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Application of artificial neural networks to predict the behavior of stocks

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***Keywords*— Stocks, Artificial Neural Networks, Multi-Layer Perceptron with Backpropagation, Probability of series behavior.**

***Abstract*— Statistical data point to the fact that the vast majority of the world population, even after working for a lifetime, when they retire, do not have significant reserves of financial resources in order to guarantee a good quality of life in the elderly. Bearing in mind that the financial stock market offers a viable opportunity for lifelong capital expansion; Through this work, we sought to develop an innovative technique to allow a simple support based on mathematical models, for support decision making by common people, for buying or selling market stocks. This is because the techniques that support decision-making are relatively complex and not widely mastered by the majority of the Brazilian population. The algorithm was proposed to better perform this task. It was made by one corresponding Artificial Neural Network of the "Multi-Layer Perceptron" type with "Backpropagation". Because this ANN is suitable for learning patterns of historical series, which are usually the object of study of stock price behavior by technical analysis methodologies, that are widely used by the market. Therefore, a comparative study was carried out between the results found using the proposed ANN methodology versus the results obtained from simple technical analysis versus single purchase and sale operations in a period of one year. It was found that the ANN model used guided the achievement of superior results for operations with all the Stocks tested, thus proving to be a promising way to solve problems of this nature; related to the identification of mathematical patterns of historical series of the behavior of stock prices on the São Paulo stock exchange.*

I. INTRODUCTION

It is important to contextualize the motivation of this experiment performed with stocks on the São Paulo stock exchange called BOVESPA.

Let's address some statistical data, according to [1] Wolwacz, A & Stormer (2014), which point to the problem to be worked on:

- Only less than 2% of the world's population has more than U$60.000,00 in the bank.
- 93% of Americans reach age 65 with less than U$10,000 in their bank account.
- Working your whole life does not mean securing your future.
- Work should be associated with better resource management of the fruit of that lifetime work.

These data make us reflect on the fact that the typical professional conduct of ordinary citizens, of obtaining their livelihood through formal paid work, even over years of a professional career, does not guarantee stability and a good quality of life after retirement.

Therefore, this proposed model aims to offer a viable alternative for self-employed professionals to multiply their savings in order to guarantee good financial stability after the end of their formal professional careers.

But, how to do it using computational modeling as a decision support and witch results could be achieved?

II. ARTIFICIAL NEURAL NETWORKS

In this work, we present the methodology for applying Artificial Neural Networks in the process of predicting the behavior of stocks based on data from historical series of prices and trading volumes of stocks present on Bovespa, the São Paulo, Brazil Stock Exchange. ANNs (Artificial Neural Networks) are actually computational models that aim to mathematically simulate the behavior of biological nervous systems in human beings. These ANNs models have characteristics of adaptation by experience, learning capacity, generalization ability, fault tolerance and ease of interpretation of their architectures, characteristics that are very relevant as described by [2] Silva, I. N. D. & Spatti, H. & Flauzino, R. (2010).

Neurons are the main biological cells of the nervous system, also called the basic units of this system. According to Figure 1, a Neuron is basically composed of dendrites, which are the input terminals for information; the cell body, which has the function of processing information and finally, the axon, which corresponds to the output terminals responsible for conducting information between different neurons.

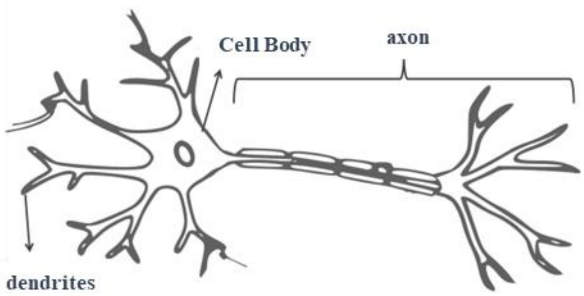

Fig.1: Scheme of a biological neuron.

