EXAMINATION OF FUZZY METAGRAPH BASED DATA MINING FOR INVESTIGATION ON STOCK MARKETS

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ABSTRACT

The aim of this research is to develop a syste m that can predict future stock market investment based on some sample of historical data sets collected from various stock marketing companies. This paper proposes an efficient algorithm for fuzzy Meta graph (FM) based decision support system (DSS) for stock market investigation. This research has dealing with the FM based data structures to support decision making and reducing some major risks in share market investment for short term and long term periods. Relative strength index (RSI), Moving Average convergence divergence (MACD) and William-%R which are the following input indicators used to train the system which is integrated with fuzzy Meta graph. These three indicators would be a new attempt in decision making on share market investment. Moreover, these three indicators have produce good profit when compare to two indicators (RSI and William-%R).

Keywords: Fuzzy meta graph, DSS, Stock marketing model, Relative strength index, MACD, William -%R, Stochastic Oscillator, Negative Volume Index.

1.INTRODUCATION

This introduction brings a simple background of fuzzy metagraph (FM) model, understanding of different soft computing models and stock market techniques that are widely used in time series decision making. Fuzzy metagraph (FM) is a graphical hierarchical data structure for directional relationships between sets of (one or more) elements.it possesses all the properties of fuzzy graph and metagraph [3,5,6,13]. An equity market is a public entity for the trading of company shares. The purpose of a stock exchange is to facilitate the exchange of shares between two people namely buyer and seller. Investing in stock market is not an easy task as it is highly vulnerable to market risk.FM based data structures help in decision making and reducing risk in share market investment for short term and medium term duration [7, 9].

2. NEED FOR THE RESEARCH

Generally, most of the investors in the stock market lose their capital money because of dynamism and unpredictable environment in the domain. It needs careful attention and right decision making skills to gain profit in the long run. The psychology of investors plays a major role in the capability of profit making. The basic rule of investment in stock market is keeping emotions away and sticking to the plan, but unable to control emotions is a major reason for most of the investor's failure to make profit [3, 4].

The software based decision support (DSS) will be a major guiding tool for investors which make decision based on logical reasoning and set of rules without any emotions.it greatly reduces lose and guaranty decent profit, developing a DSS which is fast and accurate in research interest in recent times. Graph based structures are used to provide solution for decision making in stock market. By using soft computing techniques and graph based data structures one can find better solution for decision making in stock market. Hence, it is a need to make a research in this field of study [8, 10].

3. PROBLEM DEFINITION

Some of the problems involved in investing as first the moment to buy at low rates and to sell it at higher rates becomes a non-trivial problem and it is still a dream for every investor. Secondly, the knowledge of buying and selling an appropriate stock is still in quagmire. Thirdly, analyze and extract useful information from various technical indicators available in order to make qualitative investment decision. Finally, have a reliable DSS which is fast, reasonable and accurate. Hence in this research work, FM-based DSS model is proposed to overcome the problems stated above.

4. OBJECTIVES OF THE RESEARCH

The goal of this research work is to develop a DSS model for decision making in stock market with minimal risk. Consequently, the work plan of this research has been set to study the usefulness of FM based data structures in designing an affective DSS. Secondly, develop a FM based DSS model to arrive an accurate decision making in stock investments. Thirdly, optimize the DSS model to improve its accuracy and finally, compare its performance with available existing methods. Fuzzy metagraph based DSS is to help decision making and reducing risk in share market investment for short term and medium term duration.

5. FM BASED DSS FOR STOCK MARKET MODEL

Fuzzy Metagraph (FM) makes it easy to represent and visualize fuzzy knowledge bases in a simple and convenient way. FM can be used to effectively reduce the unwanted ineffective rules from the knowledge base, thus increases efficiency and speed of the Decision Support System [10, 16]. In this process FM based DSS for short term and medium term investment in share market have been proposed. The rule base decision system will help traders to make correct decision at very low risk. Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD), WILLIAM- %R, Stochastic Oscillator (SO) and Negative Volume Index (NVI) are some of the Technical Indicators which are used as input to train the system which is integrated with FM [13,17]. Regarding for DSS of stock market, FM has been better than existing system models like Fuzzy Logic, SVM and ANN [12].

