Evaluating the Impact of Technical Indicators on Stock Forecasting

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***Abstract*—The application of time series analysis and forecasting to stock markets is particularly relevant to Technical Analysis, which uses historical values to obtain indicators that highlight possible trends in stock prices. In practice, most of these indicators are evaluated graphically and their direct impact on the quality of stock price forecasting has not been appraised so far. Therefore, the impact of different technical indicators on the prediction of stock closing prices was evaluated in this paper. Under the machine learning perspective, each technical indicator was used as input for artificial neural networks (multilayer perceptrons) trained to forecast the daily stock closing prices of five companies with high representation in the Brazilian IBovespa index. The results have led to two main conclusions: (*i*) lagging technical indicators such as the *Exponential Moving Average* and *Weighted Moving Average*, when used as isolated inputs of the neural networks, can improve the accuracy of the stock forecast when compared to forecasts made with the original series of closing prices; and (*ii*) the combination of different indicators as inputs to the same neural network can improve even more the forecasting performance. These results may contribute to the development of more robust forecasting techniques for stock prices in the future.**

I. Introduction

Forecasting the movement of the stock market is not an easy task, so contributions to this area have attracted great interest of investors. To buy, sell or sometimes even hold a stock is a decision that investors must frequently make during the administration of their portfolio. These decisions are not trivial, as the stock prices and the movements of the market are often influenced by macroeconomic factors such as political events, economic conditions, commodity price indexes, bank rates, investor's expectations and even psychological aspects [1].

To help investors operate on the stock market, different strategies to analyze movements of the stock quotes were developed over the years. Among them, *Technical Analysis* (also known as *Chartist Analysis*) is widely adopted. Technical Analysis uses historical stock prices to calculate indicators that are plotted together with the stock prices on the same chart. In these charts, investors search for particular patterns that may indicate future movements of the market, thus providing additional basis for their decisions [2], [3]. There is a multitude of indicators proposed for Technical Analysis and each of them provides different information about the market. For example, *moving averages* indicate trends of the market, while *momentum* and *relative strength* provide a perspective on how *overbought* or *oversold* a given stock is [2].

Time series forecasting is a field of *Time Series Analysis* intended to develop models that can be used to predict future values of a series of timely ordered values (the *time series*). Given that the price of a stock can be considered a time series, as its values vary over time, techniques developed for time series forecasting can also be used to predict stock prices. In this context, different areas such as Statistics and Computational Intelligence provide tools for time series forecasting [4]. Among them, *Artificial Neural Networks* (ANNs) such as *Multilayer Perceptrons* (MLPs) have been widely adopted, as researchers have shown that they can be effective and even outperform traditional statistical methods such as ARMA and ARIMA [5], [6].

Many works in the literature adopt artificial neural networks to forecast time series from the stock market. In these works, stock prices, fundamental information and technical indicators are used to predict the closing prices of stocks from different markets [3], [6], [7]. Technical indicators, in particular, are used both in isolation and in combination with other indicators as inputs to several predictors, such as ANNs [3], [8]. Besides, such predictors are also used to obtain new indicators, in an attempt to improve the quality of the forecasts [9], [10]. In this scenario, most works from the literature are dedicated to using technical indicators to improve forecasts for a particular problem, and not to evaluating which indicator (or class of indicators) can lead to the highest improvements in time series forecasting for stock markets.

Therefore, the aim of this paper is to evaluate the impact of technical indicators on the quality of artificial neural networks-based stock closing price forecasts. Stock quotes from five companies that heavily contribute to the IBovespa index (the main index of the Brazilian stock exchange BMF&Bovespa – [11]) were selected to be used in the experiments, together with twelve technical indicators widely adopted in the literature. After the evaluation of the individual impact of each indicator on the forecasting performance, an exhaustive search was made to identify whether combinations of indicators as inputs for ANNs may lead to even better forecasting performances for each company. Statistical tests were applied to all the experimental results reported here to verify whether the differences observed were statistically significant or not.

This paper is organized as follows. Section II provides a brief overview of the theoretical aspects adopted in this paper, together with a review of related works from the literature. The experimental methodology and the results are thoroughly described and discussed in Section III, and the final conclusions are given in Section IV.

II. Theoretical Aspects and Related Work

One of the most popular techniques to aid investors with their decisions in the stock market is *Fundamental Analysis*, which is based on companies' indexes such as profit, debts, cash flow, supplies, market demand and many more. These indexes are known as *fundamental information* and they may help investors to assess the general health of a company or even of a particular sector of the economy [12]. Another widely adopted technique is known as *Technical Analysis*, which can be defined as the process of analyzing the historical prices of a given stock in an attempt to identify possible future prices and tendencies [2], [13], [14], [15].