According to [3] Zorzetto, R. (2012), "The cell count revealed that the human brain has, on average, 86 billion neurons. This number is 14% lower than the previous estimate and close to that proposed in 1988 by Karl Herrup, from Rutgers University (New Jersey - USA)". In addition, the same article reveals two more interesting and curious aspects of the human brain: the first is its disharmony in relation to the number of neurons versus the weight of the brain itself and its smaller component called the cerebellum (which has the original Latin meaning, being "small brain"). The brain is 1,200 grams and occupies more than half of the skull, but houses only 16 billion neurons. The cerebellum, with its only 150 grams, has 69 billion neurons, which we can describe in computational language as "basic data processing units". It follows, therefore, from this fact that the size of an organ does not in itself represent a greater processing capacity. The second curiosity refers to the number of other cell types in the brain, such as "glial" cells. These cells, previously considered only physical support for neurons, perform other essential functions such as helping in the transmission of nerve impulses, nourishing neurons, defending the central nervous system from invading microorganisms and also obviously occupying space. The dogma itself was that the total number of "glial cells" (10 times greater than that of neurons – origin of the idea that we only use 10% of the brain. However, "This high rate of glial cells was taught in books didactic, although experiments already indicated that the ratio was actually 1 to 1", says by Helen Barbas, from the University of Boston.

More than the number of glial cells, which are 85 billion in humans, more concentrated in the brain than in the cerebellum, but what most surprised Suzana was the fact that they practically did not undergo morphological changes during the so-called "evolution". Their size is almost constant between monkeys and humans, while that of neurons size varies 250 times. The researcher went so far as to state that: "The functioning of glial cells must be adjusted in such a fundamental way that nature has eliminated any change that has arisen". This statement leads to the interpretation that only a part of the brain organism would have evolved and another vital part would have already "hypothetically emerged" so well elaborated that it dispensed with the need to evolve, a really intriguing statement.

The fact is that we can scientifically state that we use 100% of the brain, and not just 10% as we could previously imagine; it should only be understood that about 50% of the brain mass has the role of data processing itself (neurons) and the other half (glial cells) have other roles that are equally important and necessary for the maintenance of the entire system. Therefore, it can be said that the neurological system is composed of qualitatively and quantitatively complex cellular elements.

Artificial neurons are simplified mathematical models of biological neurons. As well as Artificial Neural Networks, which in a more simplified mathematical way than biological networks, aim to simulate the behavior of a natural human neural system as well as its learning process.

In figure 2 we can see a simplified artificial neuron. Where the sum of the product of all entries with their respective weights can also be represented by equation (1) below:

$$net_j = \sum_{i=1}^{n} x_i w_{ij} \tag{1}$$

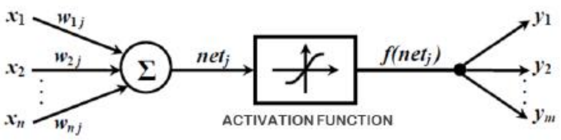

Fig.2: Artificial Neuron Model. Source: [4] Lopes, P.S. (2007).

In this model, the dendrites are represented by the input signals *x1,...,xn*; the values of *w1,…,wn* represent the synaptic weights. The symbol ∑ represents the linear combination that aggregates all the input signals that were weighted by the synaptic weights that result in the *netj* value, which is the input value of the activation function, which in turn filters the input by activating or inhibiting the neuron. *f(netj)* is the output value of the function when the neuron is activated, which results in the m output terminals *y1,..., ym*.

Before talking about the "Backpropagation" algorithm itself, we must first mention its origin in MLP (Multilayer Perceptron Networks). This type of network is characterized by the presence of at least one hidden intermediate layer of neurons, which is positioned between the input and output layers. Therefore, these networks have at least two layers of neurons before the output.

MLP-type networks are quite versatile in terms of application possibilities in different types of problems such as function approximation, system optimization, process identification and control, and even for pattern recognition and for forecasting time series, these last two applications are the ones that really interest us in the study of predicting the behavior of stocks on the stock exchange.

MLP networks have the "feedforward" architecture, which means that the flow of information that starts in the input layer and goes through one or more intermediate layers and ends its course in the output layer, follows its flow in only one direction, therefore without any type of feedback, as shown in Figure 3.

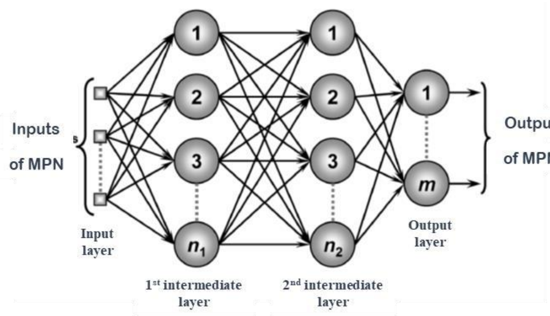

Fig.3: Illustration of a Multilayer Perceptron Network

The figure above illustrates a type of "Perceptron" network known as "Adaline", it consists of a topology that has an output network, which can be composed of several (m) neurons.