5.1.COLLECTION OF STOCK DATA AND TECHNICAL ANALYSIS

The stocks listed in Bombay Stock Exchange (BSE) in India are used to evaluate the performance of the system. The dataset has been collected from popular Indian companies like Tata Consultancy Services (TCS), Reliance Industries Ltd (RIL), Rural Electrification Corporation (REC), Oil and Natural Gas Corporation (ONGC) and Bharat Heavy Electricals Ltd (BHEL) from January 2011 to December 2014. That year has been very a challenging year for Indian share market [11, 13].

The price histories of stock, with time and volume information have been considered as the main data of the decision making system. Down and up trends of the price on the stock market depend on supply and demand of stocks. The important technical indicators including price and volume have been used for data preprocessing and predicting the stock market [15].

5.1.1 Technical Indicators and its Calculation

The technical indicators give important information about pattern and future possible movement of stock market. The technical indicators are calculated by using historical stock information including open price, close price, traded volume, day high price and day low price. Historical stock information is used to calculate technical indicators using the formula given for respective indicators [6, 8, and 15].

5.1.1.1. Relative strength index (RSI)

It is a momentum oscillator that measures the speed and direction at which prices are moving. RSI oscillate within the band of zero to 100.
The formula used to calculate RSI is,

$$RSI= 100-(100/1+RS)$$

Where, RS=Average gain/Average loss

Simple 14 period averages are used as initial value for average gain and loss. For subsequent values the following formula is used

Average Gain = [(previous Average Gain) x 13 +current Gain] / 14.

Average Loss = [(previous Average Loss) x 13 + current Loss] / 14.

RSI can also be used to identify the general trend. Buy signal is generated when RSI is near 30 and sell signal is generated when RSI is near 70.

- If RSI decreases to below 30 (implies oversold) then buy.
- If RSI is between 30 and 70 (implies normal) then hold.
- If RSI increases to above 70 (implies overbought) then sell.

5.1.1.2. Moving average convergence and divergence (MACD)

The two most popular types of moving averages are the Simple Moving Average (SMA) and the Exponential Moving Average (EMA). An *SMA* is calculated by adding the security's prices for the most recent "n" time periods and then dividing by "n" .This calculation is done for each period in the chart.

EMA=Price (t) * k+ EMA (y) * (1-k)

where *t* represents today, *y* denotes yesterday, *N* is the number of days in EMA and k=2 / (N+1). MACD indicator tries to forecast market trends by comparing short and long-term tendencies. It is the difference between a security's 26-day and 12-day EMAs.

MACD =26days EMA - 12days EMA

A 9-day exponential moving average is the "signal" (or "trigger"), signal line is plotted on top of the *MACD* to show buy/sell opportunities. If MACD is above the signal line then buy. If MACD is below the signal then sell.

5.1.1.3. William -%R

William-%R, developed by Larry Williams, is a momentum indicator which reflects the level of the close relative to the highest high and lowest low for the look-back period. William- %R oscillates from 0 to -100. A stock is considered overbought when William-%R Reads from 0 to -20. Readings from -80 to -100 are considered oversold. The default setting for William- %R is 14 periods, which can be days, weeks, months or an intraday time frame. The buy signal is generated when William -%R is near -80. Sell signal is generated when indicator is near -20.

5.1.1.4. The Stochastic Oscillator (SO)

The Stochastic Oscillator (SO) gives an indication of the stock‘s last closing price by relating to the stock‘s recent trading range. This is one of the most recognized momentum indicators used in technical analysis. The SO is plotted within a range of 0 to 100 and signals over-bought conditions above 80 and oversold conditions below 20. The SO is a momentum indicator that shows the location of the close relative to the high-low range over a set number of periods. It follows the speed or the momentum of price. The oscillator, which is range bound, is also useful for identifying overbought and oversold levels. The steps are,

%K = (Current Close - Lowest Low)/ (Highest High -Lowest Low) * 100
%D = 3-day SMA of %K
Lowest Low = lowest low for the look-back period
Highest High = highest high for the look-back period

- IF SO increases above 80 (implies overbought) THEN SELL
- IF SO is between 20 to 80 (implies normal) THEN HOLD
- IF SO is below 20 (implies oversold) THEN BUY

5.1.1.5. Negative Volume Index (NVI)

The NVI is a cumulative indicator. When the smart money is active, the NVI is used the change in volume to decision making. NVI works under the assumption that the smart money is active on days when volume decreases and the not-so-smart money is active on days when volume increases. Its Steps are,

1. Cumulative NVI starts at 1000
2. Add the Percentage Price Change to Cumulative NVI when Volume Decreases
3. Cumulative NVI is Unchanged when Volume Increases and
4. Apply a 255-day EMA for Signal.

