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An intelligent short term stock trading fuzzy system for assisting investors in portfolio management

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ABSTRACT

Financial markets are complex systems influenced by many interrelated economic, political and psychological factors and characterised by inherent nonlinearities. Recently, there have been many efforts towards stock market prediction, applying various fuzzy logic techniques and using technical analysis methods.

This paper presents a short term trading fuzzy system using a novel trading strategy and an "amalgam" between altered commonly used technical indicators and rarely used ones, in order to assist investors in their portfolio management. The sample consists of daily data from the general index of the Athens Stock Exchange over a period of more than 15 years (15/11/1996 to 5/6/2012), which was also divided into distinctive groups of bull and bear market periods.

The results suggest that, with or without taking into consideration transaction costs, the return of the proposed fuzzy model is superior to the returns of the buy and hold strategy. The proposed system can be characterised as conservative, since it produces smaller losses during bear market periods and smaller gains during bull market periods compared with the buy and hold strategy.

1. Introduction

Stock market prediction is of great importance since, as Guresen, Kayakutlu, and Daim (2011) note, better prediction is always crucial for making better economic decisions. Recently, a variety of artificial intelligence techniques have been proposed (Dymova, Sevastianov, & Kaczmarek, 2012). The latter became a necessity since financial markets are complex non-linear systems (Manahov & Hudson, 2014), involving huge numbers of participants influenced by many interrelated economic, political and psychological factors (Ballings, Poel, Hespeels, & Gryp, 2015; Lan, Zhang, & Xiong, 2011). These factors cause many uncertainties in financial markets and accordingly have positive or negative effects on stock values.

It is reasonable to assume that since stock price data are affected by deterministic and random factors (Bao & Yang, 2008), stock market forecasting can be successful only with the use of tools and techniques that can overcome the problem of uncertainty, noise and nonlinearity of prices (Chang, Fan, & Lin, 2011). Vanstone and Finnie (2009) claim that soft computing are amongst these techniques, since they can handle such problems.

Fuzzy logic is one of the soft computing techniques, which are nonlinear in nature and are considered to be part of artificial intelligence (Kumar & Ravi, 2007; Melin et al., 2007; Russell & Norvig, 2014). Fuzzy systems have thus been used with success in many applications in the real world (Crespo, Cuadrado, Carrasco, Palacios, & Mezcua, 2012).

Technical analysis is used to forecast future stock prices by studying historical prices and volumes. Since all information is reflected in stock prices, it is sufficient to study specific technical indicators (created by a rather complicated mathematical formula) in order to predict price fluctuations and evaluate the strength of the prevailing trend (Bao & Yang, 2008; Cheng, Chen, & Wei, 2010). The combination of various technical analysis techniques is a difficult task and requires decisions by using subjective assessments (Dymova, Sevastianov, & Bartosiewicz, 2010). Some techniques can provide contradictory results, the evaluation of which demands specific human expertise, subjective assessments and appropriate justification (Majhi, Panda, & Sahoo, 2009). The development of fuzzy models can address such issues in a satisfactory manner.

The large majority of studies use the same technical indicators, such as moving average (MA) and moving average convergence/divergence (MACD) (da Costa, Nazαrio, Bergo, Sobreiro, & Kimura, 2015; Fang, Jacobsen, & Qin, 2014; Ince, 2014; Metghalchi, Chen, & Hayes, 2015; Murphy, 2000; Tan, Quek, & Yow, 2008; Ulku & Prodan, 2013). However, it is suggested that if a successful strategy predicting the stock market is found (and published), all researches which will follow (concerning future time periods) might not be successful anymore because the market will have adapted accordingly

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(Black, 1993; Malkiel, 2003). This assumption has been investigated by various researchers (LeBaron, 2000; Mills, 1997; Sullivan, Timmerman, & White, 1999) using the same trading rules as in previous studies and found that these trading rules were not equally profitable for future periods. Others claim that despite the documented success of the technical trading rules, there is a widespread notion that their performance is temporal with prolonged alternating periods of success and failure, probably due to the increasing interest and use of these rules when market conditions are favourable. This ultimately drives their profits back down to zero (Taylor, 2014). Indeed, Neely, Weller, and Ulrich (2009) who examined the evolution over time of the excess returns of technical trading rules, assert that they decline over time and that by mid-1990 s profit opportunities from MA rules had disappeared. Thus, the need to try novel approaches becomes apparent and it is constant. One way to achieve this is by introducing new technical indicators or smart modifications of those who are well established, since each indicator has unique characteristics which might determine his profitability in various market conditions and therefore can be distinguished from others. Moreover, the above mentioned very common indicators are calculated by using only closing daily prices and, thus, important information contained in other daily price data such as open, high and low are not considered. Therefore, the choice of technical indicators that make full use of daily data with open, high, low and close, becomes apparent, since it broadens the information on which decisions are based.

It is common practice for various researchers (Chang & Liu, 2008; de Oliveira, Nobre, & Zαrate, 2013; Lam, 2001; Patel, Shah, Thakkar, & Kotecha, 2015; Pereira & Tettamanzi, 2008; Pokropinska & Scherer, 2008; Wu, Yu, & Chang, 2014; Zhai, Hsu, & Halgamuge, 2007) to use many indicators, and combine them in an effort to achieve good performance, by disposing different ways to analyse price movements. However, each technical indicator has been created for specific purposes, they express different and uneven characteristics and therefore it is doubtful whether any combination of them can be functional. Their careful selection ensures that their characteristics will act cumulatively, otherwise a combination of dissimilar technical indicators may cause erratical results, since the indicators may negate each other.

The creation of intelligent system which can perform prediction tasks accurately and in a robust way, was always of immense importance for investors and financial analysts (Hafezi, Shahradi, & Hadavandi, 2015).

A trading strategy with technical indicators can be formulated with various ways. Momentum oscillators (i.e. trend-reversion indicators), indicate whether a market accelerates or decelerates (Araque, Salguero, Carrasco, & Martinez, 2008) and the underlying assumption is that when prices move too higher (or lower) than the average, then a reversal is eminent and accordingly a sell (or buy) signal is generated (Balvers & Wu, 2006; Zhang et al., 2015), while this style of investing is called contrarian strategy (Teplova & Mikova, 2015). Using technical trend indicators, one of the trading strategies is based on the assumption that when prices are becoming higher (or lower) than the indicator, then a buy (or sell) signal is generated, while this position is held till the opposite signal (Colby, 2003; Papailias & Thomakos, 2015; Powers & Castelino, 1991). This paper builds a novel trading strategy, based on this (classic) strategy with technical trend indicators, using it as a starting point and extends it with an observation made by Papoulias (1990) that when the space between the technical indicator and price shortens then the current move of the market is ending, and when this space broadens the current move is confirmed. Thus the proposed strategy is as follows. When prices are becoming higher (lower) than the technical indicator, then a buy (sell) signal is generated (*If Cl>Ti => Buy, If Cl<Ti => Sell*). This signal remains valid till the opposite signal is given. Moreover, when a buy signal is given and until the opposite signal of sell will be given, if a stenosis (narrowing) between the price and a technical indicator appears, this is an indication that the degree of certainty of the present order (buy) decreases and increases the possibility that the opposite order (sell) is imminent. Therefore the investor should reduce the portion of his capital which is invested in equities, (*If Cl>Ti Then If* Cl_t-Ti_t < Cl_{t-1}-Ti_{t-1} *=> Decrease buy position*). Similarly, if the distance between the price and a technical indicator increases, this is an indication that the degree of certainty of the present order (buy) increases as well and the possibility that the opposite order (sell) is delayed. Consecutively, the invested part of the portfolio in equities should be increased, (*If Cl>Ti Then If* Cl_t-Ti_t > Cl_{t-1}-Ti_{t-1} *=> Increase buy position*). On the contrary, when a sell signal is given and until the opposite signal of buy will be given, if a stenosis (narrowing) between the price and a technical indicator appears, this is an indication that the degree of certainty of the present order (sell short) decreases and increases the possibility that the opposite order (close short position or buy long) is imminent. Therefore the investor should reduce his position (*If Cl<Ti Then If* Cl_t-Ti_t > Cl_{t-1}-Ti_{t-1} *=> Reduce sell short position*). Similarly, if the distance between the price and a technical indicator increases, this is an indication that the degree of certainty of the present order (sell short) increases as well and the possibility that the opposite order (close short position or buy long) is delayed. Consecutively, the invested part of the portfolio in equities should be increased (*If Cl<Ti Then If* Cl_t-Ti_t < Cl_{t-1}-Ti_{t-1} *=> Increase sell short position*).