The central issue of applying a network to solve a given problem is the choice of the best network topology that allows obtaining the results with less error and more assertive. This question refers to the choice of the number of intermediate layers, as well as the number of their respective neurons, for example. The choice of network topology depends on several factors such as the class of the problem to be solved, the spatial arrangement of the samples and the initial values assigned as well as their synaptic weights, as described by [5] Lopes, P.S. (2010).

However, even if the best topology of a PMC network is chosen for a given problem, the choice of the best values for the synaptic weights from the first interaction is a task, in most cases, of extreme difficulty. To get around this situation, supervised training associated with the learning algorithm called "Backpropagation" or "error retropropagation algorithm" is applied. Because in this way it is possible, from the evaluation of the error in the output, to feed back the algorithm by correcting the synaptic weights to obtain a result that is increasingly closer to the solution of the problem at each interaction of the system.

This training process of MLP networks using the "backpropagation" algorithm can be described by two specific phases: the first phase is the "forward" propagation and the second phase is the "backward" reverse propagation.

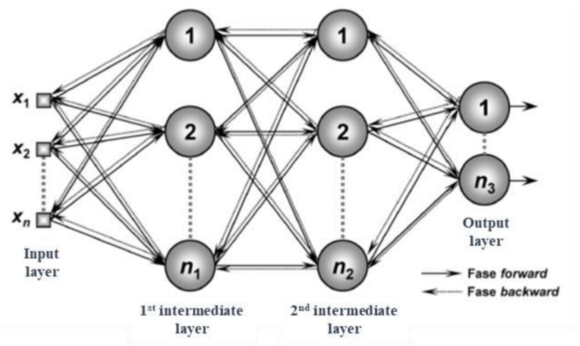

Fig.4: Illustration of the two PMC network training phases.

As illustrated in Figure 4, in the first phase, which consists of forward propagation, the input signals, {X1 to Xn} from a sample of the training set are applied to the neurons of the input layer and propagated to the first layer, later to second layer and finally produce their respective outputs in the last layer entitled "output layer". It is noteworthy that in this propagation phase the responses are obtained through the initial values of the synaptic weights and thresholds of its neurons, therefore these will remain unchanged at each execution of this same phase.

As this is a supervised learning process, right after this first phase, the answers obtained will be compared with the answers already available and their respective errors calculated. The result of these calculations will be later used to adjust both the synaptic weights and the thresholds of all neurons in the system. It is precisely this adjustment that corresponds to the second phase mentioned above, the "reverse propagation".

According to [5] Lopes, P.S. (2010), during the programming of the backpropagation algorithm, the updates of the synaptic weights are applied in the negative direction of the gradient of the quadratic error function.

We can understand the gradient method by the geometric interpretation of Figure 5. Where X0 would be a point on the outermost closed circular surface U(x). The negative gradient is the perpendicular direction that meets X1 such that U(x1) is less than U(x0). And λ is the distance traveled between X0 and X1.

In short, the gradient method, applied to update the synaptic weights, allows each new interaction to get closer and closer to the solution of the problem or model, as each interaction reduces the error of the system output.

Therefore, it is correct to state that the successive phases of "forward propagation" and "reverse propagation" allow the synaptic weights and neuron thresholds to be adjusted at each iteration.

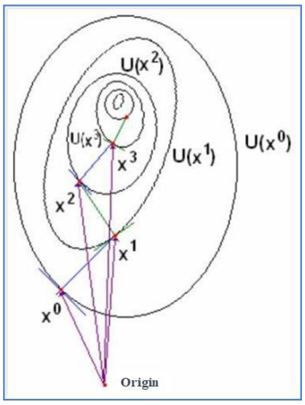

Fig.5: Geometric interpretation of the gradient method.

III. METHODOLOGY

For this work, the basic concepts of Technical Analysis were applied, a specific architecture was defined for the network, historical series available on finance websites were retrieved, data treatment was carried out with the support of electronic spreadsheets and the ANN learning with support of functions available in "Matlab".

