



Full length article

## Trading System based on the use of technical analysis: A computational experiment<sup>☆</sup>



Thiago Raymon Cruz Cacique da Costa, Rodolfo Toríbio Nazário, Gabriel Soares Zica Bergo, Vinicius Amorim Sobreiro<sup>\*</sup>, Herbert Kimura

University of Brasília, Department of Management, Campus Darcy Ribeiro, Brasília, Federal District, 70910–900, Brazil

### ARTICLE INFO

#### Article history:

Received 29 September 2014  
Received in revised form 3 March 2015  
Accepted 4 March 2015  
Available online 12 March 2015

#### Keywords:

Trading system  
MACD  
Simple Moving Average  
Exponential Moving Average  
Triple Screen

### ABSTRACT

Previous studies highlight the influence of methods of technical analysis in the search for exceptional gains in the context of the financial market. Based on this scenario, the main objective of this paper is to analyze the performance of the Simple Moving Average, Exponential Moving Average, MACD and Triple Screen techniques in an actual trading system that included 198 stocks traded in the Brazilian. This paper studies the power of predictability of such methods using various combinations of periods, brokerage fees and a policy of Stop-Loss and compares these with the buy-and-hold strategy. The results indicate that while the studied techniques lead to a high probability of obtaining a return that exceeds the investment value, they have little power of predictability in the Brazilian market. In relation to the passive buy strategy, only the smallest part of the obtained returns outweighs the results of the buy-and-hold strategy.

© 2015 Elsevier B.V. All rights reserved.

### 1. Introduction

Technical Analysis (TA) involves an attempt to predict the movement of future asset prices based on an analysis of past prices using qualitative methods, such as graphic analysis, quantitative methods, such as Moving Averages (MA), or a combination of both (Menkhoff and Taylor, 2007; Gençay, 1998, p. 937, p. 347). To measure the presence of the TA in the market, Taylor and Allen (1992) conducted a survey in British agencies and concluded that at least 90% of the respondents benefit from TA tools when making decisions related to their portfolios. Studies such as those of Fabozzi et al. (2007), Menkhoff and Taylor (2007), Marshall et al. (2008), Hsu et al. (2010),

and Menkhoff (2010) also found that TA has a large influence in the financial market. However, there are few studies regarding indicators related to TA in the academic arena (Teixeira and Oliveira, 2010, p. 6886).

Although the importance of TA in the current scenario is clear, according to Ming-Ming and Siok-Hwa (2006, p. 145), there is no consensus regarding the effectiveness of TA tools. Furthermore, few studies have attempted to investigate the results of these techniques or systems in emerging markets such as Brazil, even though, according to Chang et al. (2004, p. 295), such a market can be considered as a good alternative for investors who seek to diversify their portfolios.

From a practical perspective, autonomous asset trading programs are transforming the major stock markets in electronic financial markets (Creamer and Freund, 2010, p. 401). Thus, it is important to note that, according to Austin et al. (2004, p. 37), with the development of new computational techniques and newly available data, the construction and use of the Trading System (TS) has become increasingly more plausible. A TS can be briefly

<sup>☆</sup> This document is a collaborative effort.

<sup>\*</sup> Corresponding author.

E-mail addresses: [thiagorccc@gmail.com](mailto:thiagorccc@gmail.com) (T.R.C.C. da Costa), [rodolfotio@gmail.com](mailto:rodolfotio@gmail.com) (R.T. Nazário), [sharp\\_gabriel@hotmail.com](mailto:sharp_gabriel@hotmail.com) (G.S.Z. Bergo), [sobreiro@unb.br](mailto:sobreiro@unb.br) (V.A. Sobreiro), [herbert.kimura@gmail.com](mailto:herbert.kimura@gmail.com) (H. Kimura).

defined as a set of rules that define necessary conditions to start or exit a negotiation (Chande, 2001, p. 3).

Within this context, the main objective of this paper is to analyze the performance of a *TS* based on Simple Moving Average techniques (*SMA*), Exponential Moving Average (*EMA*), Moving Average Convergence Divergence (*MACD*) and Triple Screen in 198 stocks traded in the Brazilian stock market from January 2000 to February 2014, noting various combinations of periods, brokerage fees and a Stop-Loss mechanism. More specifically, this paper aims to study the following aspects:

1. Which *TA* tool performs best?
2. What is the influence of brokerage fees on the performance of *TA* methods?
3. What is the impact of the Stop-Loss mechanism on operations?
4. Upon observing a wide range of results, which of the *TA* methods are capable of overcoming the buy-and-hold strategy?

We posit that the main results of this work contribute to or advance the discussions about the effectiveness of *TA* tools and about the automated systems with respect to the predictability of the behavior of prices or returns, which according to Campbell et al. (1997, p. 27), is one of the main issues in financial econometrics:

*'ONE OF THE EARLIEST and most enduring questions of financial econometrics is whether financial asset prices are forecastable. Perhaps because of the obvious analogy between financial investments and games of chance, mathematical models of asset prices have an unusually rich history that predates virtually every other aspect of economic analysis. The fact that many prominent mathematicians and scientists have applied their considerable skills to forecasting financial securities prices is a testament to the fascination and the challenges of this problem.'*

Campbell et al. (1997, p. 27).

This paper is structured as follows. The second section presents a brief description regarding the concepts of *TA* and a brief historical contextualization of the topic. The third section is devoted to the presentation of the methods and the computational model used in the experiment, while the fourth section presents the results. The fifth section highlights the main conclusions of the study.

## 2. Theoretical reference

The technical analyst uses past prices and other statistics when making investment decisions, believing that past data contain important information about future stock market behavior (Zhu and Zhou, 2009, p. 519). Accordingly, Murphy (1999, p. 3) defines the three assumptions underlying the precepts of *TA* described below:

1. Prices reflect market events;
2. Changes in the prices move in trends; and
3. Historical prices tend to repeat.

On a historical scope, although the *TA* has gained prominence with the work of Charles Dow in 1884 and William Peter Hamilton in 1900 and in the Wall Street Journal (Vanstone and Finnie, 2009, p. 6671), Cowles (1933) is considered one of the first empirical studies in the area of *TA* published in a specialized scientific journal. In this article, the result of an analysis of effort prediction of 45 professional agencies in selecting specific stocks that could provide higher than average market return results is presented. The results show that the average income of agency forecasts was 4% below the overall market average.

Important studies have discussed the power of predictability of the market. Papers such as Alexander (1961), Fama and Blume (1966) and Levy (1967) demonstrate the presence of the random walk in the markets analyzed in their respective articles. In short, the random walk is an assumption that involves the Efficient Market Hypothesis (*EMH*). In this context, Fama (1991) states that the *EMH* assumes that asset prices reflect all available market information and follow a random behavior. Adding to the discussion, Fama and Blume (1966, p. 226) claim that successive price changes are independent, that is, follow the theory of random walk. This independence implies that the historical series of changes in the price of an asset may not be used to predict future movements in the value of the asset in any path in a significant way.

After the publication of these studies, the *EMH* was considered the theory that governs the movement of stock prices (Zhu and Zhou, 2009, p. 521). However, later influential studies gave greater value to *TA* in the academic arena. Rejecting the theory of random walk with the use of weekly stock returns based on a simple test of volatility specified, the study of Lo and MacKinlay (1988) is considered one of the major works in the area of *TA*. Thus, to investigate the predictive capacity of the market, the article of Brock et al. (1992), one of the influential studies, used the popular strategies of *TA*, specifically, Moving Averages (*MA*) and the Trading-Range Breaks techniques, on the Dow Jones Industrial Average from 1897 to 1986. Excessive returns and the evident power of predictability of the method used in relation to the market studied by the authors have resulted in increased credibility of the *TA*.

Proof of the great influence of the study of Brock et al. (1992) is the wide replication of his method by several researchers, such as, Parisi and Vasquez (2000), Kwon and Kish (2002) and Chang et al. (2004) in different markets. Among these replications is the study of Hudson et al. (1996), which used as a sample the British stock market for the period 1935 to 1994. Such research, whose method used resulted in excessive returns in relation to the considered market, is widespread in academic studies of price behavior, thus contributing to the acceptance of *TA* in the study of financial markets.

