Modeling Derivatives Market Data with Artificial Intelligence Based on Fuzzy Logic to Automated Trading Algorithm for Individual Investors in Thailand

K. Muayteng[1], P. Budsaratragoon[2*], and C. Nuthong[3*]
Technopreneurship and Innovation Management, Chulalongkorn University, Thailand[1]
Banking and Finance, Chulalongkorn University, Thailand[2]
Computer Engineering, King Mongkut Institute of Technology Ladkrabang, Thailand[3]
**Corresponding Author: pornanong@cbs.chula.ac.th, chaiwat.nu@kmitl.ac.th*

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Abstract

Investment is the way to make one's wealth grows. One attractive investment is to invest in the derivatives market. Nowadays, The Securities and Exchange Commission of Thailand (SEC) issues Automated Trading Technology under regulations issued at the end of 2017, which allows applying Algorithmic trading directly to the derivatives market known as Thailand Futures Exchange (TFEX).

Furthermore, broker businesses increasingly use the Financial Technology of Automated Trading Software to connect with individual investors. This new trading algorithm software is expected to be robust. Hence, it is required product development and process innovation. The robust trading algorithm is the key component of automated trading software developed from historical market data that contains a closing price, volume, and technical indicators. It is also aimed to create new values for individual investors, which can be further commercialized. Examples of possible business models are subscription model, profit-sharing model, or commission model depending on management for the future trend of financial innovation technology.

The automated trading algorithm generates bi-directional trading signals (buy and sell) for both long and short positions. The algorithm trading itself is unable to be written down as a formal mathematical model. However, by applying the fuzzy logic approach, a qualitative trading system is feasible. This work proposes the use of fuzzy logic to develop a trading algorithm that provides automated trading software for derivatives market in the case of SET50 Equity Index futures in Thailand.

The experimental results show that the fuzzy logic approach has the potential to predict the future performance of SET50 Equity Index futures up to 68.71% accuracy. However, the results can further be improved by modifying the parameters of the algorithms.

Keywords: Derivatives market, fuzzy logic, technical analysis, derivatives price prediction, automated trading software

1. Introduction

The derivatives market is riskier than the Stock market because of leverage. This also makes trading in the derivatives market more complex. However, technology such as algorithmic trading had made trading operations possible to be carried out faster and taken advantage of market opportunities. The algorithmic trading is the process that uses a computer program to define and execute a set of specifications at a speed and frequency that is impossible for a human trader. The established rule sets used in the algorithmic trading are based on timing, price quantity, or mathematical model.

Treleaven P. et al. (2013) reported studies the typical trading strategies used in algorithmic trading, such as the Trend following, trading range (Mean reversal), Volume Weighted Price (VWAP), Time Weighted Average Price (TWAP), Percentage of Volume (POV). Strategy Implementation and Mathematical Model-Based Strategies implemented in Technical Analysis.

Murphy J. (1999) described Technical Analysis (TA) involved in an attempt to predict the movement of future asset prices based on an analysis of past costs using qualitative methods and quantitative methods such as Moving average or combination of both. A typical investment strategy based on technical review is a trend following. In general, the popular classifications of technical indicators are the trend, non-trend, raw data, and volume.

Bendtsen M. et al. (2016) explained Strategies based on mathematical models, machine learning, and artificial intelligence to design algorithmic trading design. In a proposed trading system, fuzzy logic is applied for defining the trading rules and managing the capital to invest. The fuzzy trading system is tested in two markets (NASDAQ100 and EURO STOXX). The main conclusion suggested that the application of fuzzy logic was a useful tool for capital management in Algorithmic Trading.

Menknoff L. (2007) described Algorithmic Trading (AT) as any form of trading using

sophisticated algorithms (programmed systems) to automate all trades of market cycles. AT usually involved learning, dynamic planning, reasoning, and decision making to buy or sell. The pre-trade analysis identified a trading opportunity using historical market data and real-time market data. The researcher developed an algorithm from historical data and identified the pattern on the underlying financial product without any views on the behavior of the derivatives product. This system is shown in figure 1.

