Research Journal of Computer and Information Technology Sciences E-ISSN 2320 – 6527
Vol. **4(4),** 1-10, April **(2016)** *Res. J. Computer and IT Sci.*

Fuzzy Aggregate Candlestick and Trend based Model for Stock Market Trading

Partha Roy[1*], Ramesh Kumar[1] and Sanjay Sharma[2]
[1]Department of Computer Sc. and Engg. Bhilai Institute of Technology, Durg, India
[2]Department of Applied Mathematics. Bhilai Institute of Technology, Durg, India
royalproy@yahoo.com

Available online at: www.isca.in, www.isca.me
Received 24th February 2016, revised 17th March 2016, accepted 15th April 2016

Abstract

Forecasting stock markets is always fascinating. In this paper we have used fuzzy rule base and approximate reasoning for creating a model that can be used to predict stock market trend and forecast crisp values. A unique approach is implemented by creating a single aggregate candle from a range of observations and that aggregate candle is fuzzified such that it represents the sentiment of the traders. The concept of time windows is used to generate fuzzy antecedent and consequents. Using Mamdani implication and fuzzy inference mechanism the future trend is forecasted in fuzzy terms and after which crisp futuristic value is generated as the next target for the stock market. The final output from our proposed system is in the form of decision rules that would suggest which Action (buy/sell) the trader should take and for how much Target (crisp value) the trader can expect after taking the specified action in the next trading session. The forecasting efficiency of the proposed model is calculated in the terms of RMSE and compared with other benchmark models the proposed fuzzy model displays promising results. Transaction data of CNX NIFTY-50 index of National Stock Exchange of India is used to experiment and validate the proposed model.

Keywords: Approximate reasoning, Candlestick chart, Fuzzy logic, Prediction, Time series.

Introduction

Stock markets are largely chaotic and dynamic in nature, which are both time and sentiment driven. The time series generated through stock market data can only represent a financial time series of prices but cannot represent the overall sentiment of the market players who trade and invest in the stock markets. The stock market data is a series of prices that are observed in a series of certain time intervals (minutes, hours, days or weeks etc).

There are two main forces that drive the stock markets, one is the buyers and other is the sellers. The trade takes place only when a buyer agrees to buy a stock in a price that the seller has quoted. The law of demand and supply works here well. When the sellers are more and buyers are less then prices go down and when buyers are more and sellers are less, then the prices go up. Also as human beings are involved hence the entire process of buying and selling becomes a resultant of thought processes that run through the minds of the buyers and sellers. The buyers and sellers get inputs from news, rumors, suggestions from other fellow traders, suggestions from broking houses, etc. There are numerous inputs that traders get and accordingly decide to buy or sell in the stock markets. The manner in which the stock markets move is the result of the collective psychological effect of the buyers and sellers. This psychological effect can also be termed as sentimental effect.

Fuzzy logic can be used to closely model the human cognition and behavior. We have used fuzzy logic to model our system so that it can mimic group sentimental behavior of the stock market participants and provide a conclusion than can help a trader or investor to quickly take decisions regarding buying or selling.

We have proposed the design of a fuzzy model using which, firstly we can model the collective sentimental behavior of the stock market participants, secondly using the sentimental information we build a knowledgebase, thirdly using the fuzzy knowledgebase we build an fuzzy inference mechanism that can be used to predict the future direction of the markets and fourth, according to the trend information forecasted, crisp value is generated which can become the next target of the stock market price.

Transaction data of CNX NIFTY-50 index of National Stock Exchange of India is used to experiment and validate the proposed model.

Understanding Bullish/Bearish sentiment with Japanese Candlesticks: Japanese candlestick charts are a combination of line chart and bar chart. According to the Japanese candlestick theory the area between the trading session's open and close values represent the body of the candle. The low and high values represent the extreme ends emerging from the body of the candle, called the wicks or shadows of the candle. Figure 1 illustrates a typical candlestick formation, when the trading session's close value is lower than the open value then the candle is filled with any dark color and if the close value is higher than the open value then the candle is filled with white color.

