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Application of Fuzzy logic in stock market

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Abstract : The Indian Capital Market though an emerging market, has in recent times been adjudged to be one of the most resilient in the world even in the heat of the global economic meltdown. It offers high returns on investment as compensation for its high risk. In this research, we have investigated the predictive capability of the fuzzy inference system (FIS) on stocks listed on the Indian Stock Exchange, within a two-month window. For each selected stock, the technical indicator-based fuzzy expert system developed in Matlab 16.0 provides the buy, sell or hold decision for each trading day. A web-based user interface enables the investor to access the trade forecast for each day. Using the Netbeans IDE, we implemented the user interface with Sun Java. Our results show that the FIS can reliably serve as a decision support workbench for intelligent investments..

Keywords: fuzzy logic, stock market, Forecasting, Decision making, technical indicator.

I. INTRODUCTION

Financial markets are one of the most fascinating inventions of our time. They have had a significant impact on many areas like business, education, jobs, technology and thus on the economy (Hiransha et al. 2018). Over the years, investors and researchers have been interested in developing and testing models of stock price behaviour (Fama 1995). However, analysing stock market movements and price behaviours is extremely challenging because of the markets dynamic, nonlinear, nonstationary, nonparametric, noisy, and chaotic nature (Abu-Mostafa and Atiya 1996). According to Zhong and Enke (2017), stock markets are a_ected by many highly interrelated factors that include economic, political, psychological, and company-specific variables. Technical and fundamental analysis are the two main approaches to analyse the financial markets (Park and Irwin 2007; Nguyen et al. 2015). To invest in stocks and achieve high profits with low risks, investors have used these two major approaches to make decisions in financial markets (Arévalo et al. 2017). According to Hu et al. (2015), fundamental analysis is mainly based on three essential aspects (i) macroeconomic analysis such as Gross Domestic Product (GDP) and Consumer Price Index (CPI) which analyses the e_ect of the macroeconomic environment on the future profit of a company, (ii) industry analysis which estimates the value of the company based on industry status and prospect, and (iii) company analysis which analyses the current operation and financial status of a company to evaluate its internal value. Di_erent valuation approaches exist for fundamental analysis. The average growth approximation technique compares Stock-A with other stocks in the same category to better understand valuations, i.e., assuming two companies have the same growth rate, the one with the lower Price-to-Earnings (P/E) ratio is considered to be better. Hence the fair price is the earnings times target P/E. The P/E method is the most commonly used valuation method in the stock brokerage industry (Imam et al. 2008). The constant growth approximation technique such as Gordon's growth model (Gordon and Shapiro 1956; Gordon 1959) is one of the best-known classes of dividend discount models. It assumes that dividends of a company will increase at a constant growth rate forever but less than the discount rate. Dutta et al. (2012) demonstrated the utility of fundamental analysis through the use of financial ratios to separate good stocks from poor stocks. The authors compared their one-year return against the benchmark—i.e., Nifty—which gives an accuracy of 74.6%. This is one of the few papers which focus on using fundamental features (i.e., company-specific ratios) to identify stocks for investments.

II. LITERATURE SURVEY

This paper presents a literature study on some of the most popular techniques that have been applied for stock prediction.

2.1. Statistical Approach : Numerous statistical techniques have been tried and tested for stock market analysis and prediction. The Exponential Smoothing Model (ESM) is a popular smoothing technique which is applied on time series data, it essentially uses the exponential window function for smoothing time series data and analyse the same (Billah et al. 2006). De Faria et al. (2009) compared the ANN and adaptive ESM model for predicting the Brazilian stock indices. Their experiment revealed the predictive power of ESM and the results for both methods show similar performances although the neural network model i.e., the multilayer feedforward network slightly outperformed the adaptive ESM in terms of the Root Means

