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SHORT PRESENTATION PAPERS/ABSTRACTS

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On Parameter Extension of q-Divergence-based Fuzzy *c*-Means Clustering

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Abstract. Fuzzy c-means (FCM) proposed by Bezdek [1] is a pioneering fuzzy clustering algorithm. The method used in this study is referred to as B-type FCM (BFCM) to distinguish the other FCM-like algorithms. In BFCM, the fuzzificating is done by replacing the membership in the hard c-means [2] with its power. This fuzzification technique is referred to as B-type fuzzification, and the exponent is referred to as B-parameter. Miyamoto proposed the (Shannon) entropy-regularized FCM (EFCM) [3], and Menard proposed the Tsallis-entropy-based FCM (TFCM) [4]. These algorithms were extended by introducing a cluster size controller, resulting in the modified BFCM (mBFCM) [5], modified EFCM (mEFCM) [6], and q-divergence-based FCM (QFCM) [7]. In QFCM, fuzzification is performed by regularizing the mBFCM algorithm using q-divergence. This fuzzification technique is referred to as the Q-type. QFCM is reduced to mBFCM if the regularizing parameter value is set to one, whereas QFCM is reduced to mEFCM if the B-parameter value is set to infinity. Therefore, QFCM enables to produce more flexible clustering results and outperforms mBFCM and mEFCM in terms of clustering accuracy.

Penalized FCM, proposed by Yang [8] is another variant of the fuzzy clustering algorithm that penalizes BFCM using the logarithm of the cluster size controller. This method is referred to as Y-type FCM (YFCM) in this study, and the fuzzification technique in YFCM is referred to as Y-type. Both the QFCM and YFCM objective functions are similar to each other, have two fuzzification parameters: the B- and regularizing, and have factors of the power of membership. However, QFCM does not become YFCM and vice versa even if their fuzzification parameters are set to any value, which contrasts the fact that QFCM is reduced to mBFCM or mEFCM with a specific fuzzification parameter value. QFCM and YFCM produce accurate clustering results; hence, an algorithm that includes both yields more accurate clustering results.

In this study, a novel clustering algorithm is proposed, including QFCM and YFCM. First, we observed the difference in the fuzzification parameter effect between QFCM and YFCM. The B-parameter in QFCM affects both the membership and cluster size controllers, whereas the B-parameter in YFCM does not affects the cluster size controller, only the membership. To adjust for such a difference, the QFCM objective function was extended by splitting the B-parameter into two: one for the membership and the other for the cluster size controller. These extensions produces a general objective function that is reduced to QFCM if two B-parameter values are the same, whereas it remains slight different from YFCM. This problem is solved by splitting the regularizing parameter in QFCM into two, one of which is the same for YFCM and the other for the remaining term. Then, we propose a novel objective function with four fuzzification parameters, where one setting of fuzzification parameter values produces the QFCM objective function, and another setting produces the YFCM objective function. The proposed algorithm is referred to as an extended QFCM (eQFCM). Notably, the algorithm consists of all the explicit updating equations with various fuzzification parameter values, whereas other studies [9–11] used some fuzzification parameters consisting of algorithms only if their fuzzification parameters were set to a limited value, or included a complicated numerical calculation. The theoretical discussion is substantiated through numerical experiments using an artificial dataset. Furthermore, numerical experiment using real datasets show that the proposed algorithm outperforms conventional algorithms in terms of clustering accuracy.

Keywords: Fuzzy Clustering · q-Divergence · parameter extension.

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On Some Fuzzy Clustering based on the Multivariate Power Exponential Distribution

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Abstract

Clustering is a method of classifying a dataset into several subsets known as clusters. Objects that are allocated to the same cluster exhibit similarity greater than those allocated to other clusters. In the fuzzy clustering approach, each object belongs to several clusters. Several fuzzy clustering algorithms have been derived by extending probabilistic mixture models. The most representative mixture models are based on Gaussian distributions. Ichihashi et al. proposed the KL-divergence regularized fuzzy c-means (KFCM) algorithm [1] by introducing KL-divergence regularization to the lower bound of the log-likelihood of the Gaussian mixture model (GMM). In this study, this fuzzification type is referred to as KL-type fuzzification, and the KFCM algorithm is KL-type fuzzy clustering based on GMM (KL-FC-G). Yang proposed the Fuzzy Classification Maximum Likelihood (FCML) algorithm [2], in which the power of membership is introduced into the GMM classification maximum likelihood (CML). In this study, this fuzzification type is referred to as Y-type fuzzification, and the FCML algorithm is Y-type fuzzy clustering based on GMM (Y-FC-G). Ishii et al. proposed q-divergence regularized fuzzy clustering based on GMM (Q-FC-G) [4], which adopts q-divergence regularization of the lower bound of the GMM q-log-likelihood. This is referred to as Q-type fuzzification. Ishii et al. also proposed Bezdek-type fuzzy clustering based on GMM (B-FC-G) [4], which involves diverging a certain fuzzification parameter of the Q-FC-G objective function, which is referred to as B-type fuzzification.

