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Design and Performance Study of Improved Fuzzy System with Genetic Algorithm

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Abstract— Technical trading relies heavily on analysis, most of which is statistical in nature. When the data to be modeled is nonlinear, imprecise, or complicated, fuzzy inference systems (FISs) are used in conjunction with computational, mathematical, and statistical modeling methodologies to simulate technical trading. Fuzzy logic may be modeled using linear, nonlinear, geometric, dynamic, and integer programming. These techniques, when combined with fuzzy logic, help the decision-maker arrive at a better solution while still facing some degree of ambiguity or uncertainty. The moving average method is a useful metric that may give trade recommendations to aid investors further. While trading signals inform investors of when to purchase and sell, a simple moving average provides no such information. In this research, we suggest a fuzzy moving average approach in which the intensity of trading signals, measured in terms of trading volume, is determined by using the fuzzy logic rule. In this research, we propose using fuzzy logic technical trading rules, which are more resistant to decision-making mistakes, to mitigate the trading uncertainty inherent in the conventional technical indicators method.

Keywords- Fuzzy set, Expert system, Moving Average, Dynamic Programming, Genetic algorithms, trading, technical analysis

I. INTRODUCTION

1.1 Fuzzy Logic

Based on the concept of fuzzy sets, fuzzy logic may be constructed. Fuzzy sets, as opposed tomore conventional sets (intervals), include the idea of partial membership. This allows for a differentiation between phenomena-specific aspects and those that are tangentially important but entail more room for error and ambiguity [1], [2].

Each linguistic phrase ("high", "significant", and "strong") specifies a fuzzy set and hence fuzzy logic may be used to interpret information grains such as "high speed," "substantial danger," and "strong sale," among others. Fuzzy logic is seldom studied on its own and is often only explored with other methods like artificial neural networks or reinforcement learning of agent-based systems when applied to the field of financial economics. Themembership function for a fuzzy set (A) specified in X looks like this: In the notation A:X-> [0, 1], the degree of inclusion of x in A is denoted by A(x). Triangular membership functions, Gaussian membership functions, trapezoidal membership functions, polynomial membership functions sigmoidal membership functions are only a few examples. It is important to remember that greater membership degrees correspond to bigger values of a membership function [3].

There are three main parts to any fuzzy model: (1) some kind of fuzzy "rule base," typically expressed as a set of "if-then" rules (2) a Fuzzifier that takes the Input Variables and creates Fuzzy variables; and (3) a defuzzification module that translates fuzzy domain conclusion to the dependent variable (output). Data about how to build the rule basis for the fuzzy model is required for its construction. This data is usually provided by experts' understanding of the process or gleaned through analyses of past data [4]. Fuzzifying the inputs (components of technical indicators like moving averages or filter values) is the first stage in developing the output (trading recommendation) in a fuzzysystem. Because of this approach, the results for each rule's output variable are inherently uncertain. An aggregate fuzzy conclusion about the output variable is reached by summingthe rules' individual output conclusions in order to incorporate the impact of the rules' associated output membership functions on the final outcome.

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Defuzzification results in a binary trading position as the output value [5].

1.2 Moving Average

The term "time series" refers to a set of data points that have been collected at regular intervals. When analyzing time series, the Moving Average is the technique employed most often. Because of its simplicity, the unweighted moving average is by far the most often used kind of moving average. This method uses the average of the last N observations. When a new value becomes available, the previous value is replaced by removing the oldest observation from the time series data and recalculating the average. The term "movingaverage" comes from the fact that it is constantly updated as new data is added and old data is removed [6].

Time series analysis and forecasting approaches may be performed using a broad range of models. Moving averages are the simplest and least complicated method available. The data is smoothed and mistakes are reduced using moving averages. This smoothing has the effect of eliminating unpredictability, allowing us to extrapolate and predict based on this pattern going forward[7].

A moving average may be used to gauge the trend by smoothing out the data and averaging out outliers. The arithmetic mean may be affected by outlying outliers. The extreme values in this case are influenced by random fluctuations in the time series data.

Simple moving averages: In comparison to other models for making predictions, this one is the simplest and least difficult. The average of time series observations for a certain period yields a moving average and continues until the last time series observations [8].

Double moving averages: The average of two moving averages is the same as the average of two simple moving averages [9].

Multiple moving averages: Multiple moving averages may be calculated by taking the average of the averages over a specified time period[10].

