World Applied Sciences Journal 6 (11): 1457-1472, 2009
ISSN 1818-4952

A Decision Support System for Technical Analysis of Financial Markets Based on the Moving Average Crossover

Ihab A. El-Khodary

Department of Decision Support, Faculty of Computers and Information
Cairo University, 5 Ahmed Zeweil St., Postal Code 12613 Orman - Giza, Egypt

Abstract: The Moving Average (MA) crossover technique is one of the popular technical analysis tools used by investors in financial markets. The technique depends on identifying the lengths of short and long time periods, type of MA model and type of price data on which the analysis is to be based. Unfortunately, most users base their selection of these parameters on recommendations which could be not suitable for a particular market or security. Also, technical analysis software do not provide a tool through which a search for the best (optimal) rule that generates the highest return could be reached. Technical analysts recommend that users fine tune these parameters according what they see suitable for their strategy. Accordingly a decision support system was developed based on the MA crossover technique that is capable of providing descriptive statistics for the time series data of market indices and securities, evaluating the statistical significance of returns generated by any MA rule, searching for the optimal MA rule that generates the highest significant returns and scan among a group of securities for the latest signals and highest returns. The system has the added of advantage of searching for the optimal MA rule among a large universe of MA rules. The DSS system was used to investigate the predictive capabilities of the MA crossover with respect to the Egyptian Exchange Stock market. The lengths of 1-20, 1-25 and 1-30 along with the closing price emerged as the most profitable for the rules. The exponential MA model dominated as the most profitable model for many securities, while the simple MA model was effective for a few securities. The results obtained provide strong evidence that the MA crossover technique can predict the Egyptian stock market index and its securities and reject the null hypothesis that the returns earned by the technique are equal to the unconditional buy-and-hold strategy. Therefore, there could be great opportunities from applying this technique to the Egyptian market for yield enhancement and portfolio diversification.

Key words: Moving Average Crossover %Optimal Moving Average Rules %Securities, Decision Support Systems %Egyptian Exchange Stock market %CASE 30 Index

INTRODUCTION

Equity traders and short term investors have been using some form of technical analysis for their day-to-day trading. Evidence shows this fact over the past two decades. Taylor and Allen [1] surveyed dealers in the London foreign exchange and found that over 90% of the respondents use some form of technical analysis to predict returns and among these trading rules the moving average (MA) rules were the most popular. Advancement in technology has further encouraged those traders and investors to rely heavily on technical trading rules for day trading [2, 3].

Technical analysis is the study of the past market data, mainly price and volume in pursuit of a forecast of the future direction of the prices. All of the historic data up to date and what is perceived about the future combines with the specific circumstances of the investor to produce trading decisions. During the process, technical analysts may employ models and trading rules based on price and volume transformations, such as the moving averages, price correlations, cycles, or through studying chart patterns. Thus technical analysis is valuable in allowing the trader/investor (i.e. decision maker) to recognize patterns, identify resolutions to patterns, look for confirming market actions, or determine

Corresponding Author: Ihab A. El-Khodary, Department of Decision Support, Faculty of Computers and Information, Cairo University, 5 Ahmed Zeweil St., Postal Code 12613 Orman - Giza, Egypt

signs of changing supply and demand. Again, the advancement of technology has facilitated performing such analysis through software that incorporates the tools mentioned previously, better known as technical analysis software.

According to wikipedia [4], technical analysis software automates the charting, analysis and reporting functions that support technical analysts in their review and prediction of financial markets. The most common features of technical analysis applications are:

- Charting: a graphical time series presentation of price, volume and technical analysis indicators through line, bar, candle stick, open-high-low-close charts among others;
- Back Testing: enable testing of different investing timing strategies against historical price movements for one or more securities;
- Optimization: fine-tuning of technical analysis indicator parameters in order to generate an investment strategy that generates the maximum return based on historical price movements;
- Scanner: monitoring specific equities and notifying the decision maker when certain price, volume and technical analysis investment criteria are met, may be buying or selling opportunities;
- Custom Indicators: in addition to the library of de-facto standard indicators, enabling the user to customize, combine or create new indicators;
- Data Feed: providing a means for automatic updating of data, whether at end-of-day (EOD), delayed or real time data feeds;
- Broker Interface: integrating the software with brokerage platforms to enable traders to place trade orders via a user interface that they are familiar with.

Notice that not all technical analysis software have all the above features. Some software may focus on only one feature, while others may have more than one or all. In the survey of the most technical analysis software available in the market by wikipedia [4], the software incorporating almost all of the above features with a library built-in-indicators in the range of two hundred or more were Esignal and Metastock.

Technical analysis software can be classified as decision support systems since they are based on having a built-in database, contains a model base of indicators in addition to the capability of customizing and creating indicators and finally it enables decision making through the charts, indicators and the scanner. Unfortunately, in these technical analysis software, the so claimed optimization feature doesn't search for an optimal value, rather the user manually fine tunes the indicator(s) parameter(s) as s/he perceives.

Among those indicators that usually need optimization is the popular moving average (MA) and the MA crossover. Questions that need to be answered with respect to the MA, whether the best type of MA to be employed for a particular equity is the simple MA, exponential MA, weighted MA, or any other type. Along with the type of MA is identifying the associated length of period for short period and long period (i.e. the optimal period). Another question to be answered, is whether to buy or sell immediately upon a signal is generated or to hold for a period of time and if so what is the optimal hold period after signal generation.

Plenty of research and opinions have been put forward with respect to this issue, details of which will be presented in the following section "Literature Review". But in order to elaborate upon the problem associated with the lengths of periods, a simple exercise was performed on the CASE 30 Price Index for the Egyptian Exchange Stock market (EGX). The CASE 30 Price Index is a price index that measures the return of investment from the change in market value of the security (capital appreciation/depreciation) only. It includes the top 30 companies in the Egyptian market in terms of liquidity and activity. In this exercise the author applied the simple MA crossover technique, along with a number of different combinations of recommended short and long length of periods; better known as MA crossover rules. The buy and sell signals obtained from these different combinations is provided in Table 1. The CASE 30 Index available was for the periods from January 1, 1998 till December 30, 2008 giving a total of 2695 working days for the Egyptian Exchange Stock market.

Based on the numbers presented in the table, one can notice that by increasing either the short period length or the long period length, the number of buy/sell signals decrease. An interesting observation, one noticed that opposite conflicting signals were generated on the same day for different rules. Keep in mind that these signals are supposed to provide guidance to the investor/trader. The important question that needs to be answered is "which of the above rules provides the highest return for the Egyptian Exchange Stock market?"

Murphey [5] commented on the MA and how users should handle it with the following: "Moving averages are a totally customizable indicator, which means that the user can 'freely choose' whatever time frame they want when creating the average. There is no 'right' time frame to use when setting up your moving averages. The best way to figure out which one works best for you is to experiment with a number of different time periods until you find one that fits your strategy." Some researchers, including myself, beg to disagree.

In this research, the author attempted to develop a prototype for a decision support system that addresses the previously mentioned questions/problems. The main objectives of this decision support system are to:

- Calculate the return for a specific security for a specific rule, i.e., a given short/long period combination, MA type, holding duration and price data type;
- Determine the optimal short, long and holding time periods that will result in the highest return for a specific security and a specific MA type (either simple or exponential);
- Determine the best MA rule in terms of type (simple vs. exponential), the optimal short and long periods along with the best duration to hold after signal (1 vs. 2 days) and the type of data to base analysis upon (open, close or weighted average price) that will result in the highest return for a specific security or a number of securities, as well as type of upcoming signal (buy or sell);
- Scan a given portfolio for the security with a given sell signal at a given time;
- Scan a selected number of securities for the security with an entry buy signal;
- Scan a selected number of securities to determine the security with the highest return for a specific rule.