The NVI can also be used to identify the general trend. Buy signal is generated when NVI is near Positive and sell signal is generated when NVI is near Negative.

5.2. FUZZY INFERENCE SYSTEM FOR STOCK MARKET

A FIS employs a nonlinear mapping from its input space to output space through a number of fuzzy if-then rules. FIS for Stock Market architecture used in this system is shown in the Figure 5.1. The basic structure of a FIS consists of few principal components: a knowledge base (fuzzy rule base), a data base, an inference engine (decision-making logic) mechanism, and an interface of fuzzification and defuzzification[6,7]. Fuzzification is the process of converting crisp input to fuzzy value. Membership Functions (MFs) are used to convert crisp inputs into fuzzy value. The MF maps each element of input to a membership grade (or membership value) between zero and one. A single if-then rule assumes the form ‗if x is A then y is B and the if-part of the rule ‗x is A is called the antecedent or premise, while the then part of the rule ‗y is B is called the consequent or conclusion.

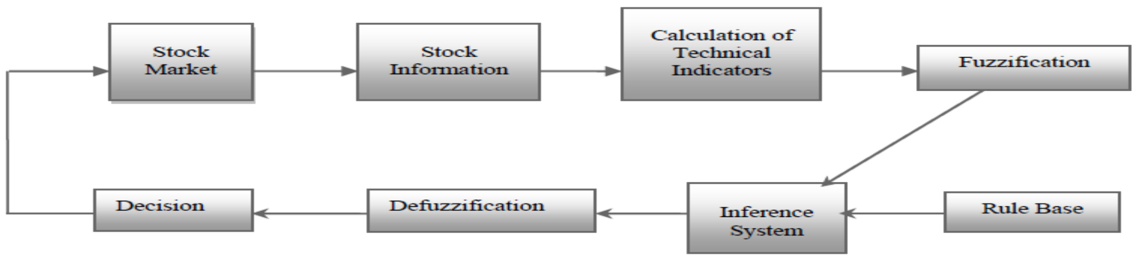

Figure 5.1 Fuzzy decision support system for stock market

A rule base containing a number of fuzzy IF-THEN rules, a database which defines the membership functions of the fuzzy sets used in the fuzzy rules, a decision-making unit which performs the inference operations on the rules [1,2]. The basic FIS can take either fuzzy inputs or crisp inputs, but the outputs it produces are always fuzzy sets. The defuzzification task extracts the crisp output that best represents the fuzzy set. The fuzzification of price and volume are obtained by passing a crisp value into the corresponding membership function.

Fuzzy logic based systems are classified according to the type of fuzzy rules. The three major types of rules are Mamdani fuzzy model, Tagaki Sugeno Kang (TSK) model and Tsukamoto model. In this research, Mamdani Fuzzy model is used. The rule based system requires some fuzzy linguistic variables, fuzzy rules, implication, and aggregation and defuzzification process. Triangular member ship function is taken to present low, medium and high for input variables. The three triangular fuzzy numbers have been taken to define the decision value of buy, hold and sell.

One of the most difficult tasks is to set the parameter value. A statistical study has been made by taking more than 500 records of each company. The parameter value has been taken by statistical analysis and public comments. Fuzzification means finding the grade of the input variables. The grades of the crisp variables will be any value in the interval n (0, 1). Different observations have been recorded on the change of technical indicators. The following nine fuzzy rules have been set on the combination of the three technical indicators [9, 10].

Rule 1: If RSI is oversold and MACD is positive then decision is buying

Rule 2: If RSI is normal and MACD is positive then decision is hold

Rule 3: If RSI is overbought and MACD is negative then decision is selling

Rule 4: If RSI is oversold and Will %R is oversold then decision is buy

Rule 5: If RSI is normal and Will %R normal then decision is hold

Rule 6: If RSI is overbought and Will %R is overbought then decision is selling

Rule 7: If RSI is oversold and MACD is positive and Will %R is oversold then buy

Rule 8: If RSI is normal and MACD is positive and Will %R is normal then decision is hold

Rule 9: If RSI is overbought and MACD is negative and Will %R is overbought then decision is selling.

