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A multiple fuzzy inference systems framework for daily stock trading with application to NASDAQ stock exchange

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ABSTRACT

The aim of this study is to develop an expert system for predicting daily trading decisions in a typical financial market environment. The developed system thus employs a Multiple FISs framework consisting of three dedicated FISs for stock trading decisions, Buy, Hold and Sell respectively. As input to the Multiple FISs framework, the system takes the fundamental information of the respective companies and the historical prices of the stocks which are processed to give the technical information. The framework suggests the investor to Buy, Sell or Hold on a daily basis for a portfolio of stock taken into consideration. Experimenting the framework on selected stocks of NASDAQ stock exchange shows that including the fundamental data of the stocks as input along with the technical data significantly improves the profit return than that of the system taking only technical information as input data. Characterised as a stock market indicator, the framework performs better than some of the most popularly used technical indicators such as Moving Average Convergence/Divergence (MACD), Relative Strength Index (RSI), Stochastic Oscillator (SO) and Chaikin Oscillator (CO). The developed framework also gives better profit return compared to an existing model with similar objective.

1. Introduction

The goal of an expert system is to acquire and apply the knowledge and inference procedures to achieve a higher level of performance on solving the problems that are difficult enough to require significant human expertise (Feigenbaum, 1984). An expert system is combination of a *knowledge base* consisting of rules for handling certain situations, an *inference engine* that draws conclusion from the knowledge base, a set of *input variables* for the knowledge base and also a module for *handling and modifying the knowledge* in store (Kosinski & Weigl, 1997). A fuzzy inference system (FIS) (otherwise called as fuzzy expert system) is an expert system that uses a collection of fuzzy membership functions and inference rules to infer the data from the knowledge base. An FIS thus becomes a combination of the expert system technology with the fuzzy logic, as the fuzzy logic concepts are used in the knowledge base development and the knowledge handling modules of the expert system (Medsker, 1995). Furthermore, Fuzzy membership functions that are used as the knowledge base of the expert system are acquired in the form of linguistic proportions (Wagman, Schneider, & Shnaider, 1994).

The multiple criteria decision making problems can be efficiently solved by using the fuzzy set theory concepts (Jones, Kaufmann, & Zimmermann, 1986). When the inputs for the knowledge base are well-defined, the expert systems are said to achieve good performance (Medsker, 1995). Thus a combination of expert system with fuzzy logic, that gives an FIS, can perform well for a multiple criteria decision making problem with data defined using fuzzy set theory. The various applications of FIS are in the areas of fault detection and diagnosis problems (Lee, Park, Ahn, Park, Park, & Venkata, 2000; White & Lakany, 2008), Electrical load forecasting (Dash, C., Rahman, & Ramakrishna, 1995; Mamlook, Badran, & Abdulhadi, 2009), Pesticide impact analysis (van der Werf & Zimmer, 1998), Wind speed and wind power generation forecasting (Damousis & Dokopoulos, 2001), Medical diagnosis (De Paula Castanho, de Barros, Yamakami, & Vendite, 2008; Fathi-Torbaghan & Meyer, 1994), Aviation risk management (Hadjimichael, 2009), Stock market forecasting (Boyacioglu & Avci, 2010; Esfahanipour & Aghamiri, 2010), etc. Over a long period of time, scholars are working in the area of stock market forecasting with a goal to get more profit return by analysing the movement of market prices (Abbasi & Abouec, 2008; Chang & Liu, 2008), predicting the stock market timing (Lam, 2001; Lee & Jo, 1999) and modelling an artificial intelligent system for decision making of whether to buy or sell a stock (Kuo, Chen, & Hwang, 2001; Moon, Yau, & Yip, 1989; Zhou, 2013).

Sahin and Ozbayoglu (2014) introduced a Trend-Normalized RSI indicator which uses genetic algorithms for parameter optimisation and provides an RSI buy-sell trigger levels and periods that are normalised to be not affected by the market trend. A trading system is developed by da Costa, Nazário, Bergo, Sobreiro, and Kimura (2015)

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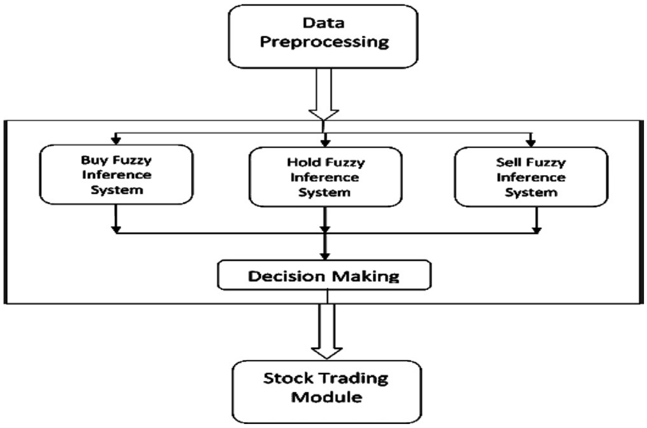

Fig. 1. System architecture.

on studying some technical indicators such as Simple Moving Average (SMA), Exponential Moving Average (EMA) and MACD with the triple screen technique using which 198 stocks were traded in the Brazilian stock market. The concept of fuzzy metagraph was used on some of the technical indicators namely, SMA, EMA, MACD, RSI, to define the rule base of the FIS used to classify and predict in a stock market environment (Anbalagan & Maheswari, 2015). Gunduz and Cataltepe (2015) discussed a model considering the combination of financial news and daily price data for daily stock prediction in Borsa Istanbul (BIST) stock trading market. A literature review by Hu, Liu, Zhang, Su, Ngai, and Liu (2015) detailed on the various techniques used in the rule discovery for application to stock trading. From this paper, it can be inferred that not many articles discussed the combination of fundamental and technical analysis variable in developing a daily stock trading decision making system which is the key idea in proposing our model.