The purpose of *MAs*, techniques that are based on the works of Brock et al. (1992) and Hudson et al. (1996), is to identify or signal that a new trend has started or an old one has finished (Murphy, 1999, p. 197). Regarding this issue, Zhu and Zhou (2009, p. 521) contend that these are the most popular and simple existing techniques. Therefore, the *MMs* were applied in the context of emerging markets in prominent studies, such as Gunasekarage and Power

(2001) and Teixeira and Oliveira (2010). Among these studies is that of Ratner and Leal (1999), whose article presented the results of the application of 10 different MAs on a sample of several indices of emergent markets in Asia and the Americas, including Brazil. The returns proved excessive in some indices, thus reinforcing the possible predictability of stock prices traded in dominant market conditions.

Using MAs as a basis for calculations, the Moving Average Convergence Divergence (MACD) indicator was created by Gerald Appel in the 1970s and is now one of the TA methods most practiced in the financial market. While not as well researched in the academic area as other tools, some studies have highlighted the use of MACD. For example, Marques and Gomes (2009) examined the use of this tool together with technical genetic algorithms and fuzzy logic. The result of their study, in addition to achieving positive returns, shows that a variation in the periods of the MACD can result in greater benefits in the final yield. Furthermore, to study the profile of the market and obtain a correlation between the change in value of the shares with negotiations of purchase and sale of assets, Chen et al. (2014), in combination with other TA tools, apply the MACD on the marketing index of Taiwan. Their study provides evidence of the predictive power of the applied technique with respect to long-term strategies.

Regarding the use of the MACD as an indicator in a Brazilian context, Saffi (2003) used five TA tools, including the MACD. Although the results favor the Efficient Market Hypothesis (EMH), the MACD exhibited positive returns in the analyzed sample. However, this result for the MACD may have occurred by chance and may not be due to the possible superiority of the tool (Saffi, 2003, p. 966). Applying the MACD in the financial market of Hong Kong (HKSE), Tung and Quek (2011) used the tool to build a system of trading options while taking into account the analysis of market volatility. Their study indicates that the analysis of these two variables, MACD and volatility, demonstrates predictability of the market.

The Triple Screen method, also reviewed in this paper, was developed by Alexander Elder in the middle of the 1980s. According to Elder (2002, p. 129), the Triple Screen consists of analyzing the market in various time scales and uses monitoring indicators of trends as identifiers of oscillation. As this method is underexplored academically, it becomes the objective of this study to empirically explore this tool. Within this context, summaries of key studies that support the present research are presented in Table 1.

### 2.1. Moving Average—MA

MAs are one of the methods most studied by academics and used by practitioners for automatically generating trading signals without relying on the subjectivity of the judgments of traders (Kuo, 2002, p. 153). Within this context, Appel (2005, p. 167) states that this technique or tool grants a smoothing of noise from fluctuations in prices. Various types of MAs are explored by scholars in the field of TA. However, this paper is limited to the use of the Simple Moving Average (SMA) and Exponential Moving

Average (EMA) because, as stated by Hutson (1984, p. 101), such popular techniques have the advantage of being easily incorporated in computer programs and the data can be easily upgraded.

#### 2.1.1. Simple Moving Average—SMA

Simple Moving Average (SMA) is possibly the most commonly used TA tool among the participants of the financial market. Such popularity of the tool may be due to its simple calculations. The SMA, which calculates the average value of data in a given period of time can be obtained as shown in Eq. (1).

$$SMA_{(k)_n} = (P_1 + P_2 + \dots + P_k)/k \quad (1)$$

where

$P$  represents the closing price of the asset;  
 $k$  represents the period considered; and  
 $n$  represents the relative position of the current period.

#### 2.1.2. Exponential Moving Average—EMA

Exponential Moving Average (EMA), according to Appel (2005, p. 167), is a better trend tracking tool than is the SMA. Corroborating this assertion, Vidotto et al. (2009, p. 296) claim that the EMA is a trend tracking tool that gives greater weight to more recent data and reacts quickly to changes in prices. In simple terms, the value of the EMA can be calculated based on Eq. (2), as shown in Tung and Quek (2011, p. 4675).

$$EMA_{(k)_n} = P_k \times \frac{2}{(k+1)} + MME_{n-1} \times \left[ 1 - \frac{2}{(k+1)} \right] \quad (2)$$

where

$P$  represents the closing price of the asset;  
 $k$  represents the period considered; and  
 $n$  represents the relative position of the current period.

### 2.2. Moving Average Convergence Divergence—MACD

Moving Average Convergence Divergence (MACD) was created by Gerald Appel in the 1970s. The calculation of the MACD is divided into two parts, obtaining the MACD line and, subsequently, creating the MACD histogram, namely, the MACDH. The MACD line is the difference between the EMA of a shorter period and the EMA of a longer period, as shown in Eq. (3), and is based on the study of Kaucic (2010, p. 1719).

$$MACD_{(k_{short}, k_{long})_n} = MME_{(k_{short})_n} - MME_{(k_{long})_n} \quad (3)$$

where

$k$  represents the number of periods included in the calculation of the EMA; and  
 $n$  represents the relative position of the current period.

It is noteworthy that  $k_{short}$  is less than  $k_{long}$ . With respect to the calculation of this tool and in a second step, the Signal Line (SL), which is represented by an EMA of the MACD line with  $k$  periods, is used to calculate the MACDH indicator as shown in Eq. (4) and defined by Fusai and Roncoroni (2008, p. 313).

$$MACDH_n = MACD_n - SL_n. \quad (4)$$

**Table 1**  
Brief summary of the main studies of TA.

Study	Contribution
Cowles (1933).	Analysis of return on effort to predict of professional agencies. The results did not corroborate the TA assumption.
Roberts (1959).	Analysis of financial trading patterns. The results indicated that statistics might support technical and graphical analysis.
Alexander (1961).	Filters applied to orders for asset trading in industrial average Standard & Poor's, between 1897 and 1959. The results establish the random walk.
Fama and Blume (1966).	Applied filters from Alexander (1961) in the Dow-Jones Industrial Average between January 1956 and April 1958. The results obtained confirm the presence of random walk in the sample.
Lo and MacKinlay (1988).	Variance estimators used in weekly returns of the stock market. The results show predictability of the market.
Brock et al. (1992).	Used MMs and Trading-Range Breaks in the Dow-Jones Industrial Average, from 1897 to 1986. As a result, positive returns prove foreseeability of the method used.
Hudson et al. (1996).	Replicated the study of Brock et al. (1992) using as a sample the British stock market for the period from 1935 to 1994. Results similar to Brock et al. (1992) were found.
Parisi and Vasquez (2000).	Replicated the study of Brock et al. (1992) in the Chilean market. Results similar to Brock et al. (1992) were obtained. However, the authors claim that the effect of brokerage was considerable.
Gunasekarage and Power (2001).	The study analyzes the performance of a group of rules of trading. The index uses four stock exchanges in the South Asian market (Bombay Stock Exchange, Dhaka Stock Exchange and Karachi Stock Exchange) and analyzes the implications of these results in the weak form of EMH. The returns do not support the EMH but rather favor market predictability.
Dempster and Jones (2001).	It was developed a trending system that combines indicators at several frequencies and lags, at the end. The results show the possibility of obtaining profit even considering transactions costs.
Chang et al. (2004).	Tested whether stock market returns are predictable. They employed the same techniques used by Brock et al. (1992), that is, the averages in emerging markets, and found predictability for this sample.
Fong and Yong (2005).	SMA was applied in the digital industry's stocks and its returns were insignificant when considering the brokerage fee.
Ellis and Parbery (2005).	Used the Adaptive Moving Average (AMA) on rates of many markets and found few significant results when considering brokerage.
Ming-Ming and Siok-Hwa (2006).	Tested the profitability of various MAs, fixed and variable, on nine Asian market indices, using data from 1988 to 2003. The results show strong support for TA.
Zhu and Zhou (2009).	The authors studied the returns generated by MAs and considered the aversion towards the risk of investors. That is, the investor chooses how to allocate investments among stocks, taking into regard its volatility. The results were positive.
Vanstone and Finnie (2009).	Presents a methodology for designing mechanical trading systems using Artificial Neural Networks (ANN). The results contribute to the use of ANN for negotiations in stock markets.
Hendershott et al. (2011).	The authors analyze if algorithm trading (AT) improves market quality. The results indicates that AT improves liquidity and the informativeness of quotes.
Holmberg et al. (2013).	The study examines the predictability of intraday technical negotiation Open Range Breakout (ORB), applied to a time series of US crude oil futures prices. It highlighted the successful application of the technique in this sample, especially in periods of high volatility.
Lee (2013).	Tested the trading behavior and the impact of high-frequency trading in the future market. The results show no profitable results, after considering transactional costs for the sample.
Chen et al. (2014).	The authors applied the MACD to the Taiwan market index. They determined that the technique presents a certain capacity to perform predictability for long-term strategies.

