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Exploring alternatives in the design of an artificial neural network for a predictive analysis and forecasting on economic time series in the foreign exchange market

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Abstract: The purpose of this paper was to evaluate the literature on a predictive analysis in time series, to examine, to compare known types of analysis and to explore the proposition of a practical method to carry out such analysis on foreign exchange market data (FOREX) with the support of neural networks over the aim of constructing an algorithm or forecasting process capable of supporting corporate decision making regarding remittance of foreign exchange or purchase and sale of foreign currency using as a derivative example the Eurodollar pair.

The objective is to demonstrate the validity of models built on neural networks for this purpose and its equivalence with other predictive models most used in the contemporary literature and for that, this paper uses hypothesis construction by comparing models through statistical analysis of variance (ANOVA). The analysis considers three neural networks with a training algorithm based on Multilayer Perceptron and a comparative baseline algorithm widely used in machine learning, the Random Forest. The study concludes by quantitatively and statistically, through ANOVA and Tukey's Test, asserting the equivalence of neural networks against other methods in the predictive analysis of financial-economic time series, using as a base for testing the FOREX data between 2013 and 2016.

Keywords: Neural network, FOREX, classification.

INTRODUCTION

The search for predictive models of Machine Learning in the use of prediction of financial time series has brought new works and proposals with an increasing focus on the efficiency of the model. It is not difficult to understand the need to find better methods of forecasting and predicting behavior of an asset or commodities. Variations in the financial markets add to the uncertainties about the investment and as a consequence, many corporations lose large sums in currency and currency conversion in the face of exchange rate changes in their business transactions and sending remittances to the parent company. The statistical methods used by economists in the past are no longer as effective. [1] states that such methods fail to capture discontinuities and nonlinearities inherent in the high complexity of financial series. Machine learning techniques have been employed with a relative degree of success in predicting behavior in economic and financial series.

In this paper, a composite model of technical analysis supported by neural networks will be analyzed, comparing models of Multilayer Perceptron (MLP) [2] and their results to one of the most successful techniques in this field within the recent literature, Random Forest [3]. Although there is an extensive literature on time series prediction and some authors present a set of neural network types with such an application [4], [5], the use of neural networks has not been extensively explored in all its context. This study aims to obtain an adequate model using neural networks in the predictive analysis on economic time series, contributing to supply the deficiency currently found in the literature and consequently present a model of practical solution of a neural network with its parameters of better performance in a FOREX (Foreign Exchange) database for solving the proposed problem on financial series. The focus of this study is also justified by its goal to contribute objective information on the study theme and the construction of knowledge by analyzing and comparing reasons pros and against the use of neural networks applied to financial models, especially the exchange of purchase and sale of foreign currency pairs. Aiming at the construction of hypotheses and solidification of the theoretical bases, this analysis explores and describes a model as well as its conceptual bases for later investigation of the problematic in the scientific community. Although the analyzes of the present study are restricted to the foreign exchange market, in particular, the Eurodollar pair, the material presented here is not only limited to such instrument but will demonstrate a basis for future comparative analysis between other pairs and instruments financial similarities. This article is divided as follows: the foreign exchange financial market, especially FOREX (Foreign Exchange), the concept of technical and fundamentalist analyzes currently employed by economic analysts will be presented, and then the scientific basis will be based on the construction of the model that will permeate the heart of the present research, later will be presented the methodological instruments used in the article and finally, in the last sessions, it concludes presenting the research and its results.

THEORETICAL REFERENCE

Basic economic and financial concepts

One of the great difficulties of analysts and economists is the search for tools that can more accurately predict changes in the foreign exchange markets including financial movements and changes in commodities. Such difficulty in specifying the movements in assets has made many economists adopt the perspective of market efficiency hypothesis, which suggests that price changes in financial markets are independent of past movements and follow random patterns [6]. For the purposes of this research, such hypothesis will be disregarded, since it aims to demonstrate that the predictability of movements in the financial market is possible and can be made with a certain degree of accuracy. The following sections present concepts related to the financial market on which this study was built, establishing the bases of the theoretical foundation applied in future sessions.

