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# Trading System based on the use of technical analysis: A computational experiment☆

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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.



## 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

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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).

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

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).

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

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).

$$MACD_{\left(k_{short}, k_{long}\right)_n} = MME_{(k_{short})n} - MME_{(k_{long})n} \tag{3}$$

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).

$$MACDH_n = MACD_n - SL_n. \tag{4}$$

**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).

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

where

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

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.

**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% |

## 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©, and all simulations were performed using Microsoft Office Excel©. 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

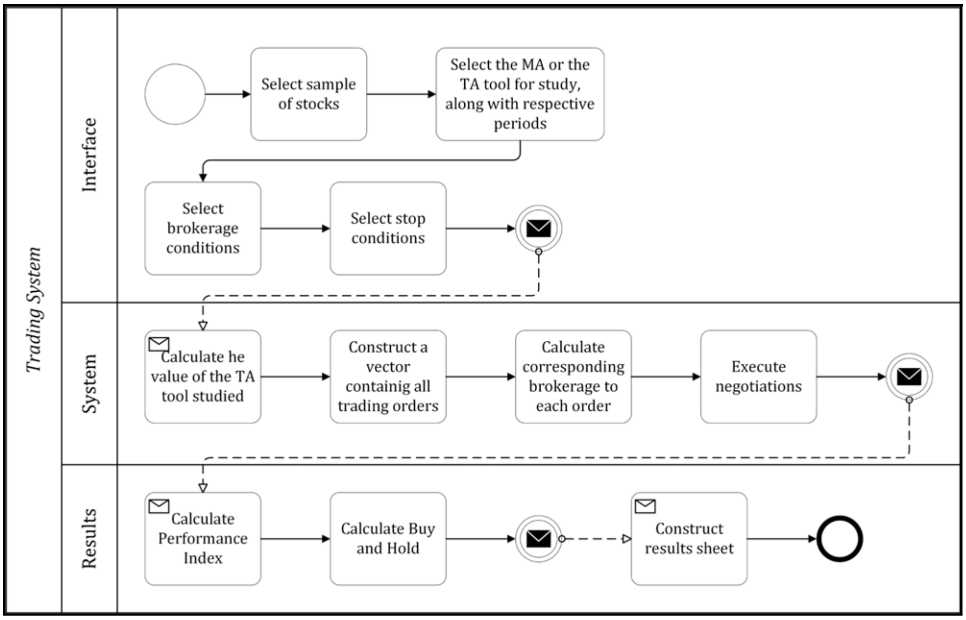


**Fig. 1.** Trading system illustration.

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[a] | Signal (Tech. analysis) | Traded quantity[f] | Cash balance | Last price | Present value | Future value | Period of application | Return ($R$)[b] | Average return ($\overline{R}$)[c] | Standard deviation[d] | Ratio ($\tau$)[e] |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | 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% | | | |
| $Stock_X$ | 01/25/20XX | Sell | 2.00 | | 50.20 | | 100.40 | | | 0.583% | 0.163% | 3.303 |
| | 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 | | | | | |

[a] Considering MM/DD/YYYY.

[b] The return was calculated on a compound basis.

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

[d] This value was calculated considering $SD\left(\overline{R}\right) = \sqrt{\left(\sum p(R) \times R^2\right) - \left(\overline{R}\right)^2}$.

[e] This value was calculated considering $\frac{\overline{R}}{SD(\overline{R})}$.

[f] 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 paper as, 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).

$$Stop = x \times \max(P_0, P_1, \ldots, P_k) \tag{6}$$

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*.