Exponential smoothing: In statistics, a subset of moving averages is known as exponential smoothing. In contrast to exponential smoothing, where weights decline exponentially over time, moving averages use uniform weights. The term "exponential smoothing" encompasses a wide variety of techniques, including "basic exponential smoothing," "double exponential smoothing," and "triple exponential smoothing"[11].

1.3 Genetic Algorithm

Natural selection inspires optimization, and the concept of emergent behavior—the notion that assembling basic components may yield complex results—forms the basis of the entire process. Nature possesses the building blocks of life, which we refer to as our genes, and it is experimenting with various gene combinations by releasing them into the wild to see which ones are successful. One way to put it is that they should actively seek for mates, and those who succeed in doing so will ensure that their traits are passed down to future generations.

The Genetic Algorithm, a kind of meta-heuristic search algorithm, takes its cues from Charles Darwin's theory of evolution. Only the strongest and healthiest people are allowed to reproduce and pass on their genes to future generations via natural selection. The progeny born in this manner are considered members of the succeeding generation [12], [13].

In its most basic form, a GA creates a population by adopting any technique or generating randomly, then it finds the ideal objective value, known as fitness, and finally, it repeats the process, i.e., generates a new population, after taking certain intermediate stages. These purported intermediary processes include selection, crossover, mutation, introducing a new group or set of values into the population, and ultimately renewing the population. The preceding steps are repeated until the desired value is reached, at which point the values are traded [14], [15].

In this paper, the trading strategy is constructed using the moving average method and the fuzzy logic rule. To further optimize our results, we include a genetic algorithm in our suggested methodology.

1.4 Organization of paper

In the next sections of this article, we will discuss the following: Under Part 2, we discuss current studies and studies in progress by additional researchers. The study data and methodology are outlined in Section 3. In Section 4, experimental findings demonstrate the effectiveness and profitability of the suggested method. The report closes with some recommendations in Section 5.

II. LITERATURE REVIEW

The price of crude oil has a profound impact on economies worldwide, and Mohamed Abd Elaziz et al.[16] provide an innovative approach for predicting this variable. The suggested strategy is predicated on enhancing the functionality of an ANFIS using a modified salp swarm algorithm (SSA). The SSA was created as a global optimization technique that mimicsthe foraging behavior of natural salp swarms.

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A robust approach to soft computing has been developed by S. Kumar Chandar and colleagues [17] at IBM Research. This technology was developed in order to reliably estimate stock values. In this investigation, the authors created a stock market prediction modelutilizing a wavelet-adaptive network-based fuzzy inference system. The model is based on a time series of closing prices, and it is constructed using fuzzy logic. The results of the experiments demonstrate that the proposed fusion model achieves a higher level of accuracy in its predictions than either of the separate models. According to the results, it would seem that the proposed fusion model provides a competitive choice for predicting the stock market and may serve as a useful resource for practitioners and economists involved in stock market forecasting. These conclusions are based on the findings of the study.

Hyejung Chung et. al. [18] explored the temporal aspect of stock market data by offering a systematic way to identify the time window size and topology for the LSTM network using GA. This was done as part of their investigation of the temporal property of stock market data. The Korea Stock Price Index (KOSPI) provided them with daily data that they utilizedto evaluate the performance of the proposed hybrid approach. The combined LSTM network and GA model is superior to the gold standard model, as shown by the experimental results.

Chong et al. [19] employed PCA, encoder, and RBM to predict future market patterns. Stock trading system based on deep neural network suggested by Sezer et al.[20] to anticipate whether to buy, sell, or hold. The parameters of the technical analysis and the system's buy/sell point were optimized using GA.

Stock market forecasting also uses qualitative data and deep learning [21]. Yoshihara et al.[22] employed text as an input variable and an RNN model combined with a limited Boltzmann machine to forecast market trends (RBM). Ding et al. [23] developed an event- driven model to predict market direction. Deep CNN was used to analyze the impact of extracted events on the S&P 500 index and individual stock movements.

III. MATERIALS AND METHODS

3.1 DATASET

Information for this analysis was gathered from the daily closing prices of crude oil futureson the New York Mercantile Exchange (NYMEX). The EIA website provided the data, which we subsequently downloaded [24]. We use the most liquid of the EIA's 12 crude oil futures contracts (contract 1) to set our pricing. From 2000 to 2014, we conducted our experiments for this study.

3.2 METHODOLOGY

Moving average analysis uses the relationship between long-term and short-term averages to determine market movement. If the price chart indicates a rising trend and the short-term line is above the long-term line, then buyers are more likely to enter the market. If the marketprice is dropping, the long-term moving average line will be above the short-term line.