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Square Error (RMSE). Dutta et al. (2012) took an interesting path by selecting the financial ratios as independent variables for a logistic regression model and then analysed the relationship between these ratios and the stock performances. The paper focused on a classification task for predicting companies which are good or poor based on their one-year performance. The results show that the financial ratios—like net sales, book value PE, price-to-book (P/B), EBITDA, etc.—classify the companies into good and poor classes with an accuracy of 74.6%, which is a good indication of why company health matters in stock analysis and prediction. Devi et al. (2013) tried to address some issues not currently addressed in most of the stock analysis literature, such as the dimensionality and expectancy of a naïve investor. The authors essentially utilize the historical data of four Indian midcap companies for training the ARIMA model. The Akaike Information Criterion Bayesian Information Criterion (AICBIC) test was applied to predict the accuracy of the model. Testing the model on individual stocks and the Nifty 50 Index showed that the Nifty Index is the way to go for naïve investors because of low error and volatility. Ariyo et al. (2014) explore the extensive process of building ARIMA models. To identify the optimal model out of all the ARIMA models generated, the authors chose criteria like the standard error of regression, adjusted R-square, and Bayesian information criteria. The best ARIMA model, based on the above criteria, did a satisfactory job in predicting the stock prices of Nokia and Zenith Bank. Furthermore, Ariyo et al. (2014) made a solid case not to undermine the powers of ARIMA models in terms of stock analysis because it can compete reasonably well against the emerging forecasting techniques available today for short term prediction. Bhuriya et al. (2017) implemented variants of regression models to predict the stock price of Tata Consultancy Services stock based on five features i.e., open, high, low, close price, and volume. The paper compares the performances of the linear, polynomial, and Radial Basis Function (RBF) regression models based on the confidence values of the predicted results. In addition, Bhuriya et al. (2017) reported that the linear regression model outperformed the other techniques and achieved a confidence value of 0.97.

2.2. Pattern Recognition : Pattern recognition techniques do pattern matching to identify future trends based on historical templates. Fu et al. (2005) suggested an approach to identifying patterns in time series data more e_ciently using human visualization concept of PIP. The results from their experiments suggest that the PIP approach not only reduces dimensionality but also allows for early detection of patterns when compared to template matching, because it uses a subsequence pattern matching approach by slicing time series data using the sliding window approach. Leigh et al. (2008) challenged the EMH (Fama 1970) theory by showing that profits obtained using the heuristic method would be better than trading randomly. They utilized a bull flag pattern, which indicates a rise in prices in the near future and built a recognizer for identifying this pattern using template matching. The technique was applied on 9000 trading days of NYSE closing prices and the results show that the trading approach beats the average market profit most of the times, hence reinforcing the credibility of the technical analysis. Parracho et al. (2010) proposed an approach to combine template matching with Genetic Algorithms (GA) for creating an algorithmic trading system. Template matching is utilized to identify upward trends and the GA helps in identifying the optimal values for the parameters used in template matching, i.e., fit buy, fit sell, noise removal, and window size. The trading strategy is trained on the S&P 500 stock data from 1998–2004 and tested on the 2005–2010 data. The results show that it outperforms the buy and hold strategy on an index and gets decent results for the individual stocks as well when compared to the buy and hold strategy. Phetchanchai et al. (2010) proposed an innovative approach to analyse financial time series data by considering the zigzag movement in the data. In order to identify the Zigzag movements, the PIP technique was selected and the Zigzag based Mary tree (ZM-tree) was used for organizing these important points. The proposed technique illustrates a better performance in dimensionality reduction than existing techniques like Specialized Binary Trees (SB-Tree). Cervelló-Royo et al. (2015) proposed a chart pattern based trading rule using the flag pattern. The study extends previous work by introducing two new parameters, stop loss and take profit, which allows the dynamic modelling of the closing of operations. It also employs intraday data to allow considerable width in the number of observations in the sample. Furthermore, Cervelló-Royo et al. (2015) considered both the opening and the closing prices to widen the information scope when deciding whether or not to start an operation. According to the authors, the results confirmed the positive performance of the flag pattern over the intraday data of the Dow Jones Industrial Average (DJIA) for a time horizon of more than 13 years. The results were also validated using two leading European indexes: the German stock index or Deutscher Aktienindex (DAX) and the Financial Times Stock Exchange (FTSE). It also provides empirical evidence which confronts the EMH (Fama 1970) indicating how it is possible to develop an investment strategy capable of beating the market in the mean-variance sense. Chen and Chen (2016) proposed a hybrid approach to identify bull flag patterns on the Taiwan CapitalizationWeighted Stock Index (TAIEX) and National Association of Securities Dealers Automated Quotations (NASDAQ) indices. The authors developed a methodology that combines the advantages of two traditional pattern recognition methods (PIP and template matching). Their proposed hybrid approach outperformed the other models like Rough Set Theory (RST), GA, and a hybrid model of GA and RST (Cheng et al. 2010) by a good margin in terms

