ISSN 1816-6075 (Print), 1818-0523 (Online)
Journal of System and Management Sciences
Vol. 14 (2024) No. 1, pp. 50-66
DOI:10.33168/JSMS.2024.0104

Assessing the Implementation and Performance of Automated Trading Software with Non-Biased Human Decisions in the Derivatives Market: Evidence from Thailand

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Abstract. In recent years, most financial firms have utilized Artificial Intelligence (AI) technology in Algorithmic Trading (AT) software instead of human traders due to their susceptibility to numerous behavioral anomalies. Therefore, novel automated trading software's profitability and robustness have become an important research area. These software systems leverage historical market data containing a closing price, volume, and technical indicators to produce bi-directional trading signals for long and short positions. However, the AT-based strategies cannot be formulated as a formal mathematical model due to their non-linear nature. Thus, applying an AI-based fuzzy logic approach can make a qualitative trading system feasible for development. Many state-of-the-art AI-based strategies are ineffective regarding risk reduction, robustness, and profit growth. Therefore, we proposed a novel trading algorithm called the Robustness Trading Model in this research study. The recommended model integrates random generation methodology to generate AT strategies for derivative markets. For a case study, we particularly leverage a vital trading market, SET50 Index, and evaluate the approach's effectiveness by comparing results with the *Buy & Hold* and *Mean Reversal* strategies. The results show that our approach outperforms these two strategies by minimizing risk and improving profits. More specifically, we have demonstrated that the proposed AI-based approach can predict the future performance of *SET50 index futures* with up to 57.28% accuracy. Furthermore, this approach can reduce risk (maximum *Drawdown*) and enhance the total profit per maximum Drawdown (return/risk) when compared with the *Buy & Hold* and the *Mean Reversal* strategies. Moreover, we found that the *profit-sharing business* model has the best commercial software for innovative evaluation systems using financial feasibility compared to the *commission-based* and *subscription business* models. Based on these outcomes, we recommend that Thailand's market regulators and policymakers can utilize our model to maximize profits and eliminate any human biases. Finally, we also suggest that the proposed model can be substantially improved by including an extensive set of parameters during the training phase.

Keywords: Derivatives Market; Random Generation; Fuzzy Logic; Technical Analysis; Automated Trading Software.

1. Introduction

The derivative market holds additional risks due to its leverage as compared to the traditional stock market. Since 2017, Thailand's Securities and Exchange Commission (SEC) has issued Automated Trading Technology under regulations, thereby allowing Algorithmic Trading (AT) directly to the derivatives market, known as Thailand Futures Exchange (TFEX). Consequently, derivative market trading has become more complex and challenging due to advanced technologies and data-driven innovative tools like Algorithmic Trading (AT), which have opened up new possibilities in this field by furnishing more efficient trading operations. As a result, these tools can help traders benefit from market prospects by leveraging advanced datasets. In contrast, in traditional markets, individual investors choose technical indicators based on their experience and investment experts' recommendations. This approach has multiple limitations, like small market sizes and a lack of in-depth insight. It differs from the Algorithmic Trading (AT) systems, which can create a diversified and unlimited number of builds through a variety of models. Moreover, these models can be developed quickly to simulate market conditions. For example, in Algorithmic Trading (AT), a complex computing algorithm executes a set of instructions at high computational speeds. In contrast, an individual trader with traditional methods cannot accomplish such efficiency due to speed and memory limitations. In AT, an algorithmic process is developed using an established set of rules modeled as complex mathematical formulations, and it incorporates multiple trade parameters, such as trends, quantities, prices, timings, market fluctuations, *etc*.

With limited liquidity, a market gap (GAP) in developing tools (Tools) helps individual investors bring products and services using AT software and algorithms from Cognitive Computing that can be used in the business model to add value in the appropriate securities business. The financial firms using AT processes should delineate their scope based on their specific business activities. In the case of any modification in the firm's strategy or vision must follow a formal approach to signify the explicit changes required in the AT activities to update the corresponding algorithm(s). Thus, these algorithms should implement various modules (or algorithmic subroutines) described within the firm's strategy. Various firms utilize different AT strategies; the most popular ones are signal processing, market sentiment, newsreader, and pattern recognition.

In a comprehensive review article, Treleaven *et al.* (2013) discussed multiple studies on various strategies utilized in AT. They include the Volume Weighted Price (VWP), Percentage of Volume (POV), trend following, mean reversal strategy or trading range, and Time Weighted Average Price (TWAP), *etc*. In most scenarios, the underlying algorithms in these strategies are complicated and are based on advanced mathematical models that incorporate multiple factors. As Treleaven et al. suggested, Fig. 1 illustrates five different AT process phases (Treleaven *et al.* 2013). First, the real-world market data and historical trends are analyzed during the research phase. Second, a pre-trade analysis is performed where robustness, risks, and transaction costs are assessed through corresponding models. At this phase, any suitable model is decided based on the inputs from the previous phase. During the third phase, the portfolio construction process is conducted to ascertain the trading signal(s). Subsequently, the trade execution is performed by deploying the execution model. Finally, when the trading process is accomplished, different post-trading analyses are carried out for any future improvements.

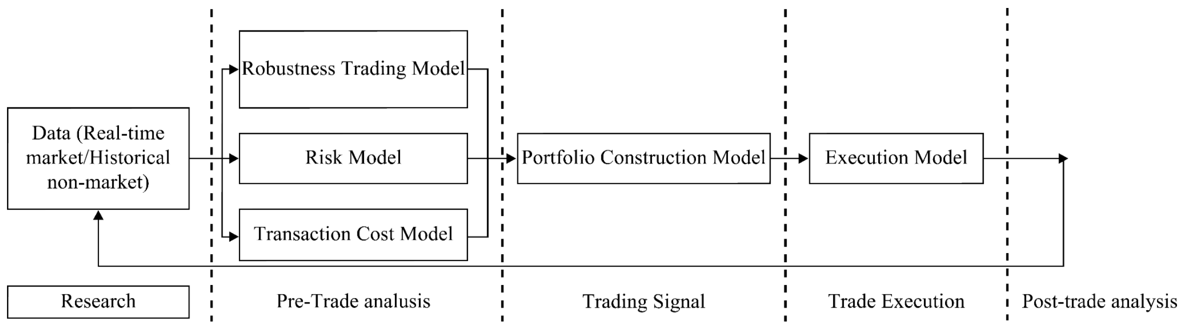


Fig. 1: Various phases of an Algorithmic Trading System (Treleaven *et al.* 2013).

A significant study by Hu et al. Hu *et al.* (2015) described an advanced algorithmic scheme based on Artificial Intelligence (AI) methods in AT processes. The authors employed prominent Evolutionary Computation (EC) algorithms in trading systems called genetic programming and genetic algorithms. Primarily, these algorithms are integrated with fuzzy logic techniques to develop improved prediction outcomes in trading systems.

Furthermore, Bendtsen & Peña (2016) developed trading algorithms using mathematical models, AI, and Machine Learning (ML) algorithms to integrate them into various trading systems. The authors leveraged fuzzy logic techniques to create a set of rules and investment strategies in trading. Moreover, they tested their model through two major trading markets, EURO STOXX, and NASDAQ100. As a result, they concluded that fuzzy logic methods could become a valuable tool for capital management in trading markets.

Muayteng *et al.* (2020) demonstrated that AT could be utilized in Thailand's SET50 index trading market. The study leveraged the AI approach by deploying fuzzy logic methods to forecast the market equity index with a moderate accuracy of 68.71%.