The techniques used to determine these moving averages and the results they produce are distinct. With that research in mind, this article focuses on four of them.

The approach uses a short-term and long-term moving average to make its predictions. In thiswork, we denote these two eras by the numbers n and m. Indicating an upward trend in the price series is a situation where the n-period moving average is larger than the m-period moving average, and the opposite is true.

The proposed Algorithm is as follows:

Step 1: Choose the 6 n values and 6 m values as given below:

$m \in \{10, 20, 50, 100, 150, 200\}$,

$n \in \{1, 3, 5, 10, 15, 20\}$.

Given that $m > n$, there are 32 possible permutations of my and n.

Step 2: Each rule in fuzzy logic consists of an "if" clause and a "then" clause. In this case, we use a moving average

approach, specify two periods in length, define a fuzzy threshold as the"if" condition, and assign a "then" value based on that condition.

Moving average Method	<m, n>	Fuzzy Extent	Recommend

Develop the seed population. Twenty individuals will be chosen at random from the bucket. Conforming to the established norms, each individual has 10 rules within them(Fig 1).

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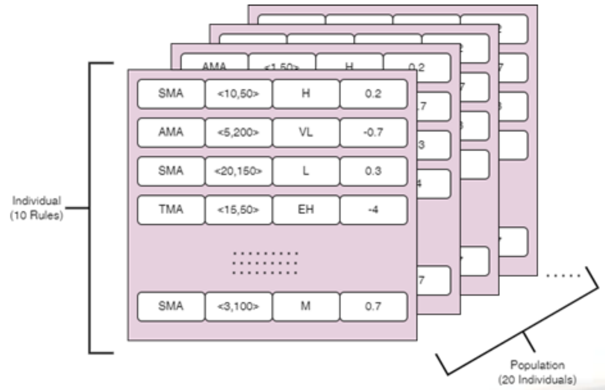

Fig. 1. Population in genetic algorithms

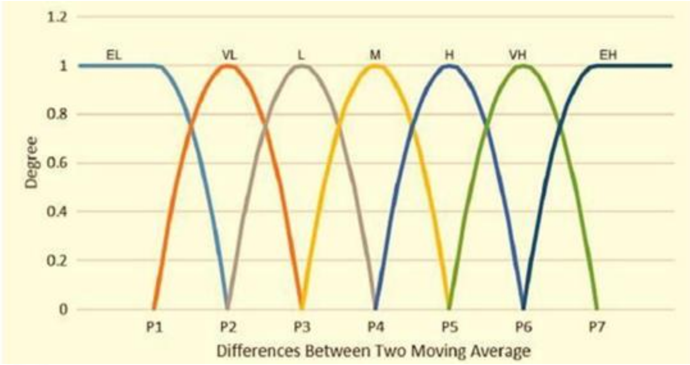

FIG. 2. MEMBERSHIP FUNCTION.

Step 3: Determine the TPMA, AMA, SMA and TMA. The following are examples of how these various moving averages are calculated:

$$SMA(k) = \frac{1}{n}\sum_{i=1}^{n} c_{k-i}$$

Where

n: Duration of a Timeframe

c: Futures market prices on a daily basis

k: Day under calculation

$$AMA(k) = SC*(C_k - 1 - AMA(k-1)) + AMA(k-1)$$

Where SC = Scalable Constant

$$TMA(k) = \frac{1}{n}\sum_{i=1}^{n} SMA_{k-i}$$

$$TPMA(k) = (high + low + close)/3$$

Where high = max(C_k-1, C_k-2, . . . , C_k-n), low = min(C_k-1, C_k-2, . . . , C_k-n), close = C_k-1.

Step 3:

There are seven possible values for the gap between two moving averages as follows:

EL: “extremely low”

VL : “very small”

L : “low”

M : “middle”

H : “high”

VH : “very high”

EH : “extremely high”

Fig. 2 shows that P1 is lowest and P7 is highest. We need a P4 number close to 0 to tell up from down. All numbers below 0 have three components. This includes non-zero values. All three Ps are less than or equal to 0. P5, P6, and P7 all exceed zero. We can compute Fig. 2's membership function using these data points.

Step 4: Use the moving average technique and the rule's length of two moving averages to calculate training period differences.