FOREX (Foreign Exchange)

The International Foreign Exchange Market (FOREX) is the largest financial asset-trading market on the planet, with more than three trillion dollars being traded daily. Its trading instruments consist of pairs of currencies offered at all times, twenty-four hours a day (with the trading volume close to zero on weekends). In addition to financial institutions, anyone can act as a trader and trade a pair of currencies, for example, sell dollars and buy euro, in this case, called buying in the EURUSD instrument. There are fees charged differently depending on the volume of purchase and account type of the negotiator, transaction costs. For the purposes of this study, only the variations on the EURUSD instrument will be considered and will not be considered profit margins or different types of negotiation [7]. This market also follows the law of supply and demand, which may interfere in the prices of its instruments, causing highs, lows and or momentary instabilities, besides being influenced by different external variables and not intrinsic to day-to-day trading.

Fundamentalist and Technical Analysis

The methods used by traders to make purchases and sales of FOREX instruments can be grouped into technical and fundamentalist analysis [8] argument. This includes economic factors of each country involved in the instrument under negotiation, economic indices disclosed in the period of analysis, trade balance, among other econometric elements influencing the production and modifiers of behavior on investors of the changed pair in question. As an example, climate change can influence agriculture and consequently interfere negatively in the trade balance of one of the countries involved, implying in a decrease in the value of an instrument in detriment of its pair. On the other hand, the technical analysis takes into account only the factors involved in the process of possession exchange of the instrument, is determined exclusively by the observable patterns in the market, and can be calculated through technical tools on historical data. This characteristic makes the technical analysis very interesting from the point of view of this research since it shares with the tooling framework used in the prediction of problems expected by machine learning techniques.

Methods of Analysis in Time Series Financial

Although fundamentalist analysis provides clear indications of economic trends, more quantitative models such as technical analysis are preferred when attempting to predict the behavior of financial time series. Here are some of these. Among some of the methods most successfully employed in the FOREX market is the trend assessment made by the average market movement (MA). It consists of detecting whether a price is above or below a long-term average on transactions in the market, indicating upward or downward trend respectively. MA stands out as one of the most important indicators of a momentary trend of price movement [5]). Another method also used in the prediction of financial series is how linear regression, also used in machine learning, follows the principles of finding the market trend (up or down) by the angular coefficient of the line drawn by the model on financial data of movements [9] and [10]. An obvious disadvantage of previous methods is that they are reactive, or can only point to the trend after it has already begun. An alternative is to view data as continuous variables, making use of linear-Gaussian conditional distributions. In that each node has a Gaussian distribution who mean is a linear function of its parents (considering a sequence). This is known as an autoregressive (AR) model [11]. In financial series, a method adapted from the latter and widely used in quantitative trading is the autoregressive integrated moving average (ARIMA). Through modeling as a linear system. Parameters are estimated using historical data. On these parameters then calculated, estimates or forecasts can be made [10].

For the sake of simplicity, many models are constructed assuming some conditions that may not be verified in the daily transaction values of FOREX pricing. The particularity of being linearly independent dimensional data for columnar predictors is not a reality for very short periods in financial series - and it is precisely for this particular reason that predictions in day trading are not reliable [12]. Currently, there is a large variety of models employing machine learning in the prediction of financial time series behavior in a successful way by the scientific community. Some of the techniques include Support Vector Machines (SVM), Random Forest, and neural networks. Among these, Random Forest is one of the best performing algorithms for FOREX predictive models, with a focus on EURUSD [1]. In [13] employed a model trained on Support Vector Machine (SVM) demonstrating the effectiveness of this method as a prediction of values on the Eurodollar pair. In subsequent works, new predictions involving still other algorithms of machine learning were used extensively on the EURUSD in FOREX, and finally [14] compared Higher Order Neural Networks, Psi Sigma Networks, Recurrent Networks and MLP showed to be much superior to the other models of neural networks, and for this reason it was chosen MLP methods in this study for comparison with the baseline (benchmark).

