From an Artificial Neural Network to a Stock Market Day-Trading System: A Case Study on the BM&F BOVESPA

Leonardo C. Martinez, Diego N. da Hora, João R. de M. Palotti, Wagner Meira Jr. and Gisele L. Pappa

***Abstract*— Predicting trends in the stock market is a subject of major interest for both scholars and financial analysts. The main difficulties of this problem are related to the dynamic, complex, evolutive and chaotic nature of the markets. In order to tackle these problems, this work proposes a day-trading system that "translates" the outputs of an artificial neural network into business decisions, pointing out to the investors the best times to trade and make profits. The ANN forecasts the lowest and highest stock prices of the current trading day. The system was tested with the two main stocks of the BM&FBOVESPA, an important and understudied market. A series of experiments were performed using different data input configurations, and compared with four benchmarks. The results were evaluated using both classical evaluation metrics, such as the ANN generalization error, and more general metrics, such as the annualized return. The ANN showed to be more accurate and give more return to the investor than the four benchmarks. The best results obtained by the ANN had an mean absolute percentage error around 50% smaller than the best benchmark, and doubled the capital of the investor.**

I. Introduction

Predicting trends in the stock market is a subject of major interest for both scholars and financial analysts. The subject was vastly studied in the last years [1]-[3], but predicting future stock prices accurately and developing business strategies capable of "translating"these predictions in profits are still big challenges.

The difficulty of this problem is mainly related to the dynamic, complex, evolutive and chaotic nature of the markets [4][5]. These latter characteristics of the market clearly showed the limitations of classical statistical methods for stock price time-series predictions, and asked for more powerful methods to accomplish the task. In particular, when dealing with market trends, we want methods able to deal with large amounts of noisy and non-linear data, with a high degree of uncertainty and a random nature [6]-[8].

Given the drawbacks imposed by statistical methods, soft computing techniques [9], such as artificial neural networks (ANNs) and genetic algorithms, were introduced as an alternative. The main advantage of these techniques over the statistical ones is their ability to explore the tolerance of systems to data uncertainty, imprecision and partial truth. In particular, ANNs became an attractive tool for predicting stock market trends because (i) they can easily deal with irregularities [8], (ii) they work with uncertain, incomplete and/or insufficient data, which change fast over short periods of time [10] (iii) they are powerful tools to find patterns in data [11], including non-linear relationships [3][12][13].

Although ANNs became popular methods for stock market predictions [1], their use and evaluation in real-world scenarios, making correct predictions and investment profits, is still understudied. This is because the majority of the ANNs systems proposed so far are evaluated using classical model prediction metrics, such as the mean absolute error (MAE) or the mean squared error (MSE). These metrics give us an idea of the model generalization, but no insights about the behavior of the system in the real market.

One way to assess the real quality of ANN predictions into a real-world scenario is to integrate the ANN with a trading system [14]. A trading system is a tool that can convert predictions (which can be the ANNs outputs) into business decisions, based on a set of operation rules and the stock market constraints (e.g. brokerage commission rates, slippage, etc).

Given the needs of better evaluation approaches, this paper proposes a stock market day-trading system that uses the outputs of a ANN to guide the user into buying and selling stocks. A day-trade is characterized by two operations (called entry and exit) made within the same day, i.e. a buy (entry) followed by a sell (exit) or a sell (entry) followed by a buy (exit). Day-trades are specially interesting in periods of economic crisis, where the high daily volatility gives investors a great opportunity to raise profits at a higher risk.

In order to best fit the proposed day-trading system, the ANN outputs, which are used as inputs to the proposed system, are the minimum and maximum stock prices in the trading day. To the best of our knowledge, this approach was not previously used in the literature, where most of the proposed systems perform entry/exit operations in different days.

The day-trading system was tested in the BM&F BOVESPA Stock Exchange. The main motivation to use this scenario is the lack of studies in this market. From the 100 surveyed paper in [1], only one referred to the São Paulo Stock Exchange (BOVESPA) [15]. This is a very low number, taking into account that in 2008, after merging with the Brazilian Mercantile and Futures Exchange (BM&F), the new BM&F BOVESPA became the world's third largest stock exchange (according to its market value) [16].

