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Modeling Fuzzimetric Cognition of Technical Analysis Decisions: Reducing Emotional Trading

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Abstract

Stock traders' forecasting strategies are mainly dependent on Technical Analysis (TA) indicators. However, some traders would follow their intuition and emotional aspects when trading instead of following the mathematically solid forecasting techniques of TA(s). The objective of this paper is to help traders to rationalize their choices by generating the maximum and minimum tolerances of possible prices (termed in this paper as "fuzzy spectrum") and hence reducing their "emotional" trading decisions. This would be an important aspect towards avoiding an undesired outcome. Fuzzy logic has been used in this paper to identify such tolerances based on the most popular TA(s). Fuzzification of these TA(s) was used via a modular approach of fuzzy logic and by adopting "fuzzimetric sets" described in this paper to achieve the "fuzzy spectrum" of forecasted price tolerances when buying and selling decisions. Experimental results show the success of developing the "fuzzy spectrum" based on the "fuzzy" tolerances discovered from the TA(s) outputs. As a result, this paper contributes towards a better "rationalized" decision making when it comes to buying and selling stocks in this kind of industry.

Keywords: Cognitive modelling, Fuzzy system, Technical analysis, Trading systems, Stock trading optimization, Fuzzimetric sets.

1 | Introduction

The Stock trading is usually based on technical trading rules to identify the buying/selling signals based on either short or long history of stock prices [53]. The future prices are difficult to predict, as the information gathered at any moment in time may reflect the market efficiency rather than the actual price [1] and [2]. However, current prices may also represent the information overreaction as discussed by Kahneman and Tversky [3]. Investors may overreact to available market information as well as overreact to private information, due to emotional factors about specific shares and securities [4]. In a similar fashion and more recently Ahmad and Shah [5] investigated the influences of overconfidence in stock exchange decisions where a theoretical framework of behavioral finance was adopted as the basis of their research.

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Intelligent techniques to support such decision-making scenarios gathered high interest among researchers. For example, Chopra and Sharma [6] reviewed AI implementation techniques of AI to the stock market forecasting where it was concluded that AI techniques can be a successful methodology of financial market analysis. Also, emotional and psychological factors were studied in Khayamim et al. [7], where fuzzy logic-based reasoning is used to simulate the portfolio optimization model, ignoring the emotional and psychological aspects. Hence, the main reason for inventing the technical trading rules originally was investigated by Park and Irwin [8] is to achieve the maximum profit that can be generated from trading in stocks. All of these technical indicators are of two main types: trend indicator and mean-reverting indicators (also termed as counter-trend), where each type might be suitable for a specific stock chart behavior.

Based on fuzzy logic, Gradojevic and Gençay [9] suggested a mechanism of reducing trading uncertainty, where two problems were addressed. These problems are the market timing and the order size. Along the same vein, Escobar et al. [10], proposed a technical fuzzy indicator that incorporates subjective features simulating the human decision making which uses a comparison between traditional Relative Strength Index (RSI), Moving Average Convergence Divergence (MACD) as opposed to the fuzzy-built multi-agent indicator obtaining the behavior and profit as outputs. Social network-based prediction of short-term stock trading was proposed by Cremonesi et al. [11] where semantic sentiment analysis was used as a mechanism for inspecting Twitter posts. In an attempt to reduce the scope of fuzzy boundaries, Hao et al. [12] studied the merge of information from online news to predict the price of stock price index where fuzzy sets were used to identify the outliers in such decision making. Dong and Ma [13] also, studied the optimal number of and length of fuzzy intervals were multiple relevant factors taken into consideration of a stock index forecasting model.

As such, this paper contributes by two folds. The first is to introduce one of the fuzzy variants termed as "Fuzzimetric sets" and the second is to implement the mechanism of fuzzimetric sets into the implementation of stock trade decision making where maximum and minimum possible tolerances can be identified as an attempt to reduce emotional trading. This has been accomplished by utilizing the characteristics of the most popular Technical Analysis (TA) indicators with the associated trading decision-making. Unlike other research on fuzzy implementation to trading systems, this paper renders some of the most relevant parameters of popular indicators fuzzify and then feeds them into a modular approach of the fuzzy system. The defuzzified outputs are combined into the final fuzzy output after inferring the relative outputs from these indicators. Furthermore, and as part of the characteristics of Fuzzimetric sets, the proposed system uses certain mutations of fuzzy sets to achieve low and high tolerances for each one of the sets that would help the investor in discovering the related price range expected for the security. A combination of these mutation sets provides a "De-fuzzified spectrum" of possible outputs that can act as a decision support system for traders.

The remaining parts of this paper are organized into 4 more sections. Section 2 related work to cognitive and emotional trading discussed as the main motivation of this research. Section 3 provides a brief review of the Fuzzimetric sets which is the adopted variant of fuzzy sets in this research paper. In Section 4 a short review of the most popular TAs and trading strategies where these TAs will be fuzzified as part of the proposed system. Section 5 describes the fuzzy inference mechanism adopted in this research whereas Section 6 describes the data collected and the back-test experimental results. Section 7 provides the conclusion and future work.

2 | Cognitive Decisions of Stock Traders and Emotional Trading

The most viable characteristic of stock traders is that they are of a risk-taking behavior which is dependent on the cultural, cognitive, and personality of the individual [54]. TA is the technique that most investors use to rationally conclude the stock trading investment decisions. There are many types of technical indicators which are defined as two main categories: Trend-following indicators (like MACD) and "Revert to mean" indicators (like RSI). Different indicators would require different rules

(Strategy) of selling and buying stocks. It would be very easy to make mistakes when watching charts, therefore wrong rules might be implemented due to the lack of comprehensive "cognition" of the scenario in place.

On top of possible flaws in the wrong decision when concluding the trade, emotional trading conforms to another major loss/biasedness when conducting the trade. Investors in such an environment do not always think rationally by following the TA rules, but rather irrationally by following their feelings and emotions about certain stocks [14]. Vaščák [15] proposed "fuzzy cognitive maps" as a method to overcome the limitations of rule-based systems by injecting fuzziness to such systems to reduce the complexity of dynamic systems. Adding to this ambiguity, traders' behavior might include a pattern to trade weekly, daily or even hourly. Different rules/indicators would be suitable to a specific trading scenario and the behavior of traders is not always certain, as studied by Richards and Willows [16]; moreover, the effect of such sentiment on the volatility of the market was studied by Rupande [17].

