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TREND DISCOVERY OF S&P CNX NIFTY 50 INDEX VALUES THROUGH FUZZY LOGIC

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ABSTRACT

Trend indentification is a visual process where we can draw and see the trend line, then suggest the trend. But to make the system understand this trend is very tough. Using fuzzy logic first we try to make the system understand the actual trend and verify with, what we can see and then we go on for forecasting the future trend. Fuzzy membership functions are the key elements while creating any fuzzy system[1],[2]. For generating these membership functions usually two sources are used, i.e. expert knowledge and real time data. Expert knowledge may not be available all the time, but the probability of getting real time data is more. Here we have tried to develop a method by which fuzzification of real time data can be done and then identification of the trend can be done using those fuzzy values after which forecasting of the short term trend can be done[7],[8],[9]. The type of real time data used here is the daily values of S&P CNX NIFTY 50 index used in National Stock Exchange of India for stock futures trading.
Keywords—fuzzy logic, forecasting, moving averages, correlation, least square criterion, S&P CNX NIFTY 50

I. INTRODUCTION

Fuzzy Sets Theory was introduced by L. A. Zadeh [1] in 1965. It is different from the traditional Set Theory by using membership function to deal with the questions that cannot be solved by two-valued logic of traditional set theory. After 1965, fuzzy sets have been applied to many fields such as Decision Analysis, System Theory, Artificial Intelligence, Economics and Control Theory.

Since fuzzy time series models provide us more flexibility in dealing with forecasting problems. Most previous attempts on derivation of membership functions require expert knowledge of the application area. However, these methods suffer from the problem of knowledge acquisition and subjectivity.

There are usually three types of trends found in the stock market. The Bullish trend indicates that next few sessions might show an up trend and values may move up. The

Bearish trend indicates that next few sessions might show down trend and values may move down. The Neutral trend indicates that next few sessions might show values that would be in a range bounded around few points above and below the mid distance between highest and lowest values. This information is very useful to the short term traders who purchase and sell with in a time span of one week or so. For our experiments we use S&P CNX NIFTY 50 index used in National Stock Exchange of India for stock futures trading. The real time data is collected from the websites of National Stock Exchange of India (http://www.nseindia.com), Bombay Stock Exchange (http://www.bseindia.com) and Yahoo finance India (http://in.finance.yahoo.com).

We in our proposed model try to use the most recent 5-day real time data and fuzzify them using a modified S-function, using which we can first identify the trend represented the 5-day data, secondly we use correlation, simple linear regression and least square criterion to predict the future trend which we can expect in the 6th day. Here we use a modified fuzzy value manipulation method, which may some time result values which are below zero and some times positive values, but not greater than 1.

This paper is organized as follows: Literature review is presented in section2, Identification of present trend using fuzzification of the values is explained in section3, prediction of the immediate future using correlation, simple linear regression and least square criterion is explained in section4, the practical implementation of the proposed models are shown using examples in section5 and section6.

II. LITERATURE REVIEW

The S&P CNX Nifty covers 23 sectors of the Indian economy and offers investment managers exposure to the Indian market in one portfolio.The S&P CNX Nifty stocks represent about 60% of the total market capitalization of the National Stock Exchange (NSE) of India.

The index is a free float market capitalisation weighted index. From inception, the index used full market capitalisation as weight assigned to different constituents. The S&P CNX Nifty Index was developed by Ajay Shah and Susan Thomas.

The attractive feature of the stock market is that every investor has the image to make millions in return from buying and selling stocks (cash and futures). Unfortunately, the reality of the nature of the market poses a less optimistic picture. Although, researchers have proposed many methods to somehow predict the market movements and also it is observed that the best market players have been the investors who use their professional knowledge of the markets to predict the next trend of the stock price. Here the need of an automated trustworthy forecasting tool is extremely desired, so that the investors don't have to rely on some one else to do forecasting for them. And also, the more accurately the forecasting tool performs, the more profitable it would be for the investor. In [10-13], Chen proposed several methods, such as simplified arithmetic operations, high-order fuzzy relationships and genetic algorithms to improve forecasting accuracy. In [6], Huarng points out that the length of intervals affected the forecasting accuracy in fuzzy time-series. In [2], Yu argues that the recurrent fuzzy relationships should be considered in forecasting, and recommended that different weights be assigned to various fuzzy relationships.