METHODOLOGY

The study combines both qualitative and quantitative characteristics when exploring a reference framework dealt with by some authors and by prioritizing the search for the creation of a procedure or method of predictive analysis by making use of quantitative systematic in the comparison of data from the point of view of several presented techniques the best result by analyzing the Eurodollar exchange rate (EUR-USD). This study uses a quantitative analysis in the search of a vision of the result by the positivism that in turn excels by the objectivity, quantifying and classifying the data collected. This research in its first part will be characterized by the qualitative exploration [15] and description of some models or forecasting techniques of economic time series, with emphasis on FOREX, comparing studied performances and results recorded in the literature, configuring exploratory characteristics. Although this analysis is by no means complete, it is sufficient as a comparative baseline and the adoption of the methods studied and even the hyper-parameters of the neural network chosen in the practical application are justified in the sequence in this text during the presentation of the research. In the second part of this study, the present study will focus on a quantitative analysis aiming at a quantitative analysis aiming at a quantitative analysis of the object of analysis without introducing the subjectivity of the researcher [16]. To elaborate a hypothesis about the study through a formal analysis with logical and statistical deductions that support it [17]. With this purpose, four techniques are studied in a

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data laboratory (three different types of Multilayer Perceptron, later described, and one Random Forest), in which an optimized method of predicting the future exchange rate is proposed. Compare results using software and R language in the search for the best assertiveness of the predictive model considering the Eurodollar pair.

A descriptive and comparative statistical formalization of the data collected in the sample space studied (transactions on the said pair in the exchange market from January 2013 to December 2016) is presented in the results session, as well as a variance analysis (ANOVA) as a descriptive statistical methodology on the four methods, their data and results and their comparisons are tabulated in order to formulate a hypothesis of equivalence of the use of neural networks against effective methods in such studies, through the hypothesis test of Tukey [18]–[19]. The database used contains the values of FOREX transactions over the EURUSD for 48 months from 2013 to 2016 (4 years). On this period, it is important to highlight the European crisis that occurred in the first half of 2014, where a considerable drop in the instrument created certain biases about the data collected. In this way, the researcher characterized his database as containing a pre-crisis European (2013), in-crisis (2014) and post-crisis (2015-2016) period. The choice for this period of four years is justified in the intention of creating a recent and resilient predictive model capable of demonstrating that the use of neural networks is as efficient or perhaps better than other methods of machine learning even in periods of uncertainty and fundamentalist changes in the econometric scenario.

PRESENTATION OF RESEARCH

The exploratory research aimed to compare methods of prediction using neural networks whose performance was analyzed against successful models of machine learning already recorded in the literature. Using the Random Forest algorithm as the benchmark, using the RAN algorithm of the CRAN Random Forest library in R Studio with default parameters and three other MLP (Multilayer Perceptron) models were also used with different hyper-parameters. The three algorithms of neural networks used are traditional backpropagation, resilient backpropagation with weight backtracking and another variation of resilient backpropagation with weight backtracking with autoconfiguration of the learning rate (the algorithm searched for the most appropriate rate) with a lower absolute gradient [20]. Table 1 describes the details.

Table 1: Models Configurations

	Traditional Backpropagation	Backpropagation with weights and backtracking (activ = tanh)	Backpropagation with auto calc. learning rate
Hidden Layers	1	1	2
Algorithm (name in API)	*backprop*	*rprop+*	*sag*
Activation Function	Logistic	Tangente hiperbólica	Logistic
Error function	Quadratic	Quadratic	Quadratic
Backtracking on Weights	No	Yes	Yes
Learning rate	0.01	Auto calculated	Auto calculated
Neurons per Layer	1	1	1

The table shows the use of the hyperbolic tangent function as a function of the traditional backpropagation neural network activation and a hidden layer on the artificial neurons of the network created. As a differential function calculator of the accumulated errors, we chose to use the sum of the errors with a quadratic penalty, since it presented better convergence rate in the performed tests and optimization with the gradient descending. The objective of the neural network created was to classify the entries into positive or negative according to test chosen. For example, deciding if the Euro would rise 1% against the Dollar in the EURUSD traded instrument, in this case, it was up to the output layer of the neurons to positively (1) or (0) ranks the Up label. The same would be true to determine the 1% drop or devaluation of the Euro against the Dollar (Down), predicting the behavior in the next five days.