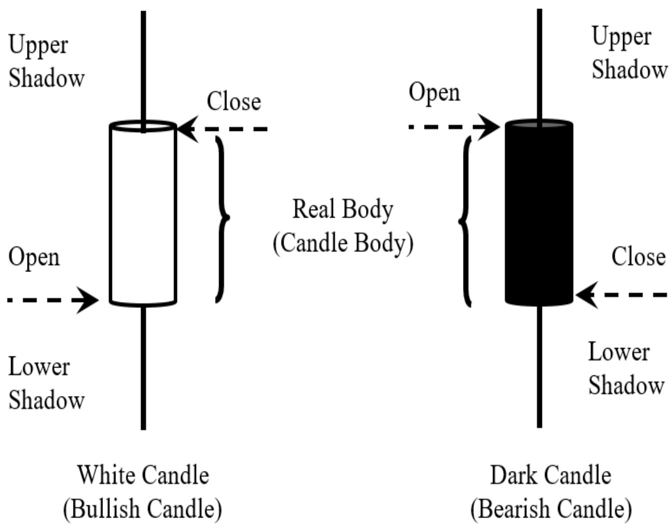

Figure-1
A typical candlestick formation

Japanese candlesticks present us with more than one dimension to understand the current market condition. The first dimension is the price; when close is higher than the open then the market is moving upwards i.e. the buyers are outnumbering the sellers and the trend is *bullish* causing the market values to go up. Similarly, when close is lower than open then the market is moving downwards i.e. the sellers are outnumbering the buyers and the trend is *bearish* causing the market values to go down. The second dimension is the length of the body of the candlestick formation; if the body length is very big then the market sentiment is very strong whether bullish or bearish and if the body length is small then there is some kind of uncertainty or indecision in the market and the market would try to attain some direction in the coming trading sessions[1].

About Fuzzy Logic Theory[2]: A fuzzy set $A\ [x]$ over a universe of discourse X is a set of pairs:
$A = \{(x, \mu A(x))\}$ such that $x \in X$, $\mu A(x) \in [0, 1]$
where$\mu A(x)$ is called the membership degree of the element x to the fuzzy set A. This degree ranges between the extremes 0 and 1:
$\mu A(x) = 0$ indicates that x in no way belongs to the fuzzy set A.
$\mu A(x) = 1$ indicates that x completely belongs to the fuzzy set A.
Zadeh L.A.[2]
In the proposed model the concept of fuzzy logic is implemented to capture the approximate nature of the fuzzy candlestick time series.

Background and Literature Review: The investors and traders in the stock markets use two types of tools for forecasting; one is the fundamental analysis and second is technical analysis. Fundamental analysis uses information gathered from business and economic structure of the company and its related markets, to predict the future stock prices of the company. Technical analysis uses the information present in the stock prices from the past to predict the future[3]. In the proposed model our approach is purely based on technical analysis.

One of the proposed applications of fuzzy logic describes its use in designing controllers for industrial plants where a Fuzzy Logic model is used to synthesize linguistic control protocol of a skilled operator. This work also illustrates the potential for using fuzzy logic in modelling and decision making. He concluded that fuzzy logic should have an auto-descriptive property found in multiple valued logics. In out proposed model we have used the Mamdani implication and fuzzy inference mechanism for decision making[4].

A TSK fuzzy based system can be built by applying a linear combination of the significant technical index as a consequent to predict the stock price. Input variables are effectively selected through the stepwise regression from the set of technical index[5]. The use of fuzzy if-then rules for a decision support system in stock trading. The three following linguistic variables well be the input for the rule: view from the expert, earning - per-share and price to earnings ratio. The purpose of this rule is to assist investors making a decision on their shares[6]. In our proposed fuzzy model we used TSK type fuzzy rule base creation mechanism and used only the information hidden in the price to predict the future.

A fuzzy logic based approach was proposed to model the stock market time series to predict market momentum, Roy Partha et. al.[7]. Our proposed fuzzy model implements a concept of aggregate candle stick approach and its fuzzification to assess the market sentiment.

From the literature review following conclusions were drawn: i. It was found that forecasting is a complex process especially for financial time series. ii. The amount of information that a time series contains, if it is fully extracted, then only the forecasting algorithms can generate more accurate results. iii. The authors have used daily data for modeling their system.

Methodology

In our proposed model we have performed some modifications while using the time series. The hidden sentiment information present in the stock market time series is extracted by treating the time series through fuzzification process. Hence the proposed representation of financial time series is more information-rich than any other way of representation. Figure 2 shows the proposed methodology.