### 2.3. Triple Screen

The Triple Screen tool is based on three different screens that allow for a more rigorous filter on purchase orders and sales in operations. Thus, this system makes use of methods of tracking trends and techniques that are

in opposition to the trends, thus avoiding false signals indicated by trends.

According to Elder (2004, p. 251), the Triple Screen analyzes the long-term chart, which is a broader measure than the intended measure. Accordingly, the first screen uses indicators to follow trends and identify long-term

**Table 2**

Summary of the Triple Screen.

Source: Adapted of Elder (2004, p. 255).

Long-term trend	Short-term trend	Action	Order
Up	Up	Stand aside	–
Up	Down	Go long	Trailing buy-stop
Down	Down	Stand aside	–
Down	Up	Go short	Trailing sell-stop

movements. When the second screen identifies smaller movements that are in contrast to the initial movements and when the trend of greater amplitude indicates an uptrend, the smaller contrary trends indicate buying opportunities while the opposite indicate opportunities to short sell. According to Elder (2004, p. 253), when the trend of greater amplitude is high, the Triple Screen considers only buy signals from smaller oscillators as, for example, the Strength Index (used in this paper), and ignores the sell signals. On the other hand, when the larger trend is down, it accepts only signs of short selling of the oscillators and ignores the buy signals.

The third screen follows the same logic and uses a movement of days that is smaller than the previous to identify opposite movements. However, this does not use a chart or an indicator and is only a technique that would help in entering the market after the first and the second screen emit a buy signal or a short sale. The third screen is called the trailing buy-stop technique in uptrends, and the trailing sell-stop technique in downtrends. According to Elder (2004, p. 255), when the larger trend is high and the lower trend is down, the trailing buy-stops captures upward disruptions up, and when the larger trend is low and the lower tendency is high, the trailing sell-stops capture downward disruptions. The synthesis of the Triple Screen is presented in Table 2.

Alexander Elder, the author of the technique, recognizes that since 1986, the year of the initial development of the system, there have been many updates to the system. Nonetheless, Alexander Elder contends that the goal is always to seek optimization by changing indicators, using new pairs, and applying new tools. Accordingly, this paper uses the 2002 version of Alexander Elder with the understanding that while his technique is able to generate results, each individual may generate new results when applying the technique. This constitutes the main aim of this work.

### 2.3.1. Strength Index—SI

The Strength Index (SI) is an oscillator created by Alexander Elder and used in Triple Screen. According to Elder (2004, p. 240), the Strength Index combines three essential pieces of market information, the direction of price change, the extent of the price change, and the volume of trading. The Strength Index is calculated using Eq. (5).

$$IF = V_k \times (P_k - P_{k-1}) \quad (5)$$

where

$V$  represents the volume at time  $k$ ; and  
 $n$  represents the closing price of in period  $k$ .

**Table 3**

Values of the brokerage fees considered.

Transaction volume (R\$)	Fixed value (R\$)	Percent value
R\$ 0.01–R\$ 135.07	R\$ 2.70	0.00%
R\$ 135.08–R\$ 498.62	R\$ 0.00	2.00%
R\$ 498.63–R\$ 1514.69	R\$ 2.49	1.50%
R\$ 1,514.70–R\$ 3029.38	R\$ 10.06	1.00%
≥R\$ 3029.39	R\$ 25.21	0.50%

According to Elder (2004, p. 243), this indicator, if used in a short run, can identify buying opportunities in uptrends and short sale opportunities in downtrends. In this way, it helps market operators to identify and better use short movements.

## 3. Research method

### 3.1. Trading System

The Trading System used in this work was built, in its entirety, using the programming language of Visual Basic for Application<sup>®</sup>, and all simulations were performed using Microsoft Office Excel<sup>®</sup>. In all simulations, the initial capital, R\$10,000.00, was chosen. Furthermore, in this system all available capital has always been invested in an operation. That is, as much stock as possible was purchased with the capital available. No short sales are conducted.

To make the Trading System more realistic, a brokerage fee was considered for each order yielded by the TA tools. Thus, a purchase order was only formalized when the amount of available cash on hand is greater than or equal to that of the possible share price possible its corresponding trading fee. With respect to sales orders, only the value of the final amount of the brokerage operation was discounted. Accordingly, brokerage is composed of a fixed part and a variable, both of which are calculated according to the total value of the transaction. Table 3 presents the values used in this study as brokerage.

On a global scale, the Trading System can be divided into three main steps, the interface, the system and the results. The first step, interface, is the environment in which there is initial user communication with the Trading System. It is in this early stage where all conditions are chosen, such as brokerage, stop and study sample. This is followed by the second step, system. In this phase, which is already fully automated, the calculations of the values of the TA tool chosen are conducted as are all negotiations, which take into account asset prices and the value of the brokerage. The final step is the results phase. As the name suggests, this stage is also fully automated. The performance indexes and the returns of the buy-and-hold strategy are calculated, and the results sheet are formalized and made available to the user. Fig. 1 illustrates these three key steps of the Trading System.

### 3.2. Sample

To accomplish this proposal, a study sample of the daily closing prices of 198 stocks traded on the Brazilian stock market was used. The historical series considered in this study covers the period from January 3, 2000 to February

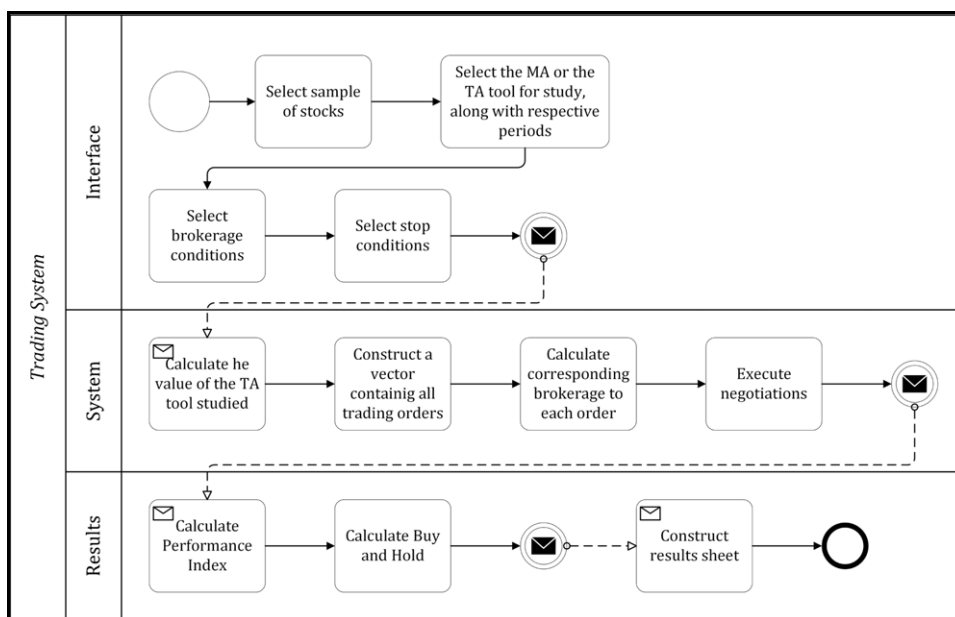


Fig. 1. Trading system illustration.

25, 2014. In addition, the closing prices considered, obtained from the Bloomberg® database, were adjusted by Brazil's index of consumer prices (Brazilian IPC). The study, therefore, takes into account an important computational effort, due to the many combinations of techniques and data. All shares of stock exchange considered in the study are listed in [Appendix](#).