All the research mentioned above utilized AT algorithms in various market contexts and demonstrated the use of AI in predicting market trends. However, the overall results in risk reduction and profit growth are generally ineffective in most cases. This research article addresses these issues and proposes a novel trading algorithm—called the *Robustness Trading Model*—integrated with random generation methods to produce an AT strategy for derivative markets. The primary objective of this study is to illustrate the efficacy of AI-based fuzzy logic implementation techniques in profit growth and risk reduction compared to traditional methods. We specifically target a significant trading market – SET50 Index. We evaluated the proposed model using a popular electronic platform, MetaTrader 4 (MT4). By comparing the proposed model with the Buy & Hold and Mean Reversal strategies, we demonstrated that our approach could minimize risk (maximum Drawdown) and improve total profit per maximum Drawdown. Finally, we noticed that the proposed model could yield much-improved results if we could adjust and add more input algorithmic parameters.

2. Literature Review

Behavioral Finance

Behavioral finance is an emerging field that combines behavioral and cognitive psychological theory with traditional economics and finance to study why people make irrational decisions. Furthermore, it also evaluates the psychology and sociology of the behavior of finance professionals. In a remarkable study, Shefrin (2002) elaborates on the study of behavioral finance and its psychological effects on financial decision-making and trade markets.

Similarly, Chayakornkongwuth *et al.* (2013) concluded that behavioral finance explains why investors make irrational financial decisions. Moreover, the study describes how behavioral finance demonstrates the impact of emotions and cognitive errors on the decision-making process of investors.

The factors leading to behavioral finance are anchoring, overconfidence, herd behavior, over and under-reaction, and loss aversions. Nonetheless, behavioral finance and investment decision-making provide a process of selecting the most optimal alternatives. However, it is a complex and challenging process for individual investors.

Technical Analysis

Technical analysis is an extensively used tool in making investment decisions. In recent years, this tool has become prevalent in the context of Big Data Analytics and AI models. In addition, the results analysis of indicators in various trading markets often becomes the basis of technical analysis research.

In a significant research study, Lui & Hu (2012) investigated multiple stock price patterns using one of the earliest techniques of technical analysis: i.e., candlesticks. In this method, the authors developed a stock price vector with a shape and scale clustering technique for stock pattern detection, including the K-means algorithm. As a result, they could perform the data analysis of 42 stock price patterns.

Široček & Šíma (2016) explored optimal methods for evaluating technical analysis indices to determine the suitability of their models for predicting the future of investment. Furthermore, they compared their expected results of investors and indicators in the market volatility with the four most frequently used indicators of technical analysis: Simple Moving Average (SMA) and Moving Average Convergence/Divergence (MACD). Feng *et al.* (2017) explored the efficacy of technical analysis inflection in the market with a particular sentiment. They concluded that using technical analysis in an effective trading market is limited. Their study used twenty-two (22) indicators based on the following stock market indices: the S&P500 Index, the S&P Midcap 400 Index, the S&P SmallCap600 Index, the Dow Jones U.S. LargeCap Index, the Dow Jones U.S. Midcap, and the Dow Jones U.S. SmallCap Index.

Corelli (2019) leveraged Artificial Neural Networks (ANNs) to assess the use of technical analysis of the equity prices in the Italian trading markets. The author conducted this study in multiple phases, eliminating all the insignificant indicators. As a result, the performance of the selected stock prices was matched by two significant indicators, including EDF and DMA. Afterward, the ANNs were applied to these indicators to offer an accurate prediction of equity prices. Teresiene & Aleksynaite (2020) determined technical analysis indicators that operate uniformly or differently in various global markets, such as the US, European, and Asian stock markets. The authors computed eight critical indicators and compared their outcomes in three selected markets. Ayala *et al.* (2021) leveraged different Machine Learning (ML) models along with technical analysis of daily trading data from three major indices: Ibex35(IBEX), DAX, and Dow Jones Industrial (DJI). Chunhawiksit *et al.* (2021) studied investment in the Thailand stock exchange based on historical financial ratios, including the Return on Equity (RoE) and Price Earnings Ratio (P/E), and screened securities along with buy and sell timing using technical analysis tools for stock selection to develop a novel stock trading model.

Multiple recent studies have used automation technologies in various domains to enhance human decision-making and improve the digital workforce in trading markets. For example, in a comprehensive review, Afriliana & Ramadhan (2022) discussed the trends of using robotic process automation technology for digital automation. Similarly, Marcel et al. (2023) proposed an extensive framework for the digital transformation of organizations for their business sustainability and to gain a competitive advantage in the market. Similarly, Adityawan *et al.* (2023) considered the case study of using digitization in the Islamic banking sector in Indonesia to get a competitive advantage. In the FinTech area, Rajan *et al.* (2022) discussed the central importance of consumer opinion in driving the market. Therefore, technology adoption must always incorporate consumers' feedback and concerns about data security and system integrity.

Most previous research studies demonstrate that technical analysis techniques leverage different statistical methods, such as historical prices and trends while making investment and trading decisions. In addition, these studies consider that historical data of past trading decisions integrate vital information about derivative market trends. In addition, technical analysis is imperative in making crucial decisions during significant trading investments, especially while designing trading algorithms and signal computations. However, optimizing these decisions is a complex and challenging task due to the complexity of dynamic markets and the parameters involved. Consequently, developing a model that can reduce risks and improve profit growth is an important research area that is largely unexplored. In this work, we have addressed this gap and proposed a novel Robustness Trading Model to create AT strategies for derivative markets.

Fig. 2 illustrates the design of the proposed system. First, the trading algorithm takes inputs from signal computations and execution confirmations. Then, the algorithm delivers the trading orders as an output. Next, this system interacts with the Futures Exchange Market, which produces real-time market and historical data.

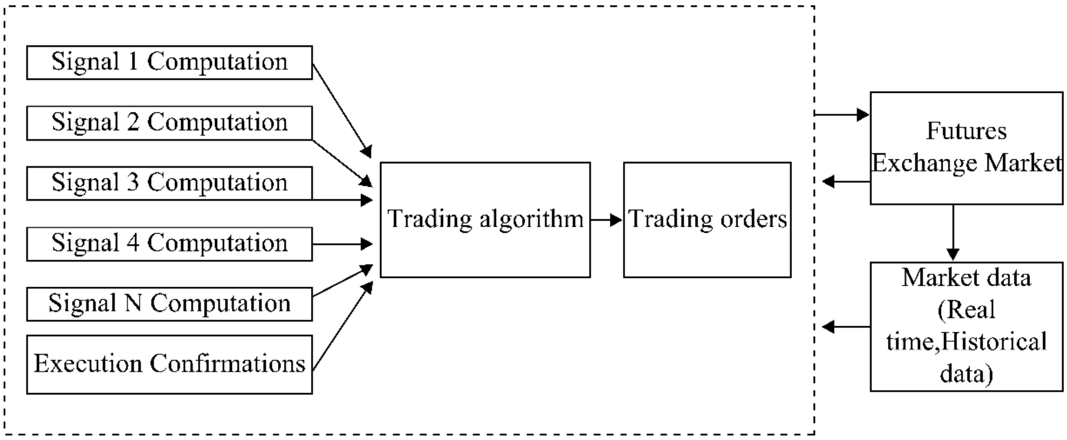


Fig. 2. Proposed Methodology.