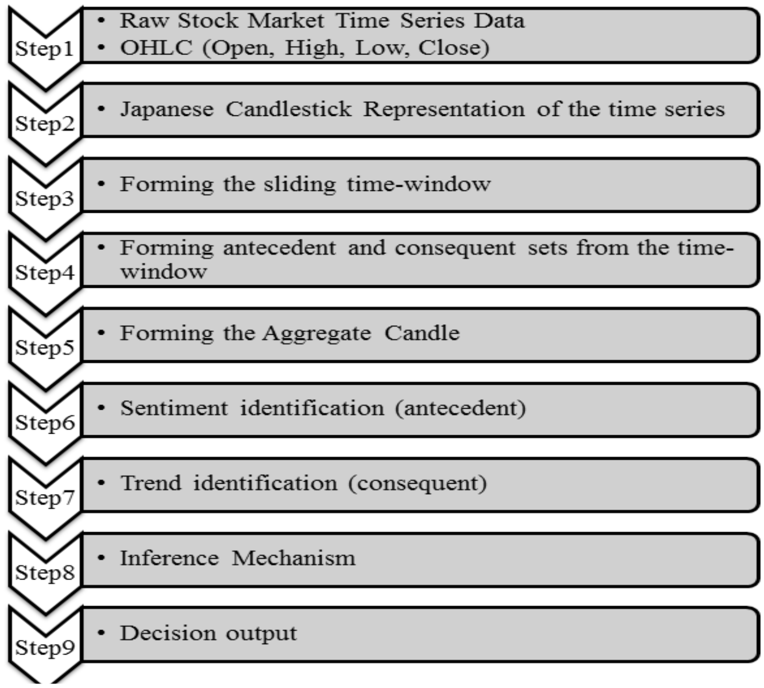

Figure-2
Proposed Methodology

Table-1
CNX NIFTY-50 index daily data with time window of 7 days

Observation No.	Candlestick	Date	Open	High	Low	Close
1	x_{i-6}	20150109	8285.45	8303.3	8190.8	8284.5
2	x_{i-5}	20150112	8291.35	8332.6	8245.6	8323
3	x_{i-4}	20150113	8346.15	8356.65	8267.9	8299.4
4	x_{i-3}	20150114	8307.25	8326.45	8236.65	8277.55
5	x_{i-2}	20150115	8424.5	8527.1	8380.55	8494.15
6	x_{i-1}	20150116	8504.05	8530.75	8452.25	8513.8
7	x_i	20150119	8550.05	8570.95	8531.5	8550.7

Table-2
Forming the aggregate candlestick

Observation No.	Candlestick	Date	Open	High	Low	Close
1	x_{i-6}	20150109	8285.45	8303.3	8190.8	8284.5
2	x_{i-5}	20150112	8291.35	8332.6	8245.6	8323
3	x_{i-4}	20150113	8346.15	8356.65	8267.9	8299.4
4	x_{i-3}	20150114	8307.25	8326.45	8236.65	8277.55
5	x_{i-2}	20150115	8424.5	8527.1	8380.55	8494.15
6	x_{i-1}	20150116	8504.05	8530.75	8452.25	8513.8
7	x_i	20150119	8550.05	8570.95	8531.5	8550.7