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

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).

$$POCID = \frac{\sum_{\mu=1}^{N} D\mu}{N} \times 100 \tag{8}$$

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 × 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 $\overline{\tau}$ 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[b] | $\bar{\tau}$ | 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)[c] | 618.236 | 0.558 (1.454)[c] | 1043.892 | 0.073 (0.226)[c] | 97.071 | 0.547 (2.213)[c] | 230.409 |

[a] Average $\tau$, considering all combinations of *MA*.
[b] Average *RAD*.
[c] 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. (%)[a] | POS. R. (%)[b],[c] | AV. P. (%) | POS. R. (%)[c] | AV. P. (%) | POS. R. (%)[c] | AV. P. (%) | POS. R. (%)[c] |
| 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 |

[a] verage *POCID*.
[b] Positive returns.
[c] 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 |

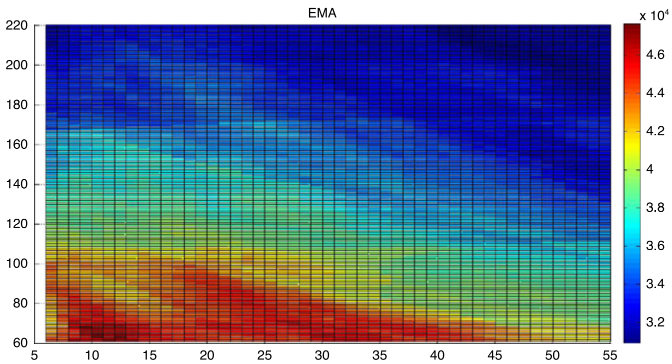


**Fig. 2.** Arithmetic average of all EMA's scenarios.

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

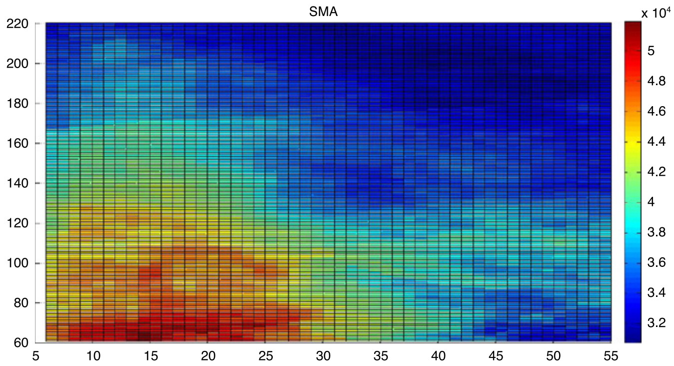


**Fig. 3.** Arithmetic average of all SMA's scenarios.

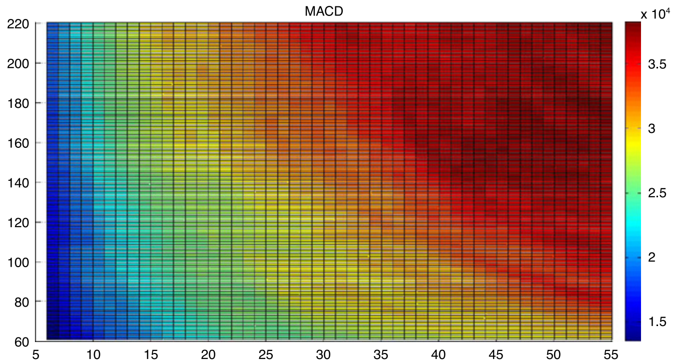


**Fig. 4.** Arithmetic average of all MACD's scenarios.

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[a] | AR[b] | WR[c] | BR[d] | More profitable stock |
|---|---|---|---|---|---|---|
| 1[e] | *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[f] | *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[g] | *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 |

[a] Standard deviation.
[b] Average return (% per day).
[c] Worst return (% per day).
[d] Best return (% per day).
[e] With brokerage and without Stop-Loss.
[f] Without brokerage and without Stop-Loss.
[g] 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 | CLSC4 | 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 Partipações | 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-Maxion 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 |
| HRTP3 | HRT Participações em Petróleo | PDGR3 | PDG Realty SA Empreendimentos |
| HYPE3 | Hypermarcas SA | PETR3 | Petróleo Brasileiro SA |
| IDNT3 | Ideiasnet SA | PETR4 | 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 |
| JBSS3 | 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 |
| SMTO3 | 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 Siderurgicas de Minas G |
| SULA11 | Sul America SA | VAGR3 | Vanguarda Agro SA |
| SUZB5 | Suzano Papel e Celulose SA | VALE3 | Vale SA |
| TAEE11 | 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.

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