Trading Strategy

In this research study, we describe three different strategies in trading systems: Buy and Hold strategy, mean reversal strategy, and AI-based fuzzy logic. These strategies have been tested in the SET50 Index. We discuss these strategies thoroughly in the following:

Buy and Hold Strategy

A Buy and Hold strategy (or position trading) is a passive investment approach. It is a highly conservative policy in which investors buy and hold stocks for a long duration regardless of market fluctuations. The strategy is based on the philosophy that the investors having their investments for an extended period will possibly earn higher returns. Many financial experts deem a Buy and Hold strategy the best investment policy, especially during a weak stock market scenario. For instance, Gitman *et al.* (2015) stated that investors tend to select high-quality shares offering current income or capital gains and holding these stocks for an extended time of approximately 10 to 15 years. In another study, Hui Ling *et al.* (2014) investigated the investment strategies in Malaysia, Singapore, Hong Kong, and Korea between 1990 and 2009. Their outcomes showed that the Buy and Hold strategy effectively reduces equity risk. Moreover, they also illustrated that the stock return volatility could be reduced from around 20% to below 1%.

Mean Reversal Strategy

The Mean Reversal Strategy relies on the mean reversion features of the price time series. The strategy is based on the principle that we can invest for a longer (or short) duration whenever the price is considerably below (or above) the mean value, and we can exit the position when the price is back at the mean. It indicates that a short-term investor tends to explore a time series that exhibits behavior as it translates to a simple set of trading rules. A study by Chan (2013) described a framework for preventing trading strategies offered by technical indicators called Bollinger Bands.

AI-based Fuzzy Logic Strategy

An AI-based fuzzy logic strategy relies on random generation and fuzzy logic, depending on the technical indicators, to produce the Buy and Sell trading signals to the varying market condition. These indicators comprise price ranges of time series, such as buy and sell stop orders.

Random Generation

The trading model is developed by deploying a combination of technical indicators, oscillators (e.g., MACD, RSI, Stochastic), and equality operators (and, or,>,<, etc.) to form the entry and exit rules to be produced for different trading models. Random Generation is a process of selecting various technical indicators and integrating them to develop a trading model, as presented in Fig. 3. The outcome of this process is the creation of entirely new random trading models, which can be as many as 2N-1 cases. For example, if N=10 technical indicators, it is possible to create 210 = 1,023 cases. Moreover, if N = 100 technical indicators, we can produce 2100 = 1,078,545 cases.

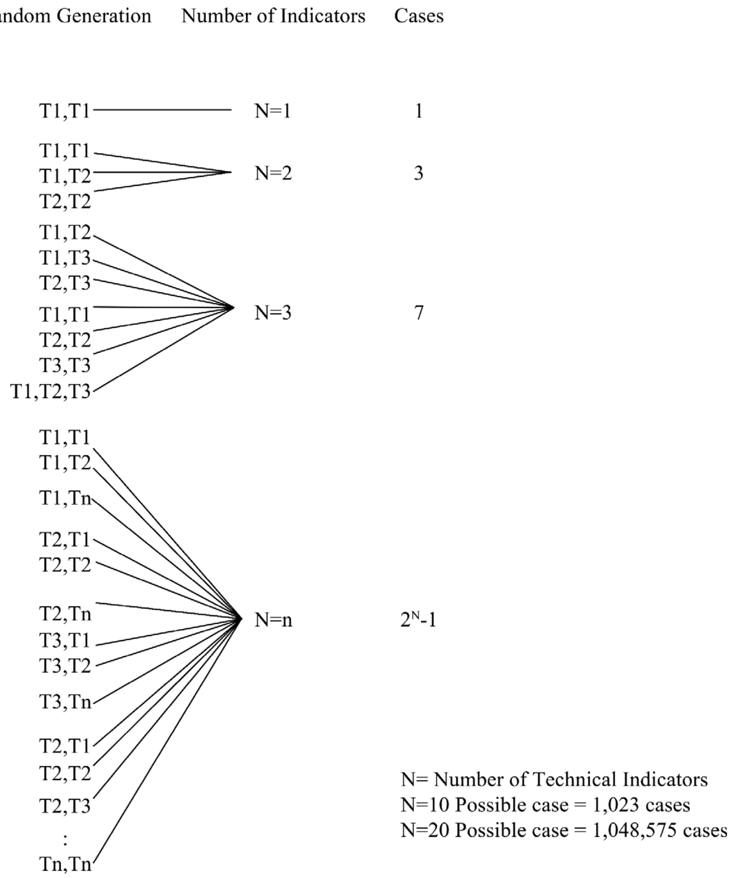


Fig. 3. The Random Generation Process.

Fuzzy Logic Fundamental

Fuzzy logic—pioneered by Lotfi Zadeh during the 1960s—resembles human rationale in its use of approximately vague, noisy, or imprecise data/information and uncertainty to produce decisions Zadeh *et al.* (1996). In 1965, Zadeh et al. offered the preliminary design of fuzzy logic development by using fuzzy sets. Contrary to the conventional interval sets, these fuzzy sets are designed upon the idea of partial association or membership. Furthermore, fuzzy logic distinguishes elements relevant to exciting phenomena and offers limited significance to the elements, including some uncertain and imprecise scenarios. Through fuzzy logic, information is processed so that each linguistic term is considered a variable. Some examples in the case of Algorithmic Trading are buy, sell, hold, etc. It is defined that a specific fuzzy set (A) for x can be specified by its corresponding membership function in the following manner:

$$0 < A(x) < 1,\ \ x \tag{1}$$

Where A(x) represents the membership degree of x.

There are multiple types of membership functions, including Polynomial, Gaussian, and Triangular functions. Furthermore, the degree of membership is directly proportional to the values of the membership function. For example, in Equation 1, x is a fuzzy set defining a membership function, which includes a map of every point of set x on the interval [0.0, 1.0].

According to the fundamental theory, a fuzzy model comprises three different modules, which are explained in the following:

i ***Fuzzy rule base:*** It is a set of "if then else" rules that establish the fuzzy model's expert knowledge.

ii ***Fuzzification module:*** It transforms the inputs (i.e., explanatory variables) into the relevant fuzzy variables.

iii ***Defuzzification module:*** This module translates the inference outcomes from the fuzzy domain to the outputs, formulated as the dependent variables in the fuzzy model.

The relevant information is gathered to develop the fuzzy rule base to design a fuzzy model. This information typically specifies expert knowledge of the fuzzy process and is assembled by observing the historical data regarding the process.

Gradojevic & Gençay (2013) discussed a fuzzy system by explaining the output production process or trading recommendations. First, the study illustrates the fuzzing method for the inputs or technical indicators in trading. Afterward, it explains the execution process of all the rules in the developed rule base system. The fuzzy process produces various conclusions about the output variables in the case of every state. Moreover, it specifies the impact of the output membership functions associated with the fuzzy process rules. Finally, after defuzzification, the model produces a single value output, identifying the required trading position as shown in Fig. 4.