The t-distribution is used in mixture models and can represent heavier tails than the Gaussian distribution. Yang et al. proposed the FCML with a t-distribution (FCMLT) [5, 6] by substituting the membership in the CML of the t-distribution mixture model (TMM) with its power. In this study, the FCMLT algorithm is referred to as Y-type fuzzy clustering based on TMM using the EM algorithm (Y-FC-T-EM). Ishii et al. proposed KL-type fuzzy clustering based on TMM using the EM algorithm (KL-FC-T-EM) [4], KL-type fuzzy clustering based on TMM using the MM algorithm (KL-FC-T-MM) [4], Y-type fuzzy clustering based on TMM using the MM algorithm (Y-FC-T-MM) [4], Q-type fuzzy clustering based on the TMM (Q-FC-T) [4], and B-type fuzzy clustering based on the TMM (B-FC-T) [4]. In addition to the t-distribution, the multivariate power exponential (MPE) distribution is also a probability distribution that can

represent heavy tails using its shape parameter, which is known as kurtosis. Although the MPE mixture model (MPEMM) [7] has been proposed, its fuzzified algorithm has not yet been presented. Fuzzy clustering derived from MPEMM may improve the clustering accuracy over that of existing models.

In this study, we propose four fuzzy clustering algorithms based on the MPE distribution. The first proposed algorithm is KL-type fuzzy clustering based on MPE (KL-FC-MPE), the objective function of which is derived by regularizing the KL-divergence of the lower bound of the log-likelihood of MPEMM. The second proposed algorithm is Y-type fuzzy clustering based on MPE (Y-FC-MPE), in which the MPE distribution is used within the FCML framework. The third proposed algorithm is Q-type fuzzy clustering based on MPE (Q-FC-MPE), the objective function of which is derived by introducing a q-divergence regularization to the lower bound of the MPEMM q-log-likelihood. The fourth proposed algorithm is B-type fuzzy clustering based on MPE (B-FC-MPE), in which the objective function is obtained by diverging the fuzzification parameter of the Q-FC-MPE objective function. Since the MPE distribution coincides with the Gaussian distribution when the kurtosis is 1, fuzzy clustering based thereon can be interpreted as encompassing fuzzy clustering based on GMM. The properties of the proposed and existing algorithms are analyzed using artificial and real datasets.

Keywords: Fuzzy clustering, Gaussian distribution, t-distribution, Multivariate power exponential distribution

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Leveraging Artificial Neural Networks to Improve Profitability of Technical Trading Rules in Thailand SET 100 Index

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Abstract. In recent years, the Thai stock market has witnessed substantial growth, emphasizing the need for investors to comprehend its unique characteristics to leverage potential opportunities. This study aims to enhance stock trading strategies by harnessing machine learning techniques to improve trend prediction accuracy and improve investor returns. The research involves collecting quantitative data, including daily stock open prices and key economic indicators such as GDP growth rate, inflation rate, and private investment index. The methodology encompasses the use of simple stock indicators, specifically 5-day and 15-day simple moving averages, to detect stock purchase or sale dates. Additionally, an artificial neural network is employed to filter out signals that prove unprofitable. The study's findings demonstrate that implementing the proposed model results in increased stock trading profits compared to relying solely on the simple moving average strategy. In addition, the results reveal the effectiveness of the artificial neural network in effectively avoiding unprofitable trades.

Keywords: Technical analysis, Trend prediction, Artificial neural network, Thai stock market, Economic indicators.

1 Introduction and Related Works

As per a survey conducted by Reuters of equity analysts, it is anticipated that the global stock markets will encounter persistent instability, with a majority of participants forecasting a correction within the upcoming three months. The year 2022 witnessed a decline of approximately 20% in the worldwide stock market. However, a year-end rally offered some respite to investors who were anticipating a halt in interest rate hikes owing to the decline in inflation and sluggish growth. However, strong labor markets, resilient economic growth, and persistent inflation have dashed expectations for rate cuts, leading to higher bond yields and market interest rate pricing (Kishan, 2023). Successful investing in the stock market necessitates a comprehensive understanding of various investment strategies since it helps to make informed decisions (Koesoemasari et al., 2022), including the use of stock indicators such as moving averages, which are widely used by investors to make informed decisions.