To create the classifier, we used some of the technical analysis algorithms (in the end the choice was based on MA - Moving Average), calculated over certain periods (if it is done minute by minute, it will get a giant base and take a lot of time with both NN as with Random Forest), the columns of the classifier were used with values 1 or 0 indicating if in the next 2 hours the opening value would increase by at least 1% for UP. In this context, a separate classifier was also created for the DOWN case, at least 1% drop (Data were prepared to be inserted in the classifier).

Data Preparation

The original data was extracted from the MetaTrader 4 software. Minute/minute, opening value, closing value (every minute), last minute maximum value and minimum value. The author preferred to carry out his studies, as a matter of fact of time, limiting them to the predictive comparison on days and not hours or minutes, with that, only the data referring to a trading day were preserved, preserving the day-to-day and not minute by minute. Therefore, the number of observations of the order of 106 to 102 was reduced, or from one million to one thousand observations comprising the 48 months as the definitive database for this research. For constructing the model, we chose to construct a predictive model of classification in a supervised way, where the label or label would predict yes or no for an increase (or decrease) of 1% in the current price of the EURUSD instrument over the next seven days. The choice of term is due to the short-term need to be able to determine minimum variations in a given trading instrument. It is not primarily aimed at the speculative exploration where a trader seeks to gain in a few hours with the variation of the traded pair, but within a period of approximately one week can indicate possible variations considering the best time for remittances or currency exchange advantages to companies that somehow make use of the exchange rate without seeking greater profits in this activity as an end. In choosing the size of this classificatory model, some independent variables or features were chosen based on the opinion of the researcher, trader, and knowledge of the FOREX market, as well as the research and opinions of other researchers about the relevance of certain indicators [8]- [21]. Table 2 presents these dimensions.

Table 2: Dimensions used in the model

	Description
Maximum value 24 hours ago	Maximum value recorded during last 24 hours
Maximum amount 5 days before	Maximum value recorded during last 5 days
Maximum 7 days ago	Maximum value recorded during last 7 days
Minimum value 24 hours ago	Minimum value recorded during last 24 hours
Minimum value 5 days before	Minimum value recorded during last 5 days
Minimum 7 days ago	Minimum value recorded during last 7 days
SMA value 20 days	SMA indicator value last 20 days
ADX Value 14 days	ADX indicator value for the last 14 days

These features (within a total of 1030 days or observations) were added to eight dimensions in the final model observed in Table 2, discussed here: the minimum and maximum values assumed by the instrument were taken in the periods of 1 day, 5 days and 7 days prior to the time at which the prediction is made. The model f(x) seeks to determine the highest hit ratio (with x such that x_i in x_1, $x_2, \ldots, x_n, n = 1030$. x_i in IR^8). The goal is to predict whether the instrument increases its value (up) or registers loss (declines) 1% in the next 7 days. The moving average (MA) and the average directional index (ADX) were also used as indicators. The first indicator, extensively used among FOREX traders may indicate a change in the market movements in a given period, in this research was evaluated on the period of $d = 21$ days, already a different temporal relation ($d = 14$ days) being observed for the ADX, the latter aiming to indicate the direction of the new trend apparently emerging. Given $f(x)$ resulting correct predictions for d days, empirically (after many tests) it was concluded that for the value of d in days, the value of the hyper-parameter d that maximizes the final result of correct predictions of the model for ADX is given by:

$$\underset{d}{\operatorname{argmax}} f(x) = 3 * d - 1 \quad (1)$$

Here is a brief justification about the choice of a period and the indicators being contrasted as part of the features of the model. Given that the final intention of the model is the behavioral classification of the EURUSD instrument in the next 7 days ($d = 7$), interpreting the market movements in a 2d day period can bring more precise information about its momentary behavior, this refined experimental measure after some tests carried out by the researcher himself. For extended periods the relation appears to be preserved, since the same behavior has not yet been shown to converge for very short periods of time, or predictions in the day trade itself or with less than two days of analysis, although the knowledge seems to indicate a reasonable possibility statistically predictive accuracy, still to be verified. The calculation base generally used in these types of indicators is presented below:

$$u(d) = \frac{1}{D_1} + \sum_{i=D_1+1}^{d} x(i) - \sum_{i=D_2+1}^{d} x(i) \quad (2)$$

According to [8], $x(d)$ is the price of the instrument on day d, and D_1 and D_2 ($D_1 < D_2$, and usually $D_2 - D_1$) comprise window size. $U(d)$ signal determines the asset price trend, such as going up or down. The present research has its database anchored in two of the most used indicators by economists and traders aiming to demonstrate the validity of models built on neural networks and their equivalence with other predictive models most used in contemporary literature [8]. Thus, in order to demonstrate such a significant statistical equivalence of the model and not merely the construction of the best possible model this study focused on making a good prediction with results equivalent or perhaps superior to the best algorithms in the literature extensively used, but with a theoretical and demonstrative; and here the researcher makes clear that refinements and better results can be obtained on this same model through the use of careful analysis on hyper-parameters and choice of indicators and other features. In order to maintain the normalization required for the problem, the features or predictors were scaled accordingly.

As mentioned earlier, the 48 months (1030 days) included in the survey contain a period of economic crisis aggravated by European macroeconomic changes and therefore exerting strong pressure on the Euro against the Dollar, which is observed by the great fall in the price recorded since the beginning of the period, which can aggravate the bias with a strong trend over the data. However, such distortion and pressure serve the purposes of this study since it is intended to demonstrate the adequacy of predictive models of neural networks to the actual performance of financial series in the market considering technical analysis data aggregating to price behaviors in a certain independent period of crises, a decision must be taken with a model that takes into account exogenous or fundamentalist macroeconomic variations or pressures, it is emphasized that the latter was not directly considered in the model, but its consequences were properly "learned" by the neural network.

Model Training

Given the recent attention made by research in machine learning attributing excellent results to Random Forest as a favorite prediction algorithm with better performance in financial time series and FOREX [9], [8], [14], this study used it as the comparative baseline against three other MLP models with backpropagation. The eight predictor dimensions of the classifier model were defined, which included variation data on the maximum and minimum values recorded in the days prior to the prediction as well as indicators of movement and market trend considering the last two weeks before the prediction was made. Such a model was trained on Random Forest and the three MLP algorithms mentioned earlier in the session. Cross-validation (10-fold) was performed on the 1030 days collected, covering the period from January 1, 2013, to December 31, 2016, 70% of the data used for training and 30% for testing in each one of the 10 validations performed [14]). Several series of data division and testing were performed at random during the months described by the researcher, using the R language on R Studio and its libraries in Machine Learning and Random Forest (neural net, Random Forest) as a tool. Several pieces of training and results were grouped into 3 test batteries (10-fold cross-validation) for each of the four algorithms, totaling 30 tests in all - disregarding the tests that failed to converge for each of the neural network models eventually.

DISCUSSION OF THE RESULTS

The cross-validated results performed with 10 subsets of the data, made in three series are included in this analysis, the means of the respective tests are presented in Table 2. Similar conditions were considered with small variations in the hyper-parameters of the executed machine learning algorithms. In the neural networks, we used 2 hidden layers for the network created on backpropagation with self-learning rate calculated by the API and 1 hidden layer for the other two, according to Table 1. Note that it is expected that the classification tests 1% drop over the next 7 days shows worse performance compared to the 1% increase rating test on the studied pair. This is justified by the introducing bias in the year 2014 when the sharp fall leading to low rates in the instrument traded price. It can be concluded that even in adverse conditions the model of neural networks tends to preserve a good prediction or at least statistically assume results as close as possible to reality considering only factors endogenous to the model combining technical analysis and variation in the medium term. The percentages presented in Table 3 indicate the mean percentages of accuracy on the total cases tested by an algorithm and their respective standard deviations (in parentheses) to the end of 30 iterations, or 3 10-fold cross-validations.