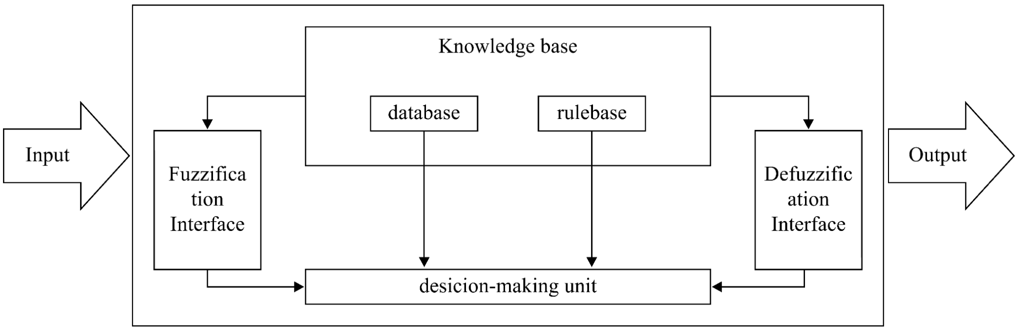


Fig. 4. Fuzzy inference system (Gradojevic & Gençay, 2013).

Narayana Rao & Sangam (2017) proposed a fuzzy logic expert system developed to evaluate the financial trading markets. In this work, the authors designed investment decision-making on the fuzzy model that can be very beneficial, especially for investors investigating reducing the risks while dealing with a long-term investment portfolio.

Another work by Dostál & Lin (2018) discussed the time series of stock titles, commodities, and currency rates affected by complicated economic and psychological phenomena. Unfortunately, the model includes a high degree of chaos. Thus, fuzzy logic and other similar soft computing tools are the best for processing and assessing economic and financial data. Yu & Yan (2020) discussed financial data containing complex, incomplete, and fuzzy information in the case of complex development trends. Furthermore, financial data variations depend on innumerably correlated and continuously varying factors. Thus, the authors concluded that predicting and assessing financial data is a non-linear and time-dependent problem.

Gautam & Abhishekh (2019) developed a novel moving average-based prognostic method and the fuzzy time series dataset. The proposed fuzzy time series method offered improved predictive output with the smallest RMSE. Similarly, Liu *et al.* (2019) leveraged the fuzzy time series to evaluate and forecast the stock prices of the State Bank of India and the Dow Jones Industrial Average (DJIA). The experimental results showed that the proposed model outperformed all the other time series models in similar stock price situations. Jankova *et al.* (2021) explained that the financial markets are steadily shifting their prediction models to advanced AI algorithms and data-driven methods like fuzzy logic and Machine Learning (ML). Furthermore, the study concluded that using AI in trading models helps capture non-linear trading behaviors.

A recent study by Erna Fransisca Angela Sihotang (2022) elaborated on the use of fuzzy logic modeling for evaluating online courses by incorporating multiple decision parameters for decision-making. The study vividly illustrates the use of fuzzy logic in a real-world application where the final decision has practical value. These studies show that AI-based models like fuzzy logic offer a strategy for acquiring definitive conclusions from incomplete, ambiguous, or inaccurate information. Consequently, it is a substantially valuable tool in stock trading prediction and AT models.

Robustness Analysis

In this analysis, the robustness of the fuzzy logic model is assessed, and it is determined that the empirical outcome could be secure for data mining.

Our research proposes an automated trading strategy created through fuzzy logic integrated with random generation. This strategy has been validated through Monte Carlo (MC) analysis to satisfy the confidence level. However, multiple research studies have indicated that the trading models must be validated for the impacts of the potential slippage in the real markets before going live and testing the future's dynamic market robustness.

Evaluation and Feasibility in Business Model

This research study offers an innovative evaluation strategy for a commercial system. Chayakornkongwuth *et al.* (2013) designed and developed an innovative assessment system to evaluate a project's feasibility. Their results indicated that five factors, including marketing, project management, finance, social, and environmental, are vital for assessing a system. Thus, the proposed innovative evaluation system for determining commercial software is based on financial feasibility in three business models: *profit-sharing, commission-based, and subscription business models for the best and worst-case scenarios*.

3. System Implementation and Experimental Results

This work proposes a novel trading algorithm called the *Robustness Trading Model*. It is a data-driven model based on empirical and historical data from the derivative trading market. For evaluation, we have utilized the *MetaTrader* 4 (referred to as *MT4*), which is a well-known electronic platform for trading on a global scale. Several studies indicate that MT4 is an extensively-used platform for executing various trading orders in real-market scenarios. Furthermore, it can produce quantitative trading signals in fundamental trading markets. Fig. 2 presents the block diagram of the proposed *Robustness Trading Model*. We collected real-time trading market data along with historical data, which has been included with the data volumes and closing prices. As a result, the proposed model produces multiple signals indicating buying and selling decisions for longer or shorter positions. We employed the SET50 Index instead of *50 Stock securities* using an AI-based fuzzy logic algorithm fed with underlying data. In this case, the testing data is classified into the following categories: *in-sample data* (01.01.2012 to 31.12.2017) and *out-of-sample data* (01.01.2018 to 31.12.2021) with *historical data* of a 15-minutes timeframe. First, this data is used in our model to generate the buy and sell signals with an initial equity of 100,000 Thai Baht. Next, the testing money-management setup has the fixed position sizing of one contract in each trading position utilized with the stop-loss and profit target. In addition, the test had a check under the condition of 160 Thai Baht commission.

We used MetaQuotes Language (MQL) to implement the trading algorithm based on fuzzy logic. Moreover, fuzzy logic was described as a human-readable strategy using the *pseudocode*. As a result, the code can be conveniently read for manual trading in the market. Fig. 5 illustrates the *pseudocode* for the trading algorithm for the SET index.

```
//-------------------------------------------------------------------
// Trading rule: Trading signals (On Bar Open)
//-------------------------------------------------------------------
LongEntrySignal = FUZZY Logic Varible is true if min 67 % conditions (3 out of 4) are correct:
        - (DeMarker(Main chart,40) > 0.30)
        - Open below BollingerBands(Main chart,65, 0.6).Upperband after opened above
        - (QQE(Main chart,14, 5, 4.2.Value1[3] > QQE.Value2)
        - Bar opens below Highest(Main chart, 30) after opened above

ShortEntrySignal = FUZZY Logic. Variable is true if min 67 % conditions (3 out of 4) are correct
        - (DeMarker(Main chart,40) < -0.30)
        - Open above BollingerBands(Main chart,65, 0.6).Lowerband after opened below
        - (QQE(Main chart,14, 5, 4.2.Value1[3] < QQE.Value2)
        - Bar opens above Lowest(Main chart, 30) after opened below

LongExitSignal = FUZZY Logic, Variable is true if min 78 % conditions (1 out of 1) are correct:
        - false

LongExitSignal = FUZZY Logic, Variable is true if min 78 % conditions (1 out of 1) are correct:
        - false
```

Fig. 5. The fuzzy logic algorithm pseudocode

We inputted historical data of ten years to the *MetaTrader 4* tool using MQL and used it for the control logic of the fuzzy logic model after signifying the Input/Output (I/O) variables and rules. Fig. 7 demonstrates the normalized market data values for volume, closing prices, and technical indicators. These parameters were utilized in the fuzzy logic algorithm, which specifies rules set for the selling or buying conditions in the trading market.

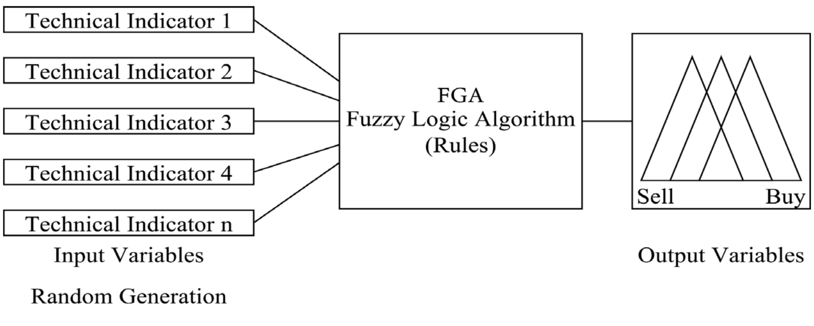


Fig. 6. Fuzzy logic function (inputs and outputs) with random generation.