The whole point was to develop a system that has the capabilities of performing analysis, data feed, optimization scanning and providing recommendations to the user based on the MA crossover technique. In other words, this system is a technical analysis based decision support tool that assists the investors in making trading decisions for equities and securities. This is the primary aim of this research. A secondary aim is to analyze the predictive capabilities of MA crossover technique when applied to the Egyptian Exchange Stock market's price index and some of its securities by applying the developed DSS to them.

The paper will proceed by documenting some of the literature with respect to the MA models, MA crossover technique and application of the MA crossover technique to a number of stock markets across the world (i.e. stories of success and failure). Then the framework of the decision support systems will be presented. This will be followed with details and screen snap shots of the DSS. Some preliminary results for the Egyptian Exchange stock market CASE 30 index will be provided. Finally, the paper will end with the customary conclusions and points for further work and research.

Literature Survey: Both researchers and technical analysts have agreed that the MAs are one of the most popular and widely used technical indicators [6-10]. Bigalow and Elliot [2] have pointed out that MAs are considered as the most profitable technical trading rules. A number of reasons has been put forward for such popularity. Among these reasons is the simplicity of the MA [6, 7] and that it helps traders in gauging trend directions [5, 10, 11], as a matter of fact the latter wrote in his article "Moving averages are excellent indicators to confirm existing trends in spite of their lag." In addition to that, it has been claimed that MA crossovers provide powerful trading signals, particularly when used in conjunction with other technical analysis tools [12].

Reference to the use of Mas goes back to almost 80 years ago. One of the pioneers was Gartley and that was in 1930 [13]. Examples regarding the important early studies of different trading strategies and techniques (among which was the MA) was carefully collected by Coslow and Schultz [14].

The main concept behind the MA is to average a number *n* of past data points/prices. This calculated average represents the price area nearest a proportionately large number of that specified period's trades. Therefore, this is the area where the fewest people have extreme gains or losses for the period and thus pressure to trade (out of fear or greed) tend to diminish. By averaging, the prices are smoothed, thus smoothing the fluctuations in the market prices. Given this smoothed data, the traders/investors would be able to determine the underlying trends rather than focusing on the day-to-day price fluctuations that are inherent in all financial markets. Also, this smoothed data signals out significant changes in direction as early as possible.

Technical analysts, traders and researchers have employed a number of different types of MAs and some actually developed modifications to the MA techniques. The most popular, widely used type is the simple moving average (SMA), which is considered the basic form of the MA. The SMA is the sum of the prices over a certain number of time periods (*n*) divided by the number of time periods to get an average price of the security or index for that period, as shown below:

$$SMA_n = \frac{1}{n} \sum_{t=k-n+1}^{k} P_t \qquad (1)$$

where k is the relative position of the period currently being considered within the total number of periods and P_t is the price of the security at time t.

The SMA has been criticized for the fact that each price in the data series being averaged is equally weighted thus assuming that old prices are equally as relevant as more recent ones.

Those critics have argued that the most recent prices are more significant than older ones and therefore should have a greater influence on the final average result. Accordingly, analysts and traders thought of different methods through which more weight is given to the most recent prices and this has led to the development of various types of new MAs, the most popular of which is the exponential moving average (EMA). The EMA is calculated by adding a percentage of yesterday's MA to a percentage of today's price value, according to the following:

$$EMA_k = \alpha P_k + EMA_{k-1}(1-\alpha) \qquad (2)$$

where k as mentioned above and " is a smoothing factor calculated by *2/(1+n)* and is a number between 0 and 1. Thus, the EMA applies the weighting factors which decrease exponentially, where the weighting for each older price decrease exponentially, giving much more importance to recent observations without discarding older observations entirely. Notice that n-periods in an n-day EMA only specify the ″ factor and not a stopping point for the calculation, as was the case in the SMA. An article [15] claims that "the most commonly used moving average is the exponential moving average based on closing prices without any shift."

A modification to the EMA was put forth by Kaufman [16]. He suggested multiplying two different smoothing factors of the EMA by an efficiency ratio (ER) that measures the volatility to result in a constant that is then used instead of the smoothing factor in the EMA. By doing so, the MA would be further from the current prices in volatile markets. This method seeks to adapt to changing market conditions by the use of this ER and hence the name adaptive moving average (AMA). The ER is calculated by dividing the momentum (i.e., the total price change for period) by volatility (i.e., sum of absolute price changes between each two consecutive days during period). Unfortunately, several studies have indicated that despite the AMA is an interesting newer idea with considerable intellectual appeal, it doesn't show any practical advantage to this more complex trend smoothing method [17, 18]. Yet, they recommend that traders shouldn't ignore the idea of the AMA since it could have potential in developing a profitable trading system when combined with other indicators. As a matter of fact, it is suggested that ER can be used as a stand-alone trend indicator to spot the most profitable trading opportunities. Nevertheless, Carr [19] has noted that the AMA is included as an option in almost all trading software packages.

Other types of MAs are available including time series MA, triangle MA, weighted MA and volume adjusted MA.

Keep in mind that all these types of MAs don't predict market movements; rather they lag the current price. Accordingly, in a rising market the MA will be below the rising price line and in a falling market it will be above. When the price changes direction, the MA line will cross the price line. Therefore, depending on the direction of the crossing will identify the buy or sell signals. The general rule is:

- Buy signal is generated when the current price crosses the MA from below; and
- Sell signal is generated when the current price crosses the MA from above.

Moving Average Crossover: Another type of crossover, which is by far the most commonly used of the MA methods [20] and has been the subject of a lot of research, is that when a short-term average crosses through a long-term average, better known as the MA crossover. This signal is used to identify that momentum is shifting in one direction and a strong move is likely approaching. The general rule in this case is:

- Buy signal is generated when the short-term average crosses above the long-term average; and
- Sell signal is generated when the short-term average crosses below the long-term average.

The premises for this behaviour is that a price that is moving up (or down) during period t is likely to continue to move up (or down) in period $t+1$ unless there is evidence to the contrary. When the short-term average crosses above the long-term average, this means that average prices over the short period are relatively higher than those over the longer period and hence the prices have an upward momentum. This provides a lagged

Table 1: No. of buy and sell signals for different MA crossover rules

Short Period	Long Period	Buy Signals	Sell Signals
1	20	115	114
1	50	73	73
1	150	21	21
3	150	14	14
5	150	10	10
1	200	21	21
2	200	17	17
1	240	14	14

indicator that the price is moving upward relative to the historical prices. The opposite is true when the short-term average moves below the long-term average. Thus, the signals generated through the crossovers are very objective, which is why it is so popular.

As noticed from the previous discussion, the whole system depends on the duration of the short and long periods used for calculating the MAs. Short term periods are more sensitive to price changes, whereas long term periods are less sensitive and hence will result in a more smoothed out average. Consequently, shorter MAs are faster, generate more signals and swift for early entry. However, they will also generate more false signals resulting from the whipsaws in the price data. The crossover MA technique attempts to trade off "between timeliness and possibility of whipsaws" [15], i.e. an attempt to reduce whipsaws while minimizing the lateness of signals received. There is, more or less, an agreement among technical analysts researchers on the ranges for identifying the short, medium and long-term trend periods and these are less than 20 days, 20 to 100 and more than 100, respectively [5, 12, 15].