Unlike traditional trading strategies, this is not a merely mathematically objective strategy, but incorporates subjective factors and the fuzzy notion of certainty, which are implemented in later stages of the model, with the membership functions of the system.

The aim of this paper is to propose a model comprising of a small number of novel short term technical indicators and a novel trading strategy with an appropriately designed fuzzy system, which outputs the percent of the portfolio that should be invested on a daily basis.

This paper contributes to the literature in a number of ways. First, presents a novel “amalgam” of short term technical indicators. This research proposes the use of four technical indicators that have never been used before simultaneously in academic research. Bearing in mind that truly effective technical indicators are not published in academic journals, but are instead kept secret (Pinto, Neves, & Horta, 2015; Vanstone & Finnie, 2009), the technical indicators chosen as predictors in this study are an amalgam of various indicators with some novelty. Two of the indicators are very rarely or never used in research papers (Parabolic SAR and GANN-HiLo). A novel indicator is created by using the MA of a range of MA for different periods of time. Finally, the MACD indicator is also used, but since there are some reports suggesting that it cannot provide better returns than the buy and hold (B&H) strategy (Colby, 2003), it is used here with a different trigger. Furthermore, the calculation of the first two indicators, except daily closing prices, as is often the case, uses the high and low daily measures of price, while all technical indicators have been adjusted to perform better in short periods.

Second, it uses a novel trading strategy which differentiates it from previous studies in that connects the distance between the price and the technical indicator, with the subjectivity and fuzziness of the current order.

Third, explores the profitability of an intelligent stock trading fuzzy system, aiming to assist short term investors in their portfolio management, by combining within the system independent technical analysis signals which have been given outside of the system. These signals undergo a transformation within the system which is specific for every signal, in order to explore the limits of elasticity of the slope of the curve that maps appropriately their behaviour, between reaching the maximum performance and maintaining the fuzzy characteristics of the curve.

The model was tested in various market environments for a period of over 15 years and for 3.879 daily data, using the general index of the Greek (Athens) stock market. The applicability of the system is enhanced with two additional tools, one to check and show all errors of historic data and the other to facilitate investors in their trading decisions by providing information about their daily position in the market and information for their portfolio.

2. Literature review

In the past few decades, various financial researchers have developed many conventional numeric forecasting models (Cheng et al., 2010). According to Ballings et al. (2015) common methods are the autoregressive method (AR), the moving average model (MA), the autoregressive-moving average model (ARMA) and the threshold autoregressive model (TAR), while Engle's (1982) autoregressive conditional heteroscedasticity (ARCH) model, Bollerslev's (1986) generalised ARCH (GARCH) model and Box and Jenkins' (1976) autoregressive integrated moving average model (ARIMA), being some of the most cited.

However, the stock market is a complex and dynamic system with noisy, nonstationary and chaotic data series (Evans, Pappas, & Xhafa, 2013; Lo & MacKinlay, 1988; Peters, 1994; Ticknor, 2013; Wen, Yang, Song, & Jia, 2010). Therefore, it is no surprise that recently many researchers have tried to predict stock market movements by building automatic decision-making systems that employ a soft computing approach (Bao & Yang, 2008; Geva & Zahavi, 2014) such as fuzzy logic and neural networks, because these are tolerant of imprecision, uncertainty and approximation. As a result, they have become popular in the academic community (Vanstone, 2005).

The conventional fuzzy time series models are referred as Type 1 and use only one variable for forecasting. However, there are cases where some variables consist of many different observations which can be included in models to improve forecasting. Zadeh (1975) introduced Type 2 fuzzy sets where the degree of membership is considered to be a fuzzy set, as opposed to a crisp value in Type 1. Some researchers assert that first-order fuzzy models are insufficient for solving nonlinear and complexity issues. Chen (2014) proposed for stock trading a high-order fuzzy time series model, which uses entropy-based partitioning during the fuzzification procedure, applies an artificial neural network (ANN) to compute the fuzzy logical relationships and in the defuzzification procedure uses the adaptive expectation model to adjust the forecasting. In the same context, Cheng, Wei, Liu, and Chen (2013) integrated high-order data into the adaptive network-based fuzzy inference system (ANFIS) using the ordered weighted averaging operator to predict stock prices in Taiwan, Chen, Manalu, Shih, Sheu, and Liu (2011) presented a new method for fuzzy forecasting concerned two factors to construct high-order fuzzy logical relationship groups. Recently, Egrioglu (2014) proposed a high order fuzzy time series method which is based on particle swarm optimisation and which, when applied to stock exchange data, had better performance than other methods. Askari and Montazerin (2015) presented a forecasting algorithm based on fuzzy clustering, which is high-order and multi-variable simultaneously. It is suitable for system identification, forecasting and interpolation and it is claimed that it is more accurate than popular fuzzy time series algorithms and other forecasting tools and systems such as ANFIS, Type II fuzzy model and ARIMA model. We argue that for the purpose of the present study and the variables which will be examined, the creation of a first-order fuzzy model is adequate and avoids the excess of computational power, which would be needed otherwise. Therefore the rest of the review will be in first-order fuzzy systems or other soft computing techniques.

Dourra and Siy (2002) claimed that technical analysis blends very well with a variety of soft computing techniques. Recently, a noticeable number of research papers, proposing models which combine various methods for prediction with soft computing techniques, have appeared (de Oliveira et al., 2013; Patel et al., 2015; Pereira & Tettamanzi, 2008). Technical analysis is one of these methods, while trend indicators, momentum oscillators, chart patterns and candlesticks are often used.

Some researchers have focused on predicting the direction of the market over the next trading days. Vaidehi, Monica, Mohamed, Deepika, and Sangeetha (2008) propose a fuzzy system to predict the possibility for market prices to rise or fall with almost 80% accuracy (for six Indian stocks), by combining a subtractive clustering algorithm and a fuzzy system identification method. Bekiros (2010) introduced a hybrid neuro-fuzzy system that uses technical analysis for 10 of the most prominent stock indices in the US, Europe and Southeast Asia while the total profits of the system were shown to be superior to a recurrent neural network and a B&H strategy for all indices. Atsalakis and Valavanis (2009) also propose a neuro-fuzzy system, composed of an Adaptive Neuro-Fuzzy Inference System (ANFIS) controller and a stock market process model with technical analysis to suggest the best stock trend prediction for the next day for the Athens and New York stock exchanges. The above literature insists on using fuzzy systems, either as a stand alone system or in a combination with another soft computing technique, like ANN. However, some researchers prefer to employ different soft computing techniques, using each one in the area where prevails, while others have chosen to benchmark some methods against various other known models. Abraham, Nath, and Mahanti (2001) used principal component analysis to pre-process the data, which were imported afterwards into a neural network that was already trained appropriately and finally the results of this process were imported into a neuro-fuzzy system in order to analyse the trend of the market. Their intention was to predict 1 day ahead the direction of the market, while Ballings et al. (2015) extended this prediction to 1 year ahead. They compared the performance of ensemble methods (Random Forest, AdaBoost and Kernel Factory) against single classifier models (ANN, Logistic Regression, Support Vector Machines and K-Nearest Neighbour). They tested thousands of European stocks, using yearly data and a plethora of important predictors in extant literature plus other important financial indicators and showed the potential of ensemble methods. They both used other method of prediction than technical analysis, as is the case with Bekiros and Georgoutsos (2007), and Doeksen, Abraham, Thomas, and Paprzycki (2005)), while Atsalakis, Dimitrakakis, and Zopounidis (2011)), Bisoi and Dash (2014), de Oliveira et al. (2013)), Kara, Boyacioglu, and Baykan (2011)), and Patel et al. (2015)) using various soft computing techniques and technical analysis as the main prediction method, investigated the same area (predicting the direction of the market).

However, whichever the achieved forecasting accuracy of the prediction of the direction of the market is, these approaches usually offer very little information about the amount of movement and, consequently, whether it is worth for someone to invest. Therefore their contribution as to the portfolio management is very limited.