A stock market environment is basically a more complex system which involves a high number of participants with an eye on making more profit. Modelling a stock market thus involves maintaining and interpreting a high volume of data. Since the obtained data is interpreted in a more meaningful way using the linguistic terms, the stock market trading scenario is a perfect candidate for modelling using fuzzy logic (Othman & Schneider, 2010; Simutis, 2000). The proposed framework involves in developing a stock market decision making system using FISs and simulating the system in performing the stock trading process with a multi-agent environment. The Multiple FISs framework consisting of three FISs dedicated to the important decisions of buy, hold and sell that is to be used by the agents(investors/traders) for stock trading. The framework is discussed in two variants with and without the fundamental analysis variable, Earnings per Share (EPS), to study the significance of combining technical and fundamental analysis for stock market decision making in daily stock trading environment.

2. Architecture of the multiple FISs framework

The proposed Multiple FISs framework consists of different stages with which the input data is being processed to provide a decision on whether to buy, sell or hold and thus perform the trading. The architecture of the framework in the form of a process flow diagram is given in Fig. 1.

2.1. Data preprocessing

The proposed framework concerns with a selected group of stock data from the NASDAQ stock exchange (http://www.nasdaq.com/markets/). The historical price data with everyday open, high, low and close prices are extracted along with the fundamental information of the selected group of stocks. The data preprocessing involves calculating the profitability and volatility of the stock price by using the extracted data. The profitability is calculated as the mean of logarithmic returns and the volatility is calculated as the standard deviation of logarithmic returns. The logarithmic return R_t for a particular day t is given as,

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

and the Profitability is given as,

$$Pro_{\ t} = \frac{1}{n}\sum_{i=t}^{i=t-(n-1)} R_i \qquad (Profitability) \quad and \tag{2}$$

$$Vol_{\ t} = \sqrt{\frac{\sum_{i=t}^{i=t-(n-1)} (R_i - Pro_i)^2}{n}}\ (Volatility) \tag{3}$$

where n is the number of days of data considered.

2.2. Fuzzy inference systems (FISs)

The framework consists of three FISs of the Takagi–Sugeno type which have a common structure with different rule bases for Buy, Hold and Sell decisions. The Takagi–Sugeno type FIS is modelled using the structure given in Fig. 2 using the Fuzzy Toolbox of Matlab.

The most common way of representing human knowledge in the field of artificial intelligence is by forming it into natural language expression (Ross, 2009) of the type

$IF\ \ premise\ (antecedent)\ THEN\ \ conclusion\ (consequent)$

This form is commonly referred to as the IF-THEN rule-based system. The multiple conjunctive antecedents are represented as,

$IF\ x_1\ is\ X_1\ and\ x_2\ is\ X_2\ and\ \ldots\ and\ x_k\ is\ X_k\ THEN\ y\ is\ Y$

where $X_1,\ X_2, \ldots,\ X_k$ are fuzzy sets. Here we consider the fuzzy rule base of multiple-input-single-output (MISO) form as f: $R^K \rightarrow R$ with the Tagaki–Sugeno–Kang (TSK) inference method

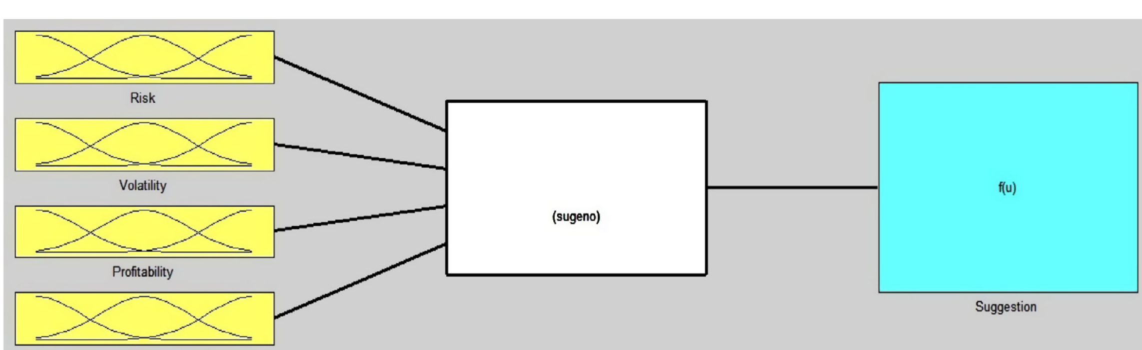

Fig. 2. Structure of FIS.