The ongoing saga with respect to MAs is to identify an MA rule along with the appropriate lengths that is sensitive enough to detect correct signals while at the same time remaining insensitive to wrong signals for a particular market and or security (refer to Table 1). Such an MA will be the most profitable to apply. The process adopted by technical analysts, investors and researchers for identifying the appropriate lengths has been trial and error. Analysts and investors apply trial and error until they arrive at a rule that they feel that they are comfortable with since the rule fits their strategies [5], whereas researchers base their comparisons on finding rules that are economical (by calculating average returns) and at the same statistically significant.

A modification to the MA crossover rule is to impose a band around the MA in order to filter out false signals, i.e. signals that would result in losses, especially when the short and long MA lines are close to each others. Two types of bands could be imposed, either variable resulting in variable length moving average (VMA), or fixed better known as the fixed length moving average (FMA). In the VMA version, buy (sell) signals are generated when the short MA is above (below) the long MA by at least a specified percentage. On the other hand, in the FMA, the focus is on the period immediately following a MA break. Thus if the short MA is above (below) the long MA plus the filter band, a buy (sell) signal is generated which lasts for the specified *n* holding period. Any other signals that show up during this period are ignored.

The application of the MA crossover to a number of markets and securities by researchers along with their main conclusions and recommendations will be the subject of the following paragraphs.

Common Moving Average Rules: Early investigations of the MA in 1960's [21, 22] proved that none of the rules tested were successful when compared to a buy-and-hold strategy. Nevertheless, several researchers in the 1990's changed this view and proved that MA crossovers do actually have predictive abilities and are, therefore, worth paying attention to. A very influential research is that of Brock *et al*. [6]. Brock and his colleagues investigated the predictive ability of VMA and FMA rules given daily Dow Jones Industrial Average Index (DIIA)-U.S., over 90 years from 1897 to 1986. The VMA rules that they applied included (1, 50), (1, 150), (5, 150), (1, 200) and (2, 200) with zero percent and one percent bands. These same rules were employed for the FMA with a 10-day holding period. Therefore, a total of twenty MA rules using the simple MA method were tested. Their findings revealed that the buy signals generated higher returns than sell signals which were in turn higher/lower, respectively, than the returns generated from a buy-and-hold strategy. Hence, the VMA and FMA rules have predictive ability especially if sufficiently long series of data are considered. Similar findings were also obtained by Hudson *et al*. [7] who have applied the same rules that [6] have previously applied, but to the daily Financial Times Industrial Ordinary Index (FTI)-U.K., for the period from July 1935 to January 1994.

Bessembinder and Chan [23] applied a few rules from those presented by [6] to six daily equity market indices in Asia, namely Hong Kong, Japan, Korea, Malaysia, Thailand and Taiwan over the period of 1975 to 1991. The authors found very strong forecasting capabilities for the Malaysian, Thailand and Taiwan stock markets. Ratner and Leal [24] applied the 10 VMA rules from [6] to ten emerging markets in Latin America and Asia, among which a few markets considered by [23], from 1982 through 1995. Similar to the study by [23], the authors reached the conclusion that substantial profits could be achieved for Thailand and Taiwan, as well as Mexico.

Parisi and Vasquez [8] also followed the same rules offered by [6] on to the Chilean equity market index (IPSA). The study covered the period from 1987 till 1998. Their results were similar to those put forward by [6], thus providing strong support for the VMA and FMA. The same was obtained when these rules were used to analyze their performance with respect to four emerging south Asian markets (Bangladesh, India, Pakistan and Sri Lanka) over a 10 year period from 1990 to 2000 [25].

Furthermore, Chang *et al.* [26] attempted a prediction comparative study using five [6]'s VMA rules (those with zero percent band) between eleven emerging stock markets indices and two developed country indices (US and Japan). The eleven emerging countries included some of those that have been the subject of other studies. These countries included Argentina, Brazil, Chile, Mexico, the Philippines, India, Indonesia, Malaysia, South Korea, Taiwan and Thailand. The data series for all thirteen markets included daily closing prices from 1991 through 2004. Employing the VMA showed that there are some evidence of forecasting power for the emerging markets studied. The Malaysia and Philippines market indices produced high abnormal returns as a result of employing the technical trading rules. Nevertheless, for the US the VMA rule suggested in the study by [6] lost its forecasting power when employed to the recent data set.

Another recent study [9] examined the profitability of 10 VMA rules and 10 FMA rules on nine Asian markets indices during the period from 1988 to 2003. The rules employed were different than those examined by [6]; they were (1, 20), (1, 60), (1, 120), (1, 180) and (1, 240) with zero percent and one percent bands for the VMA and 10 holding days after generation of signal for the FMA. The authors came to the conclusion that the VMA and the FMA have economical significance in eight of the nine markets and these were China, the Philippines, Singapore, Indonesia, Malaysia, Korea, Taiwan and Thailand. The ninth market left out was that for Japan. The profits generated from the VMA were higher than those by the FMA.

Although the survey above provides evidence of the success of the moving average crossover rules in many equity markets, other research discuss the instability of the MA rules. Ready [27] applied the three most profitable MA rules suggested by [6] to the S and P 500 index (Australia) for which he divided the data into 5-years sub periods from 1970 till 1995. In this study, the author found out that the trading rules generally under performed the buy-and-hold strategy, except for the first sub-period (1970-1974). Le Baron [28] applied the best performing MA rule (the 150-day MA rule) obtained by [6] to the same DJIA data plus 10 more years (i.e. from 1988-1999). Le Baron [28] concluded that this once best performing rule failed badly in the most recent decade. A similar conclusion for the DJIA was also arrived at by Sullivan *et al.* [29]. A study by Mills [30] on the FIT index of the UK, revealed that the MA trading rules out performed the buy-and-hold strategy prior to 1974 and failed during the following 20 years.

A thorough analysis of the previous literature has revealed a number of short comings. The first of these short comings is that the majority of these studies confined their analyses to a small set of MA rules (at the most twenty rules following those by [6]) rather than drawing from a large universe of MA rules. Also these studies have employed the simple MA, although technical analysts recommend the use of the exponential MAs [5, 15]. Furthermore, as demonstrated in the previous paragraph, adding new data could result in the failure of old successful rules (i.e. instability). In other words, the MA rule could need recalibration (finding new optimal settings) every while. On top of that, no one rule is suitable for all country indices or securities, demanding that for each country index/security an optimal rule should be searched for. Therefore, there are mixed empirical evidence depending on the time frequency, country, security, MA rule and time span among other characteristics.

Fong and Yong [31] attempted to address a few of the above problems, namely the time span and drawing rules from a large universe of MA rules, through a simple recursive trading strategy. The aim of the recursive MA was to simulate real-time speculation, where the investor is assumed to trade each day using the MA rule that is considered "best" using data up to the previous day. Unfortunately, the recursive strategy failed with respect to the set of securities being studied and was not able to generate superior returns, relative to a buy-and-hold strategy.

Decision Support System: In this research, I attempted to overcome most of the previously mentioned shortcomings, as well as adding extra features, through a system that aids users (mainly technical analysts and investors) in reaching trading decisions.