Using fuzzy logic, we generated several different automated trading algorithms, and Table 1 shows their performance data. Then, we selected 421 Automated Trading (AT) algorithms with a maximum *drawdown* of less than 30% sorted by *Net profit* vs. *Drawdown,* as depicted in Fig.7.

Table 1. Example performance data of automated trading model generated by AI-Fuzzy logic.

Strategy	Symbol	Net profit	Drawdown	% MaxDD	% Win	Ret/DD Ratio	Trades	Annual % Return	Win/Loss ratio	Annual % Return/ MaxDD%
1	TFEXS50M15	32,960	3,660	3.06	55.66	10.77	106	2.89	1.26	1.1
2	TFEXS50M15	26,540	3,160	3.16	68.66	8.4	67	2.38	2.19	0.96
3	TFEXS50M15	26,500	3,620	3.62	56.52	7.32	93	2.4	1.3	0.73
4	TFEXS50M15	25,280	3,620	3.62	67.5	6.98	80	2.28	2.08	0.76
5	TFEXS50M15	30,060	3,780	3.78	59.26	7.95	82	2.68	1.45	0.72
6	TFEXS50M15	40,420	3,880	3.88	53.26	10.42	92	3.44	1.14	1.19
7	TFEXS50M15	25,680	3,920	3.92	67.27	6.55	110	2.34	2.06	0.66
8	TFEXS50M15	48,360	3,960	3.96	66.67	12.21	109	3.99	2	1.28
9	TFEXS50M15	65,660	4,400	4.40	59.15	14.19	164	5.13	1.45	1.32
10	TFEXS50M15	69,760	4,480	4.48	57.65	15.57	197	5.39	1.36	1.32

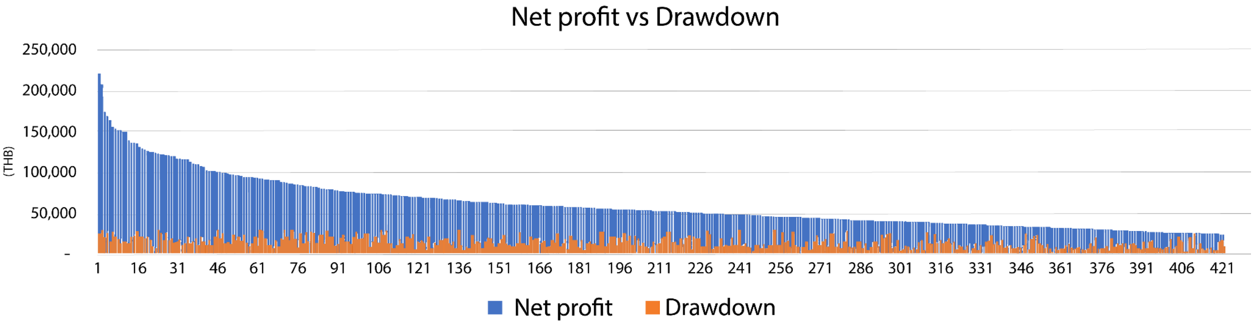
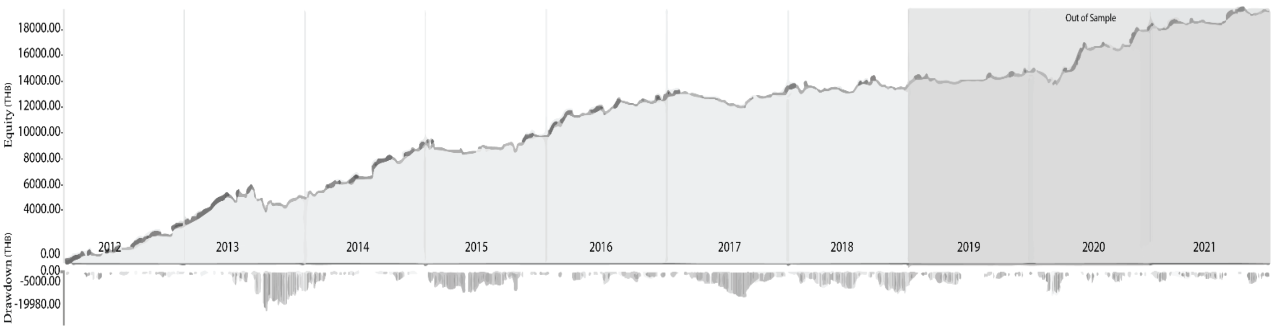


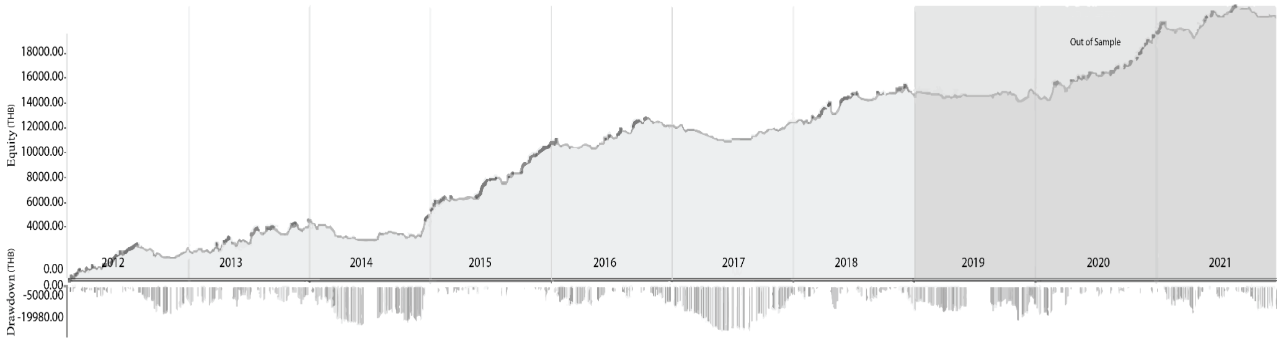
Fig.7. Automated Trading models generated by random generation and fuzzy logic.

For experimental results, the *Buy & Hold* strategy of the SET50 index has used factors such as *Momentum, Aroon, Keltner Channel,* and *ATR technical indicators*. Furthermore, the *Mean Reversal Strategy* of the *SET50 index* employed parameters like *RSI, Awesome Oscillator,* and *RSI technical indicators*. Similarly, AI-based fuzzy logic with the adaptive algorithm of *SET50* used factors like *Keith Channel, Williams % R, Bollinger Bands,* and *ATR technical indicator*. Fig. 8 and Table 2 present the outputs of each equity curve. It can be observed from these *Equity Curve* results that the annual yield of the *SET50 Index futures* is approximately 16.1% and approximately 6.03% with Maximum Drawdown. Moreover, the *Sharpe Ratio* is 2.08. In the case of the fuzzy logic algorithm, the % winning of *SET50 index futures* is calculated to be 57.28%. Consequently, the total profit/maximum downtown of the fuzzy logic algorithm is 25.35, which is much higher than the *Buy & Hold* (9.32) and *Mean Reversal* (11.21) strategies.