The data used as an input referred to weekly recordings, it means weekly candles of historical periods of approximately one year, of certain stocks on the Brazilian stock exchange. It was defined as output, the estimate of valuation or devaluation of these certain papers, always for the coming weeks.

Below is the methodological flowchart applied on this study:

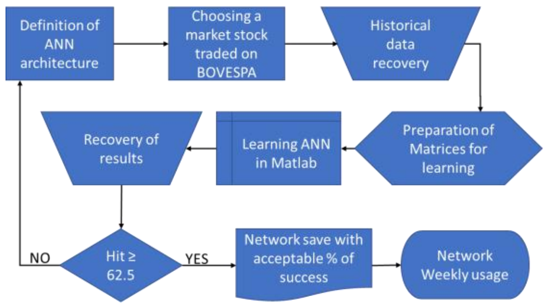

Fig.6 - Applied methodological flowchart

Regarding the Network architecture, seven input data were considered for each weekly interval retrieved: High Value, Open Value, Close Value, Close Value, Close Value adjusted, Volume and Moving Average 8 weeks.

Therefore, the network had the architecture of an input layer with seven inputs, a first hidden layer, a second hidden layer and an output layer with only one output that refers to the tendency of valuation or devaluation of one Stock Exchange.

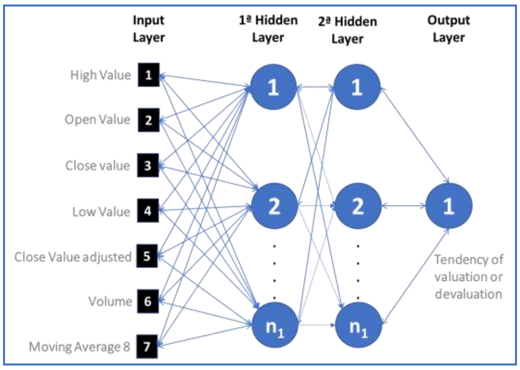

Fig.7 - Architecture of the artificial neural network chosen for this work.

From fifty-three weeks retrieved in .CSV file format and with the aid of an electronic spreadsheet, the calculation of the arithmetic mean of eight periods from the closing to the ninth week was carried out with the first eight weeks. Subsequently, the arithmetic averages of all the other forty-five weeks were calculated, since the arithmetic averages are not available along with the historical data. Then, the results of the exits of each week until the fifty-second week are obtained, which simply corresponds to the value 1 (one) when in week +1, there is appreciation of the stock and 0 (zero) when in week +1 there is devaluation of the paper. And finally, 36 weeks are separated for learning the network and 8 weeks for testing the network, dispensing with the last week that was used only to obtain the output of the fifty-second week, see the explanatory figure below:

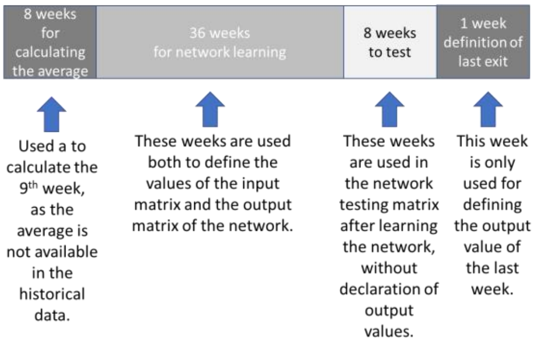

Fig.8: Illustration of preparing the tables

After processing these data, files are created: data entry for learning for the 36 weeks; output for the same 36 weeks and test with the 8 weeks used for testing the network accuracy.

IV. RESULTS

The Stocks studied were AMAR3, RRRP3, TRPL4 and WEGE3.

Results from 3 different methods were compared:

- A purchase at the beginning of the one-year period and a sale at the end of the period.
- Purchases and sales guided by the arithmetic average of 8 weeks.
- Purchases and sales guided by ANN.

At this article we will present the stock that we have obtain the best result using ANN that was RRRP3.

This role corresponds to that of the company RRRP3 Petroleum Oleo and Gas SA; company that operates in the oil and gas sector.

A period of one year was chosen for learning, always taking into account data corresponding to the weekly results of this paper for the study.

Fig.9: Graph of RRRP3 stock during the analyzed period.