The results obtained by the proposed trading system in the period varying from May 2nd to December 2nd 2008 gave the investor a very high profitability, allowing him/her to double his/her initial capital. Note that the period studied also included the world crisis months. Moreover, experiments

L. C. Martinez, D. N. da Hora, J. R. M. Palotti, W. Meira Jr. and G. L. Pappa are with the Computer Science Department, Federal University of Minas Gerais - Brazil (email: {leocm, dnhora, palotti, meira, glpappa}@dcc.ufmg.br).

with different subsets of input data showed that information about the minimum and maximum prices in the 5 previous days to the prediction is valuable, but data such as the opening and closing prices in the same 5 previous days to the prediction do not improve the performance of the system.

The remainder of this paper is organized as follows. Section II briefly discusses some related work. Section III presents the proposed artificial neural network, while Section IV discusses how it was integrated to the day-trading system. Section V presents the results obtained by both the ANN and the day-trading system for the two most traded BM&F BOVESPA stocks, namely Petrobras PN (PETR4) and Vale R Doce PNA (VALE5). Finally, Section VI presents some conclusions and directions for future work.

II. Related Work

There is a vast number of papers in the literature that study the problem of predicting stock market trends, and a great number of them use an ANN as their predicting model. Among the surveys about the subject, [1] analyzes 100 relevant works that used soft computing techniques to address this problem. It classifies these techniques according to (i) the market from which the training and test data were obtained, (ii) the input variables, (iii) the methodology and parameters (preprocessing, size of the dataset, type of network implemented, training method), (iv) the models used as benchmarks and (v) the performance metrics used to evaluate the proposed method.

Taking into account item (iii), [17]-[26] are all works where feed-forward multi-layer networks were used in order to predict variables related to stock market trends. Regarding the training algorithm, [8][27] successfully trained their networks with the back-propagation. More specifically, [28]-[38] used models with characteristics very similar to the ones employed here. The main difference between our method and the others is the output of the network. While in most systems the ANN output is an action that should be taken by the user, such as buy, sell or no action, here the outputs of the network are the minimum and maximum predicted stock prices in the current day. The reader is referred to [1]-[3] for good surveys on the subject.

III. A neural network for predicting daily stock prices

Most of the studies that proposed ANNs to make stock market predictions used a multi-layer feed-forward neural network trained by the back-propagation algorithm with great success. Based on that, the ANN proposed in this work also uses this architecture.

The network has the three classical layers, with up to 33 input and two output neurons (described in Sections III-A and III-B). The number of neurons in the hidden layer is equals to the square root of the product between the number of neurons in the input and output layers (i.e. the geometric mean over these two values) [39].

Each neuron implements a logistic function, which requires some pre- and post-processing steps of the raw data. For each dataset, the input (output) values are divided (multiplied) by the maximum input value times 2. This approach was followed to guarantee that values greater than the ones presented in the dataset could be represented by the network. The number 2 was chosen because a daily growth in stock prices superior to 100% is very unlikely.

When training the network, the learning rate was set to 0.01, and the back-propagation algorithm also used a momentum of 0.8. The network was trained for 100.000 epochs. These three parameters were obtained in a set of preliminary experiments.

A. Input data

Most of the works that use ANN for stock prediction use as input data to the network the stock opening, closing, lowest and highest daily prices [17]-[19][40]-[44]. The inputs can also include many other indicators obtained from the two most influential schools of stock market analysis: the fundamentalist [15][45]-[47] and the technical [48]-[51] schools.

The fundamentalists believe the stock prices reflect the macro-economical, political and administrative scenarios of the company. Hence, data about these scenarios are gathered and used to estimate future prices. The technical analysis, in contrast, assumes that all the necessary information about the future of stock prices can be found in the past prices. Thus, historical data about the prices have to be analyzed in order to estimate future prices.

When following the technical analysis, there are two approaches to estimate the stock price. The first involves the analysis of graphics that show the price fluctuations, where the analyst focuses on graphic patterns formations. This technique is highly subjective, and difficult to be adapted and used together with ANNs. The second approach uses technical indicators (mathematical formulas) to assist on the decision making process.

According to [14], prediction systems which are designed to operate at long-term periods should use fundamentalist indicators. However, those that operate at short-term periods, as the one proposed here, should focus on technical indicators. Following these recommendations, we used two classical technical indicators as input to the ANN: the exponential moving average (EMA) and the bollinger bands (BB) [52].