Buy and Hold Strategy



Mean Reversal Strategy



AI-based Fuzzy Logic Strategy

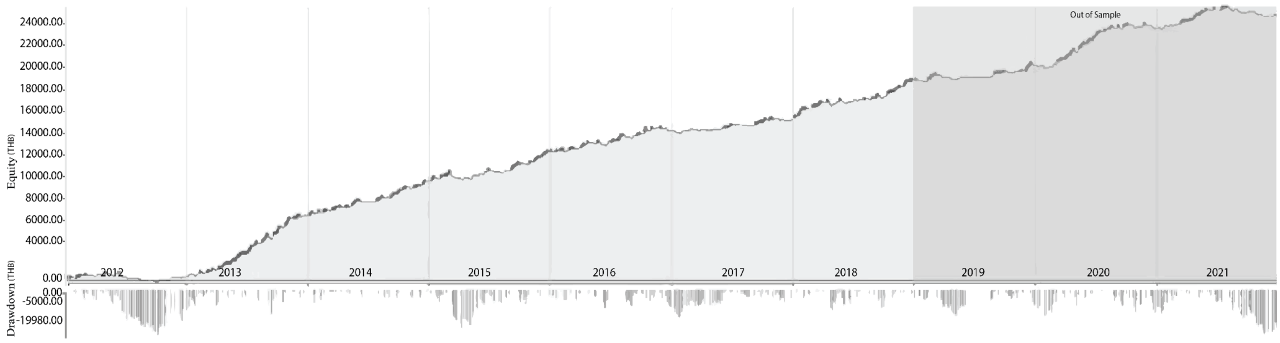


Fig. 8. The output of the equity curve view as a strategy that operated automated and executed to the market.

SET50 Index

Table 2. The statistical performance (the equity curve viewed as statistical data).

Description	Buy and Hold	Mean Reversal	AI based Fuzzy logic
Initial Balance (THB)	100,000	100,000	100,000
Total Profit (THB)	193,480	164,100	161,220
Draw down (THB)	20,760	14,640	6,360
%draw down	12.3	9.07	6.03
Annual yield	13.9	16.4	16.1
CAGR (Compound Annual Growth Rate)	11.37	10.2	10.08
Profit factor	1.4	1.45	1.44
Sharpe ratio	1.5	1.3	2.08
%Winning (No. Profitable trade/No. Tota. trade) x100	45.45	55.28	57.28
Reward/Risk	1.68	1.17	1.34
No. Trade (Total)	2,132	1,043	996
No. Trade (Long position)	2,132	570	458
No. Trade (Short position)	0	473	538
No. Long position (Profit)	993	323	265
No. Short position (Profit)	0	255	305
%Long Position (profit),(No.Profitable/No.Long position)x100	46.58	56.67	57.86
%Short Position (profit),(No.Profitable/No.Short position)x100	-	53.91	56.69
Total Profit / Maximum Drawdown	9.32	11.21	25.35

Fig. 9. depicts the performance of returns tested annually for the *SET50 index futures*. The values of PL each year between 2012 and 2021 are positive and show growth.

SET50 Index-Fuzzy logic with an adaptive algorithm.

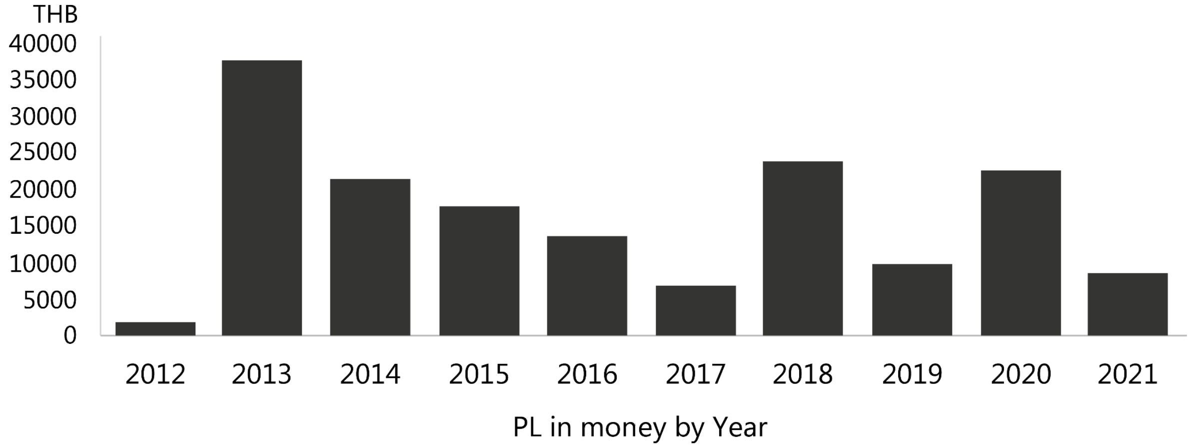


Fig. 9. Performance Return each year.

In addition, the robustness testing with Monte Carlo (MC) returns was tested with the *SET50 index futures*, and the corresponding results are presented in Fig. 11. Besides, the *Confidence Level* outcomes of AI-based fuzzy logic are shown in Table 3. We can observe the robustness using *Monte Carlo analysis* with *Out of Samples* data ensures a *Confidence Level* of 90-95%. Therefore, the AI-based fuzzy logic strategy is valuable to sustain growing equity. Moreover, as presented in Table 3, it can produce a net profit with a drawdown for the *Confidence Level* at 90-100%.

SET50 Index

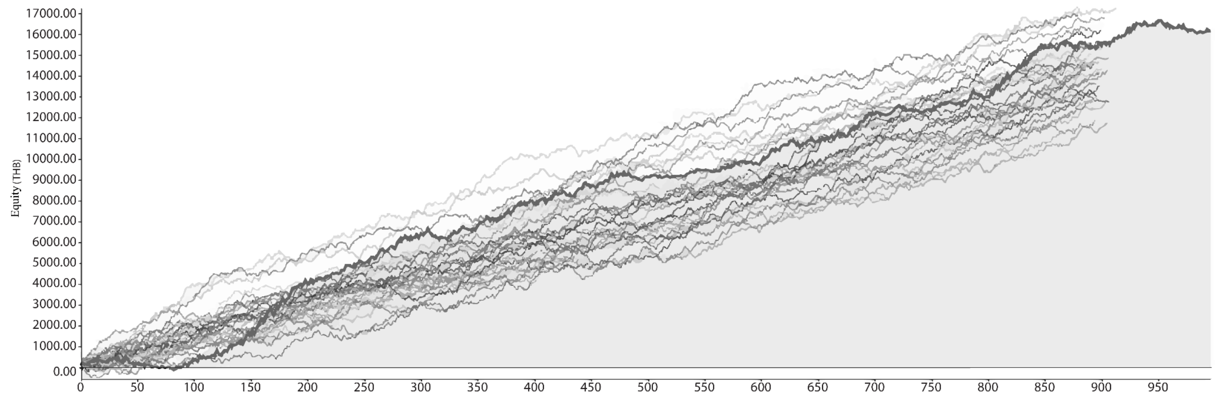


Fig. 10. Robustness testing with Monte Carlo analysis.

Table 3. Confidence Level of Fuzzy Logic Algorithm.