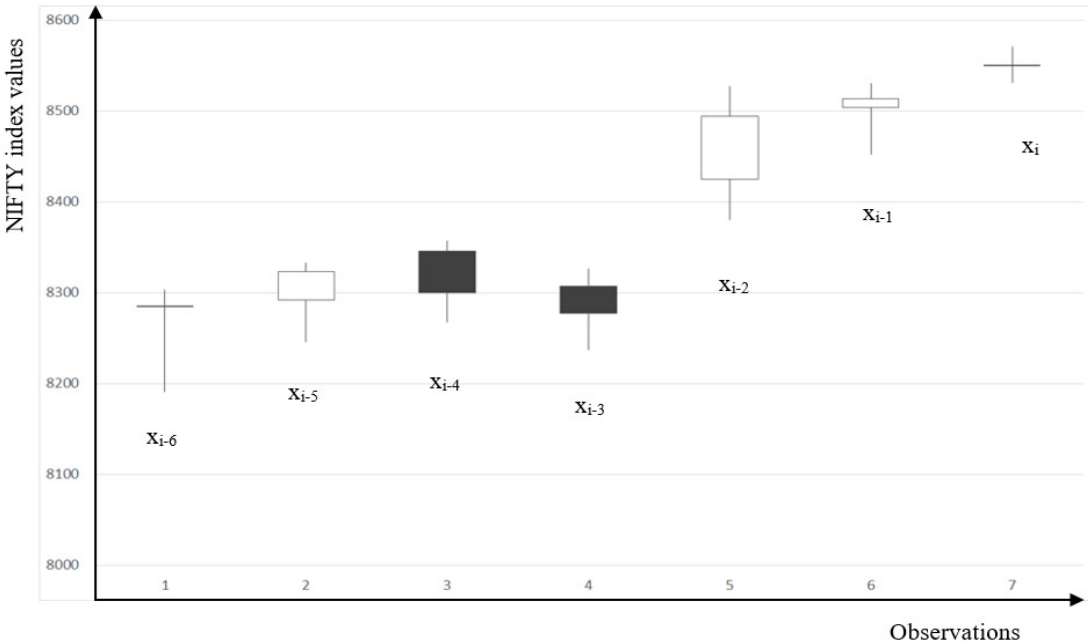

Figure-3
Candlestick chart representation of the time-window data

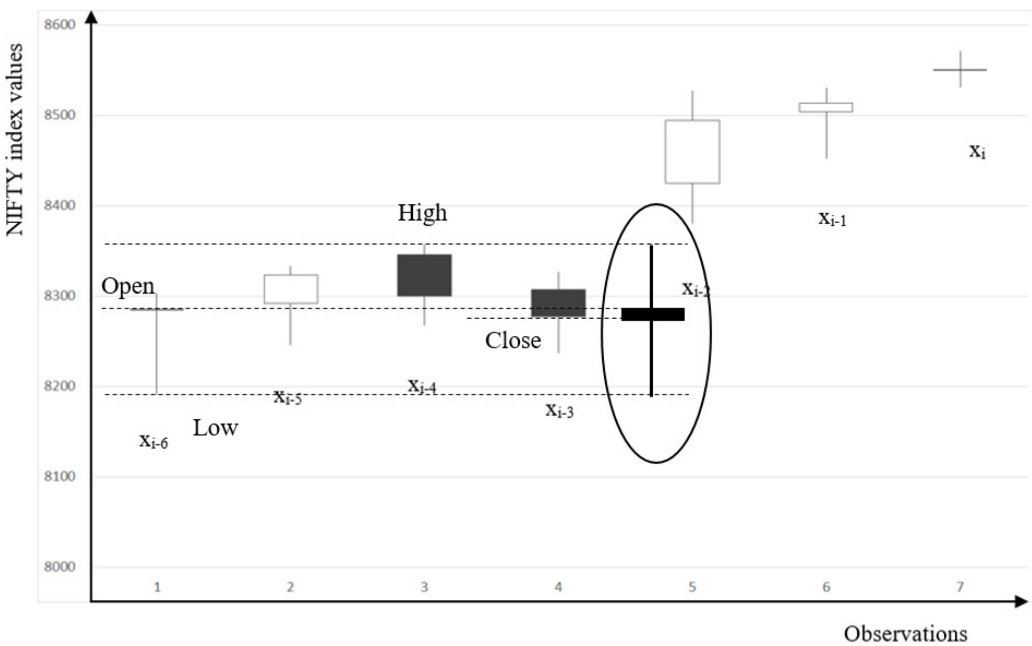

Figure-4
The Aggregate Candle

Following part of this section describes the proposed methodology in details.

Collecting OHLC data*:* The daily Open, High , Low and Close (abbreviated as OHLC) values of NIFTY-50 are collected from the National Stock Exchange of India website and are put together in a chronological order to form the basic time series.

Japanese candlestick representation of the time series data: Using the concept described in previous the daily OHLC data is converted to Japanese candlestick equivalent chart for further analysis.

Forming the sliding time-window: The daily observations of the time series are divided into sliding time window of seven consecutive observations. The sliding time window would shift further in the time series are the fuzzification process completes for the previous window position. Table-1 represents a sample data of NIFTY-50 index in a time-window. Every row presents daily Open, High, Low and Close values of the NIFTY-50 index. The data under the column header "Observation No." represents the observation sequence number of the daily observations in a chronological sequence. The column header "Candlestick" indicates the candlestick bar number in the time window, the candle x_i is the latest observation and the candle x_{i-6} is the oldest observation in the time window. Every candle bar x_i represents information about Open, High, Low and Close values of the i^{th} observation instance.

$x_i = \{ Open_i, High_i, Low_i, Close_i\}$

The column header "Date" represents the observation date in YYYYMMDD format, the column header "Open" represents the opening/staring value of the observation day, the column header "High" represents the highest value of the observation day, the column header "Low" represents the lowest value of the observation day and the column header "Close" represents the closing/last achieved value of the observation day.

Forming antecedent and consequent observation sets: Every seven observations in the time window is divided into two halves. The first half consists of four observations from left of the time window to the middle of the time window forming the antecedent observation set and second half consists of four observations from the middle of the time window to the last observation in the time window forming the consequent observation set. In Table-1 the highlighted row value 4 in the "Observation No." column is the middle of the time window. Figure-3 is the candlestick chart representing the data presented in Table 1. The observations are marked from x_{i-6} to x_i in the Figure-3, that represent the daily observations from observation no. 1 to 7 presented in Table-1. In Table-2 the highlighted row represents that, the observations 1 to 4 will be used to create the aggregate candlestick as the antecedent and observations from 4 to 7 will be used to assess the trend that the market has assumed and it would work as the consequent.

Forming the aggregate candle: The first four observations from x_{i-6} to x_{i-3} are converted into a single candlestick whose open value is the open of x_{i-6} candle highlighted in first row under column header Open in Table-2, high is the highest of all the observations from x_{i-6} to x_{i-3} highlighted in third row under the column header High in Table-2, low is the lowest of all the observations from x_{i-6} to x_{i-3} highlighted in first row in under column header Low in Table-2 and close is the closing price of x_{i-3} candle highlighted in fourth row under column header Close in Table-2. This treatment to the time series is done to represent the combined sentimental effect of the market movements of four trading days i.e. x_{i-6} to x_{i-3}. Figure-4 represents the aggregate candle formed from the observations represented in Figure-3. The candlestick formed from the aggregation process is represented inside the oval shaped boundary in Figure-4. So, now we have a single candle representing the antecedent from the time series data from x_{i-6} to x_{i-3} and rest of the time series from x_{i-3} to x_i is kept as it is to form the consequent part. Note that we have included the observation x_{i-3} in the consequent part, this is done to include more information to the consequent so that more accurate forecasting results can be achieved.