The 33 variables used as inputs to the ANN are described in Table I. Apart from using all of them as inputs to the network, other 2 data input configurations were tested. The first configuration considers 15 variables, namely the ones described in lines 1,3,7,8 of Table I. These variables were chosen to test the ability of the ANN to learn using only information about the lowest and highest values of the previous days, without any knowledge about the opening (except for the price of the current day) and closing (except for the BB) ones. The second configuration includes information about the latter, using 25 attributes – described in lines 1,2,3,7,8 of Tables I, as inputs to the network.

The choice of the 33 variables used in this study was based on experts knowledge and supported by a vast literature in the area [1]. However, we recognize this approach is ad-hoc, and the literature is certainly missing more systematic ways to address this specific feature selection problem. As a future research direction, we plan to study the effect of a number of indicators in the network learning, as well as the relevant amount of historical data that should be considered in the inputs of the network (i.e. information regarding the previous 1, 2, 5 or 10 days, for instance).

TABLE I
INPUT VARIABLES GIVEN TO THE NEURAL NETWORK

Id	# of Inputs	Description
1	10	Lowest and highest prices of the 5 previous days
2	10	Opening and closing prices of the 5 previous days
3	2	EMA of the lowest and highest prices of the 5 previous days
4	2	EMA of the opening and closing prices of the 5 previous days
5	4	BB of the lowest and highest prices of the 5 previous days
6	2	BB of the opening prices of the 5 previous days
7	2	BB of the closing prices of the 5 previous days
8	1	Opening price of the current day

B. Output data

As mentioned before, this work presents a day-trading system. Hence, the output values of the network correspond to the minimum and maximum predicted prices of the stocks for the current day. The idea is to use these variables together with a trading system to find the optimal time of the day to buy/sell stocks using ideally one trade (i.e. to buy(sell) stocks when they reach the minimum(maximum) predicted price and then sell(buy) them when they reach the maximum(minimum) predicted price).

C. Dataset

The dataset used throughout this work corresponds to a historical series of data about the opening, closing, minimum and maximum prices of the two stocks that have the highest financial volume registered in BOVESPA: the Petrobras PN (PETR4) and the Vale R Doce PNA (VALE5). The series represents a period of 1283 days[1], varying from 1st October 2003 to 2nd December 2008. They were obtained from the software Agência Estado Broadcast Investidor Pessoal [53].

D. Network training

As training the network is an expensive process, in these preliminary experiments a sample of 128 consecutive days of the PETR4 stock with 33 variables, varying from 18th May 2007 to 23th November 2007, was chosen for training. This number is quite arbitrary and not optimized. However, as showed in the experiments in Section V, it is representative.

In a first experiment, a standard training procedure was performed using test data from 26th November 2007 to 2nd December 2008. In a second experiment, named updated training, we kept the training data as close (in terms of time) to the test data as possible. In other words, we train the network with the initial training set, and then predict the first 10 days in the test set. We then insert these 10 previously tested days (and remove the first 10 days of the training set, to keep the size of the training set constant and equals to 128 days), and retrain the ANNs.

While the standard training obtained a standard average error of $2.29 \pm 0.27\%$ and $1.60 \pm 0.17\%$ for the minimum and maximum prediction values, respectively, for the updated training these numbers were $1.96 \pm 0.21\%$ and $1.51 \pm 0.15\%$. Note that these results are calculated over 30 different runs. Although these results are statistically the same, we chose to use updated training in the experiments reported in Section V.

[1] From the original 1283 days, the first 5 were omitted, as they were need to build the EMA inputs to the network

IV. THE PROPOSED DAY-TRADING SYSTEM

As stated before, simply measuring the performance of an ANN by looking at its accuracy on forecasting does not bring useful information about how it would perform in the real stock market, helping the investor to make decisions. A better way to assess the performance of the ANN is to use its outputs as inputs to a trading system.

The day-trading system introduced in this section is responsible for “translating”the ANN predictions into business decisions, i.e. when to buy or sell stocks.

According to [54], a trading system is composed of three main parts: (i) a set of rules to enter and exit trades, (ii) a risk control mechanism, and (iii) a money management scheme. Besides, it has to take into account all the constraints imposed by the real market, such as brokerage commission rates, slippage, the volume being negotiated and round lot trades.

The proposed trading system works by following the stock market in real time, but takes into account price changes occurred in fixed intervals of 15 minutes (one minute intervals could have been used, but we chose a more conservative approach). Hence, every 15 minutes the system consults its trade rules, and can advice the investor to perform an enter or exit trade.