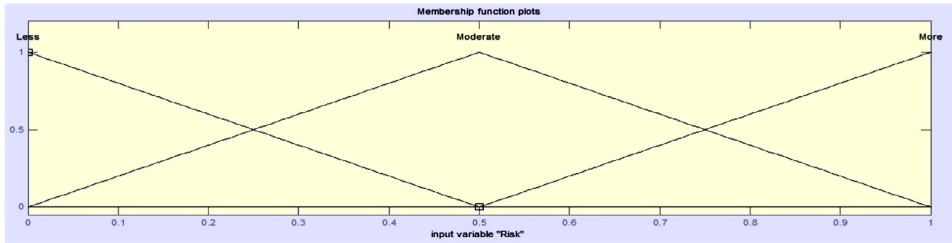

Fig. 3. Risk.

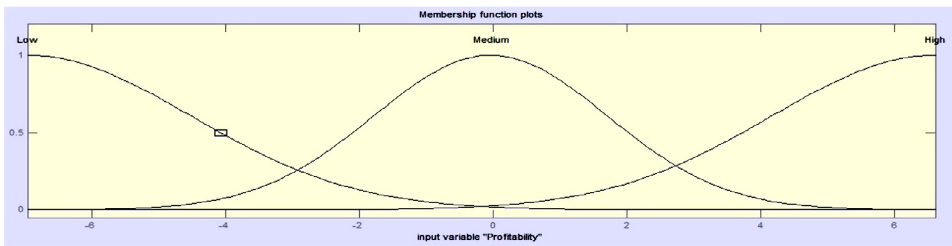

Fig. 4. Profitability.

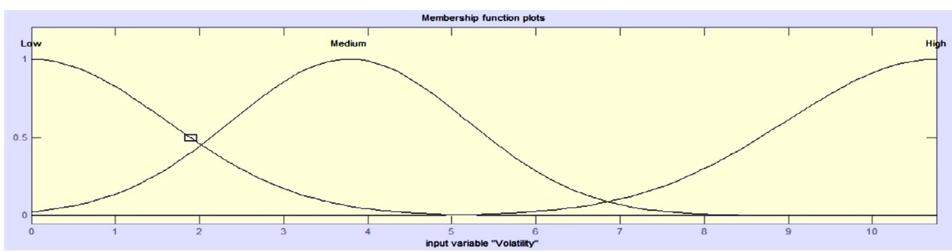

Fig. 5. Volatility.

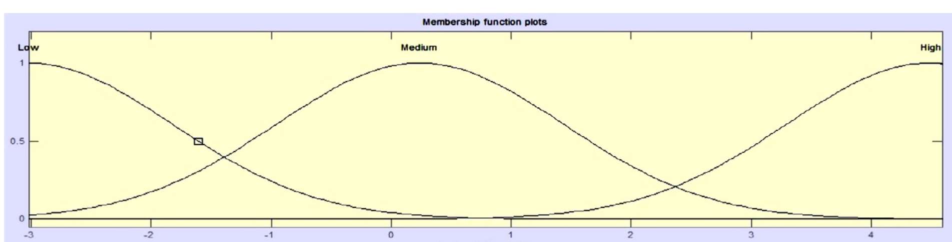

Fig. 6. EPS.

(Nakashima, Ariyama, Kitano, & Ishibuchi, 2005; Sugeno & Kang, 1988; Takagi & Sugeno, 1985).

A fuzzy implication or a fuzzy rule i is a function f_i that maps an input vector $\bar{x} = (x_1, x_2, \ldots, x_k)$ in R^K into a scalar y in R as follows,

Implication i:

IF x_1 *is* X_1^i *and* x_2 *is* X_2^i *and* $\ldots$ *and* x_k *is* X_k^i *THEN* y *is* Y^i

where X_j^i are fuzzy input labels associated with corresponding membership functions and Y^i's are tunable coefficients. This forms the FIS for the proposed framework where the final output is determined by the TSK inference method as follows,

$$y^* = f(\bar{x}) = \frac{\sum_{i=1}^{M} y^i \times w^i(\bar{x})}{\sum_{i=1}^{M} w^i(\bar{x})} \tag{4}$$

where y^i's are tunable parameters determined by *Rule i* and $w^i(\bar{x}) = \prod_{j=1}^{k} (mf_{X_j^i}(\bar{x}))$ which is called the degree of firing of rule or implication i.

The four input variables (i.e. $k = 4$) considered are the profitability of the stock's closing price, its volatility, the risk behaviour of the agent (investor) and Earnings per Share (EPS) value of the stock which is the fundamental data depicting the profitability of the industry/organisation. The fuzzification of these inputs is by using the Gaussian membership curves as shown in Figs. 3–6.

The rule base is developed for each FIS separately using expert knowledge on the effect of all the input variables that is taken up for the development of the FIS. Some of the crucial decision rules that are being developed in the process of constructing rule bases for the respective FISs are as follows.