Antecedent sentiment identification: The aggregate candle has to be converted into information rich form so that it can be used as the antecedent in our fuzzy rule base and fuzzy inference system. The aggregate candle has four attributes namely Open, High, Low and Close. Apart from these attributes the sentimental information is hidden in the color of the candlestick, length of the upper shadow, length of the real body and length of the lower shadow (Figure-1). Our prosed fuzzy model is used to convert the sentimental information of the candlestick into fuzzy linguistic terms that is used in fuzzy knowledgebase. The proposed fuzzification process is explained in details in the coming sections.

Consequent trend identification: The trend information is extracted from the time series observation sequence x_{i-3} to x_i and this trend information is fuzzified by our proposed model. The fuzzy trend information becomes the consequent of the fuzzy knowledgebase. The distance between x_{i-3} to x_i is used as the trend information, if the difference ($x_i - x_{i-3}$) is zero or positive then the direction of the trend is up and if this difference is negative then the direction of the trend is down. But this direction information is not enough to decide the outcome as we need to know to how much degree that a trend is up or down, then only the information in fuzzy knowledgebase becomes more optimized. Hence, the amount of upward or downward trend is identified by using our proposed fuzzy model.

The inference mechanism: Once the antecedents and their respective consequents are formed by moving the time windows throughout the time series data, the knowledgebase is created by our proposed model. Using Mamdani type fuzzy inference system we predict the future trend. Now that we have got the future trend's fuzzy value, the next step is to calculate crisp futuristic value that the market would attain in next trading session. The crisp value is calculated by observing the non-negative average difference between the closing prices of the previously observed data's first half of the time window i.e. average of difference between the closing prices from x_{i-6} to x_{i-3} using the equation specified below.

$$amt = \left[\frac{|x_{i-6} - x_{i-5}| + |x_{i-5} - x_{i-4}| + |x_{i-4} - x_{i-3}|}{3}\right] \qquad (1)$$

Decision output: Following decision rules are used to decide the crisp futuristic values and buy/sell decision:

DR1: IF *Predicted Trend* = *Neutral* THEN *Action* = *BUY* AND *Target* = x_{i-3} close value + (*amt**0.15)

DR2: IF *Predicted Trend* = *Bullish Neural* THEN *Action* = *BUY* AND *Target* = x_{i-3} close value + (*amt**0.30)

DR3: IF *Predicted Trend = Bearish Neutral* THEN *Action = SELL* AND *Target* $=x_{i-3}$ close value - (*amt**0.30)
DR4: IF *Predicted Trend = Bullish* THEN *Action = BUY* AND *Target* $=x_{i-3}$ close value + (*amt**0.60)
DR5: IF *Predicted Trend = Bearish* THEN *Action = SELL* AND *Target* $=x_{i-3}$ close value - (*amt**0.60)
DR6: IF *Predicted Trend = Very Bullish* THEN *Action = BUY* AND *Target* $=x_{i-3}$ close value + (*amt**0.75)
DR7: IF *Predicted Trend = Very Bearish* THEN *Action = SELL* AND *Target* $=x_{i-3}$ close value - (*amt**0.75)
DR8: IF *Predicted Trend = Extremely Bullish* THEN *Action = BUY* AND *Target* $=x_{i-3}$ close value + *amt*
DR9: IF *Predicted Trend = Extremely Bearish* THEN *Action = SELL* AND *Target* $=x_{i-3}$ close value – *amt*

The output of the decision rules DR1 to DR9 would be the *Action* (buy/sell) that the trader should take on the next trading session and the *Target* (crisp value) value the trader can expect the market would achieve in the next trading session.

Results and Discussion

Experimental Results and Analysis: For experiments, CNX NIFTY-50 index daily data of the National Stock Exchange of India is used. Table 3 gives a snapshot of the data that was used for generating the fuzzy knowledgebase. The range of data that was used started from 01-Jan-1997 to 25-Mar-2015.

Every row in the Table-3 represents daily Open, High, Low and Close values of the NIFTY index. The data presented in Table 3 displays date in the first column in YYYYMMDD format, Open value of the day in the second column, High value of the day in the third column, Low value of the day in the fourth column and Close value of the day in fifth column.

A moving time window with 7 consecutive observations at a time is considered for creating the fuzzy rule base. From the steps explained in the section "Proposed Methodology", the antecedent aggregate candle generated and consequent trend is generated using the proposed fuzzy model.