Both Fundamental and Technical analyses can use trend values to enrich the forecasts, but they do it in different ways: while Fundamental Analysis uses trends of the fundamental information (profits, sales, dividend rates etc.) to forecast the financial results of the companies, Technical Analysis uses historical stock quotes to calculate *indicators* to help forecasting possible behaviors of the stock prices [12], [14]. Given that, Technical Analysis is also known as *Graphical Analysis*, since the indicators often lead to new time series that can be plotted together with the original stock quotes [14].

Technical indicators can be calculated based on the stock prices, traded volume and, sometimes, even on other technical indicators. Therefore, given their different natures, each indicator may distinctly assist an investor in identifying possible future behaviors of a given stock.

Indicators can be categorized into two classes: *leading* and *lagging* [13]. Leading indicators focus on changes in the economy that are reflected on market movements, while lagging indicators attempt to follow the variations of the stock prices. Leading indicators perform best when the trading market is operating in sideways (neither an uptrend nor a downtrend is occurring) which, in other words, means that they typically try to evaluate how overbought or oversold a given stock is. Lagging indicators are useful when investors want to evaluate the trend of the stock's historical prices, which may help them infer the next movement of the market [13].

One of the oldest and most popular lagging indicator is the *Moving Average* [13], [16]. A moving average (MA) is the *average price* of a stock at a given time. To calculate this indicator, a number n of periods (also know as *window size*) must be previously specified. The *Simple Moving Average* (SMA) is calculated by dividing the sum of the stock prices over the last n instants by n. This process is repeated for all instants of the time series and, consequently, a new time series is generated. In time series analysis, moving averages try to isolate the trend of the series [16], allowing investors to verify when a new trend has begun. The classic application of a moving average is to indicate changes in price trends. When analyzing MAs, investors typically buy when a stock price rises above its moving average and sell when the price falls below its moving average [14].

Several types of moving averages have been developed over time. The *Exponential Moving Average* (EMA) is calculated by giving higher weights to the most recent samples of the time window [16]. The *Weighted Moving Average* (WMA), as the name suggests, corresponds to a weighted average of the stock closing prices over n instants [13], which leads to smaller lags between WMA and the original series when compared to that observed between SMA and the original series. The *Kaufman Adaptive Moving Average* (KAMA – [15]) was designed to consider market noise and volatility. KAMA will be close to the real values of the time series whenever price swings and noise are low, widening its distance to the real values when the situation changes.

The *Double Exponential Moving Average* (DEMA) was proposed by Mulloy [17] to reduce the amount of lag observed in traditional moving averages. DEMA can be described as a combination of a single and a double EMA. With the same original goals of DEMA, Mulloy [18] also proposed the *Triple Exponential Moving Average* (TEMA) indicator, which is a combination of SMA, EMA and DEMA.

Another lagging indicator is the *Average Directional Index* (ADX), which is used to quantify the strength or weakness of an observed trend in the market [19]. The ADX is a combination of two *price movement* indicators, the *Minus Directional Indicator* (-DI), used to evaluate the strength of downward trends, and the *Plus Directional Indicator* (+DI), used to evaluate the strength of upward trends. The ADX's calculation also uses EMA.

Indexes from the class of *leading indicators*, can also be mentioned here. *Momentum* highlights the differences between the current closing price and the closing prices observed in n past instants [13]. The percentage change in price from the current closing price to the last n closing prices is given by the *Range of Change* (ROC [13]). The *Relative Strength Index* (RSI) shows the weakness of an observed trend of a stock, considering the last n closing prices [13], [19]. The percentage rate-of-change of a triple exponentially moving average of a given stock closing price is given by the TRIX indicator [13], while *Williams %R* shows the closing price of a stock associated with the high and low prices observed in the last n instants of the time series [13].

Most technical indicators in the stock market literature are based on the transformation of the original time series, so that particular characteristics of such series can be highlighted. The use of transformed series in time series forecasting is not new, and such approach has also been used in different contexts of the financial market for years. Briza and Naval [20] proposed the use of multi-objective particle swarm optimization (MOPSO), combined with technical indicators calculated from daily historical values, to forecast stock prices. This optimization method was used to define weights for each indicator, according to the percentage profit and Sharpe ratio [21].

TABLE I
TECHNICAL INDICATORS ADOPTED IN THIS WORK.