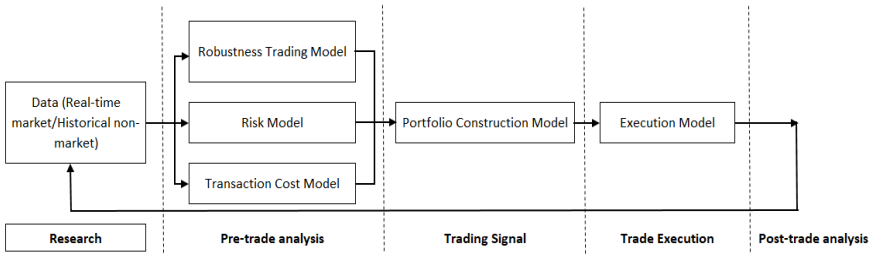

Figure 1: Components of an AT System (Treleaven P. et al. 2013)

Hu Y. et al. (2015) explained the most commonly used Evolution Computation (EC) techniques in trading rule, namely Genetic Algorithm and Genetic programming. These algorithms, combined with fuzzy logic techniques for the better algorithm.

The propose of this work is to analyze and test an Automated trading algorithm in Thailand Futures Market (SET50 Index) using the Fuzzy logic approach.

2. Literature Review

2.1 Artificial Intelligence

Yasunobu S. et al. (1983) showed that Artificial Intelligence (AI) technology, such as fuzzy logic, had been actively researched and applied to various problems.

The proposed Generic Algorithm gets in touch with five independent entities, and efficient communication between them must assure with Monte Carlo analysis for the Robustness trading model.

The signal computation will come from five technical indicators, namely, William %R, Moving Average Convergence Divergence (MACD), Stochastics, Momentum, and Keltner Channel. The trading Algorithm consists of the Genetic Algorithm to identify buy and sell order, the risk model, and the transaction cost model.

2.2 Technical Analysis

The technical analyst uses past prices and other statistics when making investment decisions, believing that previous data contain essential information about derivatives market behavior. According, Murphy J. (1999), he proposed the three assumptions underlying the concept of Technical Analysis described as shown below

(1) Price reflects the market event
(2) Changes in the price move in trend; and
(3) Historical price trend to repeat

Technical analysis is essential for signal computation and trading algorithms in investment decision making. The proposed methodology in this research is shown in figure 2.

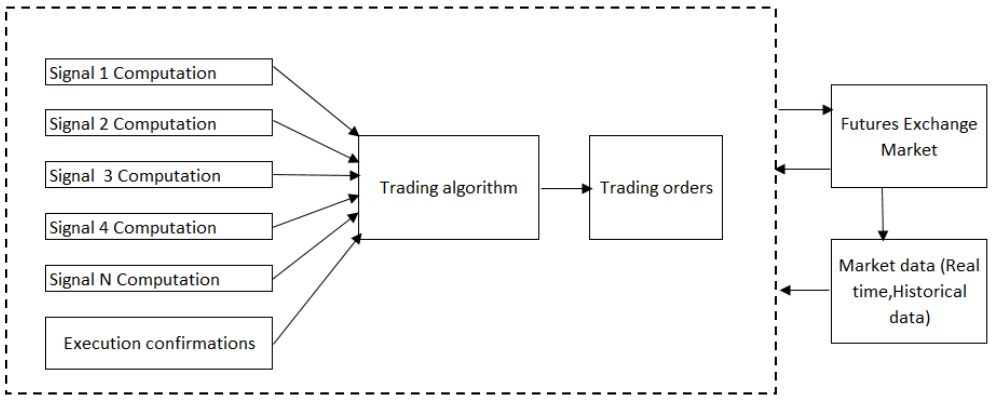

Figure 2: Proposed Methodology

2.3 Fuzzy Logic Fundamental

Zadeh L. (1965) explained Fuzzy logic building upon the notion of Fuzzy set. Unlike traditional sets (intervals), fuzzy sets allow for the concept of partial membership. It enables discrimination between elements relevant to the phenomenon of interest and borderline importance that involve imprecision and uncertainty. Information can be processed using fuzzy logic whereby each linguistic

term (buy, hold, sell). It describes a fuzzy set (A) defined in x is represented by its membership function as follows:

$$\mathbf{0 < A(}x\mathbf{) < 1}\ , \ \forall x \qquad (1)$$

where A(x) denotes a degree of membership of x

A membership function can be of various types, including triangular, Gaussian, and polynomial. It should be noted that larger values of the membership function indicate higher degrees of membership. The fuzzy set x is a membership function with a map each point of x onto the real interval [0.0,1.0]

Any fuzzy model has three components

(1) A fuzzy "rule base" in the form of a set of "if-then" rules (export knowledge about the model)
(2) A fuzzification module that transforms the explanatory variables (inputs) into fuzzy variables
(3) A defuzzification module that converts the conclusion from the fuzzy domain into the dependent variable (output)

For Designing the fuzzy model, information has to be gathered on how to construct the rule base. Typically, this information represents the expert knowledge about the process or compile by studying the historical data.