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of total index returns. Arévalo et al. (2017) o_er a robust mechanism to dynamically trade DJIA based on filtered flag pattern recognition using template matching, based on the initial work of Cervelló-Royo et al. (2015). The authors impose multiple filters before considering the flag patterns as actionable for making trades, based on Exponential Moving Averages (EMA) and price ranges of the detected patterns. Their approach performs much better than the base approach of Cervelló-Royo et al. (2015) and the buy and hold strategy, resulting in higher profit and lower risk. Kim et al. (2018) build a Pattern Matching Trading System (PMTS) based on Dynamic Time Warping (DTW) algorithm in order to trade index futures on the Korea Composite Stock Price Index (KOSPI 200). Taking the morning 9:00–12:00 p.m. time series data as input for the sliding windows, the authors then use DTW in order to match with known patterns. This forms the basis of the trading strategy to be carried in the afternoon's session on the same trading day. Their approach generates good annualized returns and shows that most patterns are more profitable near the clearing time.

III. METHODOLOGY

Fuzzy theory attempts to mimic human reasoning in its use of approximate information and uncertainty to generate decisions. Unlike traditional computing (which demands precision inherent in all system variables and domains), fuzzy set theory imparts knowledge to the system in a more natural way using fuzzy sets. This way, our stock trading problem is simplified. In this research, we shall be using the Mamdani-type fuzzy rule model of the form:

R1: If x is A1 and y is B1 then z is C1

R2: If x is A2 and y is B2 then z is C2

Where Ai , Bi and Ci, are fuzzy sets defined on the universes of x, y, z respectively.

3.1 The Fuzzy Stock Prediction System : There are four major units in the system, namely: Technical indicator module, Fuzzification module, Fuzzy processing module, and Defuzzification module. The technical indicators module transforms past historical stock prices into selected indicators (oscillators). These indicators then become inputs to the fuzzification module. The fuzzification module again transforms each crisp technical indicator input into fuzzy values (known as fuzzy indicators). These fuzzy indicators serve as input to the fuzzy processing module, which generates Buy/Sell actions to be taken for the stock in question; based on the embedded fuzzy IF/THEN rules. To finally obtain a crisp value, the defuzzification module maps the fuzzy action value into crisp decision.

3.2 Technical Indicators Here, historical prices of certain selected stocks are used to compute the indicators. The data to be used are Banking stock data from Indian stock market. We chose three popular technical indicators (RSI, Trend and MACD) as listed in Table 3.1.

The RSI Indicator: It is a price following indicator which considers whether an asset is over bought or oversold. Its value oscillates between a range of 0 and 100. When the RSI rises above 70, the action of sell will be taken, and when the RSI drops below 30, the action of buy will be taken. (Table 3.1 contains the RSI equation). The crossing boundaries for generating the signals are rather arbitrary, but we have used the following classification rules.

1. IF RSI increases to above 70 THEN BULLISH(Overbought)
2. IF RSI decreases to below 70 THEN BEARISH(Oversold)
3. IF RSI increases to above 30 THEN BULLISH(Overbought)
4. IF RSI decreases to below 30 THEN BEARISH(Oversold)

The MACD Indicator: (Table 3.1 contains the MACD equation). Moving Average Convergence/Divergence is an oscillator intended as an improvement on the simple moving average approach. It generates its signal from the crossing of moving average lines. The MACD line is calculated by taking two exponentially moving averages of closing prices with different periods and subtracts the moving average with the longer period from the one with the shorter period. Usually, 12/26 MACD is used, which computes the difference between the 26-day and the 12-day exponential moving averages.