In order to surpass this, other researchers have been interested in predicting the future price of a stock market index, stock, or technical indicator. Hafezi et al. (2015) adopted an Artificial Neural Network (ANN) multi-agent system with four layers, by applying both fundamental and technical data using as a case study the DAX stock market and compared the outcomes with the results of other methods. Kao, Chiu, Lu, and Chang (2013) presented a hybrid approach by integrating wavelet-based feature extraction with multivariate adaptive regression splines (MARS) and support vector regression (SVR), and the model outperformed five other competing approaches. Nair et al. (2011) also adopted a hybrid approach with a Genetic algorithm tuning the parameters of an ANN at the end of each trading session. Svalina, Galzina, Lujic, and Šimunovic (2013) used an ANFIS for the Zagreb Stock Exchange with a separate fuzzy inference system (FIS) for every day, while every daily input variable was differently created from previous closing prices and the output was the closing price 5 days in advance. Ticknor (2013) used a simple ANN model which was

Bayesian regularised to assign a probabilistic nature to the network weights, allowing to automatically and optimally penalise excessively complex models, while the inputs were daily prices and technical indicators and the results indicated that it performed as well as the more advanced models. This technique reduces the potential for overfitting and overtraining, and improves the prediction quality and generalisation of the network. Esfahanipour and Aghamiri (2010) developed a neuro-fuzzy system, based on a Takagi–Sugeno–Kang (TSK) type fuzzy rule which have been identified by fuzzy c-mean clustering, while the inputs are seven technical indicators and the TSK parameters were tuned by an ANFIS. Chang and Liu (2008) developed a TSK type fuzzy rule based system which applied various technical indexes as input variables. The model has successfully forecasted the price variation for stocks of Taiwan Stock Exchange. The real time implementation of a successful system is a well worth effort and it was attempted during the evaluation period by the previous researchers. Baba and Nomura (2005) used an ANN in order to predict the intersection of two MA several weeks in advance with Nikkei−225 historic data. Wang (2002) created a fuzzy system in Visual Basic to predict stock prices instantly at any given time through a prediction agent, which employs a fuzzification technique and demands few inputs. Chavarnakul and Enke (2008) proposed two generalised regression neural networks (GRNN) using two technical indicators that can be developed from equivolume charting and they ascertained that their method outperformed other simple technical indicators and the B&H strategy. In a further development, Tan et al. (2008) identified reversal points through an intelligent Rough Set-based Pseudo Outer-Product (RSPOP) fuzzy neural network. They tried to predict the price difference after 5 days, with the use of various technical indexes. Yu and Huarng (2010) enhanced the prediction performance by integrating the ANN architecture with the fuzzy time series, while Chang et al. (2011) integrated an ANFIS with a fuzzy time series model to predict stock market.

Another way for the prediction of future prices is through technical pattern recognition (Chen & Chen, 2011; Jun & He, 2012; Leigh, Paz, & Purvis, 2002; Parracho, Neves, & Horta, 2011; Royo, Guijarro, & Michniuk, 2015; Wang & Chan, 2009), although Zapranis and Tsinaslanidis (2012) claim that is only a small fraction of the existing literature.

The advantages of being able to predict future prices are obvious. Thus this is one of the reasons that there is such active research motivation in this area. However, all previous studies did not contain any mechanism to propose the day or price where the investor should enter or exit from the market. Thus, various researchers tried to predict the actual buy/sell signals.

Pereira and Tettamanzi (2008) used a plethora of technical indicators and an evolutionary algorithm to create a fuzzy predictive model, in order to produce a go short, go long or do nothing trading signal. In contrast, Dourra and Siy (2002) used only three technical indicators for their method, which maps the indicators into new inputs that can be fed into a fuzzy logic system in order to facilitate decision to buy/sell a stock, when certain price movements or price formations occur. Further, Ijegwa, Rebecca, Olusegun, and Isaac (2014) used four technical indicators as inputs, and they developed a similar fuzzy system which outputs a buy, sell or hold signal, with satisfactory results. However, every system should employ technical indicators with similar characteristics in order to strengthen the output and avoid their contradiction with each other. Therefore, the idea to use "as many as possible" indicators, might end up to a system which produces inconsistent signals. If the evaluation period is short the signals might seem satisfactory, although the results might be the opposite in another or in a longer period. Buy/sell signals are produced by other researches as well (Dymova et al., 2010; Mabu, Hirasawa, Obayashi, & Kuremoto, 2013; Sevastianov & Dymova, 2009; Tilakaratne, Mammadov, & Morris, 2007; Yunusoglu & Salim, 2013) although their approaches differ.

The appropriate compilation of technical analysis with soft computing techniques in the area of stock market prediction can offer significant advantages, since it can combine the hardly gained by traders experience with the unique characteristics of soft computing to face the problems of complexity, uncertainty and nonlinearity of the markets. The main disadvantage of fuzzy systems is that the knowledge about a problem must be known in advance, for a qualitative fuzzy inference system to be defined (Svalina et al., 2013). However, this can be reverted to a great advantage, since the knowledge, experience and intuition of an expert trader, which are easily handled by fuzzy systems (Bekiros & Georgoutsos, 2007), can be ensured in advance. Unlike many other soft computing techniques, fuzzy systems avoid the reliance only on quantitative data, since they require decisions which are taken using subjective assessments, while, in addition, they allow the creation of fuzzy rules in a more natural way, which represents in a better way the decision making process during the stock trading (Dymova et al., 2010).

3. Technical analysis

Numerous forecasting methods have been employed in an attempt to predict stock prices. Technical analysis is one of the primary analytic approaches used by many investors to make investment decisions to increase their investment returns (Cheng et al., 2010). It is mainly classified into technical indicators and charting patterns (Zapranis & Tsinaslanidis, 2012).

A series of surveys has confirmed the extensive use of technical analysis among investors, practitioners and professional traders. Taylor and Allen (1992) found that over 90% of the foreign exchange dealers in London place some weight on technical analysis, especially for shorter forecasting horizons. Similarly, Oberlechner (2001) and Gehrig and Menkhoff (2006) found that the shorter the forecasting horizon, the more important technical analysis is (rising over time) for foreign exchange traders, Forex dealers and rising fund managers. Finally, Menkhoff (2010) found that most fund managers use technical analysis to a certain degree and, for a forecasting horizon of some weeks, they consider it to be more important than fundamental analysis.

However, although technical analysis has over a hundred years of history among practitioners and investment professionals, only during the past two decades has its claims found support within the academic community (Booth, Gerding, & McGroarty, 2014; Jasemi, Kimiagari, & Memariani, 2011; Neely & Weller, 1999; Vanstone & Finnie, 2009). The interest of the academic community was strongly reinforced after the publication of an article by Brock, Lakonishok, and LeBaron (1992), which proposed that simple technical rules can predict major movements in stock prices and stock indices.

A technical indicator is a mathematical calculation that can be applied to a security's fields (i.e. open, high, low, close, volume) and can be used to anticipate future changes in prices (Metastock Professional, 2002). Various technical indicators are used in research papers of stock market prediction, but among them MA and MACD are by far the most common (Murphy, 2000). This tendency of using common indicators continues during the recent years (Anbalagan & Maheswari, 2015; Gradojevic and Lento, 2015; Ko, Lin, Su, & Chang, 2014; Pinto et al., 2015; Yu, Nartea, Gan, & Yao, 2013). Surprisingly, there have been very few attempts to use uncommon technical indicators or to empirically test the performance of technical indicators with uncommon characteristics that show some novelty in their formulae.

The present research attempts to fill this gap using (i) a new technical indicator created by calculating the simple MA of five exponential MA for periods of different lengths, (ii) MACD, but with a different trigger line, (iii) the Parabolic SAR, which, although is widely known to practitioners of technical analysis (Shipman, 2008), it has been rarely used in academic research works and (iv) the Gann HiLo, an indicator which, to the best of our knowledge, has not yet been used in academic research, although it offers a different perception for the prediction in stock market.

3.1. Moving average (MA)

A MA is a method for calculating the average value of a stock for a specific time period (Metastock Professional, 2002). MA is characterised by the time length x (i.e. the amount of periods for which it is calculated), such as short-term MA (e.g. 5 days), mid-term MA (e.g. 50 days) and long-term MA (e.g. 200 days). MA is used to smooth the noise of shorter-term fluctuations in order to more easily identify the significant underlying trends (Appel, 2005; Ruiz, Pérezb, & Olasoloc, 2014). According to Wang and Wang (2010) and Katz and McCormick (2000), three types of MA are the most important: simple MA, exponential MA and weighted MA. Of the other types of MA, the main difference between them is the weight they place on recent data (see triangular MA, time series MA, variable length MA and volume-adjusted MA).