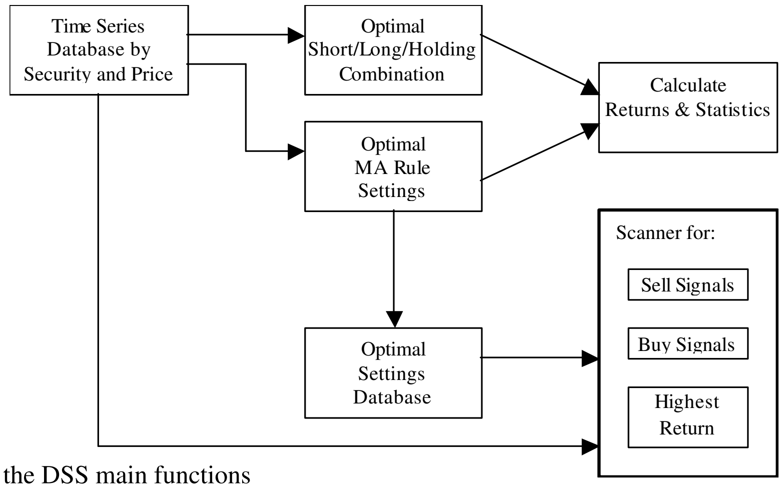


Fig. 1: Framework of the DSS main functions

Through an iterative procedure, different rule setting (model type, short-long periods, no of holding days) are tested until the optimal rule setting resulting in the highest, significant average return is arrived at. Thus this optimal rule is drawn through a search from a large universe of MA rules. Having such a system will enable users to easily find new optimal MA rule settings when new price data is added. These optimal MA rule settings are stored in a database, if needed, to scan among different securities for buy signals, sell signals, or highest return. Figure 1 shows the framework of the main functions/modules of the DSS. According to this framework, there are six main modules as follows:

C Calculating return and statistics
C Finding optimal short/long/holding MA rule combinations
C Finding optimal MA rule settings
C Scanning for index/security with sell signal
C Scanning for index/security with buy signal
C Scanning for index/security with highest return

The system was developed using MATLAB. It is important to mention that the system could be considered a prototype since there are a number of limitations and extra features to be included and these will be elaborated upon while explaining the functions of the DSS in the remainder of this section.

Database: The database required for performing any of the analyses is time series data of prices for each index/security. Usually, the summary data provided for a day's transactions include the high, low, close, open and volume-weighted average (VWAP) prices, in addition to the volume of each index/security. For the purpose of this system, the volume is of no concern at this stage. In Egypt, it is common to find this data in either Metastock format or Excel format. For this DSS to read the data it needs to be in the Excel format. An Excel file for each index/security has to be available for the analysis to be performed. One of the future additions to this system is to enable the DSS to read data in different file formats.

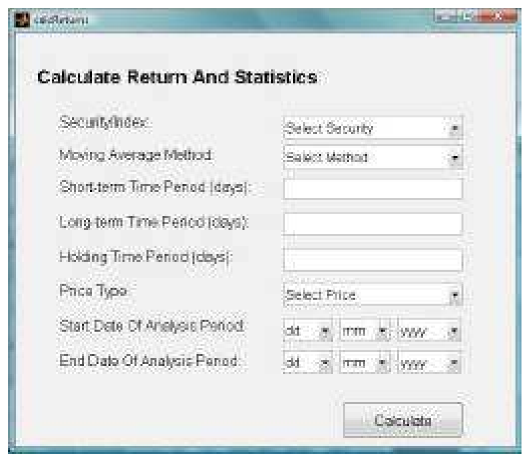


Fig. 2: The Calculate Return and Statistics Input Screen

Calculating Returns and Statistics Module: In order to evaluate an MA rule, it is necessary to calculate the rate-of-return generated through it and provide its corresponding statistics. This is exactly the purpose of this module.

When selecting this module, the screen shown in Figure 2 is displayed to the user. Through this screen, the user specifies the settings for which s/he wants to validate and generate its statistics. Accordingly, the user is requested to select:

- The index/security for which the analysis to be performed;
- The type of MA method, either simple or exponential;
- Short-term time period in days, which is limited to less than 20 days;
- Long-term time period in days, minimum 20 and open, as user desires, although, it is recommended a maximum of 250;
- Holding time period in days following the FMA, which ranges between 0 (i.e. buy/sell on the day following the generation of the buy/sell signal) and 10;
- Type of price data on which the analysis is to be based and which could be either the opening price, closing price, highest price, lowest price, or VWAP;
- Start date of analysis period, default is the first date in the database file for this particular index/security which could be changed if a subset of the time series data is to be analyzed; and
- End date of analysis period, with the default being the last date available which also could be changed as before.

This module starts by calculating the daily returns and then provides some simple descriptive statistics for these returns. The daily returns calculated are the logarithmic (continuously compounded) returns, rather than the arithmetic returns, since they are considered symmetric whereas the arithmetic returns are not. Nevertheless, the difference between both types is large only when percent changes are high, as both are approximately equal for small returns. The logarithmic daily returns are calculated according to the following:

$$R_t = \ln\left(\frac{P_t}{P_{t-1}}\right) \tag{3}$$

where P_t and P_{t-1} are the prices of the security at times t and $t-1$, respectively. For these daily returns, a number of descriptive statistics are generated such as the mean, standard deviation, skewness, kurtosis, minimum value, maximum value and the number of observations which is presented as the duration of the study period (Figure 3).

The module then calculates the two MAs based on the specified short and long periods, model type and price type. Accordingly, the buy and sell signals are generated and hence the periods of buy and sell are identified, as well as neutral periods where no buy or sell are allowed

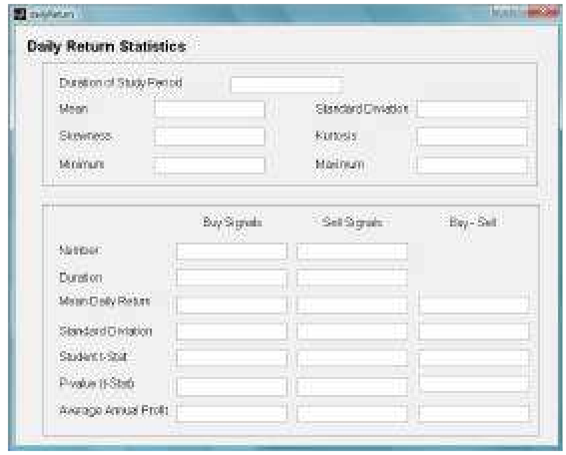


Fig. 3: Daily Return and MA Rule Statistics Output Screen

(i.e., if a holding period is specified). Based on these, identified periods, the number of buy and sell signals are reported, the mean daily return during buy periods and sell periods are calculated and the date of last buy/sell signals are displayed.

Finally, it is important to evaluate the performance of the MA rule. The strategy adopted for determining the profits is that followed by [6] and many others which is the "double-or-out" strategy which is then compared to the naïve "buy-and-hold" strategy. The "double-or-out" strategy is basically that, when a buy signal is generated the investor barrows at a risk free interest rate in order to double his investment in the index/security. This position is held until a sell signal is generated, upon which the investor sells and invests in a risk-free index/security. On the neutral days, the investor is assumed to hold position in the security. Hence, the investor is making profit by being in the rising market (during buy periods) and another profit by being out in the declining market (during the sell periods). This strategy assures that there is no short sell. On the other hand, the "buy-and-hold" strategy dictates that the investor buys the index/security at the start of the analysis period and sells at the end of the period.

Thus, according to the "double-or-out" strategy, the average annual profit generated as a result of the buy signals is calculated following [8, 9, 25]:

$$\text{Profit (buy)} = (\text{Daily buying mean return} * \text{average no. of yearly buy signals}) - \text{Risk free interest rate} \tag{4}$$

While the average annual profit earned or cost savings for being out of the market as a result of the sell signals is:

Profit (sell) = Risk free interest rate-(Daily selling mean return * average no. of yearly sell signals) (5)

Hence, the average annual profits or returns in excess are the combination of the profits from the buy signals and the cost savings of the sell signals.