In general, methods can be classified in four major categories: (i) Technical Analysis, (ii) Fundamental Analysis, (iii) Traditional Time Series Forecasting and (iv) Machine Learning Methods. Technical Analysis is probably the most common approach to trend forecasting. A large literature is available[18]. Technical analysis makes use of composite functions, such as indicators and oscillators, derived by time series, and heuristic rules able to reveal signals of change in the market trends. Popular examples of methods are Moving Average Convergence Divergence (MACD), Relative Strength Index (RSI), Stochastic oscillator. This approach relies on the belief that markets are mostly driven by psychology, more than economics. Therefore, trading opportunities can be discovered by carefully analyzing the behavior of other investors, that is reflected on price movements. Indeed, detected trends are assumed to be based on supply and demand issues which often have cyclical or noticeable patterns. Although, this approach is very popular among practitioners to predict the market, it received several criticisms, especially from academia. The major source of criticism is that, rule used to identify trend signals, often relying on visual patterns on charts, the large number of parameters on which indicators and oscillators are based, the absence of a theoretical framework able to explain why this approach works and how to choose and tune the different tools, make this class of techniques largely subjective. In addition, being these mostly based on human judgment, makes technical analysis not appropriate for algorithmic trading. However, recent studies provides support to Technical Analysis as useful fro predicting market trends [19]. Fundamental Analysis assumes that market trends are driven by then economic context and financial figures of companies traded. Fundamental Analysis aims at estimating the intrinsic value of a stock, so that if the current value is lower than the intrinsic value, additional investments are expected, otherwise disinvestment will occur. However, although this approach relies on economic fundamentals [20], and can lead to profitable trading strategies [21], this approach is more appropriate for long-term strategies, than near-term strategies, as those employed by day trading. Both Technical and Fundamental Analysis do not perform any quantitative analysis of time series. Traditional Time Series Forecasting relies on linear models able to translate the body of knowledge of stochastic signal processing, providing a quantitative approach to Finance [22]. For a dated, but still valid overview of statistic forecasting see reference [23]. Trend forecasting can be regarded as a problem of pattern matching or approximation, so that methods studied in the area of Machine Learning, Soft Computing and Computational Intelligence have being experimented for this task. These methods use a set of samples to generate an approximation of the underling function and relationship between data. In common, they share the aim of drawing predictions when unseen data are presented to a model. There is a rich literature related to the forecast of the market on daily basis. Among the different models, probably Artificial Neural Networks are the most prominent example. As an example, Saad, Prokhorov and Wunsch [24] discuss a comparison three architecture of neural networks, namely time delay (TDNN), recurrent (RNN) and probabilistic neural networks (PNN), for stock trend predictions. They argue that short-term trends are particularly attractive for neural network analysis and they can be used profitably. However, false trading signals can lead to wrong decisions and losses. They advocate neural networks are able to filter out false trading signals, if properly trained.

In our approach we use fuzzy logic as it does not need tones of data as in the case of ANN, and also the results are achieved fast. From the above suggested method, the fuzzification of the NIFTY values is done in an easy way using S-function to assess the short term trend.

We took the actual 5-day data and fuzzified it, we successfully made the system understand the current trend and then we successfully made the system predict the future trend for the 6^{th} day. The approximations presented by both the methods are good.

III. IDENTIFICATION OF PRESENT TREND

Trend indentification is a visual process where we can draw and see the trend line, then suggest the trend. But to make the system understand this trend is very tough. Using fuzzy logic first we try to make the system understand the actual trend and verify with what we can see, then we go on for forecasting.

Here we collect the previous 5-day real time data and convert each value to its equivalent fuzzy membership value. Here the universe of discourse will be the range of values that lie between the lowest and highest values in those 5-days. After fuzzification the 2-day moving averages are found and this process is repeated till two values are left and finally the difference of those values are found.