In order to rigorously model the behavior of stock traders, two main driving forces would contribute towards their investment decision-making. *Fig. 1* shows the rational and irrational driving forces where the need for a cognitive development model represents the intersection between the human-trader cognition and the cognitive developed analytics based on the rules generated from technical indicators. Such a "Decision support system" would be a necessity in such a scenario where it can aid the trader in the appropriate decision to take. Ototsky and Manenkov [18] were able to recognize this fact and introduced the concept of "Cognitive Centres" to emphasize the cognitive technology used in management modeling practices by integrating cognitive and information technologies. In order to combine emotions with cognitive architecture, Marco et al. [19] proposed a unified emotional-cognitive-affective architecture to be integrated with intelligent agents to influence and modify the behavior of the agent in real-time, to achieve a more realistic and believable interaction with the user. 'Emotion' management in stock trading organizations can also be a factor towards reducing emotional-driven decision making. Kouatli [20] introduces a Framework Architecture for Managing Emotions (FAME) as a method of controlling emotional intelligence within organizations. A classification of "emotion-based account was studied by Duxbury et al. [21] where a conceptual analysis of how emotions influence the financial market behavior was proposed to buy and sell in asset markets. A similar study of the relationship of social media emotions and stock market crash was studied by Ge et al. [22] where a cognition-based framework of "Emotion-Cognition-Market" has been adopted. Yuan [23] also identified the relationship between cognitive biases and decision-making behavior in financial markets.

To be able to categorize the different stocks, Sun et al. [24] for example, proposed a bi-clustering trading pattern of stock investments styles. Maciel and Ballini [25] proposed a fuzzy-rule-based model to forecast high and low stock prices. A generic framework for Cognitive Analytics Management (CAM) was proposed by Osman and Anouze [26] which was later used to investigate and study the governmental e-services from users' perspective [27]. Cabrera-Paniagua and Rubilar-Torrealba [28] proposed an Artificial Autonomous System (AAS) for the stock market domain where the personality profiles of the individual were considered as one of the proposed "big five" models towards decisions in financial investments. Kareem [29] also studied the personality issue and the emotional and cognitive influence towards decision making in the Iranian stock market where fuzzy analysis was used to provide priority weighting. Kouatli and Arayssi [30] introduced the idea of reducing emotional trading and proposed to build a fuzzy-based model where traders can use. This paper explores and experiments on the proposed strategy of implementing such a model where traders can use it to view the minimum and maximum tolerances and consequently achieve a "fuzzy spectrum" where traders can use as a guideline instead of just following intuition (irrational decisions) and accordingly reducing emotional trading.

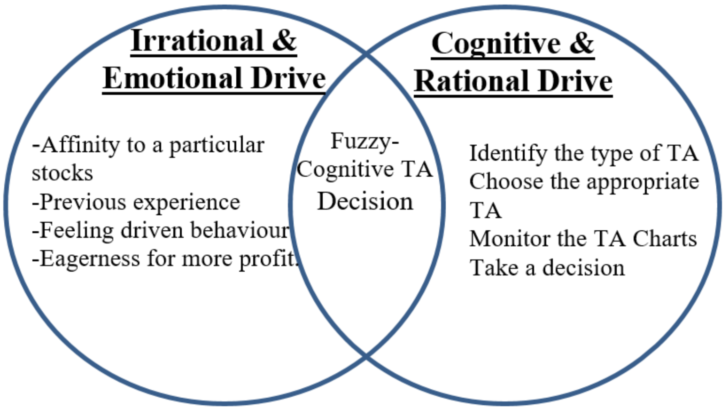

Fig. 1. Stock trader driving forces of investment decisions and the need for fuzzy cognitive decision support system.

3 | The Background of Fuzzimetric Sets

In *Fig.1*, the fuzzy logic started by Zadeh [31] as a mechanism of decision making to deal with uncertainty. It was based on an extension of set theory, where instead of a crisp description of a member belonging (or not) to a set, a member can have partial membership in a specific set. Since the introduction of the traditional fuzzy set theory, other extensions of the theory emerged like type-2 fuzzy sets, intuitionistic fuzzy sets, and hesitant fuzzy sets. Recently, fuzzimetric sets, a newly defined extension of fuzzy sets also emerged which will be briefly reviewed in this paper where more details can be found in Kouatli [32]-[34]. Fuzzy logic was utilized by different researchers to model a cognitive systems. For example, García-Vico et al. [35] used fuzzy logic Fuzzy Rule-Based System (FRBS) to extract patterns in big data to improve decision making process patterns in big data environments. Intuitionistic fuzzy sets was also utilized by Liu et al. [36] to propose a new decision making method. In order to enhance the decision process of stock trading, this paper utilizes the concept of "Fuzzimetric sets" to identify the possible stock price spectrum based on maximum and minimum possible tolerances of fuzzimetric sets where the principle briefly reviewed in the next paragraph(s). This principle of Fuzzimetric sets in the universe of discourse and can be defined as Positive Zero (P0), Positive Small (PS), Positive Medium (PM) and Positive Big (PB) (*Fig. 2. a*). These fuzzy variables can be defined as:

$$PO = {}_{0}\int^{\pi/2}|\sin(\pi/2 - x)|. \tag{1}$$

$$PS = {}_{0}\int^{\pi}|\sin(x)|. \tag{2}$$

$$PM = {}_{\pi/2}\int^{3\pi/2}|\sin(\pi/2 - x)|. \tag{3}$$

$$PB = {}_{\pi}\int^{3\pi/2}|\sin(x)|. \tag{4}$$

Assuming sinusoidal function, then these representations can be defined in an analogy to trigonometric functions with an exception of taking the absolute values only. Hence, based on the definition of fuzzimetric arcs [42], the concept defines a mechanism of selection, mutation and cross-over fuzzy set shape and hence affecting the overall decision making de-fuzzified value. For example, triangular, trapezoidal etc., can be achieved by a simple mutation of fuzzy sets using a genetic operator:

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$$\mu = \frac{\text{ARCSIN (Fuzzy Variable)}}{T} \tag{5}$$

$= 1$ for $\mu > 1$.