For the purposes of the present research, a number of in-depth tests were carried out on the various types of MA before the exponential MA was chosen as the most appropriate. This is a weighted MA in which the weights are reduced by an exponential degree. The most recent value gets the higher weight, while the weights in every older value are exponentially decreased. According to Katz and McCormick (2000), it is calculated by using the formula $a_1 = (\sum_{k=0}^{i} c^k s_{i-k})/(\sum_{k=0}^{i} c^k)$, where a_i is the value of the exponential MA on the i-th day, s_i is the i-th day of the initial time series, m is the period of the MA and c is a coefficient that defines the period of influence of the exponential MA, which is usually calculated by using the formula $c = \frac{2}{m+1}$.

There are two widely used trading rules with MA. One rule is to buy when the short term MA crosses from below the long term MA and sell when the short term MA crosses from above the short term MA (Katusiime, Shamsuddin, & Agbola, 2015; Ni et al., 2015). The other trading rule results from the first, since it considers that the parameter of the short term MA is 1 day and therefore it is identical to the stock price, and therefore the rule is to buy when prices cross from below the MA and sell when prices cross from above the MA (Colby, 2003; Papailias & Thomakos, 2015; Powers & Castelino, 1991).

It should be stressed that MA, as a trend following indicator, always gives late buy and sell signals, although it reduces the risk by keeping the investor in line with the market trends (Bai, Yan, Zheng, & Chenc, 2015). Therefore, MA has better predictive results when prices follow relatively long trends (Achelis, 2001). Furthermore, a stenosis (narrowing) of the area between the MA and actual prices indicates that the present movement of the market will soon end (Papoulias, 1990). Brock et al. (1992) test various time lengths and conclude that the technical trading rule of intersection between MA and daily closing prices assists in the prediction of price changes. This was confirmed by Sullivan et al. (1999), but Fang et al. (2014) and Taylor (2014) assert that the same trading rule was not profitable during the out-of-sample period following that paper's research period.

Cai, Cai, and Keasey (2005) study the American and Chinese stock markets and find that although MA had a predictive ability during the 1970 s, this ability disappeared for most of the 1990 s. By studying the stock markets of Japan, Hong Kong and China, they find that the predictive ability of MA for the 1990 s gradually decreased. Predictive ability which decreases by the years was also found by Yu et al. (2013) for some other Asian markets. Dzikevičius and Šaranda (2010) study the S&P 500 from 1950 until 2009 and ascertain that exponential MA is more suitable for predicting prices than is a simple MA. In addition, Millionis and Papanagiotou (2008) have examined the general index of the Athens stock exchange (ASE) for the period 1993–2005, confirming the predictive ability of MA by finding that for all the time lengths tested (5–100), the performance of MA surpassed the performance of the B&H strategy.

3.2. Moving average convergence divergence (MACD)

As the name implies, MACD measures the degree of convergence and divergence between short- and long-term MA. The most popular parameters among practitioners as well as the technical analysis software supplied by most data vendors are 26 and 12, i.e. MACD is calculated by subtracting the MA of 26 days from the MA of 12 days (Ulku & Prodan, 2013). The calculation of MACD is for the close of day k, with lengths of MA N_1 and N_2:

$$M_k^{N_1 N_2}(c) := E_k^{N_1}(c) - E_k^{N_2}(c)$$

where $E_k^{N_1}(c)$ and $E_k^{N_2}(c)$ are N_1 and N_2 days MA after the close of day k. MACD defines a new sequence of values $m^{[k]}$ with $m_0^{[k]} := M_k^{N_1,N_2}$ and $m_i^{[k]} := m_{i-1}^{[k-1]}$ (Klinker, 2011).

The buy and sell signals given by the transaction of these two MA or, in other words, the intersection of MACD with the horizontal zero line are rather slow. Therefore, when Appel (1979) introduced MACD, he suggested that the buy and sell signals given by the intersection of MACD with his exponential MA of 9 days indicate a signal line or trigger line. A buy (sell) signal is given when MACD crosses the signal line upwards (downwards). MACD, as the difference of two MA, can fluctuate above or below the horizontal zero line (Benning, 2007; Kaufman, 2003). It is a trend following indicator that provides time-delayed signals and performs better in trending markets or in sideways markets with high fluctuations. However, during prolonged periods of sideways price fluctuation, it may provide the wrong signals (Colby, 2003; Kahn, 2010; Tung & Quek, 2011).

The well-known professional trader Ed Seykota (1991) doubts about the usefulness of MACD. Further, Colby (2003) mentions that when using standard time lengths in monthly data from 1928 until 2000 in DJIA, assuming a fully invested strategy, reinvestment of profits, no transaction costs and no taxes, the return would have been only 0.99% greater than using a B&H strategy. Chong and Ng (2008), using 60 years of data from the FT30 index of the London Stock Exchange, also claims that only in some cases could the use of the MACD create higher returns than the B&H strategy. These findings indicate that instead of using MACD with the standard parameters, it might worth trying others. Indeed, in order to optimise the performance of an automated trading system, Tucknic (2010) uses MACD created from MA with different time lengths from the standard, although he also uses the standard signal line.

3.3. GANN-HiLo

GANN-HiLo was initially presented in the webpage of Daryl Guppy (www.guppytraders.com). After the initial presentation, the formula was converted into an Exploration (a procedure used in Metastock for the automatic investigation of a given command to discover buy and sell signals or rank securities) by Mike Arnoldi.

Gann-HiLo can be calculated with the formula:

```
Periods:=Input("Enter the number of periods: ",1,50,3);HLd:=
    If(CLOSE>Ref(Mov(H,Periods,S),−1),
    {then}1,{else}If(CLOSE<Ref(Mov(L,Periods,S),−1),
{then}−1,{else}0));HLv:=ValueWhen(1,HLd<>0,HLd);
HiLo:=If(HLv=−1,{then}Mov(H,Periods,S),{else}Mov(L,Periods,S));
    HiLo;
```

http://www.tradingstrategies.net.au/list_indicators.php#, Retrieved July 06, 2012).

However at present, the formula has been erased from the above link, and can be found, slightly modified, in various other addresses, e.g. http://www.meta-formula.com/Metastock-All-Formulas.html, Retrieved July 12, 2015).

GANN-HiLo has been used as the basis for creating other technical indicators such as GANN-HiVisual and LoVisual (see http://trader-online.tk/MSZ/e-w-GANN_HiVisual_LoVisual.html, Retrieved July 12,

2015) and used in various other trading systems such as the Gann Hilo DMI System (see http://www.forexfactory.com/showthread.php?t=59119, Retrieved July 12, 2015). No research papers for GANN-HiLo indicator were found.

3.4. Parabolic SAR

Parabolic SAR (Stop and Reversal) was developed by Wilder (1978). A stop, which is a function of price and time, is generated daily and this moves gradually at first, but then begins to move up rapidly and, finally, becomes a function of price. Ranganatham (2009) notes that, as the trend develops the indicator soon catches up to the price momentum of the share. Every day, the stop is plotted on the chart as a dot, creating a shape that resembles a parabolic curve, which gives the name to the indicator.

According to Kirkpatrick and Dahlquist (2007), it is a trend following technical indicator that has been designed as a trading system with long- and short-term signals, but it is also a very sensitive stop rule. According to Lee, Ahn, Oh, and Kim (2010), it is calculated by using the formula $SAR_t = SAR_{t-1} + af(xp - SAR_{t-1})$ where *af* is the acceleration factor and *xp* is the extreme point. The acceleration factor and extreme point require testing to find the best level with the least whipsaws. Parabolic SAR is particularly good at setting the exit points for a stock. It is also recommended for use in conjunction with other indicators to verify the reversal signal when switching positions from long to short or vice versa (Spinella, 2007).

Chou, Hsu, Yang, and Lai (1997) use Parabolic SAR as a trading strategy and a breakout confirmation rule, setting stops such as lower bounds in bull markets and upper bounds in bear markets. Although there are other cases where Parabolic SAR has been used (Baffa & Ciarlini, 2010; Lee et al., 2010; Maier-Paape, 2013), it has rarely been employed as a technical indicator in research papers, as is the case in Goumatianos, Christou, and Lindgren (2013).

4. Data and choice of technical indicators

4.1. Collection of historical data

All empirical research must obtain reliable data that cover a sufficiently long period. However, real market data often suffer from various deficiencies (Bishop, 2004). The ease of collection from Internet sources raises even more doubts about reliability. Galindo, Urrutia, and Piattini (2006); taken from Motro, 1995) note that fuzzy data are often vague, content-dependent, uncertain, imprecise, vague, inconsistent and ambiguous.