### 3.3. Method of creating purchase and sale order

This paper studies the behavior of four TA tools – the Simple Moving Average, the Exponential Moving Average, the MACD and the Triple Screen – by applying them on an automated system in the Brazilian market. To accomplish this, each method for calculating the TA has its own specific way of building trading order.

With respect to the Moving Averages tool, two identical types of MA were used simultaneously to conduct negotiations, one with the smallest  $k$  period, called the short MA, and another period with a longer  $k$  period, referred to as the long MA. At the instant that the value of the short MA is greater than the long MA, a purchase order is made. If the opposite occurs, it signals a sale. More succinctly, and based on [Ellis and Parbery \(2005, p. 401\)](#), the dynamics of the buying and selling of shares is as follows:

- Purchase: when the curve of the short MA crosses the long upward MA curve; and
- Sale: when the curve of the short MA crosses the curve of the long MA from top to bottom.

With respect to the construction of the signs of the negotiation order of MAs and MACD, all possible combinations were tested, considering the periods or values as follows:

- Short:  $k_{short} \in \mathbb{N} | 5 \leq k_{short} \leq 55$ ;

- Long:  $k_{long} \in \mathbb{N} | 60 \leq k_{long} \leq 220$ ; and
- SL:  $k = 9$ .

Taking this into account, the values for the periods when calculating the MACD line were identical to those used by the MA technique. In relation to the SL, the EMA of  $k$  periods from the line MACD are used as the referenced standard by [Vidotto et al. \(2009, p. 297\)](#) and [Tung and Quek \(2011, p. 4676\)](#) with a value of  $k$  equal to 9.

Following the methods proposed in this paper, we implement the Triple Screen method based on the information of [Elder \(2004, p. 252\)](#) whereby we use different combinations of periods. This method of TA employs the indices ( $k$ ) as follows:

- Inclination of Time Series: 65;
- EMA: 65;
- Strength Index: 2; and
- EMA Strength Index: 2.

[Table 4](#) shows an example of how the Trading System runs and elaborates indicators about the dynamics of buying and selling of shares, considering the signals generated for all Technical Analysis techniques used in this paper.

### 3.4. Stop-Loss

The stop, a tool considerably widespread among financial market participants, is defined as a pre-determined price that will determine the sale of the asset by the trader ([Dempster and Jones, 2001, p. 398](#)). The main function of the stop tool is to control risk and manage negotiations regarding previously defined exit orders ([Vanstone and Finnie, 2009, p. 6673](#)).

More specifically, there are two distinct types of stop, the Stop-Gain and the Stop-Loss. In this sense, [Warburton and Zhang \(2006, p. 32\)](#) state that the Stop-Gain is defined

**Table 4**  
Example of the calculation of values of return for a stock.

Stock	Date <sup>a</sup>	Signal (Tech. analysis)	Traded quantity <sup>f</sup>	Cash balance	Last price	Present value	Future value	Period of application	Return (R) <sup>b</sup>	Average return (R̄) <sup>c</sup>	Standard deviation <sup>d</sup>	Ratio (τ) <sup>e</sup>
Stock <sub>x</sub>	01/03/20XX	Buy	2.00		50.00	100.00		10	0.393%			
	01/13/20XX	Sell	2.00		52.00		104.00					
	01/21/20XX	Buy	2.00	6.00	49.00	98.00		4	0.607%	0.583%	0.163%	3.303
	01/25/20XX	Sell	2.00		50.20		100.40					
	01/02/20XX	Buy	2.00	4.40	51.00	102.00		5	0.772%			
	01/07/20XX	Sell	2.00		53.00		106.00					

<sup>a</sup> Considering MM/DD/YYYY.

<sup>b</sup> The return was calculated on a compound basis.

<sup>c</sup> This value was calculated considering  $R = \sum p(R) \times R$  or  $\frac{10}{(10+4+5)} \times 0.393\% + \frac{4}{(10+4+5)} \times 0.607\% + \frac{5}{(10+4+5)} \times 0.772\%$ .

<sup>d</sup> This value was calculated considering  $SD(R) = \sqrt{(\sum p(R) \times R^2) - (R)^2}$ .

<sup>e</sup> This value was calculated considering  $\frac{R}{SD(R)}$ .

<sup>f</sup> This value does not admit decimal position values.

TA the time when an exit point above the point of entry is set to ensure the expected gain. Similarly, when the asset price reaches a sufficient non-profit level, the order is out of position, and a Stop-Loss mechanism is activated. It is also important to highlight that some papers, for example, [Kaminski and Lo \(2014\)](#) have focused attention on a Stop-Loss mechanism, which, in turn, stresses the importance of Stop-Loss.

Therefore, for purposes of this study, a strategy of trailing stop, based on the work of [Glynn and Iglehart \(1995\)](#) and [Warburton and Zhang \(2006\)](#), was considered as the exit point of the operation where maximum loss accepted is determined to be a  $x$  fixed rate below the entry price. For every reported closing price, the Stop-Loss is adjusted only if this new price is the maximum price of the series of prices formed from the point of entry into operation. This method is presented in Eq. (6).

$$\text{Stop} = x \times \max(P_0, P_1, \dots, P_k) \quad (6)$$

where

$P$  represents the closing price of the day  $k$ ; and  
 $x$  represents the fixed rate of decline previously admitted.

### 3.5. Performance indices

To measure the performance of the Trading System and the applied tools, this study examined the performances of the tools both in terms of risk and return; the impact of Stop-Loss on the outcome of the strategy; and the performance of the observed methods compared to a buy-and-hold strategy. In more detailed terms, with respect to the returns obtained by the simulations, the complexity of the analysis should be considered as the period in which the capital is effectively compromised can differ greatly. Such complexity can also prevent the evaluation of similar returns as the invested capital is at risk for varied periods of time, in other words, the invested capital is exposed to greater volatility over longer periods of time. Thus, to objectively evaluate the wide range of results, the ratio between average return of trading and its standard deviation ( $\tau$ ) was considered, as shown in [Table 4](#).

The  $\tau$  proves useful for evaluating the performance of Stop-Loss and was therefore used to identify the function of the supposed decline in the volatility of the order generated. The  $\tau$  was also part of the construction of the evaluation index of the average of best performance studied. This index, called the Relative Average Deviation (RAD), has been explored in papers by [Sobreiro and Nagano \(2012\)](#); [Sobreiro et al. \(2014\)](#). RAD performs a global comparison of four techniques applied to TA and uses as a basis the value of  $\tau$ , as shown in Eq. (7). RAD indicates that the smaller its value, the better the TA.

$$\text{RAD} = \frac{(f(h) - f^*)}{f^*} \times 100 \quad (7)$$

where

$f(h)$  represents the target function related to the  $\tau$  value of the simulated technique; and

$f^*$  represents the best known value studied thus far.

Briefly, the RAD measures the distance between the value  $h$  of a particular TA tool in relation to the known best value. In this sense, the model that has the lowest value of the RAD is considered the most profitable, considering the study of the return on risk.

Additionally, to study the power of predictability of each TA tool, the percentage of correct prediction directional index—POCID was applied. This index, shown in Eq. (8), identifies the percentage of accuracy of purchase orders and sales generated by the simulation in relation to the values of closing prices. Based on studies of [Faria et al. \(2009\)](#) and [Oliveira et al. \(2013\)](#), the POCID was calculated according to Eq. (8).

$$\text{POCID} = \frac{\sum_{\mu=1}^N D\mu}{N} \times 100 \quad (8)$$

where

$$D\mu = \begin{cases} 1 & \text{if } (P_{(k+1)} - P_k) \times (O_{(k+1)} - O_k) > 0; \\ 0 & \text{otherwise} \end{cases};$$

$P_k$  represents the closing price of the asset in the period  $k$ ;

$O_k$  represents the value found by the method studied in the period  $k$ ; and

$N$  represents the total trading orders made.

Finally, similar to the studies of [Alexander \(1961\)](#) and, more recently, [Teixeira and Oliveira \(2010\)](#), among others, this paper compares its results with a passive strategy of buying, that is, the buy-and-hold strategy. For comparison, the findings are analyzed beyond the results of the buy-and-hold to include the amount of return, in percentage, which outperforms the passive strategy of buying of all simulated stocks.