As an experimental example the following Table-4 displays the fuzzy values generated by assessing the sentiment value of the aggregate candle from the data presented previously in Table-1.

After the extracting the fuzzy sentiment values from the aggregate candle the fuzzy trend information is extracted, which is displayed in Table-5.

When the antecedent and consequent fuzzy values are achieved then the fuzzy relation matrices are created which represent the relation between the Upper Shadow attribute of the aggregate candle and trend attained after the aggregate candle, this information is presented in Table-6. Similarly, the relation between Real Body and consequent trend is displayed in Table-7 and the relation between Lower Shadow and consequent trend is presented in Table-8.

Table-3
Snapshot of CNX NIFTY-50 index daily data

Date	Open	High	Low	Close
19970101	905.2	941.4	905.2	939.55
19970102	941.95	944	925.05	927.05
...	…	…	…	…
...	…	…	…	…
20150323	8591.55	8608.35	8540.55	8550.9
20150324	8537.05	8627.75	8535.85	8542.95
20150325	8568.9	8573.75	8516.55	8530.8

Table-4
Fuzzy values from antecedent aggregate candle

Aggregate Candle's Attributes	Aggregate Candle's Sentiment Information				
	Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
Upper Shadow	0.00	0.00	0.06	0.94	0.00
Real Body	0.00	0.00	0.00	0.00	1.00
Lower Shadow	1.00	0.00	0.00	0.00	0.00

Table-5
Fuzzy values from the consequent trend

Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
0.00	0.00	0.00	0.00	1.00

Table-6
Fuzzy Relation Matrix for Upper Shadow and Trend

Fuzzy Upper Shadow values	Fuzzy Trend values				
	Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
Neutral	0.00	0.00	0.00	0.00	0.00
Bullish Neutral	0.00	0.00	0.00	0.00	0.00
Bullish	0.00	0.00	0.00	0.00	0.06
Very Bullish	0.00	0.00	0.00	0.00	0.94
Extremely Bullish	0.00	0.00	0.00	0.00	0.00

Table-7
Fuzzy Relation Matrix for Real Body and Trend

Fuzzy Real Body values	Fuzzy Trend values				
	Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
Neutral	0.00	0.00	0.00	0.00	0.00
Bullish Neutral	0.00	0.00	0.00	0.00	0.00
Bullish	0.00	0.00	0.00	0.00	0.00
Very Bullish	0.00	0.00	0.00	0.00	0.00
Extremely Bullish	0.00	0.00	0.00	0.00	1.00

Table-8
Fuzzy Relation Matrix for Lower Shadow and Trend

Fuzzy Real Body values	Fuzzy Trend values				
	Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
Neutral	0.00	0.00	0.00	0.00	1.00
Bullish Neutral	0.00	0.00	0.00	0.00	0.00
Bullish	0.00	0.00	0.00	0.00	0.00
Very Bullish	0.00	0.00	0.00	0.00	0.00
Extremely Bullish	0.00	0.00	0.00	0.00	0.00

Table-9
Fuzzy values of newly observed data

Aggregate Candle's Attributes	Aggregate Candle's Sentiment Information				
	Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
Upper Shadow	0.00	0.00	0.30	0.70	0.00
Real Body	0.00	0.00	0.00	0.00	1.00
Lower Shadow	1.00	0.00	0.00	0.00	0.00

Table-10
Fuzzy Inference Matrix

Fuzzy Real Body values	Fuzzy Trend values				
	Neutral	Bullish Neutral	Bullish	Very Bullish	Extremely Bullish
Neutral	0.00	0.00	0.00	0.00	0.70
Bullish Neutral	0.00	0.00	0.00	0.00	1.00
Bullish	0.00	0.00	0.00	0.00	1.00
Very Bullish	0.00	0.00	0.00	0.00	0.70
Extremely Bullish	0.00	0.00	0.00	0.00	1.00
MEDIAN:	**0.00**	**0.00**	**0.00**	**0.00**	**1.00**

Table-11
Output generated by the proposed model

Date	Actual-value	Forecasted-value
20150327	8269.15	8300.43925
20150330	8380.75	8299.693
20150506	8083	8283.176
…	…	…
…	…	…
20150513	8089.8	8086.31525
20150514	8137.3	8194.27275
20150515	8212.2	8183.079

Table-9 represents the fuzzy information of the newly observed data whose antecedent is known but consequent is unknown. In order to create an inference matrix fuzzy composition is performed between the fuzzy relational matrices and fuzzy values from newly observed data.

Table-10 shows the fuzzy inference matrix whose values are achieved from fuzzy max-min composition operation between the newly observed fuzzy information and fuzzy relational matrices. The final results are displayed in the last row of table 10 where median of values are used for every column which represent the type of trend that is forecasted for future. From the highlighted row values the last column is found to be maximum and hence it can be inferred that after the newly observed data is encountered the future trend will be Extremely Bullish (EXBL). Now that we have got the future trend's fuzzy value, the next step is to calculate crisp futuristic value that the market would attain in next trading session. The crisp value is calculated and decision rules DR1 to DR9 specified in section "Proposed Methodology".