The fuzzy variable is any of PO, PS, PM or PB, and the T parameter is the shape alternation factor (mutation factor) with the most active range of $0 < T < 2700$. Mutations of these fuzzy variables can thus be identified as:

$$\text{Mutated-PO} = {}_0\!\int^{\pi/2} \frac{\text{ARCSIN}(|\sin(\pi/2 - x)|)}{T_P}. \tag{6}$$

$$\text{Mutated-PS} = {}_0\!\int^{\pi} \frac{\text{ARCSIN}(|\sin(x)|)}{T_{PS}}. \tag{7}$$

$$\text{Mutated-PM} = {}_{\pi/2}\!\int^{3\pi/2} \frac{\text{ARCSIN}(|\sin(\pi/2 - x)}{T_{PM}}. \tag{8}$$

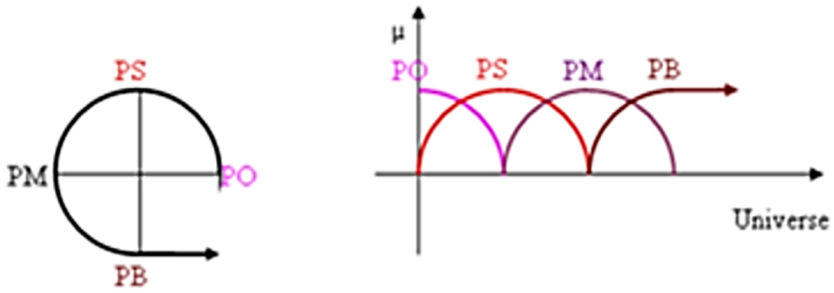
$$\text{Mutated-PB} = {}_{\pi}\!\int^{3\pi/2} \frac{\text{ARCSIN}(|\sin(x)|)}{T_{PB}}. \tag{9}$$

Altering the value of mutation factor "T" allows us to mutate the fuzzy variables where examples are shown in *Figs. 2(b)* and *(c)*. More details of fuzzy sets and utilization of this concept to the decision-making process in a manufacturing environment can be found in Kouatli [37], where a robotic example was taken as a vehicle to a step-by-step explanation of inference using fuzzy sets. Formal extended definition of the concept of fuzzimetric arcs with its extensions of mutation and crossover can be found in Kouatli [32] where the formal definition of "fuzzimetric sets" was characterized as a platform combining both types of fuzzy sets. Fuzziness control of such sets can be found in Kouatli [34] with an example of application to employee evaluation system can be found in Kouatli [33].

4 | Technical Analysis, Trading Rules and Strategy

TA uses the technical indicators formulae derived from high, low or close prices collected over a certain period of time. Traders use a graphical format of these indicators to view and analyze the current situation with stock or indices. However, to interpret such graphical charts, the user needs to be able to understand these indicators and to be able to take an action (buy/sell) accordingly. There are so many factors to look at before any decision can be made, and accordingly a cognitive decision support system in trading analysis based on multiple indicators would help towards achieving the right decisions. More detailed information about most popular indicators can be found in Kouatli and Yunis [38]. However, for readers' convenience, these most popular indications will be reviewed briefly in the following sub-sections.

Technical indicators are usually of two types: trend-following charts/indicators and "revert-to-the-mean" charts/indicators. In both types, a system would be necessary to justify the total possible tolerances given a certain situation, and accordingly stopping the traders from irrational speculation of trading and hence reduce the "emotional trading"



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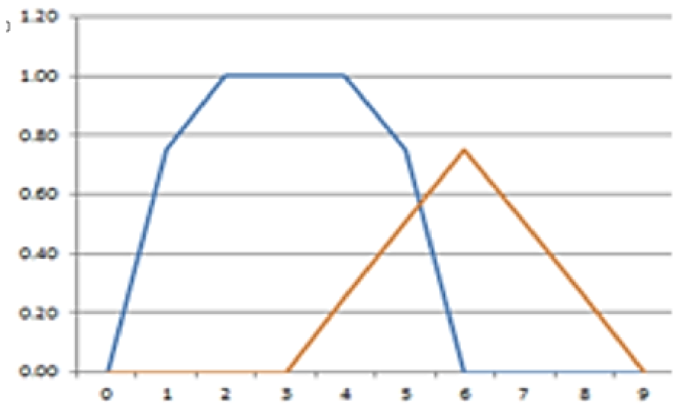

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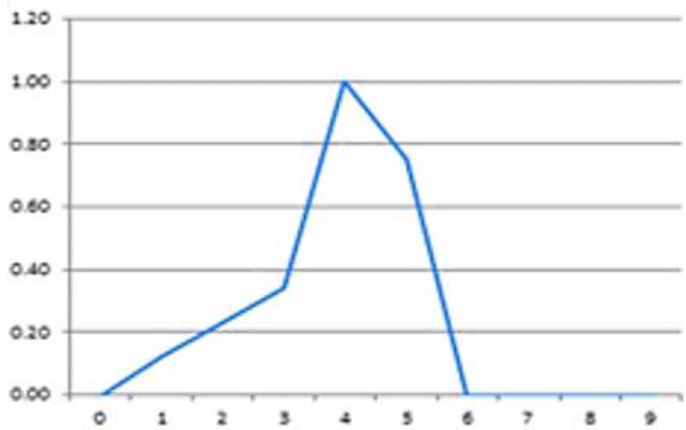


c.

Fig. 2. Evolution of fuzzimetric sets: a. positive fuzzimetric arc with the spread of different fuzzy variable on the universe of discourse; b. example of generated fuzzy set shapes using mutation factor T. Ps: Tps=40, PM: Tpm=120; c. examples of mutated and crossed-over ps fuzzy set. left-half Tps=270, Right-half Tps=40.

4.1 | Trend-Following Indicators

As its name imply, trend-following indicators "follow" a trend to indicate if it is falling or rising where they are based on moving-average (SMA or Exponential Moving Averages (EMA)) with lower and upper bounds. SMA calculates the average price over a fixed number of periods (long and/or short period of time). If the stock price is exceptionally volatile, then a moving average will help to smooth the data and hence filters out any random noise and offers a smoother perspective on the price (EMA). On top of moving average, traders uses a momentum indicators to help them predicting the change in a pattern. Example of these types of indicators are Bollinger Bands (BB) and MACD.