#	Indicator	Type	Parameters	Values
1	ADX	Lagging	Window size for EMA	14
2	DEMA	Lagging	Window size for EMA	5
3	EMA	Lagging	Window size	5
4	KAMA	Lagging	Window size for SMA	5
5	Momentum	Leading	Diff. between closing prices	10
6	ROC	Leading	Window size	5
7	RSI	Leading	Window size	14
8	SMA	Lagging	Window size	5
9	TEMA	Lagging	Window size for moving averages	5
10	TRIX	Leading	Window size for TEMA	5
11	Williams %R	Leading	Window size	5
12	WMA	Lagging	Window size	5

González et al. [10] introduced a new method to calculate the Relative Strength Index (RSI) using an artificial neural network. This new technical indicator was named iRSI and was applied to predict stock values from IBEX 35 (Spain). The results revealed that the new indicator provides better results when compared to the original RSI indicator.

A neural network was combined with indicators from fundamental and technical analysis in [3] to predict the future behavior of stock closing prices. Experiments were made with stocks from Petrobras, traded on BMF&Bovespa (Brazil), and the results indicated that the proposed method presented good performance on a set of previously unseen data.

Lee and Chen [8] used two technical indicators (Stochastic K%D and Williams %R [13]) as inputs for Multilayer Perceptrons (MLP) trained with the backpropagation (BackProp) algorithm to forecast stock trends from Taiwan Stock Exchange [22] and Nasdaq [23]. The results have shown that the Williams %R led to a better performance over the Stochastic K%D indicator.

Although all these works point out that the use of technical indicators contribute to a better accuracy in the time series forecasting problem, none of them have thoroughly studied whether there is one indicator that leads to the smallest errors and, if so, which one. Therefore, in this paper, an extensive set of technical indicators were used as inputs for multilayer perceptrons independently trained to forecast the closing prices of different stocks, in order to evaluate which indicator leads to the best accuracy.

Table I lists the indicators described in this section, which were also used in the experiments reported later on.

III. EXPERIMENTAL METHODOLOGY AND RESULTS

As previously mentioned, the goal of this paper is to evaluate the impact of individual technical indicators on stock closing price forecasts. To do so, a diverse set of indicators (with respect to how they are calculated and to their type – leading or lagging) was chosen and each of them was used as inputs to MLPs. The MLPs were configured to forecast one-day ahead closing prices of stocks from five companies of different sectors with high representativeness on the IBovespa Index [11] and high volume of daily trading. These companies are summarized in Table II, while the technical indicators evaluated here, together with the parameters used to calculate each of them, are given in Table I.

TABLE II
COMPANIES LISTED ON IBOVESPA USED IN THE EXPERIMENTS.

Symbol	Name	Sector	% IBovespa
ABEV3	Ambev S/A	Consumer/Beverage	7.54
BBAS	Banco do Brasil	Financial/Banks	2.15
CCRO3	CCR S/A	Construction/Transportation	1.46
PETR4	Petrobras	Oil/Gas/Biofuels	5.87
VALE5	Vale	Basic Materials/Mining	3.56

Since the focus is on daily stock quotes, moving averages were calculated considering swing trade operations with a period of 5 days, which corresponds to one week of trading [12]. For ADX and RSI, Wilder [19] recommends 14 instants as the default time window, while Achelis [13] recommends an interval of 10 instants for Momentum and of 5 instants for ROC. All these recommended values were adopted here.

The forecasting results obtained with the MLPs trained with indicators as inputs were compared to those obtained with MLPs trained with historical values of the original closing price series, in order to verify whether the use of indicators leads to gains or not. After the individual evaluation of each technical indicator, experiments were also made to try to identify the combination of technical indicators that, when used as inputs to a single MLP, leads to the best forecast for each stock considered here.

The experiments were performed on a virtual machine running on Microsoft's Azure platform with a 2.2 GHz processor, 14 GB of RAM and Windows Server 2012 64 bits. The implementation was made using C# in the Microsoft .NET platform, the Encog Machine Learning Framework [24], [25] and TA-Lib [26].

A. Datasets Preparation

For each company listed in Table II, the historical series of daily stock closing prices from Jan-2013 to Dec-2014, were downloaded from Yahoo Finance [27] and the new time series associated with each technical indicator were calculated with the parameters presented in Table I.

To obtain the training samples for the MLPs, the *sliding window* approach [28] was adopted here. In such approach, the n values of the time series associated with instants before or equal to t are considered the inputs of the MLP, while the desired output is the value in $t+1$ [3], [28]. This approach is repeated for all t and the user must only define the window size to be used, which can change according to the problem being solved [28].

Recent works in the literature [3], [28] verified the impact of the size of the forecasting window on the quality of financial time series forecasts obtained with machine learning algorithms, and concluded that three instants leads to the best performance. Therefore, this recommended value was adopted here.

The preparation of the training samples from the technical indicator series is slightly different as, in these cases, the inputs of the MLPs come from the indicator series, while the output comes from the closing price series.