Table-11 presents a snapshot of the comparison of the actual closing value and forecasted closing value generated from our proposed model.

The column 'DATE' represents date in YYYYMMDD format and every row represents one trading day. The column 'ACTUAL-VALUE' represents daily observed values of the NIFTY-50 index from 27-March-2015 to 15-May-2015 and the values presented in the column 'FORECASTED-VALUE' are the values generated by the proposed model. The error is calculated for each row and RMSE value is evaluated as 81.4774.

The performance analysis of the proposed model is done by calculating the Root Mean Squared Error (RMSE).The RMSE (also interpreted as the root mean square deviation, RMSD) is a measure used frequently to calculate the difference between predicted values generated by a model and the actual values observed from the real-time environment from where the model is created.

The individual differences so calculated are also called residuals, and the RMSE helps to aggregate these residuals into a single measure of predictive power. Lower values of RMSE relative to the number of observations suggest better predictability of the model.

The RMSE is calculated as the square root of the mean squared error, where, $X_{obs,i}$ is observed or actual value of the i^{th} instance and $X_{model,i}$ is modelled or forecasted value for the same i^{th} instance:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (X_{obs,i} - X_{model,i})^2}{n}} \qquad (2)$$

In order to verify the efficiency of the proposed model a number of experiments were performed with the same set of crisp values with other well-known algorithms through data-mining software WEKA 3.7.12.

The contents of Table-12 displays the comparative of the already established benchmark models' and the proposed model's performance.

Table-12
Performance comparison between proposed fuzzy model and other benchmark models

Model used	RMSE
Holt-Winters triple exponential smoothing	308.9428
RBF Network	105.978
Random Forest	57.5037
Proposed Method	81.4774