Table 3: Comparison between presented results (accuracy) after 30 iterations

	Random Forest	(BKPROP)	(RPROP)	(SAG)
Up 1%	77,8% (11,5%)	75,4% (3,21%)	76,6% (3,38%)	74,8% (3,72%)
Down 1%	71,2% (15,4%)	67,7% (4,2%)	69,8% (4,03%)	66,3% (4,59%)

The data in Table 3 point to good performances for the three neural networks and baseline algorithms (Random Forest). This applies whether predicting high or low of the study instrument. To confirm the statistical equivalence, we used the Analysis of Variance (ANOVA) on the groups of algorithms, with a confidence interval of 95% ($\alpha = 5\%$). Confirming the permit tests (normality, homoscedasticity and independence of the data), then the Tukey test [18] was used. The result of this test is presented in the following table and its p-values discussed in the following sequence:

Table 4: Comparison between Turkey test results

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  Tukey multiple comparisons of means
    95% family-wise confidence level

Fit: aov(formula = Acuracia ~ Algoritmo + Problema, data = data)

$Algoritmo
                  diff        lwr        upr     p adj
BKPROP-RFOREST  -3.455 -5.7710488 -1.1389512 0.0166501
RPROP-RFOREST   -1.820 -4.1360488  0.4960488 0.0926811
SAG-RFOREST     -4.490 -6.8060488 -2.1739512 0.0078547
RPROP-BKPROP     1.635 -0.6810488  3.9510488 0.1200410
SAG-BKPROP      -1.035 -3.3510488  1.2810488 0.3110338
SAG-RPROP       -2.670 -4.9860488 -0.3539512 0.0341138
```

Given that for the three algorithms (BKPROP, RPROP, and SAG) the ANOVA test on presents p-value as 0.012, 0.067 and 0.005 respectively, rejecting the null hypothesis of equality of performance. In Table 4 we observe the multiple comparisons of the obtained results and it can be verified that the lack of evidence in the results for rejection of the equivalence allows this study to conclude that algorithms of neural networks can obtain equivalent performances to the algorithms of learned machine learning in the use of financial time series such as Random Forest.

CONCLUSION

The study was favorable to the use of machine learning in the prediction of time series, especially attention to the use of neural networks. With performance very similar to Random Forest, one of the most established and reliable algorithms referenced in the literature for economic time series forecasting. The ability of the model to make close-to-reality the detected crises and the consequent introduction of possible biases are added to the positive factors of the use of neural networks in the prediction of FOREX financial series.

We emphasize that improvements and refinements can be made on the predictive model, besides the addition of significant dimensions, since only two of the main indicators were considered in the construction of this model as a study and justification of obtaining results. For the purposes of this study, no fundamental analysis was considered, which would definitely improve the performance of the model and certainly can be considered in the construction of better predictive models including for the generation of models of Quantitative Trading, where machine learning allied to different analyzes is effective. It is worth mentioning the EURUSD pair, which in the year 2014 experienced a great turbulence and strong downward pressure due to problems and instability in the Euro component countries, especially Greece and Portugal, leading even to conjectures of the currency break so strong. Such fundamentalist impact will not be considered in the analyzes of this study, although this one makes its considerations taking into account the performance of neural networks even in particular economic conditions.