After the time series were processed and the samples to be used in the MLPs were obtained, the final dataset was then divided into three parts: 60% of the samples were reserved to train the MLPs (*training dataset*), 20% of the samples for the *validation dataset* and the remaining 20% of the samples for the *test dataset*. The validation dataset was used to verify whether the error of the MLP being trained is being minimized not only for the training data samples, but also for previously unseen data. This approach was adopted to minimize overfitting [29]. The test dataset was used after the MLPs were trained, to verify their overall performance.

B. Configuration of the MLPs

As previously mentioned, MLPs were chosen here mainly due to their high capability to approximate functions [29], [30]. However, the challenge of using MLPs is to correctly identify the number of hidden layers and the number of neurons in each hidden layer. The literature indicates that a single hidden layer is sufficient to obtain good results, and that the inclusion of two or more hidden layers may not improve the model [10]. For this reason, the number of hidden layers in the MLPs adopted here was set to one.

To identify a suitable number of neurons for the hidden layer, an automatic procedure named *Incremental Pruning* was adopted here [24], [31]. Incremental Pruning requires the training dataset, a criterion to evaluate the MLP and the maximum and minimum numbers of neurons to be considered in the hidden layer, so that it can perform an exhaustive search for the best neural network configuration. Here, the *Mean Squared Error* (MSE) was chosen to evaluate the performance of each MLP and the minimum and maximum number of neurons in the hidden layer were defined respectively as 1 (one) and twice the number of inputs minus one [10], [32].

During Incremental Pruning, the MLPs were trained with the *Resilient Propagation* (RProp) algorithm [33], configured with maximum number of epochs equal to 1000 and acceptable MSE equal to 0.0001 as stop conditions. To avoid problems with the random initialization of each neural network, the process was repeated ten times for each evaluated configuration. This approach was used to identify the best MLP configuration for each experiment performed here.

After the best MLP configurations were obtained for each experiment, such networks were trained considering a random initialization of the weights in the interval $[-1, 1]$, hyperbolic tangent as the activation function for all neurons and a hybrid strategy that combines the RProp algorithm with Simulated Annealing [34]. The stop criterion of the training phase was defined as a maximum number of 1000 epochs and the validation dataset was used in the training procedure so that, at the end of the 1000 epochs, the best MLP with respect to this dataset is returned as the final network to be used. The RProp algorithm was chosen because several works from the literature indicate that it performs better than the classical BackProp in different contexts [35], [36], [33], and the hybridization with Simulated Annealing was adopted because preliminary experiments have indicated that it often leads to MLPs with higher accuracy than those trained by RProp alone.

The training procedure of the MLPs was repeated 10 times for each experiment performed here, and the final averages and standard deviations of the MSE were analyzed.

C. Experimental Results

In order to evaluate the performance of closing price forecasts that employ technical indicators as inputs to the MLPs, two additional neural networks were trained for comparison, both using the original closing price series as inputs: the first one with three delays in the forecasting window, as adopted for the MLPs trained with technical indicators, and the second one with 16 delays in the forecasting window, so that the maximum number of delays used in the calculation of the technical indicators are covered in the inputs of the neural network[1].

The average and standard deviation of the MSE obtained after 10 repetitions of the experiments for each technical indicator, original series (with 3 and 16 delays) and stock considered in this work are given in Table III. These results were obtained with the *test* dataset.

The smallest MSEs in Table III indicate that four out of the five stocks considered in this work (ABEV3, BBAS3, CCRO3 and VALE5) had daily closing prices more accurately forecast when technical indicators were used as inputs in the MLPs. Among these four stocks, the best results for three of them were obtained with variations of the Moving Average indicator, being DEMA the best indicator for ABEV3 and VALE5, and TEMA the best one for CCRO3. The best result for BBAS3 was obtained when WMA was used as inputs to the MLPs. Notice that all these indicators are lagging indicators.

The forecasting results were not superior when technical indicators were used as inputs for the MLPs only for PETR4. For this stock, the smallest MSE was obtained when three delays of the original series were used as inputs for the MLPs.

To verify whether the differences observed in the experimental results are statistically significant, the nonparametric Mann–Whitney U Test (also known as Wilcoxon Rank Sum Test [37], [38]), with significance level of 5%, was applied to all possible pairwise comparisons for each stock. The obtained results are reported in tables IV to VIII, where "1" indicates that the pairwise difference between two forecast models (MLPs) is statistically significant and "0" indicates otherwise.

From the results reported in Table IV (ABEV3), it is possible to infer that, although DEMA presented the smallest MSE its results can be considered equivalent to those presented by TEMA and by the forecasts made using the original closing price series, as the observed differences were not considered statistically significant. For BBAS3 (Table V), the results

[1] As the calculation of RSI uses 14 delays of the original time series and three delays of the indicator series are used as inputs to the MLPs, these three delays actually contain information associated with 16 delays of the original series.