The rules corresponding to Buy FIS are,

IF Risk is Less and Volatility is High and Profitability is Low and EPS is Low THEN Strength is Low

IF Risk is Moderate and Volatility is High and Profitabilityis Mediumand EPS is Low THEN Strength is Medium

IF Risk is More and Volatility is High and Profitability is Low and EPS is High THEN Strength is High

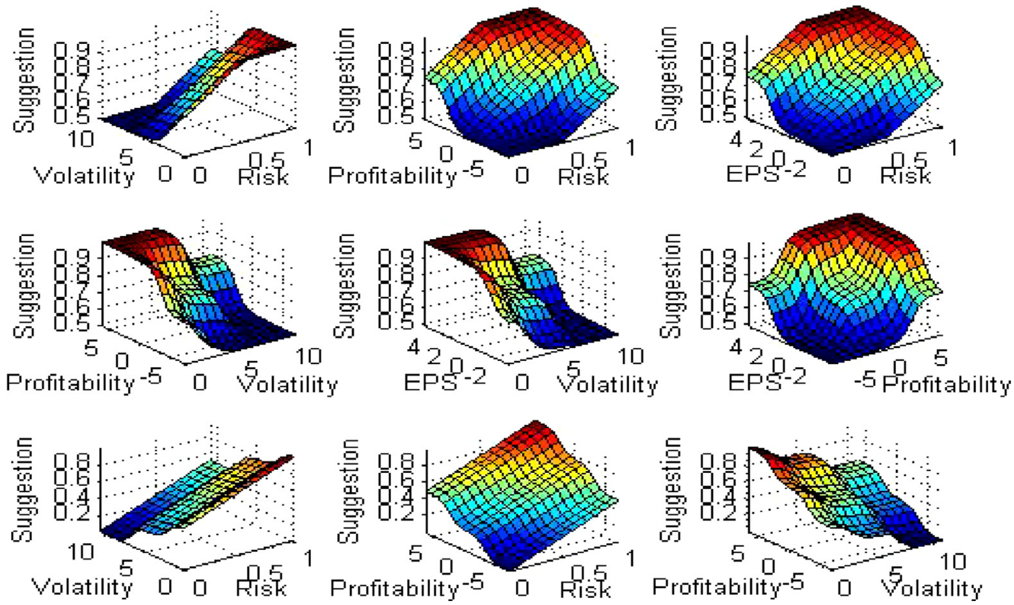

Fig. 7. Buy FIS Surface plots.

The rules corresponding to Hold FIS are,

IF Risk is Less and Volatility is Low and Profitability is Low and EPS is Low THEN Strength is Medium

IF Risk is Moderate and Volatility is High and Profitability is High and EPS is High THEN Strength is High

IF Risk is More and Volatility is Medium and Profitability is Low and EPS is High THEN Strength is Low

The rules corresponding to Sell FIS are,

IF Risk is Less and Volatility is High and Profitability is Low and EPS is Medium THEN Strength is High

IF Risk is Moderate and Volatility is High and Profitability is Low and EPS is High THEN Strength is High

IF Risk is More and Volatility is High and Profitability is Medium and EPS is Medium THEN Strength is Very High

The output ($y \in [0, 1]$) from each FIS gives a level of acceptance (strength) for each decision.

2.3. Decision making and trading

The final decision is made by setting a threshold and applying a strategy of making decisions whenever more than one output is greater than the threshold. When the output of the FIS i.e the strength of each decision is greater than the threshold, the corresponding decision is used for trading. The decision making strategy followed is expressed as follows,

Strategy 1: When the strengths of Buy and Hold decisions are greater than the threshold, the Buy decision is selected for trading

Strategy 2: When the strengths of Buy and Sell decisions are greater than the threshold, the Hold decision is selected for trading

Strategy 3: When the strengths of Hold and Sell decisions are greater than the threshold, the Sell decision is selected for trading

The trading is carried out with the selected decision with everyday trading limit of 10 shares per company. Multiple agents (investors) are simulated with varying the values of risk behaviour for each agent. According to the risk behaviour, each agent performs trading with the suggestions from the proposed framework. Each agents' profit return is being recorded day by day. The cumulative profit return is also calculated for performance analysis.

3. Simulation set up and results

The validation of the Multiple FISs framework as a daily stock trading system is initiated by taking four years stock data of 25 companies of the NASDAQ stock exchange. The Fuzzy Toolbox of Matlab and a supporting program is indulged in the simulation of the proposed framework. To show the significance of including EPS value as a profitability measure from the fundamental information of the stock, two different versions of the Multiple FISs framework were simulated and are referred here as with EPS and without EPS. The framework without EPS is developed with only the risk behaviour, profitability and volatility as inputs for the FISs which bears $3^3 = 27$ rules in fuzzy processing for the buy, sell and hold FISs respectively. The framework with EPS is developed with four inputs including the EPS value of the stock (yearly basis) which gives us $3^4 = 81$ rules. Fig. 7 depicts the three dimensional view of the rule base for the framework:

In each figure, the first six surface plots occupying the first two rows of the figure are the surface plots corresponding to the rule base of the Multiple FISs framework with EPS. The last row of the figure consists of three surface plots that refers to the rule base of the Multiple FISs framework without EPS. Figs. 8 and 9 for Hold FIS and Sell FIS also depict the same order of surface plots of both the frameworks.

Four year historical data and the fundamental data of the following 25 stocks of NASDAQ stock exchange is considered as the input (crisp) values for the proposed framework (Table 1).

The daily stock trading is carried out taking the database of technical and fundamental information of these 25 stocks from 2011 to 2015. The values of profitability and volatility changes with the number of days of observations are taken into consideration. The profit return is calculated for different values of number of days of observations which shows an increase in profit return for decreasing number of days of observations (say n) shown in Fig. 10.