Fuzzy Sets

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.

Membership Grade: M(x)

We propose the following fuzzy sets:

$M_O(x)$, $M_H(x)$, $M_L(x)$, $M_C(x)$: representing fuzzy values of the Open, High, Low and Close values.

$M_T(x)$: represents the present fuzzy trend value.

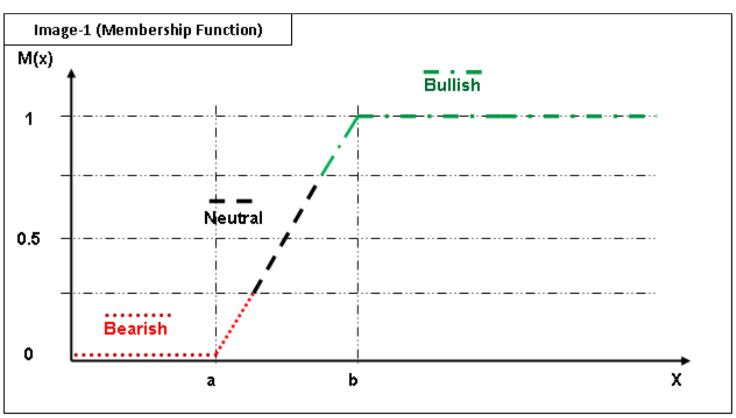
Using the following equation we can calculate the membership grade for every value of ‘x’, where ‘x’ is the daily NIFTY value, which the universe of discourse.

The value of **a** is the lowest value and **b** is the highest value in the universe of discourse.

$$M(x) = \begin{cases} 1.0 & \text{if, } x \geq b \\ \frac{x-a}{b-a} & \text{if, } a \leq x \leq b \\ 0 & \text{if, } x \leq a \end{cases}$$

Figure.1: Membership Grade M(x)

Image 1: Membership Function



Following table (Table 1) gives an interpretation of the $\mathbf{M_T(x)}$ values

Table.1: Trend Interpretation

$\mathbf{M_T(x)}$	**Interpretation of Trend**
Less than 0	Bearish
0 to 0.01	Neutral
Above 0.01	Bullish

Steps in Trend Identification:

Step1: We accumulate the five day Open, High, Low and Close values.

Step2: Considering the values of a,b and c given in the Table-3a we now calculate the fuzzy values MO(x), MH(x), ML(x) and MC(x) representing fuzzy equivalent for Open, High, Low and Close values for every day separately.

Step3: Then using the fuzzy values we find the 2-day moving averages progressively till we are left with two values.

Step4: Now we obtain the difference between the last two values i.e. last_value – second_last_value. This is our MD(x). This MD(x) value is obtained for Open, High, Low and Close values, so MDO(x), MDH(x), MDL(x) and MDC(x) are obtained respectively.

Step5: To get the final trend value we obtain the average of MDO(x), MDH(x), MDL(x) and MDC(x) and achieve the current trend value, MT(x).

Step6: Using the value obtained for MT(x) and guidelines given in Table-2 we can interpret the current trend.

IV. FORECASTING OF THE TREND

With the help of the fuzzified values of previous 5-days we use Correlation, Simple Linear Regression[5],[6] and use the Least Square Criterion to predict the fuzzy value that may be achieved on the 6th day. The idea is to achieve an equation of line that can indicate the next move of the market.

Steps in Trend Forecasting:

Step1: We find the coefficient of correlation ‘r’ using the formula:

$$\mathbf{r} = \frac{n\sum XY - \sum X \sum Y}{\sqrt{n\sum X^2 - \left(\sum X\right)^2} * \sqrt{n\sum Y^2 - \left(\sum Y\right)^2}}$$

Step2: For prediction we try to fit a line that passes through the values

Ypred = B0 + B1*X

Here Ypred is the predicted value of Y w.r.t. X.