A. Entry and Exit rules for trades

Defining the exact conditions in which an investor will choose to buy or sell a stock is the most important part of any trading system. In our system, these rules will tell how the minimum and maximum daily prices provided by the ANN will be used to make decisions about the right time to trade.

Hence, every 15 minutes the trading system checks the closing price (for the interval) and compares it with the minimum and maximum predicted prices. If the closing price is smaller than the minimum predicted, the system advices the investor to buy the stocks. If the closing price is greater than the maximum predicted, the investor is advised to sell the stocks. It is important to notice that more than one buy or sell operation is allowed in the same day, and that the order in which they occur is irrelevant (as long as they are alternated).

A day can also be closed without any trade. This occurs when the stock price remains higher than the minimum and lower than the maximum predicted values during the whole day.

In contrast, if the first operation is performed (regardless of being a buy or a sell), the second operation is compulsory within the same day. Hence, if at the end of the day only the first operation (entry) was executed but the second operation (exit) was not, it is executed in the last minute of the day, according to the day closing price. Finally, the concept of stop-loss, which is detailed in Section IV-B, is also incorporated into the rules, and work as a risk controlling mechanism.

In summary, let min_{ANN} and max_{ANN} be the minimum and maximum values predicted by the ANN, and $close$ be the 15-minute interval closing stock price. The 6 rules of the proposed trading system are:

1) Buy when $close \leq min_{ANN}$, sell when $close \geq max_{ANN}$;
2) Buy when $close \leq min_{ANN}$, sell in the last minute of the day;
3) Buy when $close \leq min_{ANN}$, sell with the stop-loss price;
4) Sell when $close \geq max_{ANN}$, buy when $close \leq min_{ANN}$;
5) Sell when $close \geq max_{ANN}$, buy in the last minute of the day;
6) Sell when $close \geq max_{ANN}$, buy with the stop-loss price.

B. Risk Control

Establishing ways to control the risk involved in the trades is an important feature of a trading system. When we talk about risk, we refer to the amount of money that can be lost in an operation. Usually, a trading system will lead the investor to perform a higher number of trades that will bring him/her loss than trades that will bring him/her gain. The challenge is to make small losses in unsuccessful trades and high gains in profitable ones. A common strategy used to achieve this is the TOPS COLA, aka "Take Our Profits Slowly, Cut Off Losses At once", described in [54].

One way to control the risk involved in trades is to pre-establish exit rules. In this work, the stop-loss strategy is used for this purpose. The stop-loss strategy defines a default price that, if reached, will cause the exit. This price is calculated using the trade entry price. We performed experiments varying the percentage of stop-loss from 0.1% to 2.0%. A low stop-loss can avoid profitable operations, while a high one can cause a higher loss. The system performed better with stop-loss rules than without them, and the value of 0.5% gave us the best results.

C. Money management

The money management refers to the amount of available resources that will be used in each trade, considering the risks involved and the total capital available. As we are using the stop-loss approach, we created a simple methodology where all the available capital is used in all the trades. Different strategies were tested, but they did not give as good results as the ones following this approach.

D. Real world constraints

There are many real-world constraints that need to be incorporated to a trading system when simulating the real-world scenario. The first of them refers to the brokerage commission rates. Here we assumed a fixed cost of R$15.00 (U$6.00) per operation (buy or sell), which is the value used by most brokerage houses in Brazil. This cost is reduced from the net value of each trade. Most of the works proposed in the literature take the commissions into account by multiplying the number of trades performed in the test period by the cost of each operation and reduce it from the final capital. Nonetheless, this approach gives a false profitability, as investments with money that does not exist are performed.

Another constraint to be considered is the slippage, i.e., the difference between the price indicated by the system and the actual trade price. It is not always that we can perform a trade according to the trading system prices. This occurs because buy and sell orders made previously by other investors with the same trade price have a priority. While these other trades are executed, the price can oscillate.

The two stocks we are working with have high market liquidity. Hence, low values of slippage are permitted. For all trades, we assume they will be performed by a price 0.1% worse than the one indicated by the trading system. In average, this represents a loss of R$0.04 per trade for both stocks in the period of test.