It was also noted that during the tests with larger numbers of neurons in the networks the error rate increased, and different functions of activation and error minimization can produce better results. This last consideration, although it may seem not to favor the use of deep neural networks, for deep classification of financial series, should be better reviewed in future works and possibly new models of indicators and data as predictors may favor more networks complex and non-linear. Probably the model studied here as a classifier may not be complex enough for DL and deep nets. New DL tests were performed by the author and successful, but they fall outside the scope of this analysis and may become the object of future study. There are also other areas not explored in this study, such as the search to reduce the drawdown of the market when in unfavorable positions, a constant preoccupation of the trader, others may include refining the intervals considered for each indicator, as well as optimizing the maximum time in the market. to predict the results. Although the objective is not to look for the best predictive model for use in series built on FOREX (especially with EURUSD pair), this study was able to conduct an intense research and to produce results in favor of demonstrating the equivalence of the use of networks compared to classic models presenting good results mentioned in the literature on financial series. Thus, the present analysis fulfilled its objectives of demonstrating the effectiveness in the use of neural networks in financial time series.

REFERENCES

[1] K. Theofilatos, S. Likothanassis, and A. Karathanasopoulos, "Modeling and trading the eur/usd exchange rate using machine learning techniques," *Engineering, Technology & Applied Science Research*, vol. 2, no. 5, pp. 269–272, 2012.

[2] F. Rosenblatt, "Principles of neurodynamics. perceptrons and the theory of brain mechanisms," CORNELL AERONAUTICAL LAB INC BUFFALO NY, Tech. Rep., 1961.

[3] L. Breiman, "Random forests," *Machine learning*, vol. 45, no. 1, pp. 5–32, 2001.

[4] J.-C. Chappelier and A. Grumbach, "Time in neural networks," *ACM SIGART Bulletin*, vol. 5, no. 3, pp. 3–11, 1994.

[5] C. Ullrich, D. Seese, and S. Chalup, “Foreign exchange trading with support vector machines,” in *Advances in data analysis*. Springer, 2007, pp. 539–546.

[6] B. G. Malkiel and K. McCue, *A random walk down Wall Street*. Norton New York, 1985, vol. 8.

[7] P. J. Kaufman, *The new commodity trading systems and methods*. John Wiley & Sons Inc, 1987.

[8] Y. S. Abu-Mostafa and A. F. Atiya, “Introduction to financial forecasting,” *Applied Intelligence*, vol. 6, no. 3, pp. 205–213, 1996.

[9] D. C. Montgomery, L. A. Johnson, and J. S. Gardiner, *Forecasting and time series analysis*. McGraw-Hill Companies, 1990.

[10] C. W. J. Granger and P. Newbold, *Forecasting economic time series*. Academic Press, 2014.

[11] A. S. Weigend, *Time series prediction: forecasting the future and understanding the past*. Routledge, 2018.

[12] D. Zhang, *R for Programmers: Quantitative Investment Applications*. CRC Press, 2018.

[13] C. Serjam and A. Sakurai, “Analyzing predictive performance of linear models on high-frequency currency exchange rates,” *Vietnam Journal of Computer Science*, pp. 1–10, 2018.

[14] C. L. Dunis, J. Laws, and G. Sermpinis, “Modelling and trading the eur/usd exchange rate at the ecb fixing,” *The European Journal of Finance*, vol. 16, no. 6, pp. 541–560, 2010.

[15] A. C. Gil, “How to design research projects,” *São Paulo*, vol. 5, p. 61, 2002.

[16] ——, *Métodos e técnicas de pesquisa social*. 6. ed. Ediitora Atlas SA, 2008.

[17] M. d. A. Marconi and E. M. Lakatos, *Fundamentos de metodologia científica*. 5. ed.-São Paulo: Atlas, 2003.

[18] J. Hsu, *Multiple comparisons: theory and methods*. CRC Press, 1996.

[19] W. Härdle and L. Simar, *Applied multivariate statistical analysis*. Springer, 2007, vol. 22007.

[20] M. Riedmiller and I. Rprop, “Rprop-description and implementation details,” 1994.

[21] T. Kuremoto, S. Kimura, K. Kobayashi, and M. Obayashi, “Time series forecasting using a deep belief network with restricted boltzmann machines,” *Neurocomputing*, vol. 137, pp. 47–56, 2014.