In a fuzzy system, Gradojevic N. et al. (2013) described the process of generating the output (trading recommend) beginning with fuzzing the inputs (Component of Technical indicators) and then executing all current rules from the rules base. The process generates fuzzy conclusions about the output variable for each state. The findings of the current regulations use in decision making aggregate into fuzzy conclusions about the output variable. It captures the influence of the output membership functions associated with the rules. After defuzzification, a single value output (trading position) generated. This is shown in figure 3.

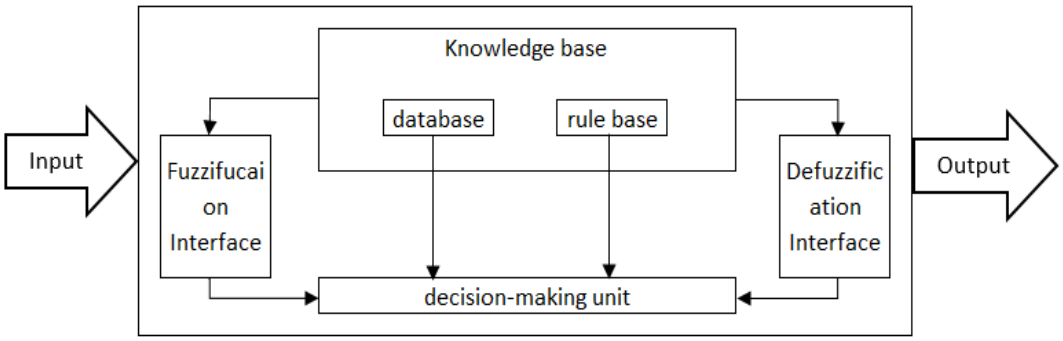

Figure 3: Fuzzy Inference System (Gradojevic N. et al. ,2013)

2.4 Robustness Analysis

The robustness concerning fuzzy model implementation is significant. By conducting robustness analysis. It will be safe to exclude the possibility that the empirical outcome could be safe for data-mining. This research paper proposes an Automated trading model developed by the Fuzzy logic algorithm and tested by Monte Carlo analysis to get a satisfying confidence level. By using the trading model to test impacts from slippage in the real market before using go live and test the robustness for the dynamic market in the future.

3. System Implementation

The objective of this work is to propose a Robustness Trading Model (trading algorithm) that is Empirical Data-Driven by gathering historical derivatives market data. By using a Genetic Algorithm on the Metatrader4 platform, which widely used for a trading platform that can automatically execute trading orders and generate trading signals as Quantitative trading to the real market. The proposed block diagram for the system is shown in Figures 2. After gathering the market data (Real-time) and Non-market data (Historical data) included with the closing price and volume. The technical indicators needed to calculate indicators such as Williams %R, MACD, Stochastic will be used to determine the output. This is the signal which shows the buying and selling decision for a long position and short position.

For data testing, the Fuzzy logic algorithm fed with underlying data (SET50 Index) instead of 50 Stock securities. Testing data is divided into in sample data (01.01.2010-31.12.2015) and out of sample data (01.01.2016-31.12.2018) with historical data in timeframe 15 minutes to generate the buy and sell signals with initial Equity (100,000 Thai Baht). Testing set up the money management by fixed position sizing (1 contract per trading position) applied with profit target and stop-loss, and check under the condition with the commission (160 Thai Baht).