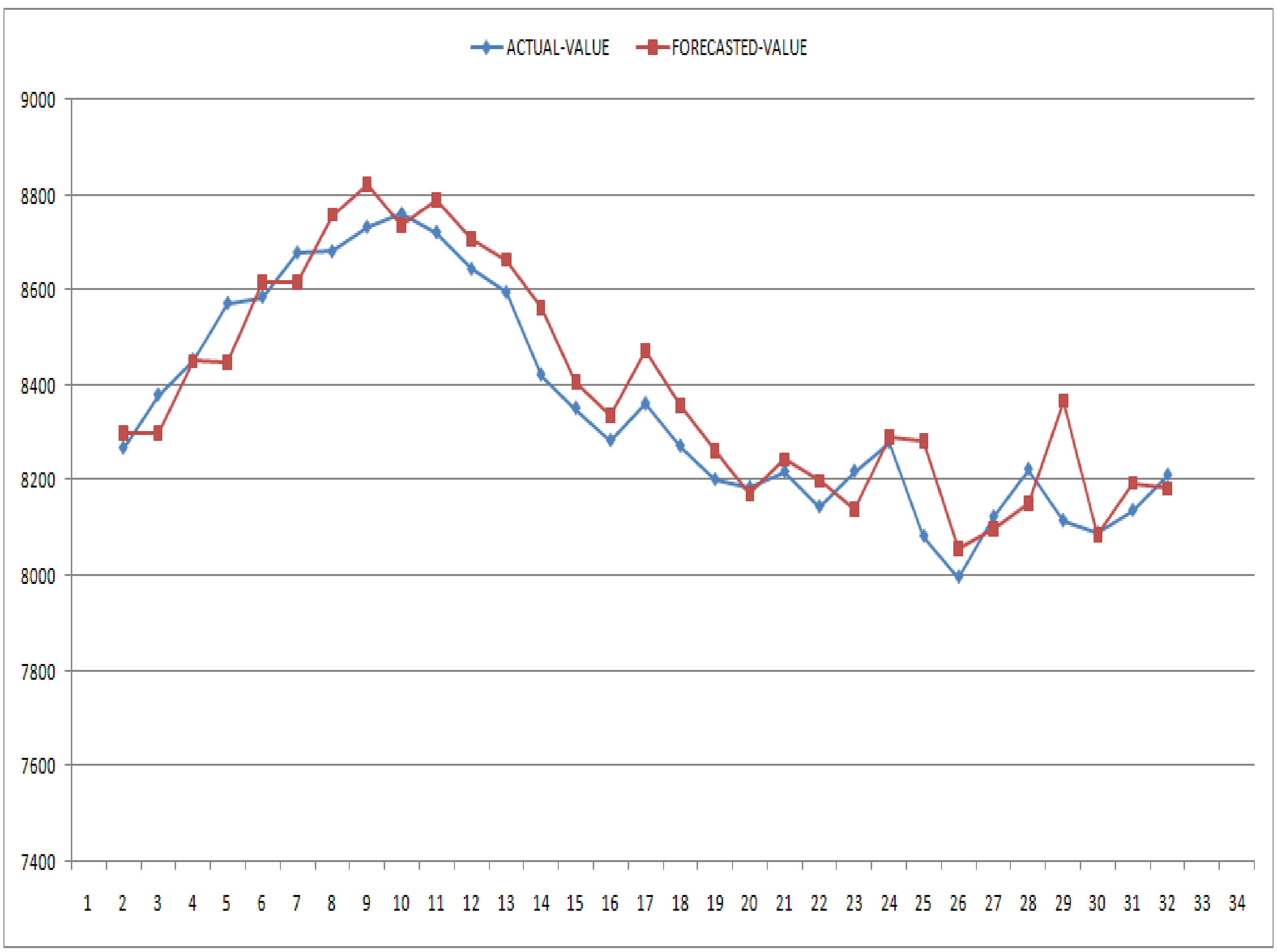

Figure-5
Actual and Forecasted values

The performance of the newly proposed model is compared with three other benchmark models namely, Holt-Winters with triple exponential smoothing, RBF Network (Normalized Gaussian radial basis function network) and Random Forest on the basis of RMSE. The comparison is done with different categories of models so that performance can be judged more critically. The RMSE comparative is tabulated in Table-12 and Figure-5 depicts a graphical representation of the actual values versus predicted values.

Conclusion

In the proposed fuzzy model the time series data is compartmentalized into time windows having seven consecutive observations from the time series at a time. This time window is shifted throughout the time series to capture the antecedents and consequents. The first half of the time window containing the initial four observations are used to act as antecedent. Then the first half of the time window containing the four consecutive observations are converted into a single aggregate candle bar that represents the sentiment of the traders that has accumulated in those four sessions, this is a unique approach to gauge the market sentiment. After the antecedent aggregate candle is converted to its fuzzy equivalent values through our proposed fuzzy model, the consequent is generated from price movement that took place in the second half of the same time window. The price trend formed is also fuzzified by our proposed fuzzy model and the pair of fuzzy antecedent and consequent is added to the fuzzy rule base. As the time window is moved further another set of fuzzy rules are created and those again get added to the fuzzy rule base repository. The inference mechanism of the proposed fuzzy model is used to forecast the future trend and after the trend is identified the crisp prediction value is generated by our system.

The entire set of raw time series data is divided into two halves, the first half which is 75% of the observations become the training set and the second half which is 25% of the total data set becomes the test set. The training set consists of daily NIFTY-50 data ranging from 01-Jan-1997 to 25-Mar-2015 and the test set contains daily observation data ranging from 27-March-2015 to 15-May-2015. The experimental results and performance analysis indicate that the proposed model has produced promising results while forecasting. Apart from using NIFTY-50 index we have experimented in stocks of Indian stock market from various categories and found the forecasting results with more that 65% accuracy.

The proposed model generates a knowledgebase that can successfully extract and model the market sentiment and price trend related information from any stock market time series. The novel approach adopted to represent the financial time series using the proposed fuzzy model has produced promising results.

However, improvisation is underway for increasing the forecasting accuracy of the model by experimenting more on the fuzzy elements of the proposed model. To increase the accuracy of forecasting, elements of fundamental analysis could also be included in the proposed model.

References

1. Nisson S. (2001). Japanese candlestick charting techniques: A contemporary guide to the ancient investment techniques of the Far East (2nd ed.). New York Institute of Finance, ISBN-13: 978-0735201811.

2. Zadeh L.A. (1975). The Concept of a Linguistic Variable and its Application to Approximate Reasoning-I. *Information Sciences*, Elsevier, 8(3), 199-249.

3. Bagheri A., Peyhani H.M. and Akbari M. (2014). Financial forecasting using ANFIS networks with quantum-behaved particle swarm optimization. *Expert Systems with Applications*, 41, 6235–6250.

4. Mamdani E.H. (2000). Application of fuzzy logic to approximate reasoning using linguistic synthesis. IEEE Transactions on Computers, C-26(12), 196-202.

5. Chang Chann Pei and Liu Hao Chen (2008). A TSK Type Fuzzy Rule Based System for Stock Price Prediction. *Expert Systems with Applications*, Elsevier Ltd., 34(1), 135–144.

6. Othman Shuhadah and Schneider Etienne (2010). Decision Making Using Fuzzy Logic for Stock Trading. *IEEE-Information Technology* (ITSim), *International Symposium*, 2, 880-884.

7. Roy Partha, Ramesh Kumar and Sanjay Sharma (2015). A Fuzzy Logic Model to Forecast Stock Market Momentum. *Int. J. Adv. Engg. Res. Studies*/IV/II/Jan.-March 98, 101.