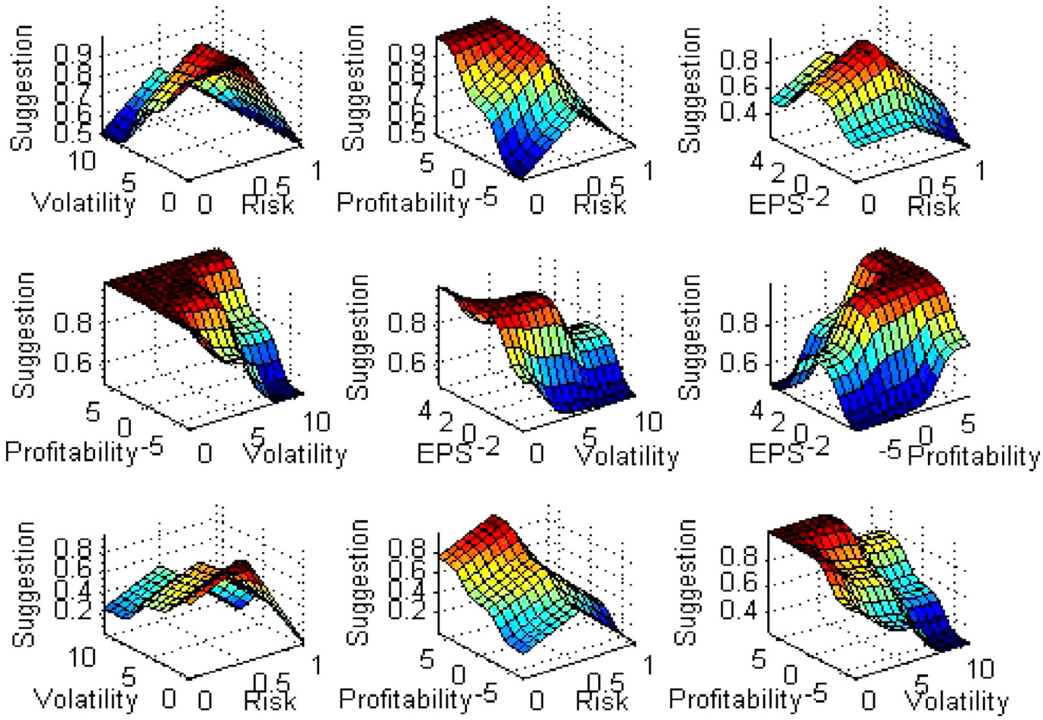

Fig. 8. Hold FIS Surface plots.

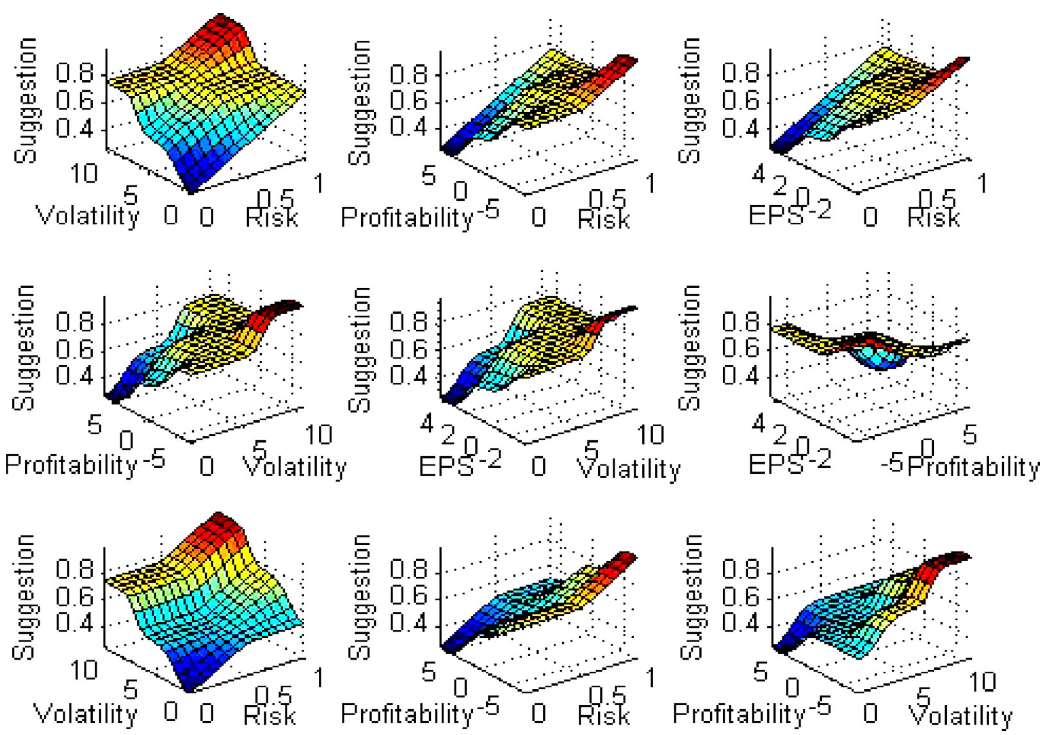

Fig. 9. Sell FIS Surface plots.

3.1. Comparison with technical indicators

The proposed framework is simulated with a single agent with highest risk value to compare it with some of the technical indicators in the literature (Colby & Meyers, 1988; Murphy, 1999). Rules leading to identifying the appropriate decision to be made according to each of the selected technical indicators are developed. The inbuilt functions of the financial toolbox in MATLAB are being used. The indicators chosen and their corresponding rules are given as follows.