TABLE III

AVERAGE $\pm$ STD. DEV. OF THE MSES BETWEEN REAL STOCK CLOSING PRICES AND MLP FORECASTS USING EACH TECHNICAL INDICATOR AND THE ORIGINAL TIME SERIES (ROWS) AS INPUTS. THE SMALLEST MSE FOR EACH STOCK (COLUMN) IS HIGHLIGHTED IN GREY.

	ABEV3	BBAS3	CCRO3	PETR4	VALE5
ADX	0.166 ± 0.029	33.343 ± 6.932	1.471 ± 0.040	21.295 ± 3.409	37.901 ± 8.957
SMA	0.070 ± 0.001	2.707 ± 0.460	0.397 ± 0.022	2.461 ± 0.657	3.025 ± 1.038
DEMA	0.061 ± 0.001	2.453 ± 0.801	0.272 ± 0.015	3.957 ± 5.983	2.118 ± 0.754
KAMA	0.082 ± 0.002	2.431 ± 0.685	0.389 ± 0.016	2.694 ± 0.868	2.341 ± 1.329
Momentum	0.138 ± 0.019	29.357 ± 6.815	1.470 ± 0.066	19.795 ± 0.692	29.071 ± 7.331
EMA	0.063 ± 0.002	2.014 ± 0.531	0.263 ± 0.015	2.368 ± 0.559	2.520 ± 0.849
ROC	0.152 ± 0.022	31.224 ± 4.929	1.483 ± 0.207	20.371 ± 3.121	30.631 ± 6.629
RSI	0.124 ± 0.025	33.748 ± 5.125	1.396 ± 0.083	19.083 ± 5.531	29.270 ± 13.560
TEMA	0.062 ± 0.002	2.007 ± 0.505	0.252 ± 0.005	2.038 ± 0.614	2.184 ± 0.575
TRIX	0.131 ± 0.023	29.945 ± 5.830	1.429 ± 0.067	19.555 ± 0.842	35.425 ± 11.118
Williams %R	0.198 ± 0.040	27.525 ± 6.2185	2.109 ± 1.716	18.459 ± 1.895	33.655 ± 6.651
WMA	0.062 ± 0.001	1.976 ± 0.621	0.290 ± 0.012	1.831 ± 0.378	2.183 ± 0.813
Closing Price (3 delays)	0.062 ± 0.001	2.036 ± 0.383	0.261 ± 0.024	1.416 ± 0.298	2.179 ± 0.777
Closing Price (16 delays)	0.077 ± 0.003	3.069 ± 1.293	0.579 ± 0.595	2.232 ± 0.757	5.238 ± 2.263

obtained with WMA, which presented the smallest MSE, were considered equivalent to those obtained with moving averages as DEMA, EMA, KAMA, TEMA and the original closing price series. TEMA led to the best results for CCRO3 (Table VI), but the Mann-Whitney U Test indicates that such results can be considered equivalent to those obtained with EMA and the original series. For PETR4 (Table VII), the quality of the forecasts obtained with the original closing price series and with DEMA were considered equivalent. Finally, for VALE5 (Table VIII), the results obtained with moving averages (DEMA, EMA, KAMA, TEMA, SMA and WMA) and the original closing prices series were considered statistically equivalent, even though DEMA presented the smallest MSE.

Therefore, it is possible to infer from the experimental results reported here that lagging indicators, particularly moving averages, led to the best closing price forecasts, even though they were considered statistically equivalent to the forecasts obtained with the original time series. The results also indicated that leading indicators are not suitable to be used alone as inputs to time series forecasters, as MLPs trained with them resulted in high MSEs. It is also possible to observe that there is no statistical significance between leading indicators for most stocks.

D. Combining Technical Indicators

To verify whether a combination of the indicators studied in the previous section would lead to better results, an *exhaustive search* (E.S.) was applied here to identify the best combination of indicators for each stock listed in Table II. Combinations of technical indicators and the original series of closing prices were also considered here. The same methodology and parameters described in Section III-B were also adopted here. However, it is important to highlight that the number of inputs of each MLP will always be a multiple of three (number of indicators times three delays). To illustrate, if a given MLP is supposed to use one technical indicator plus the original time series, it would have six neurons in the input layer: three for the delays of the technical indicator and three for the delays of the original time series.

For a given combination of indicators, after the most suitable number of neurons in the hidden layer is defined by Incremental Pruning, 10 MLPs were trained with a procedure similar to the one described in Section III-B. After that, the MSE of these 10 networks was calculated and used as the overall performance of this combination of indicators.

