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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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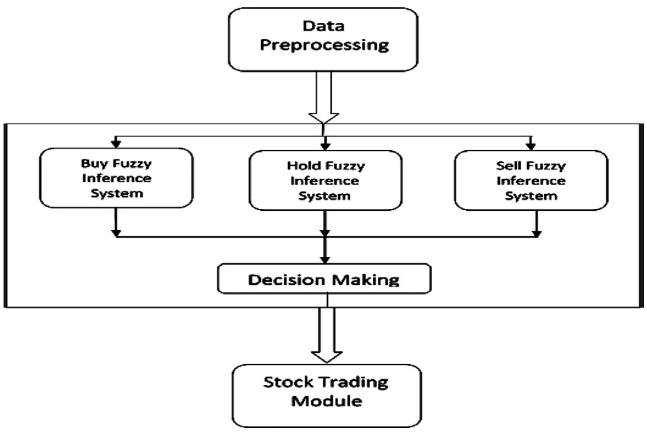

Fig. 1. System architecture.

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: $R^K \to R$ with the Tagaki–Sugeno–Kang (TSK) inference method

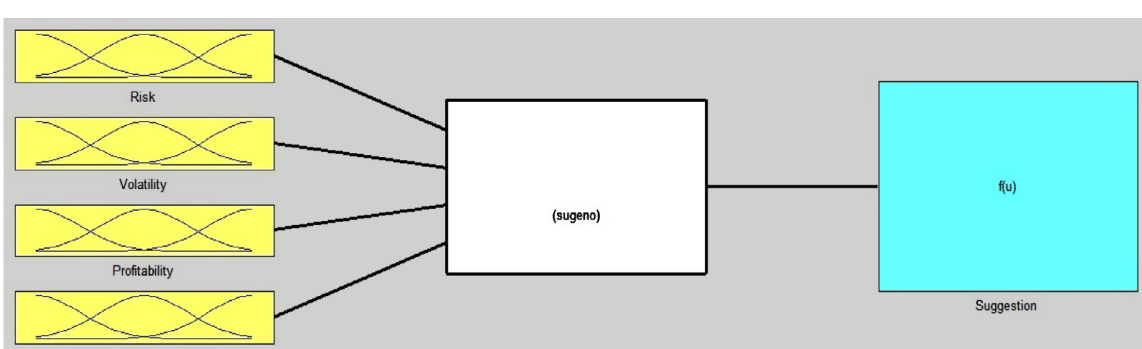

Fig. 2. Structure of FIS.