The volume being negotiated is another important point to be considered by the trading system. In our simulations, the value negotiated was always lower than R$300,000.00 (U$120,000.00), and the daily volumes negotiated by PETR4 and VALE5 were, respectively, R$873 (U$349) and R$614 (U$246) millions. Hence, we did not have to worry about availability.

At last, note that all the operations were executed using multiple round lot (100), which can have differentiated price when compared to the odd lot market.

E. Evaluation Metrics

By using a trading system, we can define new metrics to evaluate the ANN performance, based on the results of the business actions taken by following the network "advices". Here we present three evaluation metrics, which will be later used to assess the proposed day-trading system.

The first of these metrics is the annualized return, defined as $AR = (FC/IC)^{(365.25/D)} - 1$, where IC represents the initial capital invested, FC the final capital obtained and D is the number of days of investment (i.e., it adjusts the return to an annual basis). The second metric is the maximum drawdown. A drawdown represents the total percentage loss of capital experienced by the system before it starts winning again. The maximum drawdown is the highest drawdown occurred during the period considered, and represents a way to evaluate the risk associated with accepting the decisions of the trading system. At last, the average number of daily operations is used to evaluate the frequency of the entry/exit operations. A list of other evaluation metrics can be found in [14].

V. Experiments and Results

This section presents experimental results performed to test the ability of the proposed ANN to forecast stock prices in a real world scenario, and is divided in two parts. The first part evaluates the ANN generalization performance using the conventional metrics, i.e., the error rate. The second part analyzes the performance of the trading system as a whole, using the evaluation metrics proposed in Section IV-E.

In both cases, the results obtained are compared with four other simple benchmarks proposed in [28]. The first three benchmarks estimate the minimum and maximum stock values for the present day as the simple moving average (SMA) of the lowest/highest values of the previous 5 (SMA-5), 10 (SMA-10) and 20 (SMA-20) days, respectively. The fourth benchmark is the one-day lag, i.e., the minimum and maximum stock values estimated for the present day are equal the values of yesterday.

A. ANN Evaluation

The experiments reported in this section use the ANN configuration defined in Section III. Note that all the results are based on 33 different runs of the ANN. The ANN training set covered all working days from 8th October 2003 to 30th April 2008. Tables II and III present the mean absolute percentage error between the predicted and real values of stock prices for the period varying from 2nd May to 2nd December 2008 (150 work days), for both PETR4 and VALE5. It is important to observe that we are predicting stock prices in a period of serious financial crisis. Thus, the predictions are likely to present high variance.

TABLE II

Performance of the four benchmarks according to the mean absolute percentage error (and standard deviation)

Benchmark	MAPE (Minimum)	MAPE (Maximum)
PETR4		
1-day lag	$3.59 \pm 3.30\%$	$2.79 \pm 2.64\%$
5-SMA	$5.14 \pm 4.66\%$	$4.45 \pm 4.10\%$
10-SMA	$7.10 \pm 6.08\%$	$6.46 \pm 5.54\%$
20-SMA	$9.95 \pm 8.04\%$	$9.40 \pm 7.71\%$
VALE5		
1-day lag	$3.34 \pm 3.39\%$	$2.81 \pm 2.72\%$
5-SMA	$4.66 \pm 3.00\%$	$4.03 \pm 3.31\%$
10-SMA	$5.96 \pm 5.39\%$	$5.24 \pm 4.37\%$
20-SMA	$8.59 \pm 7.82\%$	$7.70 \pm 6.62\%$

Looking at Table II, we observe that the greater the number of past days used to calculated the SMA, the worse is the error obtained by the benchmark. This can be explained by the fact that, intuitively, the minimum and maximum values of a stock today are closer to yesterday's values than to the values of 5 or 10 days ago. Also note that the error for the maximum price was smaller than the error for the minimum price for all benchmarks.

Table III presents the error obtained by the proposed ANN with the three different sets of input values for the PETR4 and VALE5 stocks. Comparing the results in Table III with the ones in Table II, we observe that the errors obtained by the proposed ANN are lower than the ones obtained by the four benchmarks. We can also note that, the network with 15 inputs presents lower error rates than the others for both stocks. As occurred for the benchmarks, the maximum values predicted presented lower error rates than the minimum values predicted.