## 4. Results

The Trading System found 14,632,596 returns of which 198 stocks were studied through 8211 ( $51 \times 161$ ) combinations of periods of TA methods, including MMS, EMA, MACD and Triple Screen. To appropriately produce all results, such tools were analyzed in three different scenarios, namely, with brokerage and without Stop-Loss; without brokerage and without Stop-Loss; and without brokerage and with Stop-Loss. It is important to highlight that the scenario brokerage fees and with Stop-Loss is not considered because the brokerage fee is considered in all operations and the Stop-Loss is just one trigger to start the operation. Accordingly, [Tables 5–7](#) present the main results of the simulations performed given a Stop-Loss parameter value of 0.15. Additionally, [Figs. 2–4](#) present, specifically, the final results of MA models.

[Table 5](#) shows the influence of the three scenarios proposed in  $\bar{\tau}$  and, consequently, also indicates the performance of the TA method as measured by RAD. With respect to all scenarios examined, the MACD technique exhibits better performance when compared to the ratio of the return for risk. Although the arithmetical average of the  $\tau$  of this technique is lower compared to other techniques studied, the standard deviation of  $\tau$  related to the MACD is



**Table 5**Results relative to the  $\bar{\tau}$  and the RAD.

Scenarios	SMA		EMA		MACD		Triple Screen	
	$\bar{\tau}^a$	AV. RAD <sup>b</sup>	$\bar{\tau}$	AV. RAD	$\bar{\tau}$	AV. RAD	$\bar{\tau}$	AV. RAD
With brokerage and without Stop-Loss.	0.449	920.366	0.582	1995.508	0.002	129.288	0.502	444.221
Without brokerage and without Stop-Loss.	0.549	782.524	0.677	968.220	0.128	65.014	0.569	135.756
Without brokerage and with Stop-Loss.	0.352	151.817	0.415	167.950	0.0894	96.910	0.569	111.252
Arithmetic average	0.451 (1.124) <sup>c</sup>	618.236	0.558 (1.454) <sup>c</sup>	1043.892	0.073 (0.226) <sup>c</sup>	97.071	0.547 (2.213) <sup>c</sup>	230.409

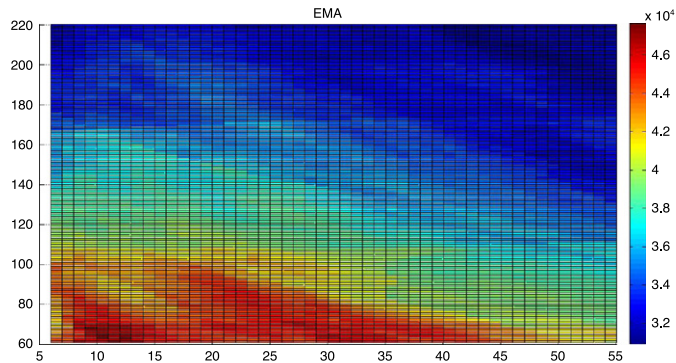
<sup>a</sup> Average  $\tau$ , considering all combinations of MA.<sup>b</sup> Average RAD.<sup>c</sup> The values in parentheses represent the standard deviation of the results of the  $\bar{\tau}$  of each technique.**Table 6**Values, in percent, for the *POCID* and the amount of positive returns.

Scenarios	SMA		EMA		MACD		Triple Screen	
	AV. P. (%) <sup>a</sup>	POS. R. (%) <sup>b, c</sup>	AV. P. (%)	POS. R. (%) <sup>c</sup>	AV. P. (%)	POS. R. (%) <sup>c</sup>	AV. P. (%)	POS. R. (%) <sup>c</sup>
With brokerage and without Stop-Loss.	46.227	73.182	45.304	71.603	45.392	49.332	41.919	77.778
Without brokerage and without Stop-Loss.	46.227	78.056	45.304	76.535	45.392	73.932	41.919	80.808
Without brokerage and with Stop-Loss.	44.347	74.606	43.925	73.498	45.179	68.162	41.919	80.808
Arithmetic average	45.600	75.281	44.844	73.879	45.321	63.809	41.919	79.798

<sup>a</sup> Average *POCID*.<sup>b</sup> Positive returns.<sup>c</sup> The positive returns variable is the arithmetical average of the ratio of positive returns in relation to all results obtained.**Table 7**

Amounts related to the percentage of higher returns for the buy-and-hold strategy.

Scenarios	Abnormal returns (%)			
	SMA	EMA	MACD	Triple Screen
With brokerage and without Stop-Loss.	48.404	49.091	35.348	41.414
Without brokerage and without Stop-Loss.	52.394	52.721	49.438	45.454
Without brokerage and with Stop-Loss.	44.352	43.157	44.546	45.454
Arithmetic average	48.383	48.323	43.111	44.108

**Fig. 2.** Arithmetic average of all EMA's scenarios.

considerably less than that of the other methods at 0.611 compared to 1.598, respectively.

Considering the data presented in Table 5, we further note the strong impact of brokerage fees in the results as a higher return leads to higher  $\tau$  for all tools. Accordingly, this highlights the significant performance improvement of the Triple Screen compared to other techniques.

The use of the Stop-Loss mechanism does not result in greater protection from risk, a function designated by the policy of stop according to Vanstone and Finnie

(2009, p. 6673). With a standard deviation of 0.401, the simulations with the Stop-Loss demonstrate greater exposure to risk compared to simulations that do not consider the strategy of previous output, whose standard deviation takes the value of 0.333. It is essential to emphasize that the Triple Screen does not admit policies of stop.

Table 6 analyzes the power of predictability of the TA techniques and the number of results that exceed the value of the initial capital invested, named as positive

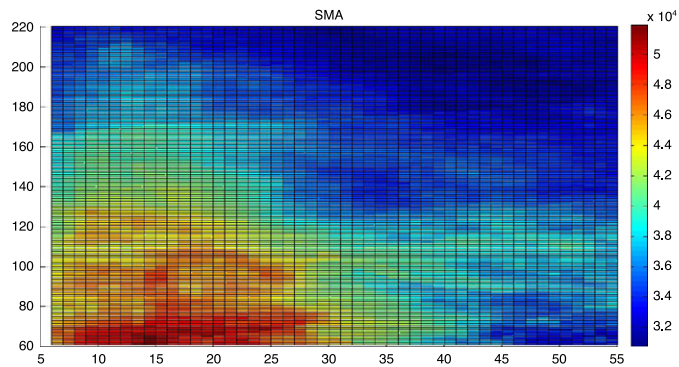


Fig. 3. Arithmetic average of all SMA's scenarios.

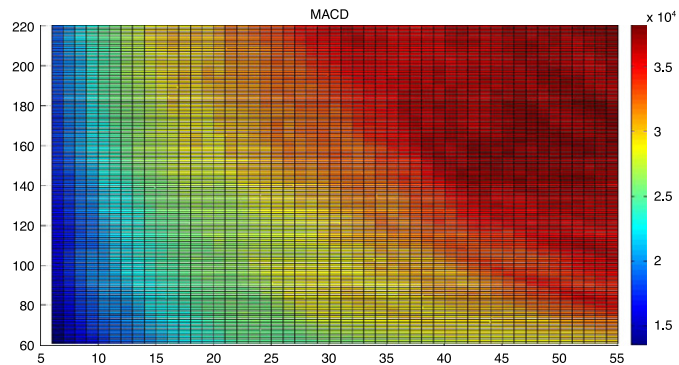


Fig. 4. Arithmetic average of all MACD's scenarios.

returns. The results for the *POCID* index and the amount of positive returns, both in percentages, are presented in this table.

The results in Table 6 show the high amount of positive returns from the *TA* methods studied in the context of the Brazilian market. However, the low predictability of the techniques is also evident based on the overall average error of 55.579% of orders created.

There is a remarkable influence of brokerage in the number of positive returns provided by *TA* techniques. In this context, we emphasize that the *MACD* tool is highly sensitive to negotiation rates. Table 6 indicates that in the scenario with brokers and without Stop-Loss, only 49.332% of all returns outweigh the initial investment. In contrast, in the scenario without brokerage and without Stop-Loss, 73.932% of all returns are positive. Thus, it is important to note that the presence of brokerage does not affect the power of the predictability of the tool studied because to generate a buy signal, in this study, we use only the analysis of the closing prices of the shares.