Bo is the Y intercept and B1 is the slope.

$$Y` = \frac{\sum Y}{n}$$

$$X` = \frac{\sum X}{n}$$

$$B0 = Y` - B1*X`$$

$$B1 = \frac{\sqrt{\sum (Y - Y`)^2}}{\sqrt{(X - X`)^2}} * r$$

Step 3: Using the following table (Table.2) we specify the trend which the results indicate:

Table.2: Trend Interpretation of Forecasted fuzzy value

$M_T(x)$	Interpretation of Trend
0 to 0.125	Very Bearish
0.126 to 0.25	Bearish
0.251 to 0.49	Bearish Neutral
0.491 to 0.5	Neutral
0.51 to 0.74	Bullish Neutral
0.741 to 0.875	Bullish
0.876 to 1	Very Bullish

V. REPRESENTATION THROUGH EXAMPLE FOR TREND IDENTIFICATION

Following is a table representing the historical values of S&P CNX NIFTY 50 index, that will be used for this experiment.

Sr.No.	Date	Open	High	Low	Close
1	06/13/2011	5,469.85	5511.45	5437.55	5,498.50
2	06/14/2011	5,485.60	5,520.15	5,484.20	5,500.50
3	06/15/2011	5,494.45	5,499.35	5,438.95	5,447.50
4	06/16/2011	5,419.65	5,447.50	5,389.80	5,396.75
5	06/17/2011	5,412.50	5421.15	5355.85	5,366.40

(Source: http://in.finance.yahoo.com/q/hp?s=%5ENSEI)

A	b
5355.85	5520.15

For Open values

$M_O(x)$	Ma1(x)	Ma2(x)	Ma3(x)	$MD_O(x)$	TREND
0.693852708					
0.789713938	0.97				
0.843578819	0.94	0.96			
0.38831406	0.72	0.83	0.89		
0.344796105	0.48	0.60	0.71	-0.18	BEARISH

For High values

$M_H(x)$	Ma1(x)	Ma2(x)	Ma3(x)	$MD_H(x)$	TREND
0.947048083					
1	0.97				
0.873402313	0.94	0.96			
0.557821059	0.72	0.83	0.89		
0.397443701	0.48	0.60	0.71	-0.18	BEARISH

For Low values

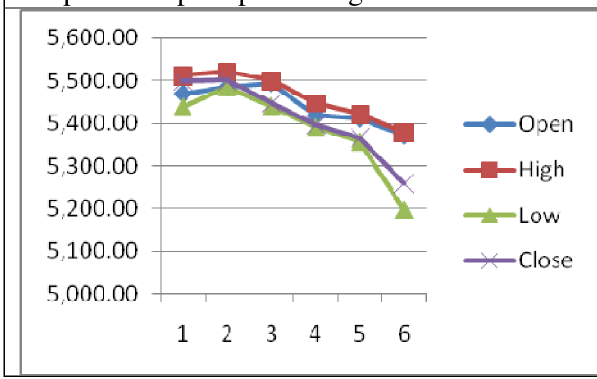
$M_L(x)$	Ma1(x)	Ma2(x)	Ma3(x)	$MD_L(x)$	TREND
0.497261108					
0.78119294	0.64				
0.505782106	0.64	0.64			
0.206634206	0.36	0.50	0.57		
0	0.10	0.23	0.36	-0.21	BEARISH

For Close values

$M_C(x)$	Ma1(x)	Ma2(x)	Ma3(x)	$MD_C(x)$	TREND
0.86822885					
0.880401704	0.87				
0.557821059	0.72	0.80			
0.248934875	0.40	0.56	0.68		
0.064211808	0.16	0.28	0.42	-0.26	BEARISH

$M_T(x)$=Average($MD_O(x)$, $MD_H(x)$, $MD_L(x)$, $MD_C(x)$)
$M_T(x)$= -0.21 which implies a **Bearish Trend**

Graph.1: Graph representing the trend



From the above graph (Graph.1) it can be observed that the slopes of the Open, High, Low and Close values are down indicating a down trend hence it can be concluded that the trend is bearish.
The experiment was conducted for various sets of real time values and it was found that our system can identify the trend to a very large extent.