TABLE III

Performance of the ANN according to the mean absolute percentage error (and standard deviation)

# of Inputs	MAPE (Minimum)	MAPE (Maximum)
PETR4		
15	$1.86 \pm 1.84\%$	$1.84 \pm 1.39\%$
25	$1.94 \pm 1.98\%$	$1.33 \pm 1.30\%$
33	$1.91 \pm 2.06\%$	$1.33 \pm 1.40\%$
VALE5		
15	$1.73 \pm 1.91\%$	$1.44 \pm 1.21\%$
25	$1.86 \pm 1.89\%$	$1.51 \pm 1.57\%$
33	$1.86 \pm 1.98\%$	$1.48 \pm 1.31\%$

B. The day-trading system evaluation

A day-trading system helps the investor to monitor the stock value fluctuations during a day, and its main functionality is to point out the right moment to buy or sell stocks. In order to test the system, we used data from the period of May 2nd to December 2nd 2008. The analysis is restricted to this period because it is not possible to obtain data for every 15 minutes using the available tool [53] for longer periods. During these 150 work days, PETR4 and VALE5 devaluated 58.6% and 58.3%, respectively.

The main goal of the trading system is to make profit. However, the performance of the system should not be assessed using only this property. Hence, all our experiments were evaluated using the three metrics defined in Section IV-E: annualized return (AR), maximum drawdown and number of operations.

Recall that all experiments presented in this section consider a brokerage commission rate of R$15.00 (U$6.00) per trade, slippage of 0.1%, stop-loss of 0.5% and initial capital of R$50,000.00 (U$20,000.00), unless stated otherwise. Tests with the three input configurations introduced in Section III-A were performed, and the network was trained with the proposed updated training.

Table IV shows the results of the trading system for the PETR4 and VALE5 stocks, using the predictions of the ANNs. As observed, the best results were obtained by the network with 15 inputs (for both stocks). This input configuration also obtained the best return with lowest drawdown. The average number of daily operations was close to two for the three networks.

We compared the performance of the trading system when using the ANN predictions with the performance of the system when using the four benchmarks previously introduced.

TABLE IV

PERFORMANCE OF TRADING SYSTEM USING ANNS

# of Inputs	AR (%)	Drawdown (%)	Trades per day (avg)
PETR4			
15	92.47	22.60	1.91
25	23.18	31.61	1.93
33	65.51	24.62	1.94
VALE5			
15	130.52	13.70	1.97
25	118.97	14.25	1.94
33	46.27	19.76	1.97

The results obtained are presented in Table V. Benchmarks "20-SMA"for PETR4 and "5-SMA"for VALE5, respectively, obtained a good return value with a very high drawdown. The drawdown shows that, at certain periods of test, the investor loses more than 40% of the capital invested (observe that the drawbacks of the ANNs are much lower). Note that the number of trades here is high if compared to the number of trades performed by the ANN. This is explained by an increase in the number of loss operations associated with the use of stop-loss.

TABLE V

PERFORMANCE OF THE TRADING SYSTEM WHEN USING THE 4 BENCHMARKS

Benchmark	AR (%)	Drawdown (%)	Trades per day (avg)
PETR4			
1-day lag	2.57	27.39	2.61
5-SMA	-4.36	42.76	3.00
10-SMA	-14.82	44.85	3.09
20-SMA	74.41	41.36	3.13
VALE5			
1-day lag	15.05	16.98	2.48
5-SMA	57.02	40.03	2.65
10-SMA	37.55	25.25	2.71
20-SMA	44.28	40.03	2.70

Recall that, according to the defined trading rules, there are three ways to exit a trade. The first is to sell above the maximum after buying below the minimum (or to buy below the minimum after selling above the maximum). This type of trade always gives the investor profit. The second way is to exit due to a stop-loss, indicating that a loss occurred. The third and last is to exit in the last minute of the day. In this case, the operation may bring profit or loss.

With this in mind, the system output can be improved by increasing the number of operations we are certain will be lucrative, i.e. the first type of operation. This can be done by increasing the probability that, if a stock price reaches the minimum or maximum predicted values, it will also reach the opposite extreme, assuring the investor profit. This probability can be increased by reducing the interval that separates the minimum from the maximum predicted values. Hence, let min_p and max_p be the minimum and maximum predicted values, and D_a the absolute difference among these two values. We can disturb them according to Equations 1 and 2:

$$min_n = min_p + \alpha \times D_a \quad (1)$$

$$max_n = max_p - \beta \times D_a \quad (2)$$

where min_n and max_n are the new values used by the trading system, and α and β are constants in the interval $(0$ and $0.5)$.