Therefore, before using such data, some degree of preparation and pre-processing is required. This must be considered to be an integral part of the modelling process, rather than being a fixed procedure carried out prior to modelling (Garibaldi et al., 2005). In this research, data pre-processing consisted of error checking and the correction of the historic data as well as the calculation of various technical indicators and relevant input variables. Initially, a methodology to search for and correct errors from data on any market was developed. Then, a tool (working prototype) was developed for this purpose. By using this methodology, four kinds of errors were distinguished and corrected, namely arithmetic errors, logic errors, prices out of set limits and date errors.

Daily data with open, high, low, close and volume were used in this research. The data file was in Metastock format, which has been widely accepted by the international community.

4.2. Choosing the parameters of technical indicators

The appropriate adjustment of the parameters (usually the number of time periods) is a crucial factor in determining the performance of a technical indicator (Pinto et al., 2015). The performance of the various technical indicators depends on the criteria set to create the environment within which they operate. In this research, once the environment had been set, extensive backtesting and optimisation was carried out in order to select the best parameters for every indicator. The automated system used for backtesting the technical indicators was the Metastock Enhanced System Tester. The criteria (technical strategy) of the testing environment were:

Table 1
Input in the short term fuzzy system: the four technical indicators with their adjusted parameters and their linguistic variables, presented in descending order of their performance.

Short term technical indicators	Adjusted parameters	Linguistic variables
A simple MA of the five exponential MA	Simple MA of the exponential MA of 2, 3, 4, 6 and 15 days	CL-MA
Gann Hi-Lo	4 days	CL-GHiLo
Parabolic SAR	Step 0.1 and maximum 0.3	CL-SAR
Classic MACD (12 days exponential MA- the 26 days exponential MA)	Trigger line (the 2 days exponential MA of MACD)	MACD-trigger(2)

- Each buy/sell order was set at the close of the same day
- No stops were used
- In every buy order, the whole amount of the available cash was used
- In every sell order, all possessed assets were sold
- No slippage and no margin were used
- There was no interest for the cash remaining in the portfolio

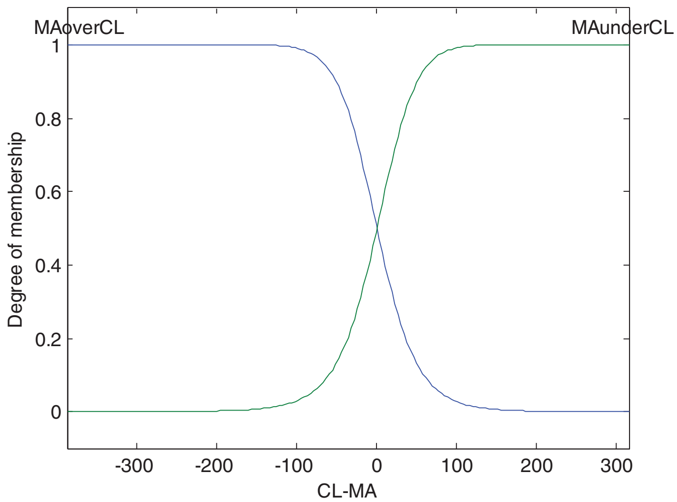
The stock market index used was the general index of the ASE and the period to test the performance of the various technical indicators in order to decide which ones to use was from 1987 until 1992 which contains many bull and bear markets as well as flat periods, while the period of the research was between 15/11/1996 and 5/6/2012.

The parameters of the four short-term technical indicators which were chosen are the exponential MA of the five exponential MA of 2, 3, 4, 6 and 15 days, the Gann HiLo of 4 days, the Parabolic SAR with a step 0.1 and maximum 0.3 and, finally, the cross-section of the classic MACD with a 2-day trigger line (Table 1). According to the technical analysis, for the first three indicators, a buy signal is given when they have a value less than the daily close, while for the fourth indicator, a buy signal is given when the trigger line crosses from above (becomes less than) MACD. Therefore, a buy signal is issued when the values CL-MA, CL-GHiLo, CL-SAR and MACD-trigger become positive, while a sell signal is issued when these values become negative. These values are calculated daily and they constitute the inputs of the system.

5. System design and implementation

For the process of the fuzzy inference, the Mamdani method was chosen, because it is widely accepted for capturing expert knowledge (Negnevitsky, 2005), a very important aspect for the present study, since fuzzy inference rules were based on the expert knowledge of an experienced technical analyst.

As Papoulias (1990) noted, the stenosis (narrowing) of the space between the MA line and stock prices is an indication that the market's movement will shortly end. This comment is part of the trading strategy which is explicitly described earlier, thus, when the positive (negative) values of CL-MA, CL-GHiLo, CL-SAR and MACD-trigger become smaller and smaller, there is an indication that progressively the degree of certainty of the present order for buying (selling) decreases. However, at the same time, this increases the possibility that these values will be diminished or even turn negative (positive) and, consequently, the opposite order for selling (buying) will be issued. Similarly, when the space between the MA (or any of the above technical indicators) and stock prices increases, the positive (negative)



Graph 1. The plot of two of the membership functions of the short term system.

values of CL-MA, CL-GHiLo, CL-SAR and MACD-trigger become larger and larger, indicating that the degree of certainty of the present order of buy (sell) increases.

The curves of the two membership functions (e.g. MAoverCL and MAunderCL) are plotted in a specific way. When one of them (e.g. MAunderCL) has very high values on the *x* axis, it expresses the almost absolute certainty that the current buy order is correct. When MAoverCL has very low prices on the *x* axis, it expresses the almost absolute certainty that the current sell order is correct. These two curves are plotted in an opposite manner. In a specific moment *t*, when both curves have a specific value on the *x* axis, one of them expresses the almost certainty that the buy order is correct, while the other expresses the minimum certainty that the sell order is correct. When both membership functions are in the area of zero (i.e. when MA approaches the prices of the ASE general index), they denote uncertainty about the strength of the order they represent and that it is entirely possible that the opposite order will be given.

In Graph 1, the *x* axis ranges from the minimum value of the linguistic variable (which for the more than 15-year testing period is −387.6 for CL-MA) and the maximum (which for CL-MA is 315.3). Therefore, it becomes apparent that the minimum and maximum values are not symmetrical to zero. The two membership functions intersect at the value 0 on the horizontal *x* axis and each one of them is bell-shaped. One of them is MA-under-CL, which represents the case where MA is under the close price (so a buy signal is issued), while the other is MA-over-CL, which represents the case where MA is over the close price (so a sell signal is issued).

The area around zero is where each curve moves from absolute certainty to absolute uncertainty. The slope of the curve in this area determines the width of the values between which this transfer occurs. The steeper the slope, the smaller is the range of values on the *x* axis within which this transfer occurs and the smaller is the elasticity of the curve. Similarly, the more gentle the slope, the more progressive is the transfer from one stage to another and wider is the range of values on the *x* axis between absolute certainty and absolute uncertainty.

The bell-shaped curve has been chosen for the present study because it has the property of being smooth and non-zero at all points (Dourra & Siy, 2002). It is given by the formula $f(x;a,b,c) = \frac{1}{1+|\frac{x-c}{a}|^{2b}}$, where *a* is the width of the curve, *b* affects the slope of the curve and *c* is the centre of the curve. In the stiff parts of the slope, the uncertainty about the strength of the current order is much higher than it is in the remaining points of the curve.

5.1. Differentiation of the slope of the curve

This slope is an important factor for the system because it defines the boundaries where the transition from minimum to maximum certainty occurs. A very steep slope indicates that the differentiation of the curve takes place on the *x* axis values close to zero and, moreover, that it is more possible that the order issued by the technical indicator will revert only when the index is near actual prices. A more progressive slope indicates many possibilities that the issued order might revert suddenly, even though the technical index has a considerable distance from the closing prices.

Every day, by using actual stock market data, the minimum and maximum of each linguistic variable (e.g. MAoverCL) are calculated in order to define the *x* axis range. Therefore, if a unique value of *b* were used for all linguistic variables (i.e. the input variables of the fuzzy system), the slope of the curve would be different for every curve. To avoid this and to have curves with similar slopes, the value of *b* should be altered according to the minimum and maximum boundaries of the input variable. Hence, the value of *b* would be different for every input variable, but the slope would have the same characteristics in order to ensure that the relative *x* axis boundaries, where the differentiation of the degree of certainty for the specific order takes place, will remain the same. Moreover, since the minimum and maximum values of each input variable on the *x* axis are not symmetrical to zero, it should be noted that in order to have analogically the same slope of the curve in the negative and positive values, a different slope of the curve on the left and right sides of zero is necessary.