4.1.1 | Bollinger bands (BB)

BB-Trend Indicator is a relatively new type of indicator proposed by Bollinger [55], which measures the strength as well as the direction. It can be found by differential values (periods 20 to 50) of lower and upper bands using the following formula:

Lower-BBTrend = |(lowerBB(20) - lowerBB(50)|,
Upper-BBTrend = |(upperBB(20) - upperBB(50)|,
BBTrend = (lower BBTrend – upper BBTrend) / middle BB(20).

Where BBTrend >0, indicates that the trend is bullish and BBTrend <0 zero, indicates that the trend is bearish where the actual value represents the momentum of the trend.

b% Indicator: is an oscillator variable used with BB. %b plots the stock's closing price as a percentage of the upper and lower bands. Where this range is measured from zero (the lower band) to 1 (the upper band). The objective of %b is to indicate how close the stock's current price is to the bands (e.g. UB=100 & price = 80, then %b=0.8). This is useful to identify when a price jumps a band determining divergences and trend changes.

4.1.2 | Moving average convergence divergence (MACD)

Based on two EMA, MACD is considered to be a trend-following indicator as well as short-term momentum indicator. Crossover-Buy Signal (also called Golden Cross): is when the short term Moving Average MACD-Fast jumps above the long-term MACD-slow which means that the downward trend is ending and a new uptrend is expected to start and hence, such "Golden Cross" suggests a buying signal.

I. Golden Cross: MACD-Fast (t) > MACD-Slow (t) & MACD-Fast (t-1) < MACD-Slow (t-1).
II. Crossover-Sell Signal: (also called Dead cross) is when the long-term MACD-Slow moves above the short term MACD-fast which means that the price is recently moving downwards relative to previous periods which also suggests a selling signal. Hence: Dead Cross (Sell signal) MACD-Fast (t) < MACD-Slow (t) & MACD-Fast (t-1) > MACD-Slow (t-1).

4.2 | Mean-Reversion Indicators

As its name imply, "Mean-Revert" type of indicator (or Oscillators) can be used to conclude a sell/buy decision as the price is usually always reverted back to the mean. Traders looks at prices drifting away from the mean to check the unsustainability in the trend using SMA or EMA with a minimum of 50-periods average. Mean-reversion usage is less popular than trend-following indicators, and it requires more trading experience than trend-following where emotional and psychological factors can be effective elements towards wrong trading decisions. Most popular indicator of "mean-reverting" are RSI and "momentum oscillator".

4.2.1 | Relative strength index (RSI)

Comparison between up and down days of share prices compromises the functionality of RSI (defaulted to 14-periods for short term trading) with a scale of 0-100 where a value of more than 70 considered being bullish and the value below 30 indicate bearish trend. RSI is also considered to be one type of momentum oscillator with a center line of 50. Above 50, RSI indicates that the momentum is upwards, where traders may consider buying; conversely, RSI value below 50 indicates that there is bearish signal started.

RSI formula is dependent on the amount of gaining over loosing for certain period of time (ideally 14). This is defined by:

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

Where RS is Relative Strength in that specific period (e.g. 14) and RS= (Average Gain)/ (Average Loss).

4.2.2 | Momentum oscillators (stochastic indicator)

Stochastic indication measure the strength of a trend with the amount of fast and strong price is going up or down. Above 80% is considered strong uptrend and below 20% is a strong downtrend. Stochastic indicator can be integrated with MACD to provide better trading signals.

%K= 100*(closing-low)/ (high-low) for 14-period.

An average of the last 3 slower stochastic values is usually termed as signal line D% where the following rules are used as trading guidance and which is illustrated in the example of *Fig. 4*.

Trading rules with stochastic Indicator

If %K >80 → overbought stocks (it might fall again).

If %K<20 → oversold stocks (might bounce back upwards).

If %K <80- and %K > %D →Buy signal.

If %K < %D → sell signal.

If %K >90 & started to fall again → sell before %K hits 80.

5 | Fuzzy Inference Mechanisms and Modular Structures

5.1 | Brief History About Fuzzy Inferences

After the initial introduction of Zadeh's [31] theory of fuzzy logic, Mamdani and Assilian [39] utilized the theory to build an inference system based on fuzzy logic to control a steam engine using linguistic control rules in a form of: "If A AND B then C". The objective was to simulate the experienced human operator in controlling such task where the input to the system was the fuzzified value of the crisp input and the output of the system was also a fuzzy set. Sugeno [40] used a similar technique to Mamdani with a main difference in the output where the final output was de-fuzzified to a crisp value by using averaging technique. A similar technique but with modular approach was proposed by Kouatli [37] with an example of robotic manipulator in controlling tasks. The first adaptation of the fuzzy set membership was proposed by Sugeno in order to achieve the desired results of the system. Sugeno proposed the same type of rules as Mamdani with few exceptions that the inputs and the output of each one of the rules can also be a function instead of being a value. Moreover, the weight of each rule can be measured by using the "AND" operator to conclude the strength of each rule. As the process of "decision making" is also "fuzzy" in nature, then the same concept can be implemented in management science and other industry fields where decision has to be taken under uncertainty.

Hence fuzzy system heuristics are built as rule-sets, describing the system model. Rules are usually in the form of (IF A … THEN B) where "A" and "B" are fuzzy variables. For a Single-Input-Single-Output (SISO) system, this would be straight forward and fuzzy inference can be conducted on the fuzzy variables representing the input and output respectively. Most real world problems are in the form of a multivariable structure composed of Multi-Input-Multi-Output (MIMO) systems. In this case, problems may arise in achieving a complete and consistent construction of all possibilities relevant to the output of the system. Rules in this case are of the form (IF A1& A2…. &An THEN B1 & B2 &...Bn). This situation results in additional complexity in knowledge discovery and accurate heuristic modeling the system. Special algorithms are necessary in this case to tune the system as well as to detect and remove irrelevant rules. For example, Babuska [41] studied rule compression and selection in the goal of maintaining completeness and consistency of the system. Instead of rule compression, a simplified modular structure was a also proposed by Kouatli [37] and [42] where the fuzzy system can be defined as three main components: The fuzzification component, the knowledge component and the Inference/de-fuzzification component and where the input/output relationships defined by creating sub-rule-sets each of which describe the relationship between one of the inputs and one of the outputs.