5.3. TECHNICAL INDICATOR USED FM BASED DSS FOR STOCK MARKET

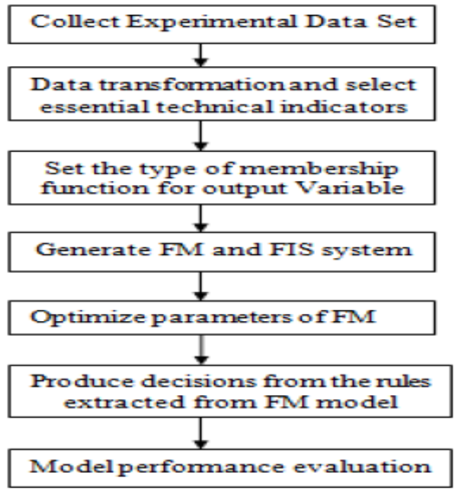

Figure 5.2 the general framework for FM based DSS of stock market model

The general framework for FM based DSS of stock market proposed model is illustrated in Figure 5.2 and three major phases are provided. Each process of the proposed model is described as follows.

Step 1: Collect experimental datasets.

Step 2: Data transformation and select essential technical indicators.

Step 3: Fuzzy Metagraph based DSS for Stock Market.

In this research, FM based DSS for short term and medium term investment in share market have been proposed. The technical indicators like RSI, MACD and William-%R are used as input vector to the fuzzy Metagraph system. The decision vector (BUY, HOLD, and SELL) is output of the system in figure 5.3

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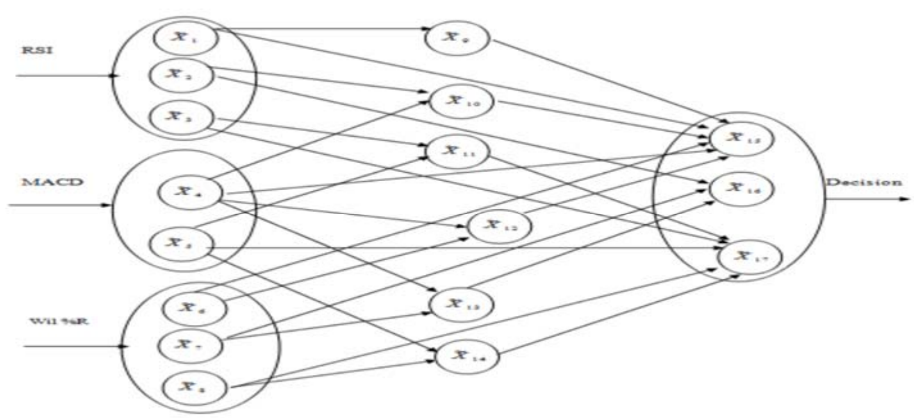

Figure 5.3 Three technical indicators are applied to FM for fuzzy rule base formation of stock market decision

6. CONCLUSION AND FUTURE ENHANCEMENT

Fuzzy metagraph (FM) makes it easier to represent and visualize fuzzy knowledge bases in a simple and convenient way. It can be used effectively to reduce unwanted ineffective rules from the knowledge base. Thus it increases the efficiency and speed of the Decision Support System (DSS). The characteristics of fuzzy metagraph are investigated. Certain investigations are used in Information Retrieval and Indexing Approach, Decision FM, FM based searching technique, Fuzzy Meta network and Group based trust model. Fuzzy Metagraph based DSS for stock market investing is proposed. This research deals with the FM based data structures to help decision making and reducing risk in share market investment for short term and medium term duration.

Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) and William-%R are some of the technical indicators which are used as input to train the system which is integrated with Fuzzy Metagraph. This approach of incorporating Fuzzy Metagraph with RSI, MACD and William-%R would be a new attempt in decision making on share market investment. The stocks listed in Bombay Stock Exchange (BSE) in India are used to evaluate the performance of the system. The dataset has been collected from popular Indian companies like Tata Consultancy Services (TCS), Reliance Industries Ltd (RIL), Rural Electrification Corporation (REC), Oil and Natural Gas Corporation (ONGC) and Bharat Heavy Electricals Ltd (BHEL) for five years. That year has been a very challenging year for Indian share market.