In particular, in relation to *MACD*, Elder (2002, p. 102) states that there is a pattern regarding this tool and the combination of periods during which this tool is employed, that is, one *EMA* out of 12 periods and one out of 26 periods, along with the *SL* value of the periods being equal to 9. Furthermore, the Elder (2002) states that changes in these standardized values do not result in significant changes in gain. In the sample studied in the present work, such a standard combination in a scenario without brokerage and without Stop-Loss has the arithmetical mean value of its

net return equal to R\$5,534.16 against the average return of R\$21,586.96, which corresponds to all simulations of the same scenario with different combinations of periods. Accordingly, it is concluded that a strategy of changing the periods of the *MACD* can yield greater gains, a finding consistent with that of Marques and Gomes (2009).

In the scope of the analysis of Stop-Loss, it is clear that such a tool detracted from the performance of the adopted *TA* techniques, especially when one considers the power of predictability of the method adopted, which affects the number of positive returns generated. To proceed with the analysis of *TA* methods, both in relation to the adopting of the policy of Stop-Loss in the other scenarios, Table 7 suggests a passive strategy of buying be applied to the analyzed sample. Accordingly, the number of higher returns from the results of this policy of buy-and-hold, named as abnormal returns, are presented in this table.

Table 7 shows the low efficiency of the methods of *TA* studied, when compared with a buy-and-hold strategy. Only a small number of all results obtained by the simulations can overcome the results of a passive purchase. Studies such as those of Alexander (1961) and Ellis and Parbery (2005) reach similar conclusions.

There is a remarkable negative influence on the results due to the Stop-Loss strategy when both trading fees are considered. For situations that consider brokerage fees, only 43.564% of the returns, on average, outperform the buy-and-hold strategy, compared to an average of 50.001% when no brokerage fees are considered. With respect to the

**Table 8**

Some information about the simulation results.

Scenarios	TA model	SD <sup>a</sup>	AR <sup>b</sup>	WR <sup>c</sup>	BR <sup>d</sup>	More profitable stock
1 <sup>e</sup>	SMA	0.242	0.037	−7.946	1.851	ABRE11
1	EMA	0.233	0.034	−8.858	0.390	MAGG3
1	MACD	0.659	−0.012	−1.372	0.445	LINX3
1	TRIPLE SCREEN	0.230	0.033	−0.747	0.344	MYPK3
2 <sup>f</sup>	SMA	0.223	0.051	−6.534	2.611	ABRE11
2	EMA	0.209	0.048	−7.460	0.397	MAGG3
2	MACD	0.568	0.061	−1.011	0.483	LINX3
2	TRIPLE SCREEN	0.220	0.047	−0.712	0.351	MYPK3
3 <sup>g</sup>	SMA	0.304	0.048	−6.534	2.611	ABRE11
3	EMA	0.293	0.046	−7.460	0.978	FJTA3
3	MACD	0.607	0.041	−1.145	1.487	CCXC3
3	TRIPLE SCREEN	0.220	0.047	−0.712	0.351	MYPK3
1	BUY-AND-HOLD	2.558	0.105	−0.700	18.210	CCXC3

<sup>a</sup> Standard deviation.<sup>b</sup> Average return (% per day).<sup>c</sup> Worst return (% per day).<sup>d</sup> Best return (% per day).<sup>e</sup> With brokerage and without Stop-Loss.<sup>f</sup> Without brokerage and without Stop-Loss.<sup>g</sup> Without brokerage and with Stop-Loss.**Table 9**

Information regarding stocks considered in this paper.

Stock code	Company name	Stock code	Company name
ABCB4	Banco ABC Brasil SA	CARD3	CSU Cardsystem SA
ABEV3	AMBEV SA	CCPR3	Cyrela Commercial Properties
ABRE11	Abril Educação SA	CCRO3	CCR SA
AEDU3	Anhanguera Educacional Participações	CCXC3	CCX Carvao da Colombia SA
AGRO3	BrasilAgro - Co Brasileira de	CESP3	Cia Energetica de São Paulo
ALLL3	ALL—America Latina Logistica	CESP6	Cia Energetica de São Paulo
ALPA3	Alpargatas SA	CIEL3	Cielo SA
ALPA4	Alpargatas SA	CLSC3	Centrais Elétricas de Santa Ca
ALSC3	Aliansce Shopping Centers SA	CMIG3	Cia Energética de Minas Gerais
ALUP11	Alupar Investimento SA	CMIG4	Cia Energética de Minas Gerais
AMAR3	Marisa Lojas SA	COCE5	Cia Energética do Ceará
ANIM3	GAEC Educação SA	CPFE3	CPFL Energia SA
ARTR3	Arteris SA	CPLE3	Cia Paranaense de Energia
ARZZ3	Arezzo Indústria e Comércio SA	CPLE6	Cia Paranaense de Energia
AUTM3	Autometal SA	CPRE3	CPFL Energias Renováveis SA
BBAS3	Banco do Brasil SA	CRDE3	CR2 Empreendimentos Imobiliários
BBDC3	Banco Bradesco SA	CREM3	Cremer SA
BBDC4	Banco Bradesco SA	CRUZ3	Souza Cruz SA
BBRK3	Brasil Brokers Participações S	CSAN3	Cosan SA Indústria e Comércio
BBSE3	BB Seguridade Participações SA	CSMG3	Cia de Saneamento de Minas Gerais
BEEF3	Minerva SA/Brazil	CSNA3	Cia Siderúrgica Nacional SA
BEMA3	Bematech SA	CTAX11	Contax Participações SA
BHGR3	BHG SA - Brazil Hospitality Gr	CTIP3	CETIP SA - Mercados Organizados
BICB4	Banco Industrial e Comercial S	CVCB3	CVC Brasil Operadora e Agencia
BISA3	Brookfield Incorporações SA	CYRE3	Cyrela Brazil Realty SA Empree
BPHA3	Brasil Pharma SA	DASA3	Diagnosticos da América SA
BPNM4	Banco Panamericano SA	DAYC4	Banco Daycoval SA
BRAP3	Bradespar SA	DIRR3	Direcional Engenharia SA
BRAP4	Bradespar SA	DTEX3	Duratex SA
BRFS3	BRF SA	ECOR3	EcoRodovias Infraestrutura e L
BRIN3	Brasil Insurance Participações	ELET3	Centrais Elétricas Brasileiras
BRKM3	Braskem SA	ELET6	Centrais Elétricas Brasileiras
BRKM5	Braskem SA	ELPL4	Eletropaulo Metropolitana Elet
BRML3	BR Malls Participacoes SA	EMBR3	Embraer SA
BRPR3	BR Properties SA	ENBR3	EDP - Energias do Brasil SA
BRSR6	Banco do Estado do Rio Grande	ENEV3	Eneva SA
BSEV3	BIOSEV SA	EQTL3	Equatorial Energia SA
BTOW3	B2W Cia Digital	ESTC3	Estácio Participacoes SA
BVMF3	BM&FBovespa SA	ETER3	Eternit SA
EUCA4	Eucatex SA Indústria e Comércio	LLXL3	Prumo Logística SA
EVEN3	Even Construtora e Incorporado	LOGN3	Log-in Logística Intermodal SA

(continued on next page)

Table 9 (continued)