Many researchers adopted the principle of modular approach when inferring the output of fuzzy systems. For example, Carrera and Mayorga [43] proposed the use of modular fuzzy inference structure to conclude a decision in supply chain environment where there is a need to optimize the right cost at the right time with the best quality from the right supplier. Junior et al. [44] presents a supplier selection decision method based on fuzzy inference modeling the human reasoning which is an advantage when compared to approaches that combine fuzzy set theory with multi-criteria decision making methods. Amindoust et al. [45] used fuzzy inference mechanism to conclude the sustainability criteria for a given set of suppliers. Lin and Hsu [46] used modular approach for fuzzy inference to handle the impreciseness and uncertainty found in storing image selection process. An example of combination of intelligent techniques like fuzzy logic and genetic algorithm can be seen in Melin et al. [47] where a genetic optimization approach of modular neural-fuzzy integration. This methodology was applied to human recognition problem where the proposed algorithm was able to adjust the number of membership function/rules as well as the variation on the fuzzy set type of logic (type-1 or type-2). In a similar hybrid type of intelligent techniques and to avoid complexity of MIMO system generated by maintaining the complete and consistent rules, Kouatli [48] proposed a modular approach in an analogy of biological structure of genes and chromosomes where each gene represents one rule connecting any one of the inputs with any one with the outputs. Based on this, a chromosome can be defined in terms of pre-fixed number of rules representing the four fuzzy variables (P0, PS, PM and PB). These "chromosomes" can then be constructed using "Input Importance Factor" ε. The value of this ε can be either normalized by the knowledge and intuition of the domain expert or can be deduced using AHP technique proposed by Saaty [49]. Full details of this technique with the mathematical details and definitions can be found in Kouatli [34]. This paper describes the implementation of this approach of modular structure of biological resemblance of intelligent algorithm where a customized strategic stock trading support system has been built to find an optimized threshold where a decision of buying/selling has to take place. The proposed system is based on fuzzifying the existing most popular technical indicators (surveyed in Section 2) in order to achieve better performance of stock trading.

5.2 | The Proposed Fuzzy Inference Methodology and Strategy of Decision Making

Fuzzy system heuristics are built as rule-sets describing the system model. Rules are usually in the form of (IF A … THEN B) (concluded rulesets in Section 4 for buying and selling are examples) where A and B are fuzzy variables. For Single Input, Single Output (SISO) system, fuzzy inferences could be conducted on the fuzzy variables representing the input and output, respectively. However, most decision-making problems are multivariable in Multi-Input, Multi-Output (MIMO) systems. In this case, problems may arise in achieving complete and consistent construction of all possibilities relevant to the output of the system. MIMO rulesets in this case are of the form (IF A1& A2…. & An THEN B1 & B2 &...Bn). This adds complexity in knowledge discovery and accurate heuristic modeling of the system (Kouatli [37]).

Special algorithms are necessary in this case to tune the system as well as to detect and remove irrelevant rules. For example, Kouatli [42] studied rule compression and selection with the goal of maintaining completeness and consistency of the system. Instead of rule compression, a simplified modular structure was also proposed by Kouatli [33] and Carrera and Mayorga [43], where the fuzzy inference can be modular in mature. In the described model, a modular approach is proposed to combine the rules described in Section 4 where equal "input importance factor" is the weighted factor to combine the rules and assumed to be equal to all rules. The final inferred output in this case is governed by the equation:

Where

Yj is the de fuzzified output using averaging method due to the effect of input Xi.

εij=importance level for input i to the output j.

($x_i \circ R_{ij}$) is the compositional rule of inference between a specific input Xi and the relation Rij.

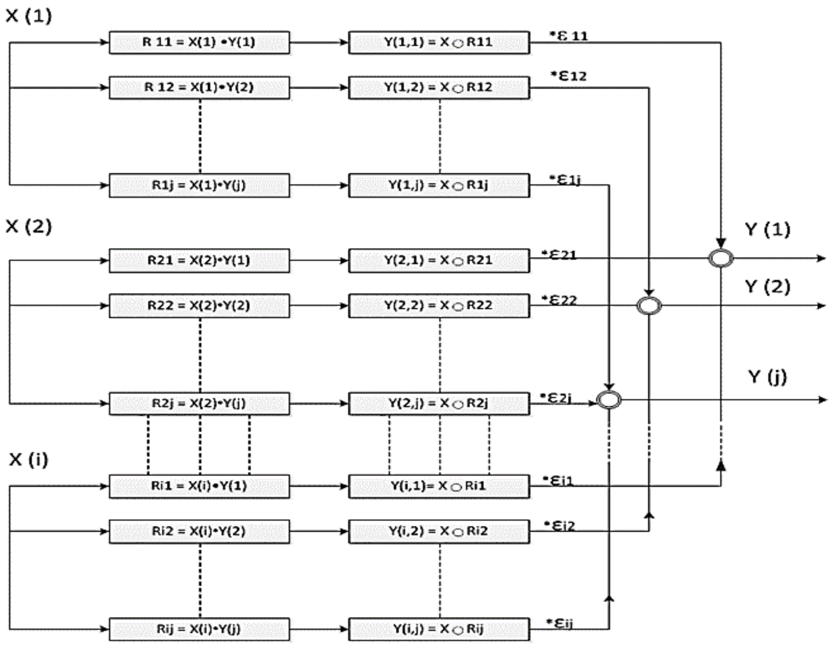
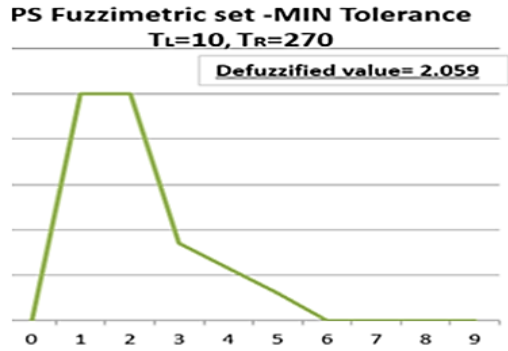


Fig. 3. Modular approach of fuzzy inference.