Table IX presents the results of the exhaustive search for each stock listed in Table II, together with the results obtained with the best technical indicator identified in the experiments reported in Section III-C (for comparison). From the best collection of indicators for each stock, it is possible to note that, except for *Momentum* which is a leading indicator, all the remaining indicators that are present in the best combination for each stock are lagging indicators. This corroborates the conclusions observed in Section III-C.

The Mann-Whitney U Test was also used to evaluate whether the differences between the results obtained with the best combination of technical indicators and the results of the individual models with best inputs identified in Section III-C are statistically significant or not. As can be seen from tables IV, V, VI, VII and VIII, the new forecast model with inputs identified by exhaustive search (E.S.) led to results with differences statistically significant with respect to all other models for CCRO3 and VALE5. In the case of ABEV3 and BBAS the E.S. method led to results with no statistically significant differences when compared with models obtained with DEMA and TEMA. For PETR4, all forecast models obtained with technical indicators (except the one obtained with the original series, which led to the smallest MSE) presented results statistically different from the results reported by E.S..

Figure 1 presents a bar-plot showing how many times each time series (technical indicators and original closing prices) was included in the best models identified by the E.S. for each stock. From Figure 1, it is possible to see that EMA and WMA were included in the best model in four out of the five stocks studied in this work, while TEMA and Momentum were included in the best models generated for three stocks.

In general, the combination of technical indicators and

TABLE IV

Mann-Whitney U Test results for the pairwise comparisons between forecast models generated with indicators (same labels reported in Table I), the original time series (labeled "Close") and a combination of indicators (labeled "E.S"). These results are for ABEV3, "1" indicates that the pairwise difference is statistically significant and "0" indicates otherwise.

	ADX	DEMA	EMA	KAMA	Momentum	ROC	RSI	SMA	TEMA	TRIX	W %R	WMA	Close	E.S.
ADX	-	1	1	1	1	0	1	1	1	1	0	1	1	1
DEMA	1	-	1	1	1	1	1	1	0	1	1	1	0	0
EMA	1	1	-	1	1	1	1	1	0	1	1	0	0	0
KAMA	1	1	1	-	1	1	1	1	1	1	1	1	1	1
Momentum	1	1	1	1	-	0	0	1	1	0	1	1	1	1
ROC	0	1	1	1	0	-	1	1	1	1	1	1	1	1
RSI	1	1	1	1	0	1	-	1	1	0	1	1	1	1
SMA	1	1	1	1	1	1	1	-	1	1	1	1	1	1
TEMA	1	0	0	1	1	1	1	1	-	1	1	0	0	0
TRIX	1	1	1	1	0	1	0	1	1	-	1	1	1	1
W %R	0	1	1	1	1	1	1	1	1	1	-	1	1	1
WMA	1	1	0	1	1	1	1	1	0	1	1	-	0	0
Close	1	0	0	1	1	1	1	1	0	1	1	0	-	0
E.S.	1	0	0	1	1	1	1	1	0	1	1	0	0	-

TABLE V

Mann-Whitney U Test results for the pairwise comparisons between forecast models generated with indicators (same labels reported in Table I), the original time series (labeled "Close") and a combination of indicators (labeled "E.S"). These results are for BBAS3, "1" indicates that the pairwise difference is statistically significant and "0" indicates otherwise.

	ADX	DEMA	EMA	KAMA	Momentum	ROC	RSI	SMA	TEMA	TRIX	W %R	WMA	Close	E.S.
ADX	-	1	1	1	0	0	0	1	1	0	0	1	1	1
DEMA	1	-	0	0	1	1	1	0	0	1	1	0	0	0
EMA	1	0	-	0	1	1	1	1	0	1	1	0	0	0
KAMA	1	0	0	-	1	1	1	0	0	1	1	0	0	0
Momentum	0	1	1	1	-	0	0	1	1	0	0	1	1	1
ROC	0	1	1	1	0	-	0	1	1	0	0	1	1	1
RSI	0	1	1	1	0	0	-	1	1	0	1	1	1	1
SMA	1	0	1	0	1	1	1	-	1	1	1	1	1	1
TEMA	1	0	0	0	1	1	1	1	-	1	1	0	0	0
TRIX	0	1	1	1	0	0	0	1	1	-	0	1	1	1
W %R	0	1	1	1	0	0	1	1	1	0	-	1	1	1
WMA	1	0	0	0	1	1	1	1	0	1	1	-	0	0
Close	1	0	0	0	1	1	1	1	0	1	1	0	-	0
E.S.	1	0	0	0	1	1	1	1	0	1	1	0	0	-

TABLE VI

Mann-Whitney U Test results for the pairwise comparisons between forecast models generated with indicators (same labels reported in Table I), the original time series (labeled "Close") and a combination of indicators (labeled "E.S"). These results are for CCRO3, "1" indicates that the pairwise difference is statistically significant and "0" indicates otherwise.