Stock code	Company name	Stock code	Company name
EZTC3	Ez Tec Empreendimentos e Participações	LPSB3	LPS Brasil Consultoria de Imov
FESA4	Cia Ferro Ligas da Bahia - Fer	LREN3	Lojas Renner SA
FHER3	Fertilizantes Heringer SA	MAGG3	Magnesita Refratarios SA
FIBR3	Fibria Celulose SA	MDIA3	M Dias Branco SA
FJTA3	Forjas Taurus SA	MGLU3	Magazine Luiza SA
FJTA4	Forjas Taurus SA	MILS3	Mills Estruturas e Servicos de
FLRY3	Fleury SA	MMXM3	MMX Mineração e Metalicos SA
FRAS3	Fras-Le SA	MPLU3	Multiplus SA
FRIO3	Metalfrio Solutions SA	MRFG3	Marfrig Global Foods SA
GETI4	AES Tiete SA	MRVE3	MRV Engenharia e Participações
GFSA3	Gafisa SA	MULT3	Multiplan Empreendimentos Imob
GGBR3	Gerdau SA	MYPK3	Iochpe-Maxim SA
GGBR4	Gerdau SA	NATU3	Natura Cosméticos SA
GRND3	Grendene SA	ODPV3	Odontoprev SA
GSHP3	General Shopping Brasil SA	OIBR3	Oi as
HBOR3	Helbor Empreendimentos SA	OIBR4	Oi as
HGTX3	Cia Hering	PCAR4	Cia Brasileira de Distribuição
HRTF3	HRT Participações em Petróleo	PDGR3	PDG Realty SA Empreendimentos
HYPE3	Hypermarcas SA	PETR3	Petróleo Brasileiro SA
IDNT3	Ideiasnet SA	PETRA	Petróleo Brasileiro SA
IDVL4	Banco Indusval SA	PFRM3	Profarma Distribuidora de Prod
IGTA3	Iguatemi Empresa de Shopping	PINE4	Banco Pine SA
IMCH3	International Meal Co Holdings	PMAM3	Paranapanema SA
INEP3	Inepar SA Industria e Construção	POMO3	Marcopolo SA
INEP4	Inepar SA Industria e Construção	POMO4	Marcopolo SA
ITSA3	Itausa - Investimentos Itau SA	POSI3	Positivo Informática SA
ITSA4	Itausa - Investimentos Itau SA	PRBC4	Parana Banco SA
ITUB3	Itau Unibanco Holding SA	PRVI3	Cia Providncia Indústria e Co
ITUB4	Itau Unibanco Holding SA	PSSA3	Porto Seguro SA
JBS3	JBS SA	PTBL3	Portobello SA
JHSF3	JHSF Participações SA	QGEP3	QGEP Participações SA
JSLG3	JSL SA	QUAL3	Qualicorp SA
KLBN11	Klabin SA	RADL3	Raia Drogasil SA
KLBN4	Klabin SA	RAPT3	Randon Participações SA
KROT3	Kroton Educacional SA	RAPT4	Randon Participações SA
LAME3	Lojas Americanas SA	RDNI3	Rodobens Negocios Imobiliários
LAME4	Lojas Americanas SA	RENT3	Localiza Rent a Car SA
SBSP3	Cia de Saneamento Básico do Es	TGMA3	Tegma Gestão Logística
SCAR3	São Carlos Empreendimentos e P	TIMP3	Tim Participações SA
SEER3	Ser Educacional SA	TOTS3	Totvs SA
SFSA4	Banco Sofisa SA	TPIS3	TPI—Triunfo Participações e
SGPS3	Springs Global Participações S	TRIS3	Trisul SA
SHOW3	T4F Entretenimento SA	TRPL4	Cia de Transmissão de Energia
SLCE3	SLC Agricola SA	TRPN3	Tarpon Investimentos SA
SLED4	Saraiva SA Livreiros Editores	TUPY3	Tupy SA
SMLE3	Smiles SA	UCAS3	UNICASA Indústria de Móveis SA
SMT03	Sao Martinho SA	UGPA3	Ultrapar Participações SA
SSBR3	Sonae Sierra Brasil SA	USIM3	Usinas Siderúrgicas de Minas G
STBP11	Santos Brasil Participações SA	USIM5	Usinas Siderúrgicas de Minas G
SULA11	Sul America SA	VAGR3	Vanguarda Agro SA
SUZB5	Suzano Papel e Celulose SA	VALE3	Vale SA
TAE11	Transmissora Alianca de Energia	VALE5	Vale SA
TBLE3	Tractebel Energia SA	VIVR3	Viver Incorporadora e Construt
TCSA3	Tecnisa SA	VIVT4	Telefonica Brasil SA
TECN3	Technos SA	VLID3	Valid Soluções e Serviços de S
TEMP3	Tempo Participações SA	VVAR11	Via Varejo SA
TERI3	Tereos Internacional SA	WEGE3	WEG SA

study of Stop-Loss, the results, for the most part, do not outweigh the buy-and-hold strategy as, on average, only 44.018% of the returns are higher than those of a passive buy.

In the context of MA, Figs. 2–4 show the arithmetic average values, in real, of the final results of three different MA studied, considering all three scenarios. Thus, the horizontal and vertical axes represent the  $k_{short}$  and  $k_{long}$  values, respectively. It is important to mention that the Triple Screen method, in this paper, uses the fixed periods

proposed by Elder (2004). Therefore, it was not done a similar figure to such TA tool.

Noting Figs. 2 and 3, it is remarkable that there is a concentration of higher results in the combination of smaller  $k_{short}$  and  $k_{long}$  values. This may signalize that, once using the SMA and EMA in the Brazilian market, short-term investments can be more profitable. Regarding MACD, Fig. 4 shows that  $k$  larger values bring better results. In this way, different from the SMA and EMA, longer-term

investment can be more profitable when used the *MACD* method in the Brazilian market.

## 5. Conclusion

To apply popular *TA* strategies and study their performances in the Brazilian market, this study tested the *SMA*, *EMA*, *MACD*, and Triple Screen tools by building a Trading System using a sample that consisted of closing prices of 198 stocks traded in the Brazilian stock market from January 2000 to February 2014. Several variations of periods that make up the calculation of the tools, as well as scenarios that take into account a Stop-Loss mechanism and brokerage fees were considered.

The results show that the application of the *TA* tools in the market considered leads to a high probability of obtaining a return that exceeds the investment value. However, trading fees have a strong influence on the return due to the use of the system; therefore, it is highly improbable that the system can overcome a buy-and-hold strategy. Although in the scope of the results, when referring mainly to the *MACD*, it was evidenced that a variation of the periods adopted for calculating the *TA* method is favorable for higher returns, thus corroborating the findings of Marques and Gomes (2009). As measured by *RAD* index, the *MACD* technique exhibits better performance when compared to the ratio of the return for risk. In this sample, the Stop-Loss did not generate greater protection from the risk, and in fact, it negatively affected the predictive power of the techniques studied.

The experiment conducted herein, which uses the constructed trading system, is valuable for investors who seek not only to apply methods of *TA* but also to study investments in the Brazilian market while taking into account the considerable number of positive returns. For future research, it is suggested that these methods be applied in other markets and especially over a greater period of time to involve larger cycles of market trends. Furthermore, to trace the level of their effectiveness, it is recommended that the study of the Stop-Loss be considered in other samples and with other parameters.

## Appendix A

For more details on results of *TA* techniques, please see Table 8.

All stocks considered in this paper are shown in Table 9.

## Appendix B. Supplementary data

Supplementary material related to this article can be found online at <http://dx.doi.org/10.1016/j.jbef.2015.03.003>.