5.3 | Fuzzimetric Sets Mutations and De-Fuzzified Values

By changing the mutation factor T for a specific interval, would alter the shape of the fuzzimetric set. For example if the fuzzy interval for PS is between {1,6}, in a scale of {1,10}, then by altering the mutation factor T would move the centroid of the mutated Fuzzimetric set from a minimum (towards level 1) or maximum (toward level 3). To be able to achieve this for any Fuzzimetric set, the mutation factor is applied per half of the set (left or right, and accordingly two mutation factors applied for each of the left and right halves of the set (TL and TR). This concept provide a mechanism of finding the minimum and maximum possible tolerances for fuzzimetric sets. *Fig. 3* illustrate this concept by three possibilities of small fuzzy set with an interval of {1-6}. *Fig. 1.a* shows a skewed trapezoidal fuzzimetric set biased towards the lower end of the interval by setting the mutation factor TL=10 and TR=270. Similarly the other extreme (*Fig. 4. C*) shows a skewed trapezoidal fuzzimetric set biased towards the higher end of the interval by setting the mutation factor TL=270 and TR=10. Obviously, if it is required to have a set as a medium (average of 1-6), then the optimum de-fuzzified value would be 3 achieved by setting TL=90 and TR=90 (*Fig. 4. b*).



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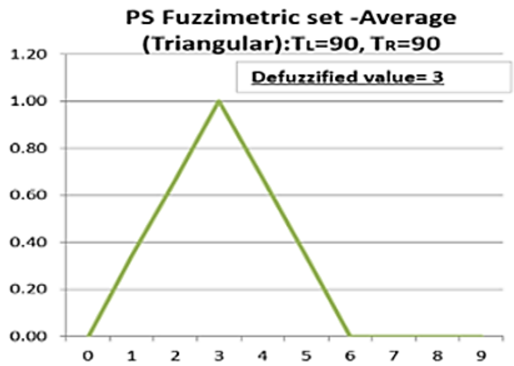

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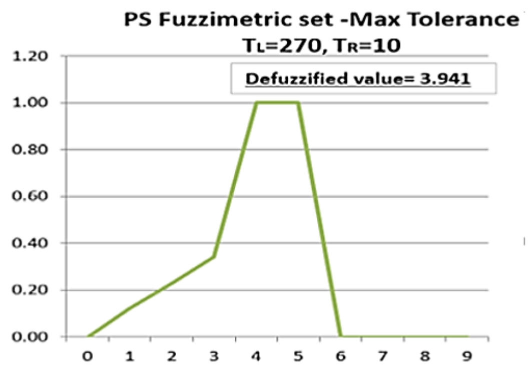


c.

Fig. 4. Variation of fuzzimetric set "small" within a specific interval: a. SMALL fuzzimetric set - min tolerance; b. SMALL fuzzimetric set - average tolerance; c. SMALL fuzzimetric set – max tolerance.

5.4 | Strategy of Finding Minimum and Maximum Possible Tolerances for TA

As can be seen from *Fig. 4*, the average non-biased, un-mutated set with mutation factor =90 would result a triangular shaped set using this mutation factor would generate a minimum and maximum tolerances of the set as explained in *Fig. 4*. Based on this concept and bearing in mind that the universe of discourse is composed of four fuzzimetric sets, then, it would be required to find the combination of tolerances as an outcome to find the minimum and maximum tolerance. Accordingly, the following steps can be adopted:

Step 1. The relative "universe of discourse" approximate scale needs to be identified: to be able to do this, a previous historical data would be necessary. For example, the previous 50 period of trading. Assuming a daily trade, then this would represent the minimum and maximum price within this "testing/observing" period.

Step 2. Scaling the maximum and minimum on the "Fuzzimetric Arc, then fuzzy sets PO, PS, PM and PB can be defined.

Step 3. Considering the PO and PS to be the minimal possible-buying price as opposed to PM and PB as the larger possible selling price, then these fuzzy sets can be mutated to be the minimum or the maximum for min and max tolerances of each of these sets.

Step 4. Following the rule-sets of buying and selling concluded in section four (which are based on the fuzzification of these most popular technical indicators), and assuming that all technical indicators have the same weight (during experimentation scenario, it is not necessary to be equal), then the final combined decision is dependent on that combination. Hence, as an oiutcome of Step 3, and to search for all mutations of the "fuzzimetric sets, then, five main possibilities can be generated:

Triangular fuzzy sets (average to all sets: fuzzimetric set without any mutation),

Triangular sets. Right TPO =90, Left TPS=90, Right TPS=90, Left TPM=90, Right TPM=90, Left TPB=90.

MINMIN (mutated fuzzimetric sets where the centroid is towards the minimum),

MINMIN sets. Right TPO =10, Left TPS=270, Right TPS=10, Left TPM=270, Right TPM=10, Left TPB=270.

MINMAX (mutated P0 and PS to minimum and mutating PM and PB to the maximum possible tolerance),

MINMAX sets. Right TPO =10, Left TPS=270, Right TPS=10, Left TPM=10, Right TPM=270, Left TPB=10.

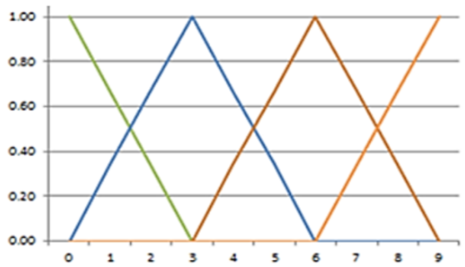
MAXMIN (mutating P0 and PS to maximum and mutating PM and PB to the minimum possible tolerance),

MAXMIN sets. Right TPO =270, Left TPS=10, Right TPS=270, Left TPM=270, Right TPM=10, Left TPB=270.

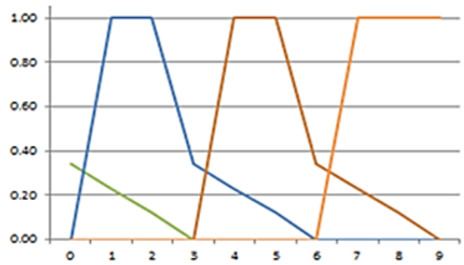
MAXMAX (Mutating all four fuzzimetric sets to the maximum tolerance),

MAXMAX sets. Right TPO =270, Left TPS=10, Right TPS=270, Left TPM=10, Right TPM=270, Left TPB=10.