VI. Representation through Example for Trend Forecasting

Following is a table representing the historical values of S&P CNX NIFTY 50 index, which will be used for this experiment.
(Source: http://in.finance.yahoo.com/q/hp?s=%5ENSEI)

Sr.No	Date	Open	High	Low	Close
1	06/14/2011	5,485.60	5,520.15	5,484.20	5,500.50
2	06/15/2011	5,494.45	5,499.35	5,438.95	5,447.50
3	06/16/2011	5,419.65	5,447.50	5,389.80	5,396.75
4	06/17/2011	5,412.50	5421.15	5355.85	5,366.40
5	06/20/2011	5,372.20	5,377.40	5,195.90	5,257.90
6	**06/21/2011**	**5,280.80**	**5,322.45**	**5,257.00**	**5,275.85**

We would try to estimate trend that may emerge on the 6th observation by using the previous 5 observations. On the basis of Open values we estimate High, Low and Close values.

Following are the fuzzy values of the above observations:

Sr.No	$M_O(x)$	$M_H(x)$	$M_L(x)$	$M_C(x)$
1	0.893446415	1	0.889128759	0.939398612
2	0.92074017	0.935851966	0.749575944	0.775944487
3	0.690053971	0.775944487	0.597995374	0.619429453
4	0.668003084	0.694680031	0.493292213	0.525828836
5	0.543716268	0.559753277	0	0.191210486
6	**0.261835004**	**0.390285274**	**0.18843485**	**0.246569005**

Using the steps1 and 2 we found the following fuzzy values:

	Actual	Predicted	Error (Actual – Predicted)
$M_H(x)$	**0.390285274**	0.431423155	-0.041137881
$M_L(x)$	**0.18843485**	0.193792457	-0.00536
$M_C(x)$	**0.246569005**	0.272831093	-0.02626
Average M(x)	**0.275096376**	0.2993489	-0.024252525

From the above table it can be observed that the error value is quite less, so the approximation of predicted values is more or less closer to actual values.

The actual average comes to **0.275** which depicts a **Bearish Neutral trend** and we predicted it to be **0.299** which depicts a **Bearish Neutral trend**. So our prediction closely represents the actual trend for the next day (6th day).

The experiment was conducted for various sets of real time values and it was found that our system can predict the trend for the immediately next trading day to a very large extent.

VII. CONCLUSION

The Standard & Poor's CRISIL NSE Index 50 or S&P CNX Nifty nicknamed Nifty 50 or simply Nifty, is the leading index for large companies on the National Stock Exchange of India. The Nifty is a well diversified 50 stock index accounting for 23 sectors of the economy.

The attractive feature of the stock market is that every investor has the image to make millions in return from buying and selling stocks (cash and futures). Unfortunately, the reality of the nature of the market poses a less optimistic picture. Although, researchers have proposed many methods to somehow predict the market movements and also it is observed that the best market players have been the investors who use their professional knowledge of the markets to predict the next trend of the stock price. Here the need of an automated trustworthy forecasting tool is extremely desired, so that the investors don't have to rely on some one else to do forecasting for them. And also, the more accurately the forecasting tool performs, the more profitable it would be for the investor.

In our approach we use fuzzy logic as it does not need tones of data as in the case of ANN, and also the results are achieved fast. From the above suggested method, the fuzzification of the NIFTY values is done in an easy way using S-function to assess the short term trend.

We took the actual 5-day data and fuzzified it, we successfully made the system understand the current trend and then we successfully made the system predict the future trend for the 6^{th} day. The approximations presented by both the methods are good.

The methodology can be enhanced to predict the long term future trends. The proposed model is simple and easy to develop which can effectively identify the present trend and also help in predicting the immediate future trend. There is ample scope of improvement and researchers can creatively use this model for trend identification and further enhance it for further trend prediction.

The proposed future work is to de-fuzzify the trend values and achieve a crisp value of how much points the market is going to rise or fall in the short term.

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