1. IF MACD is Positive THEN BUY.

2. IF MACD is Negative THEN SELL.

Fuzzification Module : This module transforms the technical indicators to fuzzy values using membership functions. Table 3.1 contains a description of the input membership functions. These membership functions are chosen based on the intuitive meaning obtained from the trading rules. Table 3.2 contains a description of the membership functions of the output (buy/sell/hold decision). Figure 3.1 is the output (Decision) membership functions

Table 3.1: Description of Input Membership Functions

Indicator	Membership Function(MF)	Type of Membership Function
RSI	High, Medium, Low	Triangular
MACD	Positive, Negative	Trapezoidal
Trend	Positive, Negative	Trapezoidal
Momentum	Low, Medium, High	Triangular

Table 3.2: Description of Output membership functions

Output	Membership Function(MF)	Type of Membership Function
Decision	Buy, Hold, Sell	Gaussian

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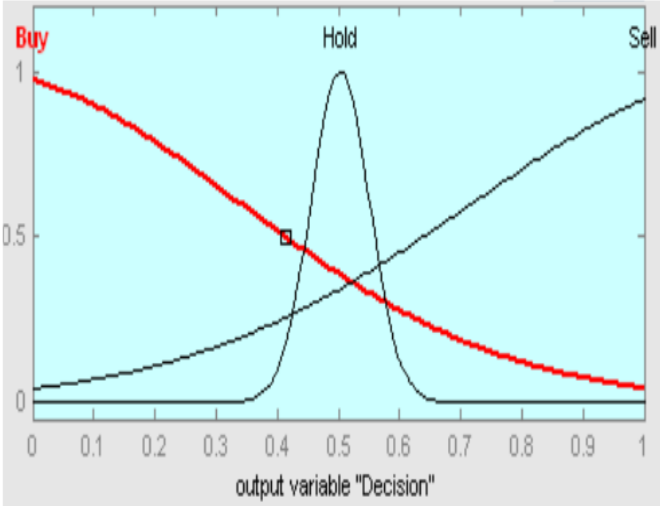

Fig. 3.1: Plot of Decision (Buy, Hold and Sell) membership functions

3.3 Fuzzy Processing Module

Table 3.3 contains a summary of the rules for the fuzzy processing module.

Table 3.3: Fuzzy Logic Rules

If (MACD is Positive) and (RSI is Low) then (Decision is Buy)
If (MACD is Negative) and (RSI is High) then (Decision is Sell)
If (RSI is Medium) then (Decision is Hold)
If (Trend is Positive) and (Momentum is Low) then (Decision is Buy)
If (Trend is Positive) then (Decision is Buy)
If (Trend is Negative) then (Decision is Sell)
If (Trend is Negative) and (Momentum is Low) then (Decision is Sell)

RSI oscillates in [0, 100] range; using fuzzy logic, we can translate this into fuzzy rule: If RSI is low then the decision will be buy and if RSI is high, then the decision will be sell.

3.4 Defuzzification Module : The Mamdani's fuzzy inference scheme (Klir and Yuan, 2002) when given the stock indicators can infer the Decision part at any point in time. The resulting output is a fuzzy value. This is transformed into a crisp decision in the defuzzification module. Our implementation is to use the centre of area (COA)/centroid methods (Klir and Yuan, 2002), a popular technique for defuzzification in the fuzzy logic research and development.