1. **Moving average convergence/divergence (MACD)**
   MACD is a technical indicator introduced by Appel (2005). The components of this indicator, the MACD and the signal line are

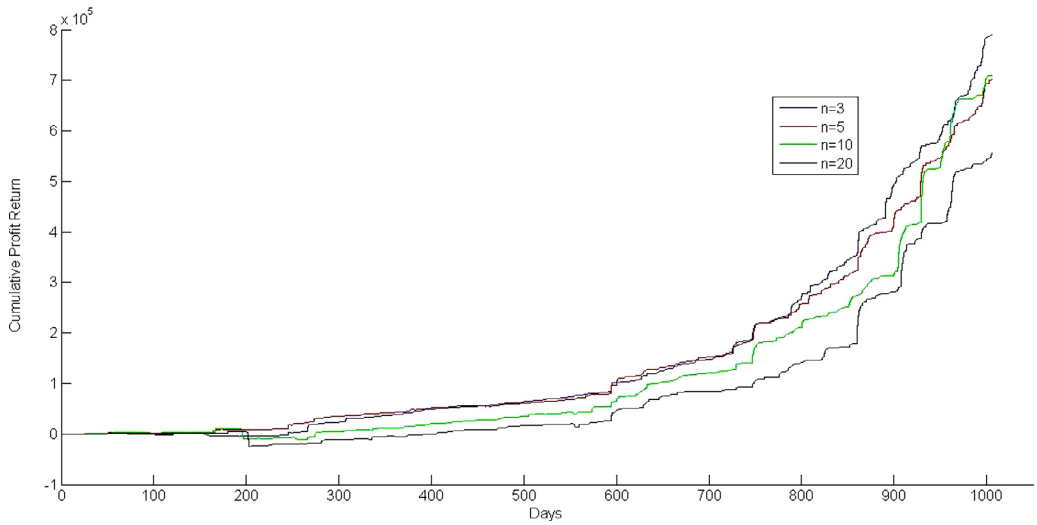

Fig. 10. Varying number of days of observations (n).

Table 1
List of stocks of NASDAQ stock exchange.

S. No.	Symbol	Company name
1	WLDN	Willdan Group, Inc.
2	CTP	CTPartners Executive Search Inc.
3	VDSI	VASCO Data Security International, Inc.
4	IG	IGI Laboratories, Inc.
5	CENX	Century Aluminum Company
6	CVTI	Covenant Transportation Group, Inc.
7	FOLD	Amicus Therapeutics, Inc.
8	RDNT	RadNet, Inc.
9	PTX	Pernix Therapeutics Holdings, Inc.
10	ANAC	Anacor Pharmaceuticals, Inc.
11	BDL	Flanigan's Enterprises, Inc.
12	MGPI	MGP Ingredients, Inc.
13	STRT	Strattec Security Corporation
14	PTSI	P.A.M. Transportation Services, Inc.
15	GTIM	Good Times Restaurants Inc.
16	RIC	Richmont Mines, Inc.
17	SWKS	Skyworks Solutions, Inc.
18	CORT	Corcept Therapeutics Incorporated
19	SMCI	Super Micro Computer, Inc.
20	PEIX	Pacific Ethanol, Inc.
21	BDSI	BioDelivery Sciences International, Inc.
22	CBPO	China Biologic Products, Inc.
23	BBW	Build-A-Bear Workshop, Inc.
24	SWIR	Sierra Wireless, Inc.
25	LUV	Southwest Airlines Company

calculated as,

$$\begin{aligned} \text{MACD} &= 12-day \text{ exponential moving average (EMA)} \\ &\quad -26-day \text{ EMA of close price} \\ \text{Signal line} &= 9-day \text{ EMA of MACD} \end{aligned}$$

The decision making rules are as follows,

$$IF\ MACD\ is\ greater\ than\ signal\ line\ THEN\ BUY$$
$$IF\ MACD\ is\ lesser\ than\ signal\ line\ THEN\ SELL$$

2. **Relative strength index (RSI)**
The relative strength (RS) developed by Wilder (1978) is the ratio of 14-day average gains to 14-day average losses and then the RSI is calculated as,

$$RSI = 100 - \frac{100}{(1+RS)}$$

The decision making rules are as follows,

$$IF\ RSI\ is\ below\ 30\ THEN\ BUY$$
$$IF\ RSI\ is\ between\ 30\ and\ 70\ THEN\ HOLD$$
$$IF\ RSI\ is\ above\ 70\ THEN\ SELL$$

3. **Stochastic oscillator (SO)**
George Lane's stochastic oscillator (Lane, 1984) consists of two variables %K and %D as,

$$\begin{aligned} \%K &= \frac{(current\ close - lowest\ low)}{(highest\ high - lowest\ low)} \\ \%D &= 3-day \text{ simple moving average (SMA) } of\ \%K \\ SO &= 14-day \text{ SMA of } \%K \end{aligned}$$

The decision making rules are as follows,

$$IF\ SO\ is\ below\ 20\ THEN\ BUY$$
$$IF\ SO\ is\ between\ 20\ and\ 80\ THEN\ HOLD$$
$$IF\ SO\ is\ above\ 80\ THEN\ SELL$$