Taking into consideration all these previous characteristics, research for a wide range of *b* values needs to be conducted. However, in order to do this, the fuzzy system has to be completed by creating fuzzy rules. Initially, all fuzzy rules created to have the same maximum weight, which is equal to one. Thereafter, for each *b* value, the output of the short-term fuzzy system is firstly calculated, followed by the calculation of the return of the portfolio and, finally, the rate of growth of this return.

However, there is a potential weakness with these fuzzy rules, arising from the fact that the profitability of the initial four technical indicators (from which the four input variables of the fuzzy system were created) differs a lot. Therefore, new fuzzy rules were created where the performance of each technical indicator strengthened or weakened each rule accordingly. After the completion of the new fuzzy system and the new fuzzy rules, the output of the short-term fuzzy system for each *b*, was again calculated. The return of the portfolio and rate of growth for the return were also calculated. The combined results of all these tests are shown in Table 2.

From the results presented in Table 2, it becomes apparent that when transaction costs are not taken into consideration, the best value of *b* equals 3/1 of the relevant width on the *x* axis of each input variable. On the other hand, when the transaction costs are subtracted from the amount gained (with transaction costs), the best value of *b* was the 1/5 of the relevant value boundaries of each input variable. These values of *b* will be used in the next stages of the current analysis.

There were 16 fuzzy rules used, as shown in Table 3.

When all linguistic variables agree (i.e. when they all give a buy or sell signal) this is represented as “In” or “Out” respectively, since they refer to the two possible extreme combinations, and logically in this case the weight coefficient is equal to one (1) in order to permit the rule obtain the maximum power.

When three of the four linguistic variables agree (i.e. when all three give buy (sell) and the fourth gives sell (buy) respectively), this is represented by the words High (Low), implying the quantity of the portfolio holdings which should be possessed. However, this basic rule is divided to another four cases according to all possible combinations of the relative performance of the three similar linguistic

Table 2
A comparison of returns of the short term fuzzy system when the *b* parameter varies.

The influence of *b* in the returns of short term fuzzy system (%)				
b	Without transaction costs		With transaction costs	
	Rules with weights equal to 1	Rules with varying weights (from 0 to 1)	Rules with weights equal to 1	Rules with varying weights (from 0 to 1)
5/1	749.29	775.18	−41.43	−40.74
4/1	744.07	779.03	−41.12	−39.84
3/1	735.21	**781.62**	−40.67	−38.59
2/1	714.05	777.74	−40.20	−37.02
1/1	639.20	729.65	−40.47	−35.69
1/2	539.85	626.49	−40.14	−35.48
1/3	488.45	566.42	−39.12	−34.68
1/4	455.99	527.32	−38.42	−34.08
1/5	431.93	498.14	−38.13	**−33.84**
1/10	358.08	406.04	−40.21	−36.46
1/15	308.56	344.27	−43.00	−39.95
1/20	269.36	297.33	−44.82	−42.41
1/25	235.90	259.90	−45.79	−43.85
1/30	207.36	229.78	−46.10	−44.40
1/35	183.18	205.18	−46.07	−44.47
1/40	162.78	184.09	−45.83	−44.40
1/45	145.28	165.89	−45.44	−44.24
1/50	130.34	150.21	−44.96	−44.00

The performance of the general index of ASE for the same period was −46.50%.

Table 3
The fuzzy rules which have been used for the short system.

Rule	CL-MA	CL-GHiLo	CL-SAR	MACD-trigg2	Output	Weight
1	S	S	S	S	Out	1
2	B	S	S	S	Low	0.1
3	S	B	S	S	Low	0.4
4	S	S	B	S	Low	0.7
5	S	S	S	B	Low	1
6	B	B	S	S	Medium	0.1
7	B	S	B	S	Medium	0.5
8	B	S	S	B	Medium	1
9	S	B	B	S	Medium	1
10	S	B	S	B	Medium	0.5
11	S	S	B	B	Medium	0.1
12	S	B	B	B	High	0.1
13	B	S	B	B	High	0.4
14	B	B	S	B	High	0.7
15	B	B	B	S	High	1
16	B	B	B	B	In	1

B: buy; S: sell; H: hold.
Out: full liquidation of portfolio holdings; In: the portfolio is fully invested.
Low, medium or high: the quantity of equities that portfolio possesses.

variables participating in the rule, while the weight coefficient ranges between 1 and 0.1. Thus, rules which contain the three best linguistic variables (i.e. those originating from the three technical indicators with the best performance) with either buy or sell signals, are given the weight coefficient of 1. Thereafter, this coefficient is decreasing gradually (taking the values 0.7, 0.4 and 0.1) as in each new rule appear more linguistic variables representing the worst performing technical indicators, and therefore the power of the relevant rule should decrease.

When there is not a specific direction from technical indicators, i.e. when half of them suggest buy and the other half suggest sell, then the final suggestion of the rule is Medium, indicating a neutral position. The maximum weight coefficient (i.e. 1) is given in order to maximise the power of the rule with the absolute balance between the linguistic variables (and consequently between the performance of the relevant technical indicators). The weight coefficients of the rules proposing Medium begin to decrease (taking the values 0.5 and 0.1), as the imbalance between the linguistic variables of buy/sell increases.

6. Experimental results and analysis

Every day, a new value for all the technical indicators was calculated and compared with the daily price of the ASE general index in order to create the relevant linguistic variable. Linguistic variables (Zadeh, 1975) fluctuate between the minimum and the maximum of the historical prices on a scale of 0–1, while as mentioned, the membership functions were chosen to be bell-shaped.

The output of the developed fuzzy system is a number ranging from 0 to 1 that expresses the percentage of the portfolio that should be invested on a daily basis in the ASE. A number of 0 means that the total amount of the portfolio should remain in cash, a number of 1 means that all available cash should be invested in the general index of the ASE, while any intermediate number, for example 43%, means that this amount should be invested and the remaining 57% should remain in cash. Every day, complementary trades should be carried out in order to ensure that the invested proportion of the portfolio is exactly the same as that suggested by the system percentage. Therefore, if the output of the system is 47% on the next day, the investor should invest an extra 4% of the cash to buy the ASE general index. A working prototype was developed in order to calculate all these changes, along with the relevant daily transaction costs, which are subtracted from the respective gains/losses.

Table 4 shows that for the first day (15/11/1996), the general index of the ASE was 890.39 units and the output of the fuzzy system was 0.213312, suggesting an investment of 21.3312% of the portfolio (which is assumed to be 10,000€) in the ASE or, in other words, the equivalent of 2133.12€. The next day, the general index has increased substantially and accordingly was increased the output of the fuzzy system which became 0.766715 and therefore a much bigger part (76.6715%) of the portfolio should be invested. Of course, the shares bought the previous day would already be worth more since the general index of the ASE was higher. The assumptions made in the portfolio management are the following:

- The initial capital was set to 10,000€.
- The portfolio would be invested solely in the general index of the Greek stock market.
- The value of the portfolio is calculated on a daily basis, based on the closing price of the general index.

Table 4
An extract of the first and last few days of portfolio management.