3.5 Fuzzy Control Module Algorithm : The following algorithm outlines the steps required to use the indicators together with the fuzzy inference system:

Function FIS()
{
[1] Input stock closing prices(SP)
[2] MovAve = Calculate(Initial Moving Average)
[3] EMA26 := Calculate(SP, MovAve)
[4] EMA16 := Compute(SP, MovAve)
[5] Calculate MACD: MACD := EMA26 – EMA16
[6] Determine RSI := Calculate(CG, CL)
Where
CG: Gain-stock closing price
CL: Loss-stock closing price
[7] Compute:
PriceChange := Price Change = [(P(t) – P(t-2))/P(t-2)]*100
[8] Compute
Momentum := closetoday – closen days ago
[9] Evaluate Fuzzy inference system
Decision := EvaluateFIS(FIS, MACD, RSI, Trend, Momentum)
[10] If Decision = 0 or Decision < 0.4
[11] then fuzzy_Decision := 'Buy'
[12] Elseif Decision >= 0.4 or Decision <= 0.5
[13] then Fuzzy_Decision = 'No Trade'
Elseif Decision = 1 or Decision > 0.5
[14] then Fuzzy_Decision = 'Sell'
Endif
}
[15] Return (Fuzzy_Decision)

3.6 Forecast Database : The fuzzy forecasts are stored in a MySQL database with following schema/relation:

Fuzzy_Forecast(
ffID INT NOT NULL,
stock VARCHAR(10)
ffDate DATE,
ffValue FLOAT,
ffDecision VARCHAR(5)
PRIMARY KEY (ffID)
)

3.7 User Interface : With the applet loaded the investor is expected to give a view of the day's prediction in the forecast database using a suitable web-browser with java runtime enabled as shown in figure 2.

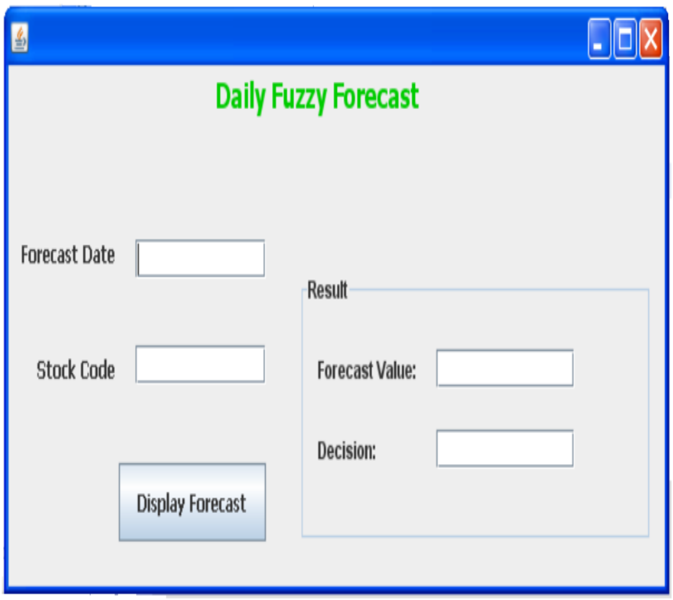

Fig. 3.2: Web Interface for Daily Fuzzy Forecasts

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IV. RESULT

The use of technical indicators is a paradigm different from the fundamental approach to market analysis. Technical analysis is based on the assumption that the forces and underlying market factors represented in the historical price patterns. Hence, the use of fuzzy-based technical indicators is an optimal strategy for stock market forecasting. The results of our simulated trades are presented in below.