	ADX	DEMA	EMA	KAMA	Momentum	ROC	RSI	SMA	TEMA	TRIX	W %R	WMA	Close	E.S.
ADX	-	1	1	1	0	0	0	1	1	0	1	1	1	1
DEMA	1	-	0	1	1	1	1	1	1	1	1	1	0	1
EMA	1	0	-	1	1	1	1	1	0	1	1	1	0	1
KAMA	1	1	1	-	1	1	1	0	1	1	1	1	1	1
Momentum	0	1	1	1	-	0	1	1	1	0	0	1	1	1
ROC	0	1	1	1	0	-	0	1	1	0	0	1	1	1
RSI	0	1	1	1	1	0	-	1	1	0	1	1	1	1
SMA	1	1	1	0	1	1	1	-	1	1	1	1	1	1
TEMA	1	1	1	1	1	1	1	1	-	1	1	1	0	1
TRIX	0	1	1	1	0	0	0	1	1	-	0	1	1	1
W %R	1	1	1	1	0	0	1	1	1	0	-	1	1	1
WMA	1	1	1	1	1	1	1	1	1	1	1	-	1	1
Close	1	0	0	1	1	1	1	1	0	1	1	1	-	1
E.S.	1	1	1	1	1	1	1	1	1	1	1	1	1	-

(possibly) the original series of closing prices led to lower MSEs when compared to the MLPs trained with a single technical indicator or the original closing price series (Table IX). For ABEV3, the MSE of the model identified by the E.S. was 3.28% lower than that generated with a single indicator (DEMA). For BBAS3, the E.S. generated model presented the lowest MSE, 5.01% better than the model generated by WMA. For CCRO3 and VALE5, moving averages such as TEMA and DEMA led to the lowest MSEs and the differences between each indicator's forecasting model and the model generated by the E.S. was 5.50%. For PETR4, the difference of MSEs between the best model (closing prices) and the ES was 4.73%.

TABLE VII

MANN-WHITNEY U TEST RESULTS FOR THE PAIRWISE COMPARISONS BETWEEN FORECAST MODELS GENERATED WITH INDICATORS (SAME LABELS REPORTED IN TABLE I), THE ORIGINAL TIME SERIES (LABELED "CLOSE") AND A COMBINATION OF INDICATORS (LABELED "E.S"). THESE RESULTS ARE FOR PETR4, "1" INDICATES THAT THE PAIRWISE DIFFERENCE IS STATISTICALLY SIGNIFICANT AND "0" INDICATES OTHERWISE.

	ADX	DEMA	EMA	KAMA	Momentum	ROC	RSI	SMA	TEMA	TRIX	W %R	WMA	Close	E.S.
ADX	-	1	1	1	0	0	0	1	1	0	0	1	1	1
DEMA	1	-	0	0	1	1	1	0	0	1	1	0	1	1
EMA	1	0	-	0	1	1	1	0	0	1	1	1	1	1
KAMA	1	0	0	-	1	1	1	0	0	1	1	1	1	1
Momentum	0	1	1	1	-	0	0	1	1	0	0	1	1	1
ROC	0	1	1	1	0	-	0	1	1	0	0	1	1	1
RSI	0	1	1	1	0	0	-	1	1	0	0	1	1	1
SMA	1	0	0	0	1	1	1	-	0	1	1	1	1	1
TEMA	1	0	0	0	1	1	1	0	-	1	1	0	1	1
TRIX	0	1	1	1	0	0	0	1	1	-	0	1	1	1
W %R	0	1	1	1	0	0	0	1	1	0	-	1	1	1
WMA	1	0	1	1	1	1	1	1	0	1	1	-	1	1
Close	1	1	1	1	1	1	1	1	1	1	1	1	-	0
E.S.	1	1	1	1	1	1	1	1	1	1	1	1	0	-

TABLE VIII

MANN-WHITNEY U TEST RESULTS FOR THE PAIRWISE COMPARISONS BETWEEN FORECAST MODELS GENERATED WITH INDICATORS (SAME LABELS REPORTED IN TABLE I), THE ORIGINAL TIME SERIES (LABELED "CLOSE") AND A COMBINATION OF INDICATORS (LABELED "E.S"). THESE RESULTS ARE FOR VALE5, "1" INDICATES THAT THE PAIRWISE DIFFERENCE IS STATISTICALLY SIGNIFICANT AND "0" INDICATES OTHERWISE.

