, 2, 3...N$). The number of nodes of the hidden layer was defined by the number of attributes and the number of classes ((attribute number + number of classes) / 2). Finally, the output layer has only one node, identifying whether or not there was a positive oscillation in the price of the asset.

This work used 14 input variables to train the neural network, where 10 of them are technical analysis indicators. The variables are:

- O_i the opening price at the moment i
- $O_i - TW$ the opening price at the moment $i - TW$
- $H_i - TW$ the high price at the moment $i - TW$
- $L_i - TW$ the low price at the moment $i - TW$
- $C_i - TW$ the closing price at the moment $i - TW$



(a) BBAS3 (b) BBDC4 (c) PETR4

(d) USIM5 (e) VALE5

Fig. 3. The Boxplot of the trainning set and the test set, grouped by the stock

- $T_j i$ the value of technical analysis indicator j at the moment i

where TW is the granularity of the time window. Indicators of technical analysis used as input to the neural network are described in Section III-B

The training parameters used to train the neural network are:

- learning rate = 0.3
- momentum = 0.2
- number of epochs = 1.000
- number of nodes on the hidden layer = (attributes + classes) / 2

The output of the artificial neural network was analyzed by comparing the predicted output (if the price of the asset oscillated positively - setting the output to 1) with the actual output over a sample period. Otherwise, the output is 0.

B. Data Set

In the experiments, the system uses a different method to generate the candlesticks. Our candlesticks do not synthesize a range of mutually exclusive time, but they use the concept of Time Window herein defined. Consider that a granularity of a candlestick is, for example, 15 time units. In common representations using candlestick, each candlestick summarize this period in a static and unique way, that is, it starts at time t_0 and comprises information until the time t_{14}. Another candlestick would start at t_{15} and end at t_{29}, and so forth. Thus, they do not have information in common with each other, being mutually exclusive.

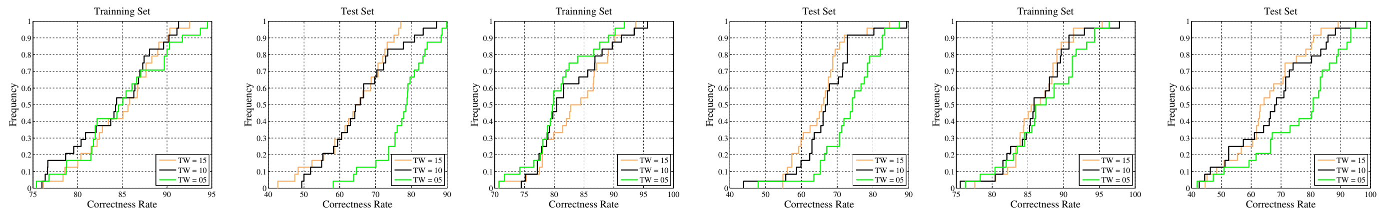
However, this offers a certain limitation for the analysis in the stock market, when is necessary to perform intraday trading and capture the dynamic behavior of the market. This limitation is by the fact that there would be a limited database to be used by the neural network. For example, for each hour of trading session, considering a granularity of 15 minutes, the system would have only 4 candlesticks, and for granularity of 5 minutes the system would have only 12.

This limitation was resolved with the candlesticks being generated through the Sliding Time Window. Thus, considering as example where the granularity is 15 minutes, there would be a first candlestick starting at time t_0 and ending at time t_{14}. The second would have start in time t_1 and finalization in time t_{15}. A third candlestick would have start in time t_2 and finalization in time t_{16}. This increases considerably the number of candlestick during the day, thereby increasing the database. Thus, a granularity of 15 minutes will have 45 candlesticks for each hour of trading session, and a granularity of 5 minutes will have 55 ones.

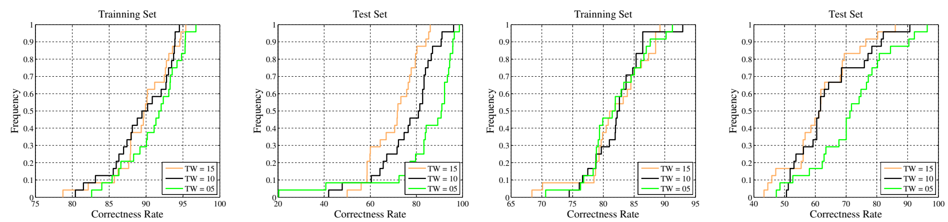
The Time Window value applied in the generation of candlesticks is the same used to check the oscillation in the stock price, just to make consistent the understanding and the execution of experiments, since these could have different values.

Since this work is interested in the direct application of these models in intraday trading on the stock market, is not necessary for previous manipulations in database, such as balancing. Thus this work is interested in evaluating the behavior of neural network directly in predicting the market movement. If the system uses the neural network in real time on a trading session, there is no way to balance the dataset. By its nature, the data in this context are unbalanced (i.e., there is more instances of class 0 than 1), providing more realistic results.

The data used for experimentation are actual information from the Brazilian Stock Exchange (BM&F Bovespa). These data were collected in real time and processed according to the method and metrics previously presented. The analysis is performed on a dataset containing 26 days from November and December 2013.