Furthermore, it is necessary to test that the daily buying mean returns and the daily selling mean returns generated by the MA rule are significantly different from the returns derived by the "buy-and-hold" strategy. Also, it is necessary to test that the difference between the returns of the buy and sell signals is statistically significant from the equality with zero. These tests are performed using the student *t*-statistic ratio as presented below:

$$t_{B/S} = \frac{\mu_{B/S} - \mu}{\sqrt{\frac{\sigma^2_{B/S}}{n_{B/S}} + \frac{\sigma}{n}}} \quad (6)$$

$$t_{B-S} = \frac{\mu_B - \mu_S}{\sqrt{\frac{\sigma^2_B}{n_B} + \frac{\sigma^2_S}{n_S}}} \quad (7)$$

where

$\mu_{B/S}$ = mean daily return for buy/sell signals;
$F^2_{B/S}$ = variance for buy/sell signals;
$n_{B/S}$ = number of buy/sell signals;
μ = unconditional mean daily return;
F = variance for the entire sample; and
n = number of observations for the entire sample.

Therefore, in addition to the daily return descriptive statistics, this module also displays the daily buying and selling mean returns, the number of buy and sell signals generated, number of observations (days) with buy or sell signals, the student *t*-statistic for the buy and sell returns, corresponding *p*-vales and the average annual profit for both the buy and sell signals. The *t*-statistic value for the comparison between the buy and sell mean returns is also provided, as well as the cumulative (overall) average annual profit (Figure 3).

Finding Optimal Values Modules: For finding optimal values there are two modules, one to search for the optimal short, long and holding periods lengths combination for a specified MA rule setting and the other to search for the optimal MA rule setting. The optimal solution is the one that result in the highest significant overall average annual profit.

Under this module, for each rule the analysis proceeds by calculating the MAs according to the short, long and holding time periods, model type and price data type. Accordingly, the buy and sell periods are determined from which the daily buying and selling means are calculated. These means are then tested for their statistical significance when compared to the buy-and-hold strategy. The next step is to calculate the cumulative average annual profit for those rules whose both daily means are significant. Finally, the rule with the highest average annual profit is selected as the optimal rule.

Optimal Short/Long/Holding Time Periods for MA Rule Module: When selecting the search for the optimal short/long/holding periods, the user is displayed with an input screen similar to that previously shown in Figure 2, but without the fields for identifying the short term, long term and holding time periods. Accordingly, the user is requested to select the index/security for which the analysis is to be performed, the MA method, the price data type and the start and end dates for the analysis period.

Since the search for the optimal solution depends on an alternative procedure, I decided to put a few restrictions on the search parameters to limit the number of possible rule combinations to search within. With respect to the short-term time period, as in the previous module, it ranges from 1 to 19 and is considered in steps of 1. On the other hand, the long-term time period, ranges from a minimum of 20 and is limited to 200. This range is considered at intervals of 5. As for the holding time period after signal generation, the options are limited to three alternatives, namely 0, 1 and 10 days after the generation of a signal. Therefore, the universe set of MA rules to select from is 2109 different rules.

After performing the analysis too different outputs are generated. The first output is a file containing all rules with their respective statistics and results. The statistics include mean, variance, number of signals, student *t*-value and corresponding *p*-value for both the buy and sell periods independently, as well as the actual number of days in buy and sell. As for the accompanying results to each rule, these are mainly the average annual profit as a result of buy and sell signals, in addition to the cumulative average annual profit. The user has the option to view this file if desired. The second output is displayed on the screen similar to that displayed for the "Calculating Returns and Statistics" module shown in Figure 3. The only addition to this screen is the best "optimal" values obtained for the short, long and holding time periods. The displayed statistics and results are those corresponding to the optimal rule.

Optimal MA Rule Settings Module: Under this module, the user is requested to identify the index/security for which the optimal rule settings are to be determined and the start/end dates for the analysis period if the analysis is to be a subset of the available data for this index/security. Given this input, the system attempts to search for the settings of the MA rule that will result in the highest overall average annual profit. These settings involve the short/long/holding time periods, the MA model type and the type of price data.

In order to limit the search set, again a number of limitations had to be imposed. The restrictions imposed on the short, long and holding time periods in the latter module are still maintained. With respect to the MA rule type, the options were limited to two options, namely the simple MA and the exponential MA. As for the type of price data, the most common types are considered and these are the closing price, opening price and the VWAP. Accordingly, the search space is limited to 12,654 different rules.

The output generated from this module is of three forms. Two are the same as that produced by the "Optimal Short/Long/Holding Time Period" module. These include a file consisting of all the rules combinations with their respective statistics and results and a screen display of the optimal settings for the MA rule with the highest profit along with its respective statistics and results. These optimal settings are then stored in the third output which is a database of the optimal settings for the different securities and indices in order to be used in the scanning modules.

Scanning Modules: The three scanning modules are a quest for finding securities and indices with particular characteristics, thus enabling the user/decision maker to take an action. The quest is for securities and indices with either recent buy or sell signals, or with the highest return.

For each module, the user is presented with a window through which s/he could select a number of securities and/or indices to compare between (Figure 4 shows the input screen for the sell signal module). While scanning for sell signals, the user is requested to select securities and/or indices that are within his/her portfolios. Whereas, when scanning for either buy signals or highest return, the user selects those securities and/or indices s/he are interested to invest in. It is important to mention that when scanning for the highest return, the user has the option to base the ranking according the buy-sell difference mean daily return or the average annual return and also to specify the analysis period for which the returns to be calculated.

Once an index/security is selected the system consults the "optimal settings" database for its optimal MA rule settings. If the index/security is available within the database, then these rule settings are displayed in front of their corresponding index/security. On the other hand, if the index/security is not within the database, then the user is given the choice of either letting the system search for the optimal MA rule settings or to manually input these settings (short, long and holding time periods, MA model type and price type). Even if the optimal settings are displayed, the user has the freedom to change them as desired.

After execution, each module displays a screen presenting a ranking of the securities and/or indices satisfying the requested scan. The "Scanning for Sell Signals" module will display a list of only the securities and/or indices among the specified portfolio that is in sell periods ranked in descending order according to the latest sell signals generated, i.e. the index/security with the most recent sell signal first. On the other hand, the "Scanning for Buy Signals" module displays a list of only the securities and/or indices among those of interest that is in buy periods. These securities and/or indices are ranked in

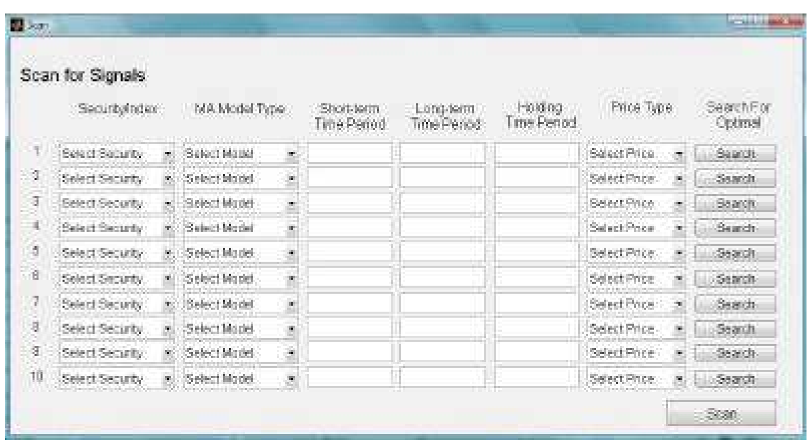
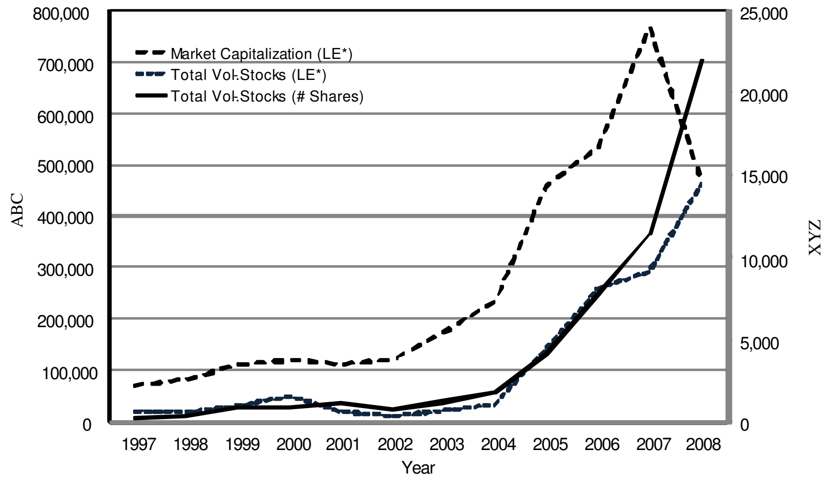