Table 4.1 : Fuzzy Forecast Buy/Sell/Hold forecast for selected Banks

Range (PriceCode)	Fuzzy Forecast			Date
	SBI Bank	ICICI Bank	UBI	
1 – 30	0.6661	0.3001	0.3001	04/18/19
2 – 31	0.7020	0.3001	0.7010	04/19/19
3 – 32	0.7020	0.7020	0.7020	04/20/19
4 – 33	0.7020	0.7020	0.7020	04/21/19
5 – 34	0.3001	0.3001	0.5000	04/22/19
6 – 35	0.5894	0.7020	0.7020	04/25/19
7 – 36	0.7020	0.7020	0.7020	04/26/19
8 – 37	0.3001	0.7020	0.7020	04/27/19
9 – 38	0.7020	0.5894	0.5000	04/28/19
10 – 39	0.7020	0.3001	0.7020	04/29/19
11 – 40	0.7020	0.7020	0.7020	05/04/19
12 – 41	0.7020	0.7020	0.7020	05/05/19
13 – 42	0.7020	0.7020	0.3001	05/08/19
14 – 43	0.3001	0.3001	0.3001	05/09/19
15 – 44	0.3001	0.3001	0.6661	05/10/19
16 – 45	0.3001	0.3001	0.6661	05/11/19
17 – 46	0.7020	0.7020	0.7020	05/12/19
18 – 47	0.6661	0.7020	0.7020	05/15/19
19 – 48	0.5000	0.7020	0.6661	05/18/19
20 – 49	0.7020	0.7020	0.7020	05/19/19
21 – 50	0.5000	0.7020	0.7010	05/22/19
22 – 51	0.7020	0.7020	0.7020	05/23/19
23 – 52	0.7020	0.7020	0.7020	05/24/19
24 – 53	0.7020	0.7020	0.7020	05/25/19
25 – 54	0.5894	0.3001	0.7020	05/26/19
26 – 55	0.7020	0.5000	0.6661	05/29/19
27 – 56	0.3001	0.7020	0.7020	05/30/19
28 – 57	0.5000	0.7020	0.5894	06/06/19
29 – 58	0.7020	0.7020	0.5000	06/08/19
30 – 59	0.6661	0.5000	0.7020	06/09/19
31 – 60	0.5000	0.7020	0.7020	06/10/19
32 – 61	0.7020	0.3001	0.7020	06/13/19
33 – 62	0.7020	0.6661	0.7020	06/14/19
34 – 63	0.3001	0.3001	0.3001	06/15/19
35 – 64	0.7020	0.3001	0.7020	06/16/19
36 – 65	0.7020	0.7020	0.5000	06/17/19
37 – 66	0.3001	0.7020	0.5000	06/21/19

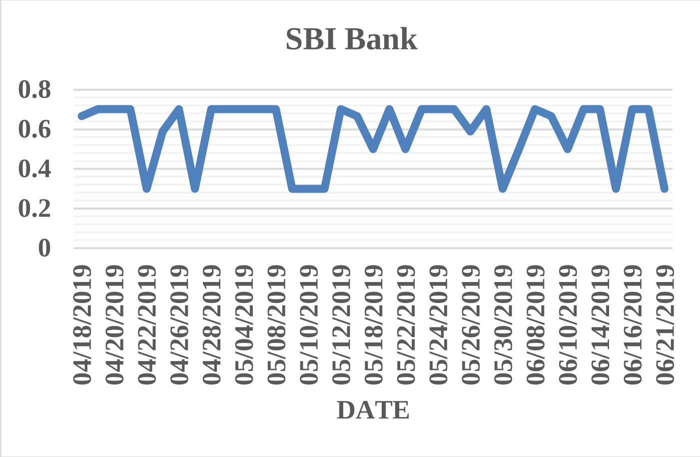

Figure 4.1 : Based on this table, we plot the following charts, for the fuzzy forecasts.

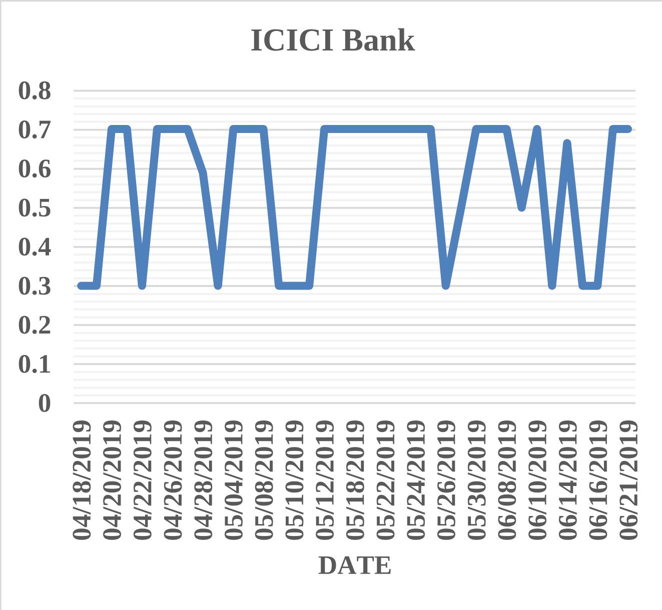

Figure 4.2 : Line Chart of SBI Bank Fuzzy Forecast (typically, 0.3 indicates buy and 0.7 indicates sell