(a) BBAS3 (b) BBDC4 (c) PETR4



(d) USIM5 (e) VALE5

Fig. 4. The CDFs for trainning set and test set, grouped by the stock

C. Experiments and Time Window Evaluation

This work investigates different time windows in the following values: 5, 10 and 15 minutes. It allows to conclude which of them is more appropriate to be used in market makers in HFT. The experiment aims to predict whether a particular stock will have a positive oscillation equal or greater than a predefined value: R$ 0.04 (four cents of Real). The Real is the current Brazilian currency.

For each analyzed Symbol, this study evaluated a dataset containing 26 days of trading session (the month is about 22 business days). Aldridge in the work [2] asserts that one moth is enough to experiment in High-Frequency Trading because the dataset is a Bigdata. For each day, this work calculated the correctness rate in the training and test dataset. The results are presented using an arithmetic average considering all days.

Table I presents the arithmetic average, standard deviation, and the coefficient of variation (CV) for each evaluated time window, grouped by symbol. According to the results, when the time window decreases there is an increase in the average of correctness rate. This behavior is similar in all analyzed symbols.

Ordinarily, stocks of different symbols have different prices when compared among them. In this context, a variation of R$ 0.04 represents different percentages for each symbol. This work investigates this fixed value (R$ 0.04) intentionally, rather than investigates an oscillation according to a percentage of the stock price, because one of objectives was to show that the neural networks can get good results even when the expected oscillation varies in a stock price function. Moreover this value is enough to cover the operation costs of HFT.

Figure 3 presents some results using boxplots, divided into training and test datasets and grouped by the evaluated time window. In the boxplot, the central line represents the median. Furthermore, the four quartiles are distinguishable in each box and the outliers are shown by hollow circles. For the training period, all symbols have similar distributions. There is no statistical discrepancy between the correctness rates. However, in the test period, there is a difference when the time window is smaller (5 minutes) if compared to the others.

TABLE I. ARITHMETIC AVERAGE AND STANDARD DEVIATION FROM RESULTS APPLIED TO DIFFERENT TIME WINDOW, GROUPED BY STOCK

Symbol	*Time Window (Minutes)*	*Arithmetic Mean*	*Standard Deviation*	*Coefficient of Variation*
BBAS3	15	63.88	9.50	0.14
	10	65.83	10.23	0.15
	05	77.58	7.73	0.09
BBDC4	15	65.25	7.25	0.11
	10	67.12	8.66	0.13
	05	73.53	8.44	0.11
PETR4	15	65.51	11.98	0.18
	10	67.50	14.51	0.21
	05	76.12	15.42	0.20
USIM5	15	70.57	10.22	0.14
	10	76.41	13.22	0.17
	05	83.86	18.11	0.21
VALE5	15	61.72	11.00	0.17
	10	64.33	11.25	0.17
	05	71.75	12.78	0.17

Figure 4 presents the Cumulative Distribution Function (CDF). Acoording to [23], the CDF describes the probability that a real-valued random variable X with a given probability distribution will be found at a value equal or less than to x. It allows to evaluate all behavior of the distribution of the results. In this analysis, the same acquired conclusion using the boxplots can be drawn in the CDF. For every analysed symbol, there is a significant difference when the time window is equal to 5 minutes in the test period.

Analyzing the results in both statistical approaches (boxplot and CDF), is possible to identify that the proposed ANN is more effective in shorter time windows (considering the period of test). This result is true for all 5 analysed symbols in this work. This provides new possibilities for market makers in HFT context, since a greater number of limit orders can be triggered when the time window is shorter. The main findings of this research can be directly applied to design new promising strategies for HFT.

V. CONCLUSIONS

This work proposed and modeled an artificial neural network (ANN) as a trigger of a Market making process to be applied in High-Frequency Trading (HFT). In its input, the neural network has used intraday technical indicators. The output indicates whether the market making process should be (or not) initiated predicting an uptrend (positive oscillation). If so, the market making process can direct your limit orders in more appropriated prices, once an uptrend was expected. Additionally, this work tested different sizes of the time windows (5, 10 and 15 minutes) to support the application in High-Frequency Trading context.

The statistical analysis of results showed that a neural network is more effective in short-term oscillations (5 minutes) when compared with the results obtained in longer periods (10 or 15 minutes). This result is important because it allows to insert a higher quantity of limit orders once they will be placed more frequently, which increases the market liquidity.

It contextualizes a new contribution in the High-Frequency Trading field, where this work proposes a new trigger to start a market making process.

The obtained results and findings have opened new possibilities, therefore the authors of this work foresee the following future directions:

- An experiment considering an Order Book Simulation process with a realistic match engine. Tests at this level can evaluate the financial return and risk associated with the market maker. One of the difficulties to execute this project is to obtain intraday data. The Brazilian Stock Exchange provides freely this information to any researcher or firm[4];
- The parameters of the ANN could be evaluated in order to optimize the model.
- Evaluate if negative oscillations can also be identified with a similar methodology and complementary of this work. This could increase the liquidity of the market, because the market maker can capture more intraday opportunities;
- The use of neural networks as a trigger for other types of strategies in High-Frequency Trading (e.g., Statistical Arbitrage).

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