## References

- Alexander, S.S., 1961. Price movements in speculative markets: Trends or random walks. *Ind. Manag. Rev.* 2 (1), 7–26.
- Appel, G., 2005. *Technical Analysis: Power Tools for Active Investor*. Pearson Education.
- Austin, M., Bates, G., Dempster, M., Leemans, V., Williams, S., 2004. Adaptive systems for foreign exchange trading. *Quant. Finance* 4 (4), 37–45.
- Brock, W., Lakonishok, J., LeBaron, B., 1992. Simple technical trading rules and the stochastic properties of stock returns. *J. Finance* 47 (5), 1731–1764.
- Campbell, J.Y., Andrew, W.L., MacKinlay, A.C., 1997. *The Econometrics of Financial Markets*. Princeton University Press.
- Chande, T.S., 2001. *Beyond Technical Analysis: How to Develop and Implement a Winning Trading System*, second ed. John Wiley & Sons.
- Chang, E.J., Lima, E.J. A., Tabak, B.M., 2004. Testing for predictability in emerging equity markets. *Emerg. Mark. Rev.* 5 (3), 295–316.
- Chen, C.-C., Kuo, Y.-C., Huang, C.-H., Chen, A.-P., 2014. Applying market profile theory to forecast Taiwan Index Futures market. *Expert Syst. Appl.* 46 (10), 4617–4624.
- Cowles, A., 1933. Can stock market forecasters forecast? *Econometrica* 1 (3), 309–324.
- Creamer, G., Freund, Y., 2010. Automated trading with boosting and expert weighting. *Quant. Finance* 10 (4), 401–420.
- Dempster, M., Jones, C., 2001. A real-time adaptive trading system using genetic programming. *Quant. Finance* 1 (4), 397–413.
- Elder, A., 2002. *Come Into My Trade Room: A Complete Guide to Trading*. John Wiley & Sons, Inc.
- Elder, A., 2004. *Como Se Transformar em um Operador e Investidor de Sucesso*, fifteenth ed. Campus.
- Ellis, C.A., Parbery, S.A., 2005. Is smarter better? A comparison of adaptive, and simple moving average trading strategies. *Res. Int. Bus. Finance* 19 (3), 399–411.
- Fabozzi, F.J., Focardi, S., Jonas, C., 2007. Trends in quantitative equity management: survey results. *Quant. Finance* 7 (2), 115–122.
- Fama, E.F., 1991. Efficient capital markets: II. *J. Finance* 46 (5), 1575–1617.
- Fama, E.F., Blume, M.E., 1966. Filter rules and stock-market trading. *J. Bus.* 39 (1), 226–241.
- Faria, E.L.d., Albuquerque, M.P., Gonzalez, J.L., Cavalcante, J.T.P., Albuquerque, M.P., 2009. Predicting the Brazilian stock market through neural networks and adaptive exponential smoothing methods. *Expert Syst. Appl.* 36 (10), 12506–12509.
- Fong, W.M., Yong, L.H., 2005. Chasing trends: recursive moving average trading rules and internet stocks. *J. Empir. Finance* 12 (1), 43–76.
- Fusai, G., Roncoroni, A., 2008. *Implementing Models in Quantitative Finance: Methods and Cases*. Springer.
- Gençay, R., 1998. The predictability of security returns with simple technical trading rules. *J. Empir. Finance* 5 (4), 347–359.
- Glynn, P.W., Iglehart, D.L., 1995. Trading securities using trailing stops. *Manag. Sci.* 41 (6), 1096–1106.
- Gunasekarage, A., Power, D.M., 2001. The profitability of moving average trading rules in South Asian stock markets. *Emerg. Mark. Rev.* 2 (1), 17–33.
- Hendershott, T., Jones, C., C.M., Menkvel, A.J., 2011. Does algorithmic trading improve liquidity? *J. Finance* 66 (1), 1–33.
- Holmberg, U., Lönnbark, C., Lundström, C., 2013. Assessing the profitability of intraday opening range breakout strategies. *Finance Res. Lett.* 10 (1), 27–33.
- Hsu, P.-H., Hsu, Y.-C., Kuan, C.-M., 2010. Testing the predictive ability of technical analysis using a new stepwise test without data snooping bias. *J. Empir. Finance* 17 (3), 471–484.
- Hudson, R., Dempsey, M., Keasey, K., 1996. A note on the weak form efficiency of capital markets: The application of simple technical trading rules to UK stock prices - 1935 to 1994. *J. Bank. Finance* 20 (6), 1121–1132.
- Hutson, J.K., 1984. Filter price data: Moving average vs. exponential moving average. *Tech. Anal. Stocks Commod.* 2 (3), 101–104.
- Kaminski, K.M., Lo, A.W., 2014. When do stop-loss rules stop losses? *J. Financ. Mark.* 18 (1), 234–254.
- Kaucic, M., 2010. Investment using evolutionary learning methods and technical rules. *European J. Oper. Res.* 207 (3), 1717–1727.
- Kuo, G.W., 2002. Some exact results for moving-average trading rules with applications to UK indices. in: *Quantitative Finance Series*, (Chapter. 5), pp. 152–173.
- Kwon, K.-Y., Kish, R.J., 2002. A comparative study of technical trading strategies and return predictability: an extension of using NYSE and NASDAQ indices. *Q. Rev. Econom. Finance* 42 (3), 611–631.
- Lee, E.J., 2013. High frequency trading in the Korean index futures market. *J. Futures Mark.* 1–21.
- Levy, R.A., 1967. Relative strength as a criterion for investment selection. *J. Finance* 22 (4), 595–610.
- Lo, A., MacKinlay, A.C., 1988. Stock market prices do not follow random walks: evidence from a simple specification test. *Rev. Financ. Stud.* 1, 41–66.
- Marques, F., Gomes, R.M., 2009. Análise de séries temporais aplicadas ao mercado financeiro com o uso de algoritmos genético e lógica nebulosa. In: *VII Encontro Nacional de Inteligência Artificial*, ENIA. pp. 749–758.

- Marshall, B.R., Cahan, R.H., Cahan, J.M., 2008. Does intraday technical analysis in the U.S. equity market have value? *J. Empir. Finance* 15 (2), 199–210.
- Menkhoff, L., 2010. The use of technical analysis by fund managers: International evidence. *J. Bank. Finance* 34 (11), 2573–2586.
- Menkhoff, L., Taylor, M.P., 2007. The obstinate passion of foreign exchange professionals: Technical analysis. *J. Econ. Lit.* 45 (4), 936–972.
- Ming-Ming, L., Siok-Hwa, L., 2006. The profitability of the simple moving averages and trading range breakout in the Asian stock markets. *J. Asian Econ.* 17 (1), 144–170.
- Murphy, J.J., 1999. *Technical Analysis of the Financial Markets: A Comprehensive Guide To Trading Methods and Applications*. New York Institute of Finance.
- Oliveira, F.A.d., Nobre, C.N., Zárte, L.E., 2013. Applying Artificial Neural Networks to prediction of stock price and improvement of the directional prediction index—Case study of PETR4, Petrobras, Brazil. *Expert Syst. Appl.* 40 (18), 7596–7606.
- Parisi, F., Vasquez, A., 2000. Simple technical trading rules of stock returns: evidence from 1987 to 1998 in Chile. *Emerg. Mark. Rev.* 1 (2), 152–164.
- Ratner, M., Leal, R.P., 1999. Tests of technical trading strategies in the emerging equity markets of Latin America and Asia. *J. Bank. Finance* 23 (12), 1887–1905.
- Roberts, H.V., 1959. Stock-market patterns and financial analysis: Methodological suggestions. *J. Finance* 14 (1), 1–10.
- Saffi, P.A.C., 2003. Análise técnica: Sorte ou realidade? *Rev. Bras. Econ.* 57 (4), 953–974.
- Sobreiro, V.A., Mariano, E.B., Nagano, M.S., 2014. Product mix: the approach of throughput per day. *Production Planning & Control* 25 (12), 1015–1027.
- Sobreiro, V.A., Nagano, M.S., 2012. A review and evaluation on constructive heuristics to optimise product mix based on the Theory of Constraints. *Int. J. Prod. Res.* 50 (20), 5936–5948.
- Taylor, M.P., Allen, H., 1992. The use of technical analysis in the foreign exchange market. *J. Int. Money Finance* 11 (3), 304–314.
- Teixeira, L.A., Oliveira, A.L.I.d., 2010. A method for automatic stock trading combining technical analysis and nearest neighbor classification. *Expert Syst. Appl.* 37 (10), 6885–6890.
- Tung, W., Quek, C., 2011. Financial volatility trading using a self-organising neural-fuzzy semantic network and option straddle-based approach. *Expert Syst. Appl.* 38 (5), 4668–4688.
- Vanstone, B., Finnie, G., 2009. An empirical methodology for developing stockmarket trading systems using artificial neural networks. *Expert Syst. Appl.* 36 (3), 6668–6680.
- Vidotto, R.S., Migliato, A.L., Zambon, A.C., 2009. O moving average convergence–divergence como ferramenta para a decisão de investimento no mercado de ações. *Rev. Adm. Conte.* 13 (2), 291–309.
- Warburton, A., Zhang, Z.G., 2006. A simple computational model for analyzing the properties of stop-loss, take-profit, and price breakout trading strategies. *Comput. Oper. Res.* 33 (1), 32–42.
- Zhu, Y., Zhou, G., 2009. Technical analysis: An asset allocation perspective on the use of moving averages. *J. Financ. Econ.* 92 (3), 519–544.