Date	GI of ASE (close)	Output of model – PoIP	PCV	TAiS	NoPS	NoAS	VoNS	Transaction costs	Transaction costs + VoNS	Cash	Value of portfolio
Initial prices			10000.00							10000.00	
15/11/1996	890.39	0.213312	10000.00	2133.12	2.396	2.396	2133.12	8.80	2141.92	7858.08	9991.20
18/11/1996	914.82	0.766715	10049.73	7705.28	8.423	6.027	5513.63	22.74	5536.37	2321.71	10026.98
19/11/1996	917.10	0.749231	10046.19	7526.92	8.207	−0.215	−197.56	1.21	−196.35	2518.06	10044.98
20/11/1996	913.10	0.677687	10012.15	6785.11	7.431	−0.776	−708.98	4.34	−704.64	3222.70	10007.81
21/11/1996	900.65	0.398796	9915.29	3954.18	4.390	−3.040	−2738.41	16.77	−2721.64	5944.34	9898.52
22/11/1996	906.02	0.469088	9922.10	4654.34	5.137	0.747	676.58	2.79	679.37	5264.97	9919.31
25/11/1996	909.03	0.556263	9934.77	5526.34	6.079	0.942	856.54	3.53	860.07	4404.90	9931.23
26/11/1996	911.96	0.602107	9949.05	5990.39	6.569	0.489	446.24	1.84	448.08	3956.82	9947.21
27/11/1996	908.08	0.603043	9921.72	5983.22	6.589	0.020	18.32	0.08	18.39	3938.42	9921.64
28/11/1996	910.52	0.631695	9937.72	6277.61	6.895	0.306	278.31	1.15	279.46	3658.96	9936.57
29/11/1996	910.19	0.613930	9934.30	6098.97	6.701	−0.194	−176.37	1.08	−175.29	3834.25	9933.22
2/12/1996	917.83	0.733926	9984.41	7327.82	7.984	1.283	1177.66	4.86	1182.52	2651.73	9979.55
3/12/1996	916.71	0.686153	9970.61	6841.37	7.463	−0.521	−477.52	2.92	−474.59	3126.32	9967.69
4/12/1996	916.99	0.667951	9969.78	6659.32	7.262	−0.201	−184.14	1.13	−183.01	3309.33	9968.65
…..	…..	…..	…..	…..	…..	…..	…..	…..	…..	…..	…..
16/5/2012	555.42	0.183521	7035.67	1291.19	2.325	0.050	27.66	0.11	27.77	5744.37	7035.56
17/5/2012	536.49	0.182646	6991.55	1276.98	2.380	0.056	29.79	0.12	29.92	5714.45	6991.43
18/5/2012	550.13	0.195400	7023.89	1372.47	2.495	0.115	63.03	0.26	63.29	5651.16	7023.63
21/5/2012	544.56	0.200972	7009.74	1408.76	2.587	0.092	50.18	0.21	50.39	5600.77	7009.53
22/5/2012	535.96	0.202779	6987.28	1416.87	2.644	0.057	30.36	0.13	30.49	5570.29	6987.16
23/5/2012	526.39	0.203305	6961.86	1415.38	2.689	0.045	23.81	0.10	23.90	5546.38	6961.76
24/5/2012	502.52	0.197910	6897.58	1365.10	2.717	0.028	13.91	0.06	13.96	5532.42	6897.52
25/5/2012	485.18	0.194375	6850.42	1331.55	2.744	0.028	13.55	0.06	13.61	5518.81	6850.36
28/5/2012	518.49	0.337011	6941.78	2339.45	4.512	1.768	916.49	3.78	920.27	4598.54	6938.00
29/5/2012	528.14	0.679835	6981.54	4746.29	8.987	4.475	2363.30	9.75	2373.05	2225.49	6971.79
30/5/2012	511.29	0.527446	6820.36	3597.37	7.036	−1.951	−997.49	6.11	−991.38	3216.88	6814.25
31/5/2012	525.45	0.668838	6913.88	4624.26	8.801	1.765	927.26	3.82	931.09	2285.79	6910.05
1/6/2012	501.90	0.218655	6702.80	1465.60	2.920	−5.880	−2951.41	18.08	−2933.33	5219.12	6684.72
5/6/2012	476.36	0.208293	6610.14	1376.84	2.890	−0.030	−14.18	0.09	−14.09	5233.21	6610.06

• General index of the ASE (close).
• Output of the model – PoIP: Output of the proposed model on a scale of 0 to 1 which is equal to the Percentage of Portfolio Invested.
• PCV: portfolio's current value (cash + amount of yesterday's stocks × today's close).
• TAiS: The total amount in stocks (yesterday's value of portfolio × percentage of invested portfolio i.e. [cash + yesterday's amount of stocks × today's price)] × today's output.
• NoPS: Number of portfolio stocks that should be possessed by the portfolio in order that the correct amount be invested (according to today's closing price).
• NoAS: Number of additional shares that should be Bought+/Sold-.
• VoNS: Value (buy+/sell-) of these new stocks.
• Transaction costs: commission + transaction costs.
• Transaction costs + VoNS: transaction costs + value (buy+/sell-) of new stocks.
• Cash of the portfolio.
• Value of the portfolio: (new cash + amount invested in stocks). This is the same as PCV but it is calculated differently, i.e. by adding today's cash in today's value of the stocks possessed.

- All transactions are made ATC, that is, "at the close" of the same day.
- The amount of the portfolio invested daily depends on the output of the fuzzy system developed by the researchers.
- For every transaction made, there are two measurements, with and without transaction costs and commissions (which from now will be named simply as transaction costs). The transaction cost adopted is the one valid in the ASE in 31/12/2012 (although it is the highest during the 15 year period).
- No slippage and no margin were used.
- No interest is calculated for the remaining cash available in the portfolio, nor are they invested in any "safe" asset, although this is particularly common (Brock et al., 1992) since it strongly increases the portfolio's performance. The reason chosen for not investing the cash is that the goal of this research is to determine the performance of the proposed model.

The final outcome of the portfolio is a percentage calculated at the end of the selected time period as follows:

$$ProfitLoss = \frac{(FinalCapital - InitialCapital)}{InitialCapital} \times 100$$

A positive number denotes that there is a gain, while a negative number denotes that there is a loss.

6.1. The performance of the suggested short-term system in the ASE general index from 15/11/1996 until 5/6/2012

The stock market index used was the general index of the ASE. Since markets change character over time (Kirkpatrick & Dahlquist, 2007), the time period for the performance tests was 15/11/1996 to 5/6/2012. This period of over 15 years includes all the changes made in the institutional framework of the ASE in 1995, including the entry of Greece into the European Exchange Rates Mechanism II of 1998 and the final entrance of the country into the Economic Monetary Union in 2001, the characterisation of the ASE as a developed market and the Olympic Games of 2004 (Kenourgios & Samitas, 2008; Liroudi, Aggelidis, Dasilas, & Georgakoulias, 2004). It also includes the Asian crisis of 1997, the world financial crisis of 2008 and the Greek fiscal crisis of 2010. Overall, it includes three major bull markets and three bear markets. On 5th June 2012, the ASE general index made its lowest low in the past 19 years.

The ASE general index during the 15-year period between 15/11/1996 and 5/6/2012 had a negative return of −46.50% and this is also the exact return for the B&H strategy. The return on the suggested short-term system was 781.62% without taking into consideration transaction costs, and −33.84% if transaction costs were considered. If the initial amount of 10,000€ of the portfolio was deposited in a safe account for the same period, taking into consideration the

Table 5
The return of the suggested system compared with the interest on a safe deposit account and the B&H strategy.

ASE general index	Comparison of performances		
	Interest on deposits in a safe account	B&H Strategy	Suggested short term fuzzy system
15/11/1996 till 5/6/2012	10,000€ → 14,562.40€	890.39 → 476.36 units	10,000€ → 88,162.22€ (without transaction costs) 10.000€ → 6610.06€ (with transaction costs)
Return	45.62%	−46.50%	781.62% (without transaction costs) −33.84% (with transaction costs)

Table 6
The bull and bear markets of ASE between 15/11/1996 and 5/6/2012.

Bull markets	Bear markets
15/11/1996 till 17/9/1999	20/9/1999 till 31/3/2003
01/4/2003 till 31/10/2007	1/11/2007 till 9/3/2009
09/03/2009 till 14/10/2009	15/10/2009 till 05/6/2012

interest rates of every period, the total interest gathered would have been 45.62%. It is evident from Table 5 that while the suggested system is unique as a model since it managed to earn 781.62% compared with −46.50% of the B&H strategy for the 15-year time period, this is not the case when the commissions and taxes for each transaction are taken into account. However, although transaction costs considerably decrease the amount gained, the performance of the suggested system is still higher than the performance of the B&H strategy (−33.84% compared with −46.50%). It should also be underlined that no interest gains were calculated for the percentage of the portfolio in cash.

6.2. The performance of the suggested system during bull and bear market periods

During the period examined (15/11/1996 to 5/6/2012), there were periods of bull and bear markets. In order to further explore their distinctive characteristics, these periods were examined separately (Table 6).

It was found that for the first bull market (15/11/1996 to 17/9/1999), the performance for the B&H strategy was 613.74%, while the return of the proposed system was 536.33%, if transaction costs were not subtracted, and 277.69% if they were (Table 7). For the second bull market (01/04/2003 to 31/10/2007), the performance for the B&H strategy was 261.75%, while the return of the proposed system was 173.64% (without transaction costs) and 36.42% (with transaction costs). Finally, for the third and smallest bull period (between 09/03/2009 and 14/10/2009), the performance for the B&H strategy was 97.15%, while the return of the proposed system was 50.27%, without taking into consideration transaction costs and 35.31% with transaction costs considered.