In recent years, Thailand's stock market has experienced significant growth, attracting both domestic and foreign investors. Various factors, including economic conditions, government policies, real GDP, money supply, and the price level impact the Thai stock market (Jiranyakul, 2009). Understanding the unique characteristics of the Thai stock market, a dynamic and rapidly evolving emerging market, is essential for investors who wish to capitalize on its opportunities.

Fundamental analysis and technical analysis are the two main methods used to analyze stock markets (Park and Erwin, 2007). Fundamental analysis entails evaluating macroeconomic data and the financial health of businesses, which take into account factors such as money supply, interest rates, inflation rates, dividend yields, earnings yields, cash flow yields, book-to-market ratios, price-earnings ratios, and lagged returns (Lakonishok, 1994). This strategy emphasizes value investing, which involves purchasing stocks at low prices when compared to earnings, dividends, book value, or other indicators of fundamental valuation. Fundamental analysis is to determine the intrinsic worth of a security and the fair value of a company's shares by examining economic and financial aspects, such as financial statements, industry trends, and macroeconomic conditions (Fama and French, 1988). Technical analysis refers to the process of examining historical market data, including information on prices and trading volumes, with the aim of identifying potential indicators of future price fluctuations. The professional traders of technical analysis hold the belief that such data furnishes insights into the underlying factors that propel returns (Blume, Easley, & O'hara, 1994). Various technical indicators, such as Moving Aver-age (MA), Moving Average Convergence/Divergence (MACD), Aroon indicator, and money flow index, are utilized in this process.

The accuracy of stock market forecasting has been greatly improved by the use of machine learning techniques (Rouf et al., 2021). The stock markets typically generate a considerable amount of diverse data, both structured and unstructured in nature. Machine learning algorithms can be used to quickly assess complex heterogeneous data and generate results that are more accurate. Several machine learning techniques have been employed for the purpose of forecasting stock market trends and others (Ballings et al., 2015) (Patil et al., 2020).

The neural network model is one of the machine learning techniques used in numerous studies for stock market analysis and prediction. Kimoto, Asakawa, Yoda, and Takeoka (1990) employed modular neural networks to forecast the timing of stock purchases and sales on the Tokyo Stock Exchange, achieving accurate forecasts and demonstrating exceptional profitability. The authors developed multiple algorithms for learning and forecasting, implementing them in the TOPIX prediction framework.

In the study of Vaisla and Bhatt (2010), the results of a neural network-based method for forecasting daily stock prices were compared with statistical forecasting. It was found that neural networks can accurately predict stock market prices when trained with sufficient data, proper inputs, and the appropriate architecture. In 2020, Chiewhawan and Vateekul further enhanced to the prediction of the Thai stock market by analyzing textual and numerical inputs using a deep neural network. Their experiments revealed that hierarchical neural networks outperformed Bidirectional Encoder Representations from Transformers (BERT), leading to a maximum profit increase of 4.4%. Furthermore, recent studies have also utilized artificial neural networks (ANNs). Mustafa et al.

(2022) trained an ANN model to detect structural changes in a financial market, such as a change in the relationship between the stock price index and market indicators. The model was trained using one year's worth of data leading up to the checkpoint.

For the other techniques used, Shen, Jiang, and Zhang (2012) proposed a new prediction algorithm that uses support vector machines (SVM) to exploit the temporal correlation between global stock markets and various financial products in order to forecast the following day's stock trend. They achieved 74.4% accuracy for the NASDAQ, 76% for the S&P500, and 77.7% accuracy for the DJIA. On the other hand, Zhang, Yi, and Chen (2020) employed the Black-Litterman model. They investigated an explainable AI model in the financial sector that utilizes hierarchical clustering to distinguish between different economic regimes. This method can dynamically adjust the classification standard based on the current market sentiment and identify abnormal stock market waves. To forecast stock market returns, Musa and Joshua (2020) developed a hybrid ARIMA-Artificial Neural Network model analyzing the daily Nigerian stock market All-Share-Index data set. The study compares the performance of the hybrid model to the performance of the ARIMA and ANN models individually. The results demonstrate that a combined model outperforms the individual models in terms of accuracy of forecasting.

To further improve, Ayala et al. (2021) proposed a hybrid trading strategy that incorporated machine learning techniques such as multivariate linear regression (LM), artificial neural networks (ANN), random forests (RF), and support vector regression (SVR) with technical analysis indicators such as the triple exponential moving average (TEMA) crossover, the exponential moving average (EMA), and moving convergence divergence (MACD). The most effective machine learning methods were ANN and LM.