	ADX	DEMA	EMA	KAMA	Momentum	ROC	RSI	SMA	TEMA	TRIX	W %R	WMA	Close	E.S.
ADX	-	1	1	1	0	0	0	1	1	0	0	1	1	1
DEMA	1	-	0	0	1	1	1	1	0	1	1	0	0	1
EMA	1	0	-	0	1	1	1	0	0	1	1	0	0	1
KAMA	1	0	0	-	1	1	1	0	0	1	1	0	0	1
Momentum	0	1	1	1	-	0	1	1	1	0	0	1	1	1
ROC	0	1	1	1	0	-	0	1	1	0	0	1	1	1
RSI	0	1	1	1	1	0	-	1	1	0	0	1	1	1
SMA	1	1	0	0	1	1	1	-	1	1	1	0	0	1
TEMA	1	0	0	0	1	1	1	1	-	1	1	0	0	1
TRIX	0	1	1	1	0	0	0	1	1	-	0	1	1	1
W %R	0	1	1	1	0	0	0	1	1	0	-	1	1	1
WMA	1	0	0	0	1	1	1	0	0	1	1	-	0	1
Close	1	0	0	0	1	1	1	0	0	1	1	0	-	1
E.S.	1	1	1	1	1	1	1	1	1	1	1	1	1	-

TABLE IX

AVERAGE $\pm$ STD. DEV., AFTER 10 REPETITIONS, OF THE MSES OF THE BEST COMBINATION OF INPUTS IDENTIFIED BY THE EXHAUSTIVE SEARCH (E.S.) FOR EACH STOCK, TOGETHER WITH THE BEST INDICATOR AND MSE IDENTIFIED IN SECTION III-C (ALSO AVERAGE $\pm$ STD. DEV.).

Stock	ABEV3	BBAS3	CCRO3	PETR4	VALE5
Indicator	DEMA	WMA	TEMA	Close	DEMA
Indicator performance	0.061 ± 0.002	1.976 ± 0.621	0.252 ± 0.005	1.416 ± 0.299	2.118 ± 0.754
Selected inputs	WMA, KAMA, Momentum, EMA, DEMA	TEMA, SMA, WMA, EMA	TEMA, KAMA, WMA, EMA	Momentum, WMA, Close	EMA, Momentum, TEMA, Close
E.S. performance	$0.059 \pm 0,003$	1.877 ± 0.638	0.238 ± 0.004	1.349 ± 0.328	2.001 ± 1.769

IV. CONCLUSION

This paper presented an evaluation of the impact of technical indicators in the quality of stock closing prices forecast. Stocks from five companies of different market segments, with good representativeness in the IBovespa index and high traded volume, were selected for the experiments and their daily historical closing prices were obtained from Yahoo Finance. For each stock, 12 technical indicators were calculated and the resulting time series were individually considered as inputs to Multilayer Perceptrons (MLPs) trained to perform one-day-ahead forecasts of their closing prices. An exhaustive search was also made to identify the best combination of technical indicators and the original time series that, when used as inputs to a MLP, leads to the smallest Mean-squared Errors (MSE) for each stock.

From the results reported here, it is possible to conclude that, when used as inputs to MLPs, technical indicators (mainly lagging indicators) may lead to high quality forecasts of stock closing prices. Besides, the quality of such forecasts may be improved if different indicators are combined with each other and with the original closing price series. Finally, it is also possible to conclude that the original closing price time series should not be ignored, as its impact on the forecasting quality can be significant.

The results obtained in this paper may contribute to users and applications that use stock closing prices forecasting in

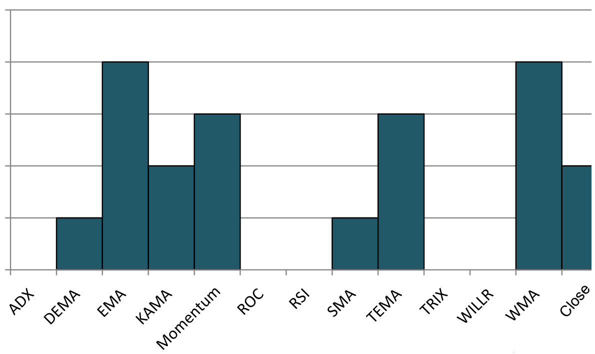

Fig. 1. Number of times each time series was included in the best model identified by the exhaustive search.

different ways: from users that combine such information with other parameters to define their strategy in the Financial Market to Decision Support Systems (DSS) that automatically generate recommendations to buy or sell stocks.

As future work we intend to expand the analysis reported here and replace the Multilayer Perceptrons with other time series forecasting approaches, such as ARIMA and Holt-Winters, in order to verify whether the observed results also hold for traditional methods.

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