Confidence Level	Net Profit (Thai Baht)	Maximum Drawdown (Thai Baht)
Original	193,480.00	20,760.00
90%	121,660.00	23,420.00
95%	101,300.00	31,620.00
99%	65,980.00	39,420.00
100%	65,980.00	39,420.00

For an innovative automated trading software evaluation system, this experiment has been classified into three business models to study financial feasibility analysis. As presented in Fig. 11, these models include the commission, profit-sharing, and subscription models for commercial software.

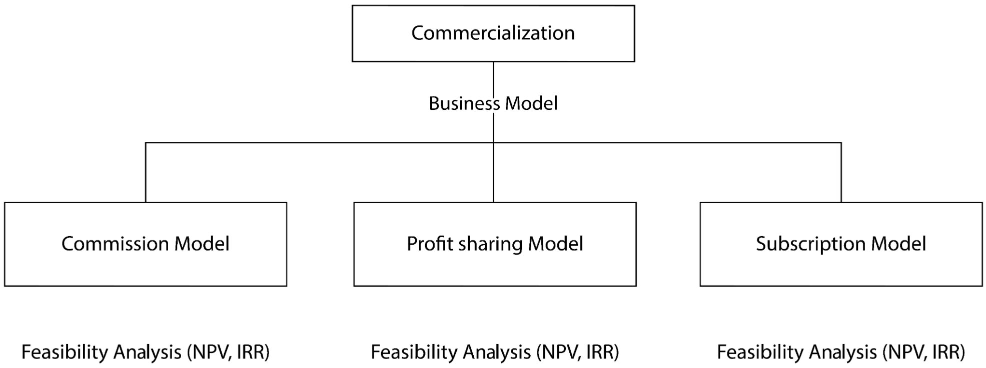


Fig. 11. Commercialization of automated trading software into three classification models.

The *Assumption of Feasibility* analysis for five years determines the initial assumption as follows. The profit-sharing model assumes one model for 10,000,000 Baht (AUM), whereas the profit-sharing model provides 20% of *broker* and *developer*, increasing 50% AUM annually. Furthermore, the commission-based model assumes one model for 10,000,000 Baht (AUM), improving 50% AUM per year, 50% cloud service per year, and 10% workforce annually. Finally, the subscription model assumes one model for 10,000,000 Baht (AUM); subscription is 1% of AUM, improving 50% AUM and increasing 10% manpower annually. This initial assumption is computed in the financial feasibility analysis for the best-case scenario. In addition, the results in the *Possibility Case Scenario* and *Worst-case Scenario* for all three scenarios in terms of NPV and IRR are presented in Table 4. It can be observed that the profit-sharing model has the best NPV and IRR values compared to the commission and subscription models.

Table 4. Summary feasibility results in the business model.

Best Case Scenario

	Commission Model	Profit Sharing Model	Subscription Model
NPV	596,574.89	2,258,936	447,421
IRR	102%	285%	88%

Possibility Case Scenario

	Commission Model	Profit Sharing Model	Subscription Model
NPV	108,404.96	818,223	(54,504)
IRR	40%	188%	39%

Worst Case Scenario

	Commission Model	Profit Sharing Model	Subscription Model
NPV	(146,292.40)	165,153	(332,649)
IRR	N/A	115%	N/A

4. Discussion on Results Analysis

Based on various *technical indicators*, we tested the proposed automated trading algorithm on the SET50 index futures. Figure 8 presents the Equity Curve results from the automatic operation to buy and sell orders for a long and short position. The annual yield of the SET50 Index futures is approximately 16.1%, and about 6.03% with Risk (Maximum Drawdown), and the Sharpe Ratio is 2.08. As a result, the fuzzy logic algorithm can predict 57.28% for the % winning of SET50 index futures. Table 2 presents all these results. Furthermore, the fuzzy logic algorithm tests the robustness using Monte Carlo analysis with new data (Out of Samples data) to ensure the Confidence Level at 90-95%. Consequently, it can sustain growing equity, as shown in Figure 10. Moreover, as presented in Table 3, it can produce a net profit with a drawdown for the Confidence Level at 90-100%. Finally, the summary feasibility analysis in Table 4 demonstrates that the profit-sharing model provides the best Net Present Value (NPV) and highest Internal Rate of Return (IRR) for the best-case, possibility-case, and worst-case scenarios. However, it should be noted that IRR is only valuable when we compare several models, and it is hard to evaluate the discount rates. Comparatively, we can use NPV when encountering many discount rates.

The proposed AT model can offer several advantages to the Thailand trading market. First, the computational speed of AT models is much higher than that of human traders, which can improve the possibilities for profit for trading companies. Second, our model can assess massive volumes of trading data, allowing it to make informed choices. Since it is trained on historical data, it can make better predictions of future market trends. Human traders cannot evaluate such substantial datasets. Third, the objective accuracy value in AT algorithms is much better than human traders, who are prone to error due to emotional biases and decisions. Consequently, the decisions by AT models are usually consistent. However, besides these advantages, the proposed model has many limitations. For instance, it primarily relies on market data; if this data is inaccurate, the model can make error-prone investment decisions. Another issue is that the computational costs of the model training can be very high if trained on a substantial amount of data.

Nonetheless, many factors should be considered while designing AT methods and algorithms. For instance, the price factor and the commission of the futures contract per trade should be incorporated to cope with the higher transaction cost. Likewise, trading time per transaction and the number of trades per transaction should be considered, as they can result in higher transaction costs without high-frequency trading in the futures market. Market timing should be considered under both normal and abnormal conditions. The contract liquidity must be considered below average. Maximum profit may come after a period of loss. Furthermore, the rollover period of the futures exchange must be prioritized before the contract expiration. Finally, the investment model must be evaluated across multiple models for diversification.

5. Conclusion

In this article, we proposed a novel trading algorithm called the Robustness Trading Model, which integrated random generation techniques to generate Automated Trading (AT) algorithms for derivative markets. We demonstrated the effectiveness of this approach by comparing the outcomes with *Buy & Hold and Mean Reversal* strategies and showed that our model could yield better risk and profit outcomes. We believe that the proposed strategy for innovative implementation using random generation based on AI-based fuzzy is imperative to develop an automated trading policy in the form of a robust trading algorithm for relevant software. More specifically, we have illustrated that the AI-based fuzzy logic approach can predict the future performance of SET50 index futures with up to 57.28% accuracy. In addition, this approach can reduce risk (maximum Drawdown) and improve the total profit per maximum Drawdown (return/risk) compared to the Buy and Hold and the Mean Reversal Strategy. For an innovative evaluation system, financial assessment is an essential factor. Therefore, using feasibility analysis to commercialize the automated trading software, the financial analysis results can conclude that the profit sharing model has the best *Net Present Value (NPV) and highest Internal Rate of Return (IRR)* for the best cast, possibility-case and worst-case scenarios.

We recommend that Thailand's market practitioners, regulators, and policymakers adopt our proposed model to maximize their gains and eliminate biased decisions. However, we observed that we could further improve these outcomes by adjusting the algorithmic parameters. Therefore, applying AI-based fuzzy logic can improve a trading algorithm for automated trading software in multiple models. In our future work, we will incorporate more input variables for efficient algorithms to acquire improved results.

Acknowledgments

We express our heartfelt gratitude to our research supervisors; Assoc. Prof. Dr. Pornanong Budsaratragoon and Asst Prof. Dr. Chaiwat Nuthong, for their invaluable guidance, insights, and unwavering support throughout our research. Their expertise and mentorship have significantly contributed to the direction and excellence of this study.