The fuzzy logic trading algorithm can be developed by MQL Language, which can be described as a strategy as human-readable by Pseudocode. It is easy to understand and used for manual trading. The Pseudocode is shown in Figure 4.

```
//--------------------------------------------------------------------
// Trading rule: Trading signals (On Bar Open)
//--------------------------------------------------------------------
LongEntrySignal = FUZZY Logic. Variable is true if min 75 % conditions (3 out of 4) are correct:
        - (Williams % R(Main chart,30)[2] is rising)
        - (MACD(Main chart,24, 52, 9).Main[1] is falling)
        - (Stochastic(Main chart,14, 3, 3).Fast%K[3] crosses above 20)
        - (Momentum(Main chart,20)[1] crosses below 80)

ShortEntrySignal = FUZZY Logic. Variable is true if min 75 % conditions (3 out of 4) are correct:
        - (Williams % R(Main chart,30)[2] is falling)
        - (MACD(Main chart,24, 52, 9).Main[1] is rising)
        - (Stochastic(Main chart,14, 3, 3).Fast%K[3] crosses below 80)
        - (Momentum(Main chart,20)[1] crosses below 120)

LongExitSignal = FUZZY Logic. Variable is true if min 68 % conditions (1 out of 1) are correct:
        - (Bar opens below KeltnerChannel(Main chart,20, 2.2).Upper after opened above)

ShortExitSignal = FUZZY Logic. Variable is true if min 68 % conditions (1 out of 1) are correct:
        - (Bar Opens above KeltnerChannel(Main chart,20, 2.2).Lower after opened below)

        Stop Loss = 170pips;
        Profit target = 190pips;
```

Figure 4: Pseudocode for Fuzzy Logic Algorithm

The ten year-historical data is fed into the Metatrader program by MQL Language and will be used to design the fuzzy control logic function by identifying the input and output variables and rules.

The normalized market data for the market data (closing price and volume) and technical indicators are shown in Figure 5 that used in the Fuzzy logic algorithm-the rules-based on buying and selling conditions.

For experiment results, shown in Figure 6,7 and Table 1, as shown below.

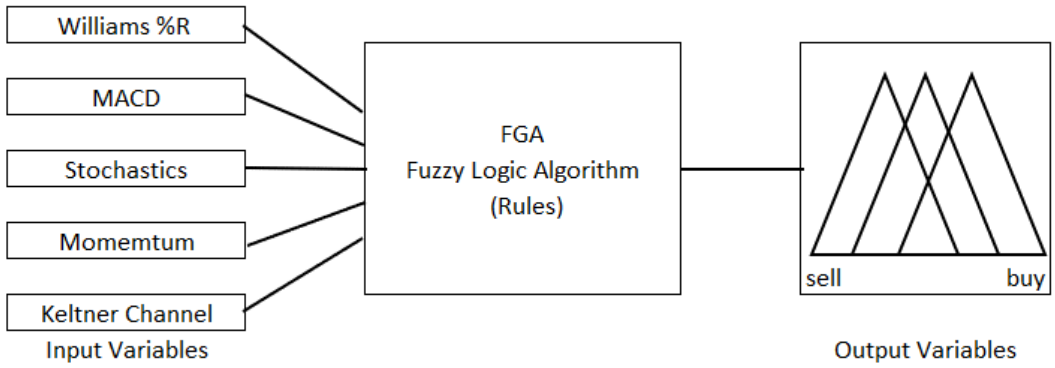

Figure 5: Fuzzy Logic Function (inputs and outputs)

Figure 6: The Output of the Equity Curve View as a Function of the Closing Price that Operated Automated Executed to the Market

Table 1: The Statistical Performance (The Equity Curve View as Statistical Data)

Description	Value
Initial Balance (Thai Baht)	100,000
Total Profit (Thai Baht)	167,180
Drawdown (Thai Baht)	23,020
%Drawdown	19.45%
Annually yield	18.56
CAGR (Compound Annual Growth Rate)	11.54
Profit factor	1.89
Sharpe Ratio	0.95
%Winning (No. Profitable trade/No. total trade)x100	68.71%
Reward/Risk	0.86
No. Trade (Total)	329
No. Trade (Long position)	184
No. Trade (Short position)	145
No. Long Position (Profit)	129
No. Short Position (Profit)	98
% Long Position (Profit), (No. Profitable Trade/No. Long position)x100	70.11%
% Short Position (Profit), (No. Profitable Trade/No. Short position)x100	67.59%