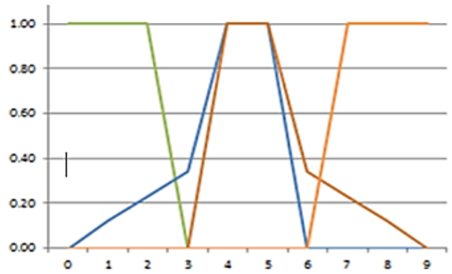
Step 5. Record the minimum and maximum possible price based on the search from Step 4(a-e) and accordingly, these would represent the minimum possible (buying) price and the maximum possible (selling) price based on the fuzzification of most popular technical indicators as explained in Section 4, *Fig. 5* shows the graphic representation of the chosen different variations of fuzzimetric sets as explained in Step 4 which is the basis of such decision support system to help traders in confirming an automated decision proposed by the system and accordingly reduce the possibility of emotional trading.



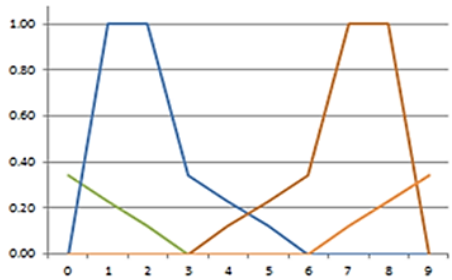
a.



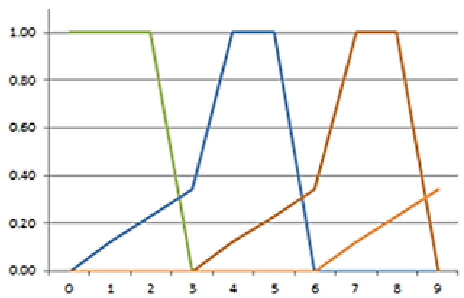
b.



c.



d.



e.

Fig. 5. Different tolerance varieties of mutated fuzzimetric sets: a. triangular; b. minimize tolerance for all sets (MINMIN); c. minimize PO & PS, maximize PM & PB tolerances; d. maximize PO & PS, minimize PM & PB tolerance; e. maximize tolerance for all sets (MAXMAX).

6 | Data and Methodology Used with the Back Test Experimental Results

Most experienced traders may use a strategy of combining two or more indicators complementing each other (e.g. a trend-following indicator combined with mean-revert indicator) before a final decision. This is usually a common practice when it comes to the development of intelligent systems. Pounder et al. [50], for example, introduced a hybrid architectures concept of a framework to artificial general intelligence termed as Cognitive Function Synthesis (CFS) to investigate the consciousness and imagination. Mella [51] proposed a combinatory system theory by constructing a formal model that explains a vast group of phenomena produced by the cybernetic behavior of the collectivity producing self-organizing synchronization. Lepskiy [52] also investigated the relationship between scientific rationality and cybernetics when developing systems. In case of stock trading example, cybernetic strategy is dependent on the combination of many other "fuzzy" factors than just combining both types of indicators. For example, the volume volatility, the effect of large emotional trading to the current prices, the emotional behavior of favoring one type of indicator to the other and the ultimate uncertainty that is usually embedded in such type of indicators. To avoid such dilemma, fuzzy logic can be used with a "linguistic" types of variables rather than an absolute variables which might be prone to errors. The concept of fuzzimetric sets described in Section 2 will be used to implement the "fuzzy variables" to the most popular indicators described in Section 3. In order to conduct fuzzy inference related to the best strategy, criteria need to be specified with respect to a known interval where fuzzy variables can then be defined as PO, PS, PM or PB (as described in Section 3), rather than crisp values.

Using Yahoo! finance, data for year 2016 was downloaded for a mixture of indices some of which are value-weighted and others are price–weighted. These are: SP500, DowJones 30, Nasdaq, Nikkie220, Russell2000 and SP500. Where a comparison between different indicators with respect to the proposed fuzzy indicator is compared in terms of total annual profit with total transactions executed. From the previous section, it can be noticed that most of the indicators and strategies can be combined together and some of them can complement each other. In order to conduct fuzzy inference related to best strategy, criteria needs to be specified with respect to a known intervals where fuzzy variables can then be defined as PO, PS, PM or PB, rather than crisp values. The chosen criteria out of the well-known most popular indicators (described in the review section) are listed as follows with the relevant fuzzy trading rules:

Buying Fuzzy rules:

BB Related: IF Price is PO AND %b is PO AND Bandwidth is PM OR PB.

MACD Related: IF Price is PO or PS AND Golden-Cross = OK.

RSI Related: IF Price is PO or PS and RSI is PO.

Stochastic Related: IF Price is PO and %K is PB AND %K > %D.

Selling Fuzzy rules:

BB Related: IF Price is PM OR PB AND %b is PB AND Bandwidth is PM OR PB.

MACD Related: IF Price is PM or PB AND Dead-Cross = OK.

RSI Related: IF Price is PB And RSI is PB.

Stochastic Related: IF Price is PB and %K is PM or PB AND %K < %D.

The strategy adopted for analysis using fuzzimetric arcs was defined into 5 main possibilities representing five main tolerances as defined in the previous section where crossover and mutation can be utilized to achieve these tolerances of buying and selling. These are:

Triangular sets. Right TPO =90, Left TPS=90, Right TPS=90, Left TPM=90, Right TPM=90, Left TPB=90.

MINMIN sets. Right TPO =10, Left TPS=270, Right TPS=10, Left TPM=270, Right TPM=10, Left TPB=2700.

MINMAX sets. Right TPO =10, Left TPS=270, Right TPS=10, Left TPM=10, Right TPM=270, Left TPB=10.

MAXMIN sets. Right TPO =270, Left TPS=10, Right TPS=270, Left TPM=270, Right TPM=10, Left TPB=270.

MAXMAX sets. Right TPO =270, Left TPS=10, Right TPS=270, Left TPM=10, Right TPM=270, Left TPB=10.

The triangular sets represents the non-biased adoption of the indicators towards buying and selling while the MINMIN sets represents the strategy of minimum tolerance of buying with minimum tolerance of selling which indicated the strategy of a trader who wait for minimum price and sell as soon as the price is acceptable (and profitable) minimum tolerance. Similarly, the MINMAX represents the minimum tolerance of buying and maximum tolerance of selling and so on. *Fig. 3* shows the graphical representation of these different definitions of fuzzimetric sets.

Back test conducted on the chosen indices for the 2016 annual trading where the data was cleansed to ensure that the first transaction is a "Buy" and the last transaction is a "Sell" in that specific year. Assuming a capital of around $50000 was utilized as the initial trading budget at the beginning of year 2016, where the actual investment is dependent on the number of shares (real whole numbers of shares disallowing fraction of a share) that can be bought within the budget limit.