Fig. 4: A Typical Scanning Module Input Screen



*Converted from US Dollars based on corresponding year's exchange rate [33, 34]

Fig. 5: Performance of the Egyptian Stock Exchange 1997-2008 [33], [34]

descending order according to the latest buy signals generated thus indicating to the user those securities that are worth investing in now to maximize profit. Finally, the "Scanning for Highest Return" module will display a list of all the securities and/or indices subject to the scanning ranked according to the rate of return again in descending order, i.e. from the most profitable to the least profitable.

Case Study from the Egyptian Stock Market: Earlier in the "Introduction" the following question was asked "which of the above rules provides the highest return for the Egyptian Exchange Stock market?" To my knowledge and after extensive investigation, I was not able to find much, if any, research relating optimal MA rules to either the Egyptian Exchange Stock index or any of its securities. Therefore, in this paper I decided to apply the developed DSS to answer the above question for the CASE 30 index and a few common securities traded in the Egyptian market and to demonstrate some of the capabilities of the system.

The Egyptian Stock Exchange is comprised of the Cairo and the Alexandria Stock Exchanges (CASE), where both have the same Chairman and Board of Directors, as well as share the same trading, clearing and settlement systems. The Alexandria Stock Exchange was the first to be established back in 1888, while the Cairo Stock Exchange started in 1903. The two Exchanges were very active throughout the 1940s and 1950s, to the extent that the Egyptian Stock Exchange ranked fourth in the world before it folded up in July 1961 following the state-sanctioned demise of Egypt's private sector [32]. The Exchange remained dormant till 1992. In mid-1997, CASE started its modernization plan and became a proper regulated platform, which resulted in attracting both retail and institutional investors to the market, leading to higher trading activities as could be emphasized upon through Figure 5. The figure illustrates that the market capital has increased by almost ten folds from 70.9 billion LE in 1997 to 765.5 billion in 2007, which then dropped to 469.5 billion LE by the end of 2008 due to the worldwide downturn in the economy. With respect to the total volume of securities traded during the period from 1997 to 2008, it increased by almost 21 folds in value (from 20.9 billion LE to 460.1 billion LE) and by 75 times in terms of number of shares (from 287 million shares to 21.9 billion shares); note the doubling in the volume over the past year. Therefore, the EGX is considered one of the promising emerging markets.

Daily data starting from the beginning of 1998 for the CASE 30 index and securities in EGX are readily available on the internet. This data includes the opening, closing, lowest and highest prices for the day, as well as the volume. The "Calculate Return and Statistics" module of the developed DSS was applied to the CASE 30 time series data in order to build some understanding for the index. The analysis was performed across the entire sample series and by dividing the series into three almost equal periods and these are from 1/1998-12/2000, 1/2001-12/2004 and 1/2005-12/2008. The summary statistics for the entire period and the three sub-periods are presented in Table 2.

As evident from the summary, these daily returns are strongly leptokurtic and show signs of significant skewness, indicating that the market is significantly deviated from normality in its securities returns. The mean daily return over the entire sample was

Table 2: Summary Statistics for CASE 30 Index Daily Returns

	Full Sample	98-00	01-04	04-08
N	2695	745	980	967
Mean	0.00054	-0.00045	0.00130	0.00050
Std.	0.0180	0.0173	0.0166	0.0198
Skewness	-0.1897**	0.1036**	1.3423**	-1.2263**
Kurtosis	10.765	4.293	19.239	8.940
Minimum	-0.180	-0.110	-0.104	-0.180
Maximum	0.184	0.105	0.184	0.068

** Significant at the 1% level for a two-tailed test

Table 3: Optimal MA Rules and Standard Results

	Full Sample	98-00	01-04	04-08
MA Rule Settings				
Model Type	Exponential	Exponential	Exponential	Exponential
Short-Long	1-25	1-25	1-20	1-20
Price Type	Close	Close	Close	Close
Standard Results				
$N_{(Buy)}$	1539	321	591	580
$Mean_{(Buy)}$	0.00462	0.00501	0.00487	0.00475
$t_{(Buy)}$	7.59**	4.70**	4.07**	5.00**
$N_{(Sell)}$	1132	401	371	369
$Mean_{(Sell)}$	-0.00492	-0.00464	-0.00450	-0.00687
$t_{(Sell)}$	-8.25**	-4.05**	-6.59**	-5.08**
$Mean_{(Buy-Sell)}$	0.00954	0.00965	0.00937	0.01162
$t_{(Buy-Sell)}$	13.66**	7.59**	9.41**	8.19**
Average Annual Profit	9.91%	2.94%	4.13%	5.29%

** Significant at the 1% level for a two-tailed test

0.54%; nevertheless this was not consistent when looking at it through the different sub-periods, except for the last one. In the first sub-period (98-00), the mean was negative (-0.45%) indicating that during this period the market was mostly in a downtrend, while the second sub-period (01-04) the mean was at its highest (1.30%) due to a few daily jumps in the index reaching a maximum daily return of 18.4%. The summary also reveals high volatility in the market represented through the standard deviation of the daily returns, being the largest during the third sub-period (04-08). It is interesting to note that the highest drop in daily returns to occur was during the third sub-period and more specifically in October of 2008 accompanying the recent downturn in the global economy which started to show its impact in the fourth quarter of the year.

Next, the "Optimal MA Rule Settings" module was applied to the CASE 30 index in a quest for finding its optimal MA rule. Again this was performed for the entire sample and the three sub-periods identified earlier. The optimal rules and their corresponding results are presented in Table 3. The MA rule setting results displayed reveal that the exponential MA model applied to the closing price type will generate the highest profits for either the entire sample or the three sub-periods. As for the short and long time periods, we notice that a 1 day time length for the short-term is the best option, while for the long-term it varies between 20 and 25 days. Although the variation in the long-term time period is not big, but this could give an indication that the optimal durations within the Egyptian market could change according to the time period studied or if new time series is added.