Step 5: Use the membership function to get a degree value

Step 6: Rating Level Calculation:

To get the recommendation value, multiply the degree value. A rating is the end outcome of applying this fuzzy logic rule. Because everyone pitches in with their own set of suggestions, we end up with 20 different scales on which to rate the recommendations.

Step 7: Overall Rating Level Calculation:

Come up with a set of 10 fuzzy logic rules. An aggregate rating may be computed by adding up the ratings for each rule in the collection.

Step 8: Genetic Algorithm Implementation:

The moving-average technique offers four distinct variations. There are 32 possible combinations of n and m. Fuzzy extent offers seven choices, whereas the recommended value has twenty-one (ranging from negative one to positive one with a tenth of a point gap). As a group, we settle on a selection of 10. We estimate that there are 8.05 X 10^{33} sets. There is no way to choose the optimal set by using all of them. The approach of evolutionary algorithms is employed in the search for the best fuzzy rule set.

For the purpose of making a selection during the training phase, the top candidates are evaluated based on their rate of return. The trainee with the greatest return rate is the most successful.

Fitness function= return = (profit + cost)/capital

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Profit refers to trading earnings and cost refers to handling fees.

Create an evolutionary population. Select the top 10% of the previous population based on their expected rate of return using genetic algorithms. Then, choose 80% of the original population and 10% of newly created individuals at random to undergo the crossover and mutation. As can be seen in fig.3, these two groups eventually merged to produce a new population.

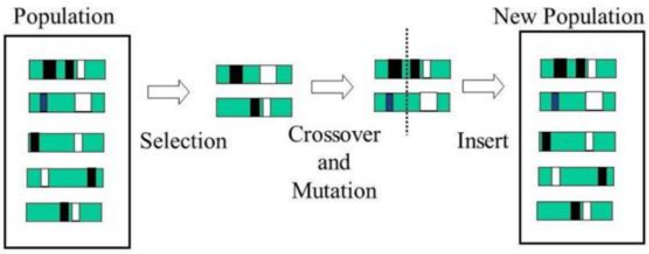

Fig.3. Crossover and mutation

IV. RESULTS

Genetic algorithms are not really random while doing experiments. We define the course of action while using the Fuzzy logic rule. In other words, when the fuzzy extent is EL, VL, or L, we establish negative recommend values and when it is EH, VH, or H, we set positive recommend values. The workload of the genetic algorithms is lightened because to this enhancement. Even more so, the moving average's foundational concept is positive. It is a good opportunity to buy when the price is below the long-term average line and to sell when it's above the short-term average line. We alter to prove this notion.

The starting capital was established at $1,000,000 while we were establishing the basic specifications. In this work, we use starting capital and creditworthiness to determine trading amounts. If the rating is poor, we will recommend making modest trades. A negative impact on the ROI is shown when the recommended trading amount is less than $1000 and the transaction cannot be completed.

Generational parameters are determined by experimental results. The crossover and mutation probabilities affect convergence speed and total effect. In this research, we set the crossover rate at 0.7 and the mutation rate at 0.01. Convergence time is measured in generations, which may be estimated by watching the experiment. We settled on 50 generations to strike a balance between efficiency and effectiveness. After the last iteration, the best population was as follows:

['tma', '10', '100', 'H', '-0.5'],

['tpma', '5', '10', 'VL', '0.1'],

['sma', '5', '150', 'VL', '-0.2'],

['tpma', '20', '200', 'VL', '-0.6'],

['sma', '15', '20', 'L', '-0.8'],

['ama', '5', '100', 'EL', '-0.2'],

['tma', '20', '200', 'EH', '0.4'],

['sma', '20', '100', 'EH', '0.7'],

['tma', '10', '50', 'EL', '-1.0'],

['ama', '5', '100', 'VH', '0.1']]

Its rate of return and profit on capital are as follows:

Rate of return: 1.3165614282729488,

Profit: 13218658.076668203

V. CONCLUSION

Given the volume of real-time data, such as transaction records, produced by the financial market, the potential for drawing useful conclusions from such an analysis is high. As a result, the goal of this research is to create an original prediction model using the aforementioned financial information. In this study, we combine the power of genetic algorithms with the flexibility of fuzzy logic and the steadiness of a moving average. The MAS issues signals for trades, and the volume of the trades is set according to a fuzzy logic rule. Genetic algorithms are used for the optimization of trading strategies. The suggested technique yields the best (set of) regulations possible, increasing users' returns and profits to their full potential. In future studies, we want to further refine the algorithm such that it is optimal for use in high-frequency financial transactions.

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