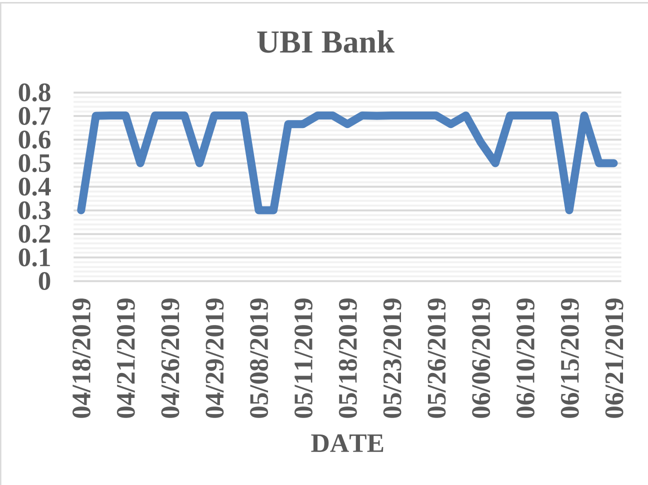

Figure 4.3 : Line Chart of ICICI Bank Fuzzy Forecast (typically, 0.3 indicates buy and 0.7 indicates sell

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Table 4.2: Technical Indicators

Indicator	Equation
MACD	12-day EMA - 26-day EMA
RSI	$RSI = 100 - \frac{100}{1 + rs}$ $RS = \frac{\sum_{n-17}^{n} D(nT)Gains}{\sum_{n-17}^{n} D(nT)losses}$, where $n \geq 17$
	Where EMA := Exponential Moving Average SMA := Simple Moving Averages D(nT) := Stock Closing Price
***EMA**	EMA = (K x (C – P)) + P Where K is a smoothing constant, defined as: $k = \frac{2}{(1+N)}$ And C = Current Close Price; P = Previous Periods EMA (A simple moving average SMA can be used for initialization on the ICICI period) (Also * means the EMA is to formulate other indicators)
Trend	*% Price Change = [(P(t) – P(t-2))/P(t-2)]*100* Where P (t) refers to the price of the stock today and P (t-2) refers to the price of the stock two periods ago.
Momentum	$momentum = close_{today} - close_{n\ days\ ago}$

V. CONCLUSION

The use of technical indicators is a paradigm different from the fundamental approach to market analysis. Technical analysis is based on the assumption that the forces and underlying market factors represented in the historical price patterns. Hence, the use of fuzzy-based technical indicators is an optimal strategy for stock market forecasting. The fuzzy system uses at least 30 days (past) stock price data to make forecast, especially the RSI and MACD indicators. What we discovered from the fuzzy system is that the fuzzy inference system is very meticulous in combining all the indicators/rules to give a crisp forecast. Results obtained from testing the fuzzy prediction gave us a 50% of success against the next day.

REFERENCES

[1] Hiransha, M., E. A. Gopalakrishnan, Vijay Krishna Menon, and Soman Kp. 2018. NSE stock market prediction using deep-learning models. Procedia Computer Science 132: 1351–62.

[2] Fama, Eugene F. 1995. Random walks in stock market prices. Financial Analysts Journal 51: 75–80.

[3] Abu-Mostafa, Yaser S., and Amir F. Atiya. 1996. Introduction to financial forecasting. Applied Intelligence 6: 205–13.

[4] Zhong, Xiao, and David Enke. 2017. Forecasting daily stock market return using dimensionality reduction. Expert Systems with Applications 67: 126–39.

[5] Park, Cheol-Ho, and Scott H. Irwin. 2007. What do we know about the profitability of technical analysis? Journal of Economic Surveys 21: 786–826.

[6] Arévalo, Rubén, Jorge García, Francisco Guijarro, and Alfred Peris. 2017. A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. Expert Systems with Applications 81: 177–92.