A closer look at the results for the optimal settings reveals a number of interesting observations. The first of these observations is that the number of buy signals generated is about 60 percent more than the sell signals generated for the second and third sub-periods and 35 percent more for the entire sample, which is consistent with an upward-trending market. The opposite was true for the first sub-period, probably because most of this period was in a downtrend; recall that the mean daily return for this period was negative (refer back to Table 2). Second, the buy returns in all cases are positive and almost equal (ranging between 0.46% and 0.50%). These when compared to their respective one-day mean returns (representing the "buy-and-hold" strategy) shown in Table 2 are significantly larger as confirmed by the two-tailed *t*-test. On the other hand, the sell returns are all negative, indicating savings for being out of the market. This latter result is in accordance with those obtained by others including [6-9 and 23-26]. The magnitude of the sell

Fig. 6: A price plot of CASE 30 Index from Mid 2007 till the end of 2008 and the Optimal MA rule (Exponential 1, 25)- Chart by MetaStock

results is almost equal for most cases (-0.45% to-0.49%) and to the buy returns. The only exception to the previous is that for the third sub-period (05-08) during which the sell return was-0.69%. An obvious interpretation for such a result is that this sub-period exhibited two bullish periods during which the index gradually increased (January 05-CASE 30 was 2650 till February 06-CASE 30 reached 8000 and June 06-CASE 30 was 4600 till May 08-CASE 30 close to 12000) and two bearish periods during which the index nosedived in very short periods (from February 06 till June 06-CASE 30 dropped from 8000 to 4600 and from May 08 till November 08-CASE 30 dropped from almost 12000 to below 4000); this trend is illustrated in Figure 6. All sell signals for the optimal MA rules are highly significantly different from the "buy-and-hold" strategy returns. Finally, all the buy-sell differences are positive in the range of 0.95%, except for the third sub-period which was 1.16% for the reasons previously mentioned. Again these differences are highly significant, rejecting the null hypothesis of equality with zero.

In order to demonstrate the scanning capabilities of the DSS and how it can help the decision maker, I decided to consider ten of the commonly traded securities in EGX. These securities cover a number of sectors including construction, housing and real estate, financial, industrial, textiles and entertainment. Before attempting to scan, I had to search for the optimal MA rule settings for each security; the results of which are displayed in Table 4. As mentioned above, these optimal settings are stored to a database. Then a scan is requested to rank the securities, once according to their buy-sell return differences and another according to the average annual profit.

The information presented by Table 4 indicates that the exponential model type dominates over the simple, since seven out of the ten securities are better represented by it; recall that most of the research presented earlier applied the simple MA only. Despite this domination we cannot rule out the simple MA model. An interesting observation is that for the short-term length, all securities without exception shared the same length of 1 day regardless whether the model type is simple or exponential. On the other hand, the long-term length varied between 20 and 30, a possible reason for the variation is the differences in the securities microstructures or other characteristics of these securities [26]. Also, unlike the CASE 30 index which exhibited more buy than sell signals, most securities exhibited the opposite (the only exceptions were ELKA and ORTE). As for the mean returns, all were statistically significant at less than 1 percent. As expected all mean buy returns and the buy-sell difference returns were positive, whereas the sell returns were negative. Notice that for all securities the buy returns were larger in magnitude than the sell returns.

Scanning among the above ten securities was then performed by the developed DSS to identify the securities with the highest returns. The exercise was done once considering the entire sample period for the securities and another considering a recent subset of the period (namely from the beginning of 2007 till the end of 2008, i.e. over a two year span). This was done to test whether the time period considered will have an influence on the ranking or not. The ranking is presented in Table 5.

Through Table 5 it is evident that the ranking does depend on both the nature of the return and the analysis duration. Based on the sample of securities selected for

Table 4: Optimal MA Rule Settings for Some EGX Securities

		MA Rule Settings		Standard Results				
Security Name	Code	Model Type	S-L* Lengths	$N_{(Buy)}$	$Mean_{(Buy)}$ (%)**	$N_{(Sell)}$	$Mean_{(Sell)}$ (%)**	$Mean_{(B-S)}$ (%)**
Arab Polvara Spinn-ing and Weaving	APSW	Exp	1-30	781	1.062	924	-0.718	1.780
Commercial International Bank	COMI	Simple	1-25	1367	0.507	1298	-0.459	0.966
El Kahera Housing	ELKA	Exp	1-30	1052	0.569	1614	-0.415	0.983
El Ezz Steel Rebars	ESRS	Simple	1-25	1119	0.567	1283	-0.461	1.028
El Nasr Clothes and Textiles	KABO	Exp	1-30	758	0.966	975	-0.782	1.748
Medinet Nasr Housing	MNHD	Exp	1-25	1263	1.129	1407	-0.961	2.090
Egyptian Media Production City	MPRC	Exp	1-20	889	1.228	1431	-0.843	2.071
Six October Develop-ment and Investment	OCDI	Simple	1-20	1001	1.483	1337	-0.955	2.438
Orascom Telecom Holding	ORTE	Exp	1-30	1123	0.803	1012	-0.698	1.501
United Housing and Development	UNIT	Exp	1-25	1126	1.189	1339	-1.010	2.198

* S-L = Short-Long Time Period Lenghts

** Significant at the 1% level for a two-tailed test

Table 5: Ranking of Securities

	Full Sample		Jan 07-Dec 08	
Rank	B-S Daily Return	Average Annual Return	B-S Daily Return	Average Annual Return
1	OCDI (2.438%)	OCDI (39.046%)	UNIT (2.241%)	UNIT (26.778%)
2	UNIT (2.198%)	UNIT (35.671%)	APSW (2.131%)	MPRC (21.552%)
3	MNHD (2.090%)	MPRC (28.910%)	ELKA (2.052%)	KABO (20.759%)
4	MPRC (2.071%)	MNHD (25.902%)	MNHD (1.989%)	OCDI (20.594%)
5	APSW (1.780%)	KABO (19.487%)	KABO (1.922%)	ELKA (19.866%)
6	KABO (1.748%)	APSW (18.885%)	MPRC (1.851%)	APSW (19.323%)
7	ORTE (1.501%)	ORTE (12.752%)	OCDI (1.826%)	MNHD (15.757%)
8	ESRS (1.028%)	ELKA (11.532%)	ESRS (1.500%)	ORTE (13.170%)
9	ELKA (0.983%)	ESRS (11.072%)	ORTE (1.306%)	ESRS (12.794%)
10	COMI (0.966%)	COMI (11.005%)	COMI (0.959%)	COMI (11.151%)

this demo, only one maintained its ranking throughout the different options and that was the COMI security in the last place, while the UNIT security either ranked the top or second best among the ten securities investigated. For the remainder of the securities all exchanged positions. When comparing based on the nature of the return, one notices that for the entire series the rankings were almost close, the differences being an exchange in ranks (if any) between two consecutive securities (for example, MNHD and MPRC, APSW and KABO and ESRS and ELKA). No pattern was obvious for the smaller sub-period. A possible explanation for this behaviour is that for the entire series, because of the large number of observations, securities exhibit more stability in their returns and their number of signals and hence their average number of signals per year is close to each other. Therefore, the question is whether to base the analysis on the buy-sell difference mean daily returns or on the average annual return. Recent research [9 and 31] has recommended the average annual return since transaction costs could be incorporated in to it and therefore is more realistic.

A comparison based on the analysis duration for the same return type shows some huge differences in the ranking for some securities. Interesting examples are featured by ELKA and OCDI. The ELKA security jumped from the ninth place (entire sample) to the third place (last two years) when compared based on the buy-sell difference return and from eighth to the fifth position based on the average annual return. This behaviour indicates that the ELKA security had a much better performance and gains as well as higher volatility in the most recent years. On the other hand, the OCDI security was ranked the best performing security over the entire sample but dropped to the seventh place among the ten securities when compared according to the buy-sell difference return, while it dropped from the first place to the fourth according to the average annual profit. Therefore, this latter behaviour illustrates a weakening in the performance of the security and hence a drop in its returns over the most recent years. Accordingly, it is wise for the investor when searching for the best performing security to base his/her analysis on a recent sample of the time series data for the securities under investigation.