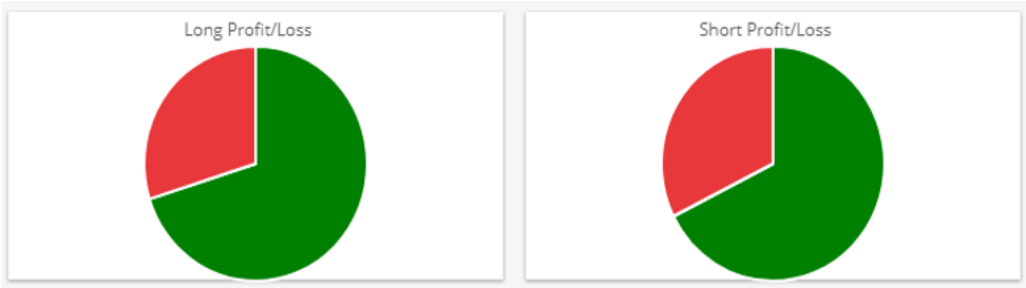

Figure 7: % Winning, Long Position (Profit) 70.1% and Short Position (Profit) 67.5%

Figure 8: Performance Return Each Year

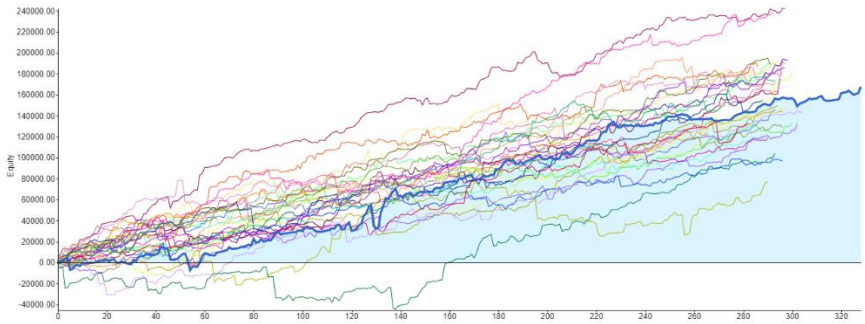

Figure 9: Robustness Testing with Monte Carlo Analysis

Table 2: Confidence Level of Fuzzy Logic Algorithm

Confidence level	Net Profit (Thai Baht)	Drawdown (Thai Baht)
Original	167,180	23,020
90%	118,400	39,500
95%	96,320	45,400
99%	76,520	51,820
100%	75,620	51,820

4. Discussion on Analysis of Results

The proposed automated trading algorithm is tested on the SET50 Equity Index Futures based on Technical Indicators. The Equity Curve is the result of the computerized operation to buy and sell order for a long position and short position, as shown in Figure 6. The Fuzzy logic strategy has annually yielded around 18.56% with Risk (Maximum Drawdown), approximately 19.45%. For Equity Growth, the Sharpe ratio is 0.86. The Fuzzy logic algorithm is able to forecast 68.71% for % winning; this is shown in Table 1. For forecasting results, the fuzzy logic algorithm has a 70.1% winning for long position and 67.5% Winning for Short position forecasting that can generate positive profitability every year, as shown in figure 8. The fuzzy logic algorithm tests the robustness by using Monte Carlo analysis with new data (Out of Samples data) to ensure the confidence level at 90% to 95%. It can sustain growing Equity, as shown in Fig.12 and Net profit with Drawdown for the confidence level at 90% to 100%, as shown in Table 2.

5. Conclusion

Artificial Intelligence (AI) Technology based on the fuzzy logic algorithm with using Technical Indicators is suitable for a synergetic relationship between humans and computers. It helps human to make a decision quickly possible. It is automatically generated the buy signal and sell signal to the market. This is used to develop an automated trading software for Innovation and Management of Broker business to succeed in individual investment.

The fuzzy logic approach has the potential to predict the future performance of the SET50 Equity Index futures up to 68.71% accuracy. However, the results can be improved by modifying the parameters of the algorithms. Therefore applying fuzzy logic can enhance the Trading algorithm by using more input variables to more efficient algorithms in future work. Furthermore, it is possible to get the opportunity in commercial software automation in other derivatives markets such as Nasdaq100 or S&P500 for individual investors.

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About Authors

K. Muayteng is a candidates of Doctoral Program in Technopreneurship and Innovation Management, Chulalongkorn University, Thailand.

P. Budsaratrogoon is an Associate Professor at Banking and Finance, Chulalongkorn University, Thailand.

C. Nuthong is an Assistant Professor at Computer Engineering, King Mongkut Institute of Technology Ladkrabang, Thailand.