4. **Chaikin oscillator (SO)**
The steps involved in calculating the chaikin oscillator (Achelis, 2001) are as follows,

$$\begin{aligned} &Money\ flow\ multiplier\ (MFM) \\ &\quad = \frac{[(close - low) - (high - close)]}{(high - low)} \\ &Money\ flow\ volume\ (MFV) = MFM \times volume \\ &Accumulation\ distribution\ line\ (ADL) = previous\ ADL \\ &\quad + current\ day's\ MFV \\ &Chaikin\ oscillator = (3-day\ EMA\ of\ ADL) \\ &\quad - (10-day\ EMA\ of\ ADL) \end{aligned}$$

The decision making rules are as follows,

$$IF\ CO\ is\ greater\ than\ 1\ THEN\ BUY$$
$$IF\ CO\ is\ lesser\ than\ -1\ THEN\ SELL$$

The simulation of the comparison module shows a better performance of the proposed framework over MACD, RSI, SO, CO and also with the proposed framework constructed without including the EPS value to it. The results obtained shows that the developed framework with EPS acts as a better stock indicator than some of the famous technical indicators and the framework without EPS performs better

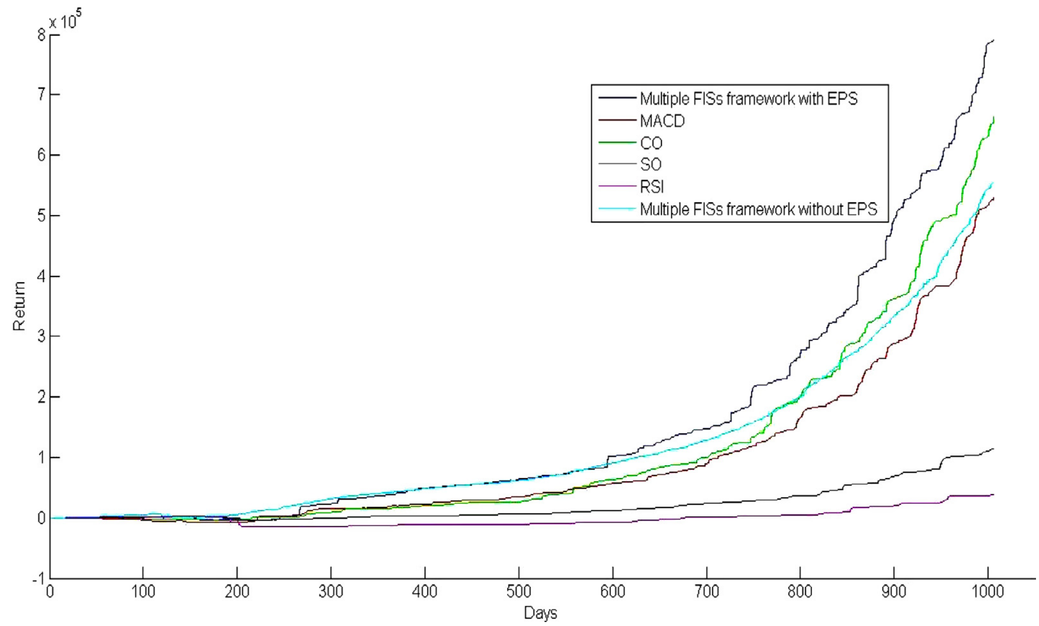

Fig. 11. Comparison of the developed framework with technical indicators.

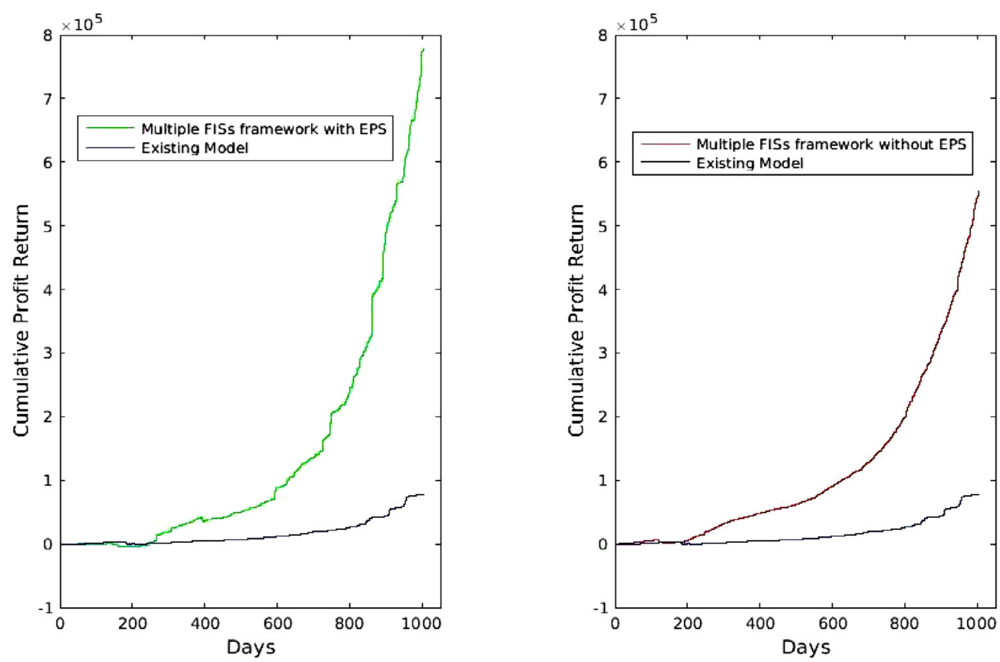

Fig. 12. Comparison of the developed framework with existing models.

than MACD, RSI and SO but not better compared to CO. The results are shown graphically in Fig. 11.