CONCLUSIONS

The primary aim of this study was to build a DSS that is capable of analyzing financial market data and providing recommendations to the investors based on the MA crossover. The main features of the system developed that it has the capabilities of providing descriptive statistics for the time series data of market indices and securities, evaluating the statistical significance of returns generated by any MA rule, searching for the optimal MA rule that generates the highest significant returns and scan among a group of securities for the latest signals and highest returns. The system has the added of advantage of searching for the optimal MA rule among a large universe of MA rules. Accordingly, an investor can use this system in making decision for his/her next move with respect to any security of interest.

A secondary aim of the study was to investigate the predictive capabilities of the MA crossover technique when applied to the Egyptian price index (CASE 30) and some securities from EGX through using the developed DSS, thus also demonstrating the DSS's capabilities. EGX is a promising emerging market that has experienced a huge upturn in its activities over the last eleven years through which the market capital has increased by ten folds and the trade by value and number of shares 21 and 75 folds, respectively. An investigation of the CASE 30 daily returns revealed that they are strongly leptokurtic with significant skewness and high volatility. Applying the MA crossover technique through the DSS to the CASE 30 showed that most profitable MA rule is exponential of length 1-25 using the close price. This was almost consistent when considering sub-periods; differences being in the lengths which varied between 1-20 and 1-25. Also, in accordance with previous research, all significant buy returns were positive (indicating profit returns for being in the market) and the sell returns were negative (for being out of the market).

When applying the DSS to a number of securities, again the results provide evidence of economical significance of the MA crossover rules. The lengths of 1-20, 1-25 and 1-30 along with the closing price emerged as the most profitable for the rules. The exponential MA model dominated, nevertheless we cannot rule out the simple MA model since it was the most effective for a few securities. The mean returns generated for these optimal rules are significantly larger than those unconditional one-day mean returns for the buy-and-hold strategy. The DSS also provided us with strong evidence that ranking of securities depends on the time-span of the analysis and the nature of the return according to which the ranking is performed, whether it is the buy-sell difference mean daily return or the average annual return.

Therefore, the MA crossover technique can predict the Egyptian stock market and its securities. There could be great opportunities from applying this technique to the Egyptian market for yield enhancement and portfolio diversification.

REFERENCES

1. Taylor, M.P. and H. Allen, 1992. The use of technical analysis in the foreign exchange market. J. Intl. Money and Finance, 11: 304-314.
2. Bigalow, S.W. and D. Elliot, 2004. Day-trading with candlesticks and moving averages. Futures: News, Analysis and Strategies for Futures, pp:40-42.
3. Schaff, W., November 2004. Pay attention to technical analysis. Information Week, pp:84.
4. Wikipedia, Updated June 2007. Technical analysis software. http:// en.wikipedia. org/wiki/ Technical-analysis-software.
5. Murphey, C., Updated September 2006. Moving averages tutorial: What are they? Investopedia. com/ university/ movingaverage/ movingaverages1.asp.
6. Brock, W., I. Lakonishok and B. LeBaron, 1992. Simple technical trading rules and the stochastic properties of stock returns. J. Finance, 47(5): 1731-1764.
7. Hudson, R., M.J. Dempsey and K. Keasey, 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. Banking and Finance, 20: 1121-1132.
8. Parisi, F. and A. Vasquez, 2000. Simple technical trading rules of stock returns: evidence from 1987 to 1998 in Chile. Emerging Markets Review, 1: 152-164.
9. Ming-Ming, L. and L. Siok-Hwa, 2006. The profitability of the simple moving averages and trading range breakout in the Asian stock markets. J. Asian Economics, 17: 144-170.
10. Jobman, D., March-April 2006. Forecasted moving averages: Creating leading indicators through intermarket analysis. The Trader's Journal. (www.traders-journal.com), 2(2): 8-12.
11. Tsokakis, D., February 2007. Anticipating moving average Crossovers. Technical Analysis of Stocks and Commodities. 25(2): 20-27.

12. Pasternak, M., July 2003. Inside the Black Box: Technical analysis made clear and simple-Using multiple moving averages. StreetAuthority Swing Trader Newsletter (www.streetauthority.com), 1(19).
13. Gartley, H.M., 1930. Profits in the stock market. H.M. Gartley Inc., New York, N.Y.
14. Coslow, S. and H.D. Schultz, 1966. A treasury of Wall Street wisdom. Investors Press Inc., Pallisades Park, N.Y.
15. Trade.com. Moving Averages. www.trade10.com/ Moving-Average. html.
16. Kaufman, P.J., 1995. Smarter Trading. McGraw-Hill, New York.
17. Colby, R.W., 2003. The encyclopaedia of technical market indicators. McGraw-Hill Publishing, New York, 2nd Edition.
18. Ellis, C.A. and S.A. Parbery, 2005. Is smarter better? A comparison of adaptive and simple moving average trading strategies. Research in International Business and Finance, 19: 399-411.
19. Carr, M., 2008. Do adaptive moving averages lead to better results? Investopedia-A Forbes Digital Company. www. investopedia. com/articles/ trading/08/adaptive-moving-averages.asp.
20. Le Beau, C., May 2004. Moving average crossovers may not be the best entry signals. www. traderclub. com.
21. Van Horne, J.C. and G.G.C. Parker, 1967. The random walk theory: an empirical test. Financial Analysts J., 23: 87-92.
22. James Jr., F.E., 1968. Monthly moving averages-An effective investment tool? J. Financial and Quantitative Analysis, 3: 315-326.
23. Bessembinder, H. and K. Chan, 1995. The profitability of technical trading rules in the Asian stock markets. Pacific-Basin Finance J., 3: 257-284.
24. Ratner, M. and R.P.C. Leal, 1999. Tests of technical trading strategies in the emerging markets of America Latina and Asia. J. Banking and Finance, 23: 1887-1905.
25. Gunasekarage, A. and D.M. Power, 2001. The profitability of moving average trading rules in South Asian stock markets. Emerging Markets Review, 2: 17-33.
26. Chang, E.J., E.J.A. Lima and B.M. Tabak, 2004. Testing for predictability in emerging equity markets. Emerging Markets Review, 5: 295-316.
27. Ready, M., 1997. Pitfalls from technical trading rules. Working paper, University of Wisconsin.
28. Le Baron, B., 1999. The stability of moving average technical trading rules on the Dow Jones index. Working paper, Brandeis University.
29. Sullivan, R., A. Timmermann and H. White, 1999. Data-snooping, technical trading rule performance and the bootstrap. J. Finance, 56: 1647-1691.
30. Mills, T.C., 1997. Technical analysis and the London Stock Exchange: testing trading rules using the FT30. Intl. J. Finance and Economics, 2: 319-331.
31. Fong, W.M. and L.H.M. Yong, 2005. Chasing trends: recursive moving average trading rules and internet stocks. J. Empirical Finance, 12: 3-76.
32. The Egyptian Exchange, Copyrighted 2005. About the Exchange-History. www.egyptse.com.
33. The Federation of Euro-Asian Stock Exchanges, 2001-2004. The Federation of Euro-Asian Stock Exchanges Yearbook 2000/2001; 2001/2002; 2002/2003; 2003/2004. Istanbul, Turkey.
34. The Federation of Euro-Asian Stock Exchanges, 2005-2008. The Federation of Euro-Asian Stock Exchanges Semi Annual Report May 2005; October 2005; April 2006; October 2006; April 2007; October 2007; April 2008; October 2008; April 2009. Istanbul, Turkey.