The first hypothesis considered only a simple purchase and sale, respectively at the beginning and at the end of the studied period. Starting from the hypothesis of initial capital in the amount of R$10,000.00 (Brazilian currency), the results obtained were:

Table 1: RRRP3 simple purchase and sale operation.

Simple purchase and sale			
Operation	**Price**	**Quantity**	**Amount Operated**
1ª purchase	R$ 40,99	243	R$ 9.960,57
1ª sale	R$ 43,66	243	R$ 10.609,38

So, the gain for the period was approximately 7%.

In the second hypothesis, purchase and sale operations were simulated using as a decision factor only the upward or downward trend of the 8-period arithmetic mean, one of the simplest methods of operating stocks on the market. Starting from the hypothesis of initial capital in the amount of R$10,000.00 (Brazilian currency), the results obtained were:

Table 2: Operations using the arithmetic mean of RRRP3.

Operating by the 8-week Arithmetic Mean			
Operation	Price	Quantity	Amount Operated
1ª purchase	R$ 45,50	219	R$ 9.964,50
1ª sale	R$ 42,09	219	R$ 9.217,71
2ª purchase	R$ 36,40	253	R$ 9.209,20
2ª sale	R$ 41,33	253	R$ 10.456,49
3ª purchase	R$ 33,50	312	R$ 10.452,00
3ª sale	R$ 32,00	312	R$ 9.984,00
4ª purchase	R$ 34,13	292	R$ 9.965,96
4ª sale	R$ 43,66	292	R$ 12.748,72

So, the gain for the period was approximately 28%.

In the third hypothesis, it was used an ANN with seven inputs, two intermediate layers of 100 neurons each and one output. After the learning period using the backpropagation method, we obtained an accuracy level of 62.5%. Considering the same initial capital of R$ 10,000.00, we calculated the week-by-week forecast of the historical series using the network saved after the learning process. And in this case the results obtained were:

Table 3: Operations using ANN for decide operations.

Operating through RNA with 62.5% accuracy			
Operation	Price	Quantity	Amount Operated
1ª purchase	R$ 40,66	245	R$ 9.961,70
1ª sale	R$ 46,79	245	R$ 11.463,55
2ª purchase	R$ 42,09	272	R$ 11.448,48
2ª sale	R$ 42,09	272	R$ 11.448,48
3ª purchase	R$ 35,09	326	R$ 11.439,34
3ª sale	R$ 38,00	326	R$ 12.388,00
4ª purchase	R$ 32,99	375	R$ 12.371,25
4ª sale	R$ 42,82	375	R$ 16.057,50
5ª purchase	R$ 41,20	389	R$ 16.026,80
5ª sale	R$ 41,33	389	R$ 16.077,37
6ª purchase	R$ 33,50	479	R$ 16.046,50
6ª sale	R$ 36,04	479	R$ 17.263,16
7ª purchase	R$ 28,38	608	R$ 17.255,04
7ª sale	R$ 31,68	608	R$ 19.261,44
8ª purchase	R$ 30,49	631	R$ 19.239,19
8ª sale	R$ 34,13	631	R$ 21.536,03
9ª purchase	R$ 33,48	643	R$ 21.527,64
9ª sale	R$ 36,84	643	R$ 23.688,12
10ª purchase	R$ 35,40	669	R$ 23.682,60
10ª sale	R$ 38,56	669	R$ 25.796,64
11ª purchase	R$ 37,40	689	R$ 25.768,60
11ª sale	R$ 39,59	689	R$ 27.277,51
12ª purchase	R$ 33,88	805	R$ 27.273,40
12ª sale	R$ 39,47	805	R$ 31.773,35
13ª purchase	R$ 42,66	744	R$ 31.739,04
13ª sale	R$ 43,66	744	R$ 32.483,04

So, the gain for the period was approximately 226%, it means strongly larger.

V. CONCLUSION

This example show that ANN was really usefully for identify the best moment to purchase and to sale this specific stock comparing with a simple purchase and sale operation and either using the arithmetic mean.

It is understood that the results obtained were quite satisfactory and encouraging to continue improving and studying the potential of expanding the application of this model.

However, is important to highlight that a learned network could suffer wear over the weeks due to changes in market patterns and therefore tends to lose its effectiveness as we have and new re-learnings become necessary to continue to obtain positive ANN results.

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