Fig. 6 shows the experimental results of the back test using the prototyped system where the initial investment with total profit for year 2016 in monetary values as well as percentage value are shown together with the comparative results of traditional as well as the defined fuzzimetric sets described in previous section where the final results shows the maximum profit were obvious using the fuzzified principle of the most known traditional indicators. It should be noted that the system was tuned to the Triangular sets where non-biased tolerances was considered for buying as well as selling transactions representing the expectation of actual traders' behaviours. However, the maximum profit does not have to be associated with the Triangular sets. As the table shows the maximum profit for Dow Jones and S&P proved to be the MINMIN tolerance being the best choice for maximum profit while the MAXMAX tolerance shows the minimum profit achieved in case of S&P 500. Nikkie 220 using Triangular fuzzy sets shows the highest profitability with highest possible spectrum as opposed of minimum volatility with minimum profitability in S&P500 using MINMIN fuzzy sets.

			Most Popular Technical Indicators				Fuzzified Technical Indicators with Type-2 sets					
			BB	MACD	RSI	St0	Triangular	MINMIN	MINMAX	MAXMIN	MAXMAX	Fuzzy Spectrum
Value-Weighted Indicies	DowJones	Year 2016 % Profit	8.23%	2.74%	14.40%	0.53%	7.18%	18.74%	18.74%	7.18%	7.18%	7.18% -18.74%
		Year 2016 Profit	2884.1	977.9	4967.92	259.26	3397.74	6462.88	6462.88	3397.74	3397.74	
		Investment	35025.42	35670.84	34493.19	49195.71	47300.22	34493.19	34493.19	47300.22	47300.22	
		No. of Shares	2	2	2	3	3	2	2	3	3	
		Profit per share	1442.05	488.95	2483.96	86.42	1132.58	3231.44	3231.44	1132.58	1132.58	
		No. of Transaction	10	18	6	2	2	6	6	2	2	
	S&P 500	Year 2016 % Profit	13.35%	1.02%	14.19%	-0.12%	3.96%	14.40%	13.26%	7.53%	3.14%	3.96% - 14.40%
		Year 2016 Profit	6634.08	507.36	6870	-60	1917.84	7004.64	6516.24	3655.92	1519.92	
		Investment	49682.75	49571.1	48416.16	48091.75	48481.86	48659.1	49135.96	48541.2	48481.86	
		No. of Shares	24	24	24	25	24	24	24	24	24	
		Profit per share	276.42	21.14	286.25	-2.4	79.91	291.86	271.51	152.33	63.33	
		No. of Transaction	18	16	6	2	8	8	12	6	8	
	Russell 2000	Year 2016 % Profit	10.14%	14.22%	18.14%	13.95%	18.36%	14.99%	12.81%	6.51%	12.11%	6.51% - 18.36%
		Year 2016 Profit	5032.28	7034.37	8893.28	6880.28	9049.5	7484.58	6396.28	3254.99	5984.44	
		Investment	49640.07	49459.33	49013.51	49311.53	49285.24	49921.57	49931.46	49987.61	49437.23	
		No. of Shares	44	43	44	44	45	43	44	41	44	
		Profit per share	114.37	163.59	202.12	156.37	201.1	174.06	145.37	79.39	136.01	
		No. of Transaction	12	20	6	6	8	6	10	2	6	
Price-Weighted Indicies	NASDAQ	Year 2016 % Profit	13.49%	-1.26%	12.73%	2.90%	14.65%	6.29%	3.73%	5.53%	4.30%	3.73% - 14.65%
		Year 2016 Profit	6738.4	-627.7	6147.4	1360.5	7013.5	3095.2	1684.98	2542	1977.9	
		Investment	49948.59	49847.77	48278.5	46870.75	47868.93	49208.18	45168.59	45986.65	45986.65	
		No. of Shares	10	10	10	10	10	10	9	10	10	
		Profit per share	673.84	-62.77	614.74	136.05	701.35	309.52	187.22	254.2	197.79	
		No. of Transaction	18	18	8	4	8	8	12	4	4	
	Nikkie	Year 2016 % Profit	20.61%	16.21%	9.32%	12.93%	21.08%	17.09%	10.14%	18.51%	19.27%	10.14% - 21.08%
		Year 2016 Profit	10291.89	7952.19	4589.94	6340.14	10461.12	5740.28	3386.08	9229.08	9558.42	
		Investment	49938.12	49048.18	49255.37	49047.46	49619.55	33587.6	33401.73	49868.09	49599.46	
		No. of Shares	3	3	3	3	3	2	2	3	3	
		Profit per share	3430.63	2650.73	1529.98	2113.38	3487.04	2870.14	1693.04	3076.36	3186.14	
		No. of Transaction	18	20	6	6	14	12	16	10	12	

Fig. 6. Back-test comparative results of the output of technical analysis trading decision.

7 | Conclusion

Prediction of the stock market behavior is not an easy task. Traditional technical indicators can provide a good sign of buy/sell signals. However, due to uncertainty of such trade, traders follow their intuition and emotional rather than the solid predictive outcome of the TAs. In an attempt to reduce emotional trading, this paper demonstrated the use of fuzzy logic to identify the maximum and minimum tolerances when buying or selling stocks and shares. Fuzzimetric sets was used to fuzzify most technical indicators where mutations of the sets provides the maximum and possible tolerances generating a "fuzzy spectrum" showing the level of the daily price variation , identifying the level of uncertainty of technical indicators and hence reducing emotional trade. The proposed trading rules was deduced from the most popular technical indcators: MACD, BB, RSI and momentum indicators. Backtests was conducted to five main indicies. These are" Dow-Jones, S&P 500, Russel 2000, NASDAK, and Nikkie to whow the development of "fuzzy spectrum" as indication of level of uncertainty in shares and stocks.

7.1 | Further Research

The modular fuzzy inference mechanism proposed in Section 5 uses a weighting factor per indicator sub-decision (MACD, RSI…) item as part of this system. Some of these technical indicators are "Trend-following" and others are designed for "revert to mean". Indices in stock market can follow either/or any one of these behaviors. Hence this paper regulate the "input importance weighting factor" εi (described in Section 5) depending on the type of the indicator. Further research would be required to automate this feature where – before running the fuzzy inference - the system should recognize the type of most suitable indicator and evaluate the appropriate ε.

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