Future works have a scope on optimization techniques applied for tuning the input parameters and to enhance the performance of the system. The model can be verified by other stock market data like China, Japan and Hong Kong. The fuzzy rule sets can be optimized by changing weight, CF and adjacency matrix of fuzzy metagraph.

REFERENCES

1. Abraham, A 2005, 'Rule-based expert systems', Handbook of measuring system design.

2. Abraham, A & Nath, B 2000, 'Hybrid intelligent systems design', Technical report, School of Computing & Information Technology, Monash University, Australia.

3. Atsalakis, GS & Valavanis, KP 2008, 'Surveying Stock Market Forecasting Techniques – Part II: Soft Computing Methods', Elsevier, expert systems with applications, vol. 36, no.3, pp. 5932-5941.

4. Baba, N, Handa, H & Hayashi, M 1996, 'Utilization of neural networks and GAs for constructing an intelligent decision support system to deal stocks', In Aerospace/Defense Sensing and Controls, International Society for Optics and Photonics, pp. 164-174.

5. Bahceci, O & Alsing, O 2015, ' Stock Market Prediction using Social Media Analysis'.

6. Bova, S, Codara, P, Maccari, D & Marra, V 2010, 'A logical analysis of Mamdani-type fuzzy inference', I theoretical bases. In Fuzzy Systems (FUZZ), 2010 IEEE International Conference on IEEE, pp. 1-8.

7. Boyacioglu, MA & Avci, D 2010, 'An Adaptive Network-Based Fuzzy Inference System (ANFIS) for the prediction of stock market return: The case of the Istanbul Stock Exchange', Elsevier, Expert Systems with Applications, vol. 37, pp. 7908-7912.

8. Chou, SCT, Yang, CC, Chan, CH & Lai, F 1996, 'A rule-based neural stock trading decision support system', 'In Computational Intelligence for Financial Engineering, Proceedings of the IEEE/IAFE Conference on 1996, pp. 148-154.

9. Dashore, P &Jain, S 2009a, 'Fuzzy Rule Based System and Metagraph for Risk Management in Electronic Banking Activities', International Journal of Engineering and Technology, vol. 1, no. 1, pp. 97-101.

10. Dashore, P, Jain, S & Dashore, SR 2010c, 'Fuzzy Metagraph and Rule Based System for Decision Making in Share Market', International Journal of Computer Applications, vol.6, no.2, pp. 10-13.

11. Dourra, H & Siy P 2002, 'Investment using technical analysis and fuzzy logic', Elsevier, Fuzzy Sets and Systems, no. 127, pp. 221-240.

12. Dunis, CL, Rosillo, R, Fuente, Ddela & Pino, R 2012, 'Forecasting IBEX-35 Moves Using Support Vector Machines', Springer link, Neural Computing and Applications, vol.23, no.1, 229-236.

13. Escobar, A, Moreno, J & Munera, S 2013, 'A technical analysis indicator based on fuzzy logic', Electronic Notes in Theoretical Computer Science, no.292, pp.27-37.

14. Huang, W, Nakamori, Y & Wang, SY 2005, 'Forecasting stock market movement direction with support vector machine', Elsevier, Computers & Operations Research, vol.32, no.10, pp. 2513–2522.

15. Ijegwa, AD, Rebecca, VO, Olusegun, F & Isaac, OO 2014, 'A Predictive Stock Market Technical Analysis Using Fuzzy Logic', Computer and Information Science, vol. 7, no. 3, pp. 1-17.

16. Kannan, KS, Sekar, PS, Sathik, MM & Arumugam, P 2010, 'Financial Stock Market Forecast using Data Mining Techniques', In Proceedings of the International Multi conference of Engineers and computer scientists (IMECS 2010),vol.1, pp. 1-5.

17. Khan, AU, Bandopadhyaya, TK &Sharma, S 2008, 'Comparisons of Stock Rates Prediction Accuracy Using Different Technical Indicators with Backpropagation Neural Network and Genetic Algorithm Based Backpropagation Neural Network', Proceedings of International Conference of Emerging Trends in Engineering and Technology, Nagpur, Maharashtra, vol.1, pp. 575-580.