The results in Table 7 show that transaction costs unevenly affect the return of the proposed short-term system. Thus, while for the first bull period (15/11/1996 until 17/9/1999), the return of the system with transaction costs was half that without transaction costs (277.69% compared with 536.33%), for the second bull period (01/04/2003 to 31/10/2007), the return with transaction costs was just one fifth of the return without transaction costs (36.42% compared with 173.64%). Finally, for the third bull market (between 09/03/2009 and 14/10/2009), the return of the proposed system with transaction costs was more than two thirds of the return without transaction costs (35.31% compared with 50.27%). Obviously, this is related to the length of each bull market period (34, 54 and 7 months, respectively) and, consequently, to the absolute number of transactions in each period. The latter is also an indication of the frequency of the buy or sell signals produced by the proposed system (sensitivity of the short-term indices used). As a result, transaction cost reduces the monthly performance of the system by 7.61%, 2.54% and 2.08% (during the first, second and third bull market periods respectively).

As far as bear markets are concerned, Table 8 shows that in the first bear market (from 20/9/1999 to 31/3/2003), the ASE general index had a negative return of −76.83%, which is the performance of the B&H strategy, while the return of the proposed system was −4.05% in the absence of transaction costs and −47.40% if transaction costs were considered. During the second bear market (between 01/11/2007 and 09/03/2009), the B&H strategy return was again negative (−72.09%), while the suggested system had a return of −26.17% without transaction costs and −43.38% with transaction costs subtracted. Finally, the B&H strategy for the third and largest ASE bear market (between 15/10/2009 and 5/6/2012) again produced negative results (−83.54%), while the proposed system had a negative performance of −51.67% without transaction costs and −67.91% with transaction costs considered. Transaction cost reduces the monthly performance of the system by 1.03%, 1.01% and 0.51% (during the first, second and third bear market periods respectively). The main conclusion that can be drawn by looking at these results is that the proposed system outperforms

Table 7
The return of the suggested system during the three ASE bull market periods.

Bull markets, ASE	Performance			
	B&H strategy (BHS)	Suggested short term fuzzy system (STFS)	STFS - BHS	(STFSb - STFSa)/months
15/11/1996 to 17/9/1999 (approx. 34 months)	613.74%	536.33% (a) 277.69% (b)	−77.41 −336.05	−258.64%/34 = −7.61%
01/4/2003 to 31/10/2007 (approx. 54 months)	261.75%	173.64% (a) 36.42% (b)	−88.11 −225.33	−137.22%/54 = −2.54%
09/03/2009 to 14/10/2009 (approx. 7 months)	97.15%	50.27% (a) 35.31% (b)	−46.88 −61.84	−14.96%/7 = −2.14%

STFSa: without considering transaction cost; STFSb: with transaction cost being considered.

Table 8
The return of the suggested system during the three ASE bear markets periods.

Bear markets, ASE	Performance			
	B&H strategy (BHS)	Suggested short term fuzzy system (STFS)	STFS - BHS	(STFSb - STFSa)/months
20/9/1999 to 31/3/2003 (approx. 42 months)	−76.83%	−4.05% (a) −47.40% (b)	+72.78 +29.43	−43.35%/42 = −1.03%
1/11/2007 to 9/3/2009 (approx. 16 months)	−72.09%	−26.17% (a) −43.38% (b)	+45.92 +28.71	−17.21%/16 = −1.08%
15/10/2009 to 5/6/2012 (approx. 32 months)	−83.54%	−51.67% (a) −67.91% (b)	+31.87 +15.63	−16.24%/32 = −0.51%

STFSa: without considering transaction cost; STFSb: with transaction cost being considered.

the B&H strategy in all three ASE bear market periods, even when transaction costs are considered.

In general, the returns of the B&H strategy are higher than the returns of the proposed system in bull markets, while the opposite is observed during bear markets. This conclusion is valid even when transaction costs are considered. Transaction costs are higher during the three bull market periods (7.61%, 2.54% and 2.08% of the monthly cost, respectively) than during the three bear market periods (1.03%, 1.01% and 0.51% of the monthly cost, respectively). These results indicate that, with the exception of the first bull market period, transaction costs can be considered to be normal, namely 2–3 times higher in bull market periods compared with bear market periods. This finding can be attributed to the frequency of the transactions (signals), which is usually higher during bull market periods.

7. Conclusions

Many recent researches for stock market prediction use soft computing techniques to tackle the problems of complexity, uncertainty and nonlinearity of the markets. A recent increasing trend is to use complex hybrid approaches combining various soft computing techniques. Some of them use technical analysis as the prediction method, combining many common technical indicators with uneven characteristics in an effort to achieve good performance, although it is doubtful whether any combination of them can be functional.

The significance of this paper is two fold. First, it proposes a robust short term trading fuzzy system which avoids the overconfidence on quantitative data and requires subjective assessments. Although it relies a lot on quantitative data (mostly to evaluate the profitability of technical indicators), it gives plenty of room to the technical analyst expert to add his subjective assessment. This allows the model to behave in a more natural way which emulates the decision making process for stock trading, without increasing the risk with subjective investor judgments. Second, it uses a novel trading strategy and an “amalgam” between a manageable number of carefully chosen uncommon technical indicators, to generate predictive signals and then inputs these signals to an appropriately designed and adjusted fuzzy system which outputs the percentage of the portfolio which should be invested.

The proposed short-term fuzzy system tested for the ASE general index for a long period (over 15 years, between 15/11/1996 and 5/6/2012) provided a 781.62% return, while the ASE general index was down by −46.50% during the same period. After taking into consideration transaction costs, the total return was −33.90%, which was still better than the −46.50% of the B&H strategy in the ASE general index for the same 15-year period. This return was achieved even though the transaction costs were over inflated, since the cost rate in 31/12/2012 (which was accepted for our calculations) was the highest in the examined period. The system has achieved this performance by avoiding big losses during bear markets, although during bull markets the gains made were significantly lower than those under the B&H strategy. Therefore, it can be considered to be a conservative system, which manages to achieve satisfactory returns, even though the testing period was over 15 years, a long period for a short-term system.

Due to higher return, in comparison to B&H strategy of ASE index even when transaction costs are considered, the proposed system can be used as a reliable, effective and easy for everyday use practical tool for the actual investor or trader.

It is our belief that it is time to move from the repetitive use of those few technical indicators which are commonly used in research papers because of their successful use in previous investigations, to the abundance of indicators which can be found in specialised sites and are fairly unknown to the academic community, but often used by practitioners. The proposed model uses a set of four relevant technical indicators, some of which are barely known (Gann-Hilo, Parabolic SAR), while others use parts of common indicators but with a variety of alterations (sum of different MAs, and MACD with another trigger). Some of the research conducted in a preliminary stage has shown that if only the three indicators with the highest initial performances (i.e. not MACD) had have been used, the returns would have been much higher. However, since it was decided during the initial stages of the construction of the model, that it will be used four indicators, the research was continued with this number of indicators and has been shown that a well constructed fuzzy model using a combination of carefully chosen short term technical indicators, can provide higher returns than a B&H strategy even for such long period. The achieved returns imply that the design of the model is promising since if transaction costs were not taken into consideration, the return would have been extremely high. Further, if interest income had been calculated for the amount of the portfolio not invested in the ASE, then the performance of the proposed system would have been even better. The proposed model uses a novel trading strategy which builds on the classic strategy, where a technical indicator generates buy/sell signals when intersects the price of the stock, and extends this with the examination of the distance between the price and the technical indicator, which incorporates the notions of subjectivity and degree of certainty for the current order. The model is designed to accept as inputs modified independent signals which have been given from technical indicators outside of the system, and which are independently transformed within the fuzzy system through a procedure, which tries to find the optimum slope of the curve between maximum performance and maintaining the fuzzy behaviour of the curve.

The proposed model is obviously restricted by the performance of the chosen indicators, as well as from their specific characteristics, which should not be contradicting between each other (e.g. they should all be short term and not momentum indicators). Further, the model is restricted from the weights of the fuzzy rules. Therefore, the expert has a very difficult job to do, since the success of the model very much depends on his ability to choose the most appropriate technical indicators and to define their relative significance. In short, the explicitly noted effort to create a model which depends less to quantitative data and more to subjective assessments, generates the biggest limitations.

The proposed model with the choice of different technical indicators can be transformed for other stock markets as well. Therefore, a similar model with fewer transaction costs, i.e. with a medium or long-term perspective (and therefore with different technical indicators), would be a logical focus for future research. Various fuzzy systems for different time periods could be created, while the formulation of a platform of such co-operating systems, in order to have a more balanced proposal for the portfolio, could be the next target. The investigation of whether it is possible to place different weight to the inputs (fuzzy systems) of this platform, according to the profile of the investor could be examined. Another possibility is that this platform could be consisted of fuzzy systems which use different types of technical indicators (trend following, momentum indicators, volume indicators), or different types of technical analysis (technical indicators, chart pattern analysis).

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