References

Adityawan, Y., Arief, M., Alamsjah, F., & Bandur, A. (2023). The Role of Digital Innovation in Improving Performance Study on Islamic Banking in Indonesia. *Journal of System and Management Sciences*, *13*(1), 103–116.

Afriliana, N., & Ramadhan, A. (2022). The Trends and Roles of Robotic Process Automation Technology in Digital Transformation: A Literature Review. *Journal of System and Management Sciences*, *12*(3), 51–73. https://doi.org/10.33168/JSMS.2022.0303

Ayala, J., García-Torres, M., Noguera, J. L. V., Gómez-Vela, F., & Divina, F. (2021). Technical analysis strategy optimization using a machine learning approach in stock market indices. *Knowledge-Based Systems*, *225*, 107119.

Bendtsen, M., & Peña, J. M. (2016). Gated Bayesian networks for algorithmic trading. *International Journal of Approximate Reasoning*, *69*, 58–80. https://doi.org/10.1016/j.ijar.2015.11.002

Chan, E. (2013). Algorithmic Trading: Winning Strategies and Their Rationale. In *Journal of Chemical Information and Modeling* (Vol. 53, Issue 9). John Wiley & Sons.

Chayakornkongwuth, N., Cooharojananone, N., & Chandrachai, A. (2013). Innovative Evaluation System to Determine the Feasibility for the Non-Profit Organization. *WMS Journal of Management*, *2*(3), 1–7.

Chunhawiksit, C., Deelers, S., Chitadisai, W., Thammachot, S., Aujirapongpan, S., & Ru-Zhue, J. (2021). Comparison of the Return of Investment from Securities Screening Using Financial Ratios and Security Trading Methods: Evidence from Thailand. *Journal of Southwest Jiaotong University*, *56*(1). https://doi.org/10.35741/issn.0258-2724.56.1.26

Corelli, A. (2019). Equity price prediction with neural networks: Technical analysis of the Italian market. *Journal of Wealth Management*, *21*(4), 65–75. https://doi.org/10.3905/jwm.2019.21.4.065

Dostál, P., & Lin, C. Y. (2018). Business applications of fuzzy logic. *The Oxford Handbook of Computational Economics and Finance*, *1*, 360–396. https://doi.org/10.1093/oxfordhb/9780199844371.013.14

Erna Fransisca Angela Sihotang, D. N. U. (2022). *Fuzzy Logic based Decision Support Model for Determining the Subject of Online Course Materials*. *12*, 169–192. https://doi.org/10.33168/JSMS.2022.0511

Feng, S., Wang, N., & Zychowicz, E. J. (2017). Sentiment and the performance of technical indicators. *Journal of Portfolio Management*, *43*(3), 112–125. https://doi.org/10.3905/jpm.2017.43.3.112

Gautam, S. S., & Abhishekh. (2019). A Novel Moving Average Forecasting Approach Using Fuzzy Time Series Data Set. *Journal of Control, Automation and Electrical Systems*, *30*(4), 532–544. https://doi.org/10.1007/s40313-019-00467-w

Gitman, L. J., Juchau, R., & Flanagan, J. (2015). *Principles of managerial finance*. Pearson Higher Education AU.

Gradojevic, N., & Gençay, R. (2013). Fuzzy logic, trading uncertainty and technical trading. *Journal of Banking and Finance*, *37*(2), 578–586. https://doi.org/10.1016/j.jbankfin.2012.09.012

Hu, Y., Liu, K., Zhang, X., Su, L., Ngai, E. W. T., & Liu, M. (2015). Application of evolutionary computation for rule discovery in stock algorithmic trading: A literature review. *Applied Soft Computing Journal*, *36*, 534–551. https://doi.org/10.1016/j.asoc.2015.07.008

Hui Ling, F. C., Ching Yat, D. N., & Muhamad, R. B. (2014). An empirical re-investigation on the "buy-and-hold strategy" in four Asian markets: A 20 years' study. *World Applied Sciences Journal*, *30*(30 A), 226–237. https://doi.org/10.5829/idosi.wasj.2014.30.icmrp.30

Jankova, Z., Jana, D. K., & Dostal, P. (2021). Investment decision support based on interval type-2 fuzzy expert system. *Engineering Economics*, *32*(2), 118–129. https://doi.org/10.5755/j01.ee.32.2.24884

Liu, Z., Zhang, T., Dong, Y., & Xu, S. S. (2019). A Second-Order Fuzzy Time Series Model for Stock Price Analysis. *Dongbei Daxue Xuebao/Journal of Northeastern University*, *40*(2), 300–304. https://doi.org/10.12068/j.issn.1005-3026.2019.02.028

Lui, K. M., & Hu, L. (2012). Does a Generic Price Pattern Exist? An Alternative Approach to Technical Analysis. *The Journal of Investing*, *21*(3), 69–77. https://doi.org/10.3905/joi.2012.21.3.069

Marcel, Ramadhan, A., Trisetyarso, A., Abdurachman, E., & Zarlis, M. (2023). Digital Transformation Adoption: An Extended Step-by-Step Framework. *Journal of System and Management Sciences*, *13*(2), 45–63. https://doi.org/10.33168/JSMS.2023.0204

Muayteng, K., Budsaratragoon, P., & Nuthong, C. (2020). Modeling Derivatives Market Data with Artificial Intelligence Based on Fuzzy Logic to Automated Trading Algorithm for Individual Investors in Thailand. *International Journal of Innovation in Management*, *8*(1), 37–42. https://siim.org.tw/IJIiM/DW/V8N1/IJIiM-20-022.pdf

Narayana Rao, T. V., & Sangam, S. (2017). Application of Fuzzy Logic in Financial Markets for Decision Making. *International Journal of Advanced Research in Computer Science*, *8*(3).

Rajan, N., George, A., Saravanan, S. V., Kavitha, J., & Gopalakrishnan, C. S. (2022). An Analysis on Customer Perception towards Fintech Adoption. *Journal of Logistics, Informatics and Service Science*, *9*(3), 146–158. https://doi.org/10.33168/LISS.2022.0311

Shefrin, H. (2002). *Beyond Greed and Fear: Understanding Behavioral Finance and the Psychology of Investing*. Oxford University Press. https://books.google.com/books?id=hX18tBx3VPsC

Širuček, M., & Šíma, K. (2016). Optimized indicators of technical analysis on the New York stock exchange. *Acta Universitatis Agriculturae et Silviculturae Mendelianae Brunensis*, *64*(6), 2123–2131. https://doi.org/10.11118/actaun201664062123

Teresiene, D., & Aleksynaite, M. (2020). The Use of Technical Analysis in the US, European and Asian Stock Markets. *Technium Social Sciences Journal*, *8*, 302–318. https://doi.org/10.47577/tssj.v8i1.890

Treleaven, P., Galas, M., & Lalchand, V. (2013). Algorithmic trading review. *Communications of the ACM*, *56*(11), 76–85. https://doi.org/10.1145/2500117

Yu, P., & Yan, X. (2020). Stock price prediction based on deep neural networks. *Neural Computing and Applications*, *32*, 1609–1628.

Zadeh, L. A., Klir, G. J., & Yuan, B. (1996). *Fuzzy Sets, Fuzzy Logic, and Fuzzy Systems - Selected Papers by Lotfi A Zadeh* (Vol. 6). World Scientific. http://www.worldscientific.com/worldscibooks/10.1142/2895%5Cnhttp://dx.doi.org/10.1142/2895