[7] Hu, Yong, Kang Liu, Xiangzhou Zhang, Lijun Su, E.W. T. Ngai, and Mei Liu. 2015. Application of evolutionary computation for rule discovery in stock algorithmic trading: A literature review. Applied Soft Computing 36: 534–51.

[8] Imam, Shahed, Richard Barker, and Colin Clubb. 2008. The Use of Valuation Models by Uk Investment Analysts. European Accounting Review 17: 503–35.

[9] Gordon, Myron J., and Eli Shapiro. 1956. Capital Equipment Analysis: The Required Rate of Profit. Management Science 3: 102–10.

[10] Dutta, Avijan, Gautam Bandopadhyay, and Suchismita Sengupta. 2012. Prediction of Stock Performance in Indian Stock Market Using Logistic Regression. International Journal of Business and Information 7: 105–36.

[11] Devi, B. Uma, D. Sundar, and P. Alli. 2013. An E_ective Time Series Analysis for Stock Trend Prediction Using Arima Model for Nifty Midcap-50. International Journal of Data Mining & Knowledge Management Process 3: 65.

[12] Ariyo, Adebiyi A., Adewumi O. Adewumi, and Charles K. Ayo. 2014. Stock Price Prediction Using the Arima Model. Paper presented at the 2014 UKSim-AMSS 16th International Conference on Computer Modelling and Simulation (UKSim), Cambridge, UK, March 26–28.

[13] Bhuriya, Dinesh, Girish Kausha, Ashish Sharma, and Upendra Singh. 2017. Stock Market Prediction Using a Linear Regression. Paper presented at the 2017 International Conference of Electronics, Communication and Aerospace Technology (ICECA), Coimbatore, India, April 20–22; vol. 2.

[14] Fu, Tak-chung, Fu-lai Chung, Robert Luk, and Chak-man Ng. 2005. Preventing Meaningless Stock Time Series Pattern Discovery by Changing Perceptually Important Point Detection. Paper presented at the International Conference on Fuzzy Systems and Knowledge Discovery, Changsha, China, August 27–29.

[15] Leigh,William, Cheryl J. Frohlich, Steven Hornik, Russell L. Purvis, and Tom L. Roberts. 2008. Trading with a Stock Chart Heuristic. IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans 38: 93–104.

[16] Fama, Eugene F. 1970. E_cient Capital Markets: A Review of Theory and Empirical Work. The Journal of Finance 25: 383–417.

[17] Parracho, Paulo, Rui Neves, and Nuno Horta. 2010. Trading in Financial Markets Using Pattern Recognition Optimized by Genetic Algorithms. Paper presented at the 12th Annual Conference Companion on Genetic and Evolutionary Computation, Portland, OR, USA, July 7–11.

[18] Phetchanchai, Chawalsak, Ali Selamat, Amjad Rehman, and Tanzila Saba. 2010. Index Financial Time Series Based on Zigzag-Perceptually Important Points. Journal of Computer Science 6: 1389–95.

[19] Cervelló-Royo, Roberto, Francisco Guijarro, and Karolina Michniuk. 2015. Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index with intraday data. Expert Systems with Applications 42: 5963–75.

[20] Chen, Tai-liang, and Feng-yu Chen. 2016. An intelligent pattern recognition model for supporting investment decisions in stock market. Information Sciences 346: 261–74.

[21] Cheng, Ching-Hsue, Tai-Liang Chen, and Liang-Ying Wei. 2010. A hybrid model based on rough sets theory and genetic algorithms for stock price forecasting. Information Sciences 180: 1610–29.

[22] Arévalo, Rubén, Jorge García, Francisco Guijarro, and Alfred Peris. 2017. A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. Expert Systems with Applications 81: 177–92.

[23] Kim, Sang, Hee Soo Lee, Hanjun Ko, Seung Hwan Jeong, Hyun Woo Byun, and Kyong Joo Oh. 2018. Pattern Matching Trading System Based on the Dynamic TimeWarping Algorithm. Sustainability 10: 4641.

 DOI : 10.35291/2454-9150.2019.0256