We performed a series of tests varying these constants, and concluded that their best values for both PETR4 and VALE5 were $\alpha = 0.1$ and $\beta = 0.4$. Table VI shows the results obtained using these constants with the three different ANN input configurations. The figures show that, by using the procedure described above, the overall performance in terms of AR and maximum drawdown of the trading system has improved significantly for PETR4. The ARs given by the 15-input ANNs were greater than 400% and 250% for PETR4 and VALE5, respectively. As expected, the number of operations increased significantly. Considering both stocks, the average number of days without operations decreased from 26.83 to 1.33.

TABLE VI

PERFORMANCE OF THE IMPROVED TRADING SYSTEM USING ANNS

# of Inputs	AR (%)	Drawdown (%)	Trades per day (avg)
PETR4			
15	423.56	17.11	3.37
25	130.49	23.34	3.40
33	302.05	23.03	3.38
VALE5			
15	260.51	15.02	3.12
25	158.16	15.17	3.23
33	121.62	19.67	3.19

Table VII presents the results obtained if the slippage constraint is removed from the system. As expected, there was an improvement in the system's performance, once the slippage used always considered pessimistic scenarios. This is aggravated in day-trading operations, where entry and exit prices are usually close due to the short trade time, leaving a small profit. Thus, by accounting the slippage, we lose a significant percentage of profits in good trades, and have our losses amplified in the bad trades. As a result, we observe that in experiments without slippage there is a great improvement in the drawdown, and a slightly reduction in the number of performed operations.

TABLE VII

PERFORMANCE OF ADAPTED TRADING SYSTEM WITHOUT SLIPPAGE USING ANNS

# of Inputs	AR (%)	Drawdown (%)	Trades per day (avg)
PETR4			
15	1892.16	8.95	3.35
25	848.92	14.04	3.09
33	1516.51	10.35	3.08
VALE5			
15	827.35	7.48	2.93
25	560.62	7.14	3.05
33	522.08	8.70	3.01

The results obtained by the proposed trading system in the period of May 2nd to December 2nd 2008 gave the investor a very high rentability, allowing him/her to double his/her initial capital during the period of the investment. adjust

VI. Conclusions and Future Work

This paper proposed a day-trading system that uses the outputs of a ANN to guide the user into buying and selling stocks. The proposed ANN predicts the minimum and maximum stock prices in the current day, and gives them as inputs to the system. The day-trading system, in turn, uses a set of trading rules to signalize to the investor the best time to buy or sell stocks.

The proposed system was tested using data from the BM&F BOVESPA Stock Exchange, which is an understudied market. Trades considering the two stocks that have the highest financial volume registered in BM&F BOVESPA were studies, namely the Petrobras PN (PETR4) and the Vale R Doce PNA (VALE5).

Moreover, the ANN was evaluated using standard evaluation metrics, such as the mean absolute percentage error in the test set, but also more sophisticated methods when inserted into the day-trade system context, such as the annualized return and drawdown. Results were compared with four benchmarks, and the ANNs showed to be more accurate and give more profit than the benchmarks. The best results presented an mean absolute percentage error around 50% smaller than the best benchmark, doubling the capital of the investor.

The proposed system also included many real-world constraints often ignored by other systems, such as slippage, round lot trades and transactional costs.

As future work directions, we want to explore a larger number of technical and also fundamentalist indicators to be used as inputs to the ANN. We intend to do it using a more systematic approach, and using feature selection algorithms to identify the features that would bring the network more predictive power.

Moreover, one of the main disadvantages of using ANNs for stock market prediction is the type of model they generate. As ANNs generate black-box models, the investors are asked to make decisions based only on the outputs of the network, without any explanations on the rationale behind the predictions. One way to minimize this problem is to use a method to extract decision rules from ANNs. Although the problem is not simple, many successful techniques were already proposed [55][56], and will be tested in the proposed ANN.

Another aspect to be explored is how to model the disturbances introduced in Equations 1 and 2. One idea would be to use a on-line confidence interval determined by the own network, according to the variance of the predicted outputs.

At last, we will study how to use other metrics or even investigate how to combine a set of metrics to guide the training process of the ANN. This is important because, when integrated to the trading system, the ANN evaluation is based not only on error-based metrics, but also on more general criteria, such as the annualized return and the drawdown.

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