The cumulative profit return corresponding to all the indicators and the framework is given in Table 2.

Table 2
Final cumulative profit return values of different models

Model	Cumulative profit return ($)
MACD	528882.8
RSI	37731.37
SO	114383.2
CO	663548.7
Multiple FISs framework without EPS	554604.1
Multiple FISs framework with EPS	**789445.6**

3.2. Comparison with existing models

In 2007 (Cheung & Kaymak, 2007) introduced a trading system combining the concept of fuzzy logic and technical analysis to find the trends in the financial markets in which the input parameters are optimised by genetic algorithms. In 2009 (Chavarnakul & Enke, 2009) a hybrid stock trading system was developed by applying the Neuro-fuzzy based Genetic Algorithm (NF-GA) on the volume adjusted moving average which is a technical indicator developed from equivolume charting. The Moving Average Indicator (MAI) and Moving Average Volume Indicator (MAVI) were fuzzified and a fuzzy rule-based system was developed to predict and perform stock market trading by Yeh, Lien et al. (2011). FISs were used for stock selection in

Table 3
Final cumulative profit return values of the models compared.

Model	Cumulative profit return ($)
Existing model	77811.4
Multiple FISs framework without EPS	554604.1
Multiple FISs framework with EPS	**789445.6**

developing a hybrid intelligent system for the portfolio investment decision support system (Casanova, 2012). Trading rules were generated for stock trading using technical analysis by Wang et al. (2014) using the stock prices for application to the Hong Kong Stocks. Papailias and Thomakos (2015) provided the threshold for trailing stop using improved version of the price and moving average crossover trading strategies, which resulted in a smaller drawdown duration. Using fuzzy logic and technical analysis (Chourmouziadis & Chatzoglou, 2015), an intelligent system was developed for portfolio management which used MACD and a rarely used indicator, called the Gann–HiLo technical indicator as input variables. Our proposed framework consists of three FISs for making the decisions of buy, sell or hold by taking the input of daily price data and the EPS value of the stocks and a trading strategy is adapted for performing the daily trading with multiple agents by applying the suggestions of the Multiple FISs framework.

A comparison with another program of an existing model, with the same objective of stock trading decision making, is carried out with a research article by Ijegwa, Rebecca, Olusegun, and Isaac (2014). The paper describes a predictive model which uses fuzzy logic over a set of technical analysis indicators forming a fuzzy rule base for daily stock market decision making. For comparing it with the performance of our proposed framework, the simulation of the same is carried out with the same data from the NASDAQ stock exchange that was used to validate our system. This existing model is thus compared with the Multiple FISs frameworks with and without EPS. The Multiple FISs framework without EPS performs better than the existing model considered for comparison with respect to the cumulative profit return value (Fig. 12). The Multiple FISs framework with EPS which is already superior to our framework without EPS shows more variation with a positively improved performance respective to the cumulative profit return. The final cumulative profit return values of all the three models are tabulated in Table 3.

4. Conclusion and future work

The Multiple FISs framework is developed for daily stock market trading. The experiments on NASDAQ stock exchange data help us to draw conclusions on the trading practice using the Multiple FISs framework. The developed framework establishes an FIS to make the decision of hold to prove that hold does not mean that the investor stays idle. A rule base is developed for making the hold decision which makes the investor to carefully wait for the correct time to make Buy/Sell orders. The study of the Multiple FISs framework by varying the number of days of observations (n) taken into consideration for calculating the profitability and volatility of the stocks justifies that as we take into account the price data closer to the present day, the profit return increases accordingly.

Most of the existing research articles take only technical analysis data as input to their systems or they consider only the fundamental analysis data of the companies for producing stock market decisions. Two variants of the Multiple FISs framework are developed in which one takes only technical information as input and the other includes both the technical and fundamental information of the stocks. The increase in the profit return of the Multiple FISs framework with EPS clearly depicts the importance of including the fundamental information of the stocks into the system.

Though the developed expert system performs well for a selected set of stocks in the NASDAQ stock exchange, the adaptability of the model with other stock exchange data is still in question. We use here a fully developed and stable market for our experimental analysis and not with a developing or unstable markets. The rule bases of the Multiple FISs framework do not employ rules that are specific to capture any dramatic change in behaviour of the stock data.

The future work may be concentrated on improving the developed framework by making it into a versatile system that adapts itself to any kind of stock data irrespective of the market stability. The current framework can include a module for analysing the feedback with respect to the profit return and for updating the rule bases accordingly to improve the efficiency of the system. A study on the proposed framework can be carried out by simulating the market scenario along with the investors following our proposed expert system for decision making to analyse the impact of our decisions and the effect it implies over the stock market. The sentimental analysis of the stock trading environment can be included in the framework to acquire knowledge on the effect of the state of mind of an investor which can positively affect the profit return of the Multiple FISs framework.

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