In our study, we applied the Simple Moving Average strategy as part of technical analysis in combination with the artificial neural networks machine learning model. The Thai economic index signal was considered a crucial element in this approach. This analysis is based on five-year stock data from the Thai SET 100 index with the goal of increasing profits in stock trading.

2 Data and Methodology

2.1 Data Collection

The time period covered by the daily historical stock price data, which was taken from the Yahoo Finance website, was 1 January 2018 to 31 December 2022, a period of 5 years. The 20 stock datasets were randomly selected from SET100 which are INTUCH, NEX, BDMS, KTC, ESSO, MINT, IRPC, DELTA, BTS, AP, COM7, TTB, TISCO, THG, PTT, PLANB, KBANK, CPF, BANPU, and AOT.

Investments have the potential to generate high returns if it is possible to reliably identify the beginning of a rising stock market during the evaluation. Therefore, investors attempt to predict when the bull market will commence. A rise in key economic indices is one of the earliest indications that market conditions are improving. The key economic indicators include Gross domestic product (GDP) growth rate, Inflation rate, Business sentiment index, and Private investment index, which are provided in monthly and quarterly data. The data were retrieved from the Bank of Thai-land site and the Office of the National Economic and Social Development Council site.

Table 1. Data source

Stock	INTUCH, NEX, BDMS, KTC, ESSO, MINT, IRPC, DELTA, BTS, AP, COM7, TTB, TISCO, THG, PTT, PLANB, KBANK, CPF, BANPU, AOT
Stock market signal	GDP growth rate, Inflation rate, Business sentiment index, Private investment index

On the stock market, stocks have different price ranges, making it difficult to compare their performances. In order to avoid the issue of multivariate analysis, it is essential to standardize stock prices. Standardization involves converting the price of each stock into a comparable value that indicates the number of standard deviations above or below the mean price. This method allows investors to compare the performance of various stocks regardless of their price ranges with greater precision. By converting stock prices to a standard value, investors can better comprehend how each stock is performing and make more informed investment decisions.

The standard deviation for each stock can be calculated as follows.

$$\sigma = \sqrt{\frac{\sum_{i=1}^{n}(x_i - \mu)^2}{n}} \tag{1}$$

where σ = standard deviation of the stock.
x_i = open price of the stock in period i, for i = 1, 2, …, n.
μ = mean (average) of the open price of the stock.
n = number of total periods.

Simple moving average (SMA) is utilized in technical analysis to smooth out price fluctuations in financial data. It is determined by calculating the arithmetic mean of a specified number of historical data points. The result is the period's average price. SMAs are utilized to identify financial market trends and potential shifts. Short-term SMAs respond rapidly to price fluctuations of the underlying asset, whereas long-term SMAs respond more slowly, smoothing the trend line over time. The simple moving average trading rules enable traders and investors to identify trends in the market and have strongly predictive ability (Hung, 2013) (Khand and Zhaojun, 2020).

This strategy utilizes the intersection of two or more simple moving averages with varying periods. If a shorter-term moving average, such as a 5-day SMA, crosses above a longer-term moving average, such as a 15-day SMA, this may generate a bullish signal indicating a possible upward trend reversal.

Fig. 1. SMA crossover with buy and sell points.

The formula for SMA is as follows:

$$SMA = \frac{\sum_{i=1}^{n} A_i}{n} \quad (2)$$

where A_i = price of the stock in period i, for i = 1, 2, …, n.
n = number of total periods.

In this study, the short-term moving average is 5 days (5-day SMA), and the long-term moving average is 15 days (15-day SMA).

Once a buy or sell signal is generated, an investor can open a position in the underlying asset and maintain it until the subsequent signal is generated. This strategy's profit return is determined by deducting the initial purchase price from the sell price and dividing the result by the initial purchase price.

2.2 Artificial Neural Networks

Artificial neural networks (ANNs) are computational models consisting of interconnected nodes, or neurons, organized into input, hidden, and output layers. These neurons receive input from one or more neurons in the preceding layer, compute a weighted sum of the inputs, and generate an output using a non-linear activation function. Through supervised or unsupervised learning processes, ANNs can learn to recognize patterns in input data and use this information to make predictions or decisions. ANNs have been applied to numerous problems, including natural language processing, speech and image recognition, and financial forecasting (Ahmad, Z., & Shahzadi, E., 2018).

Due to their ability to acquire complex patterns from large amounts of data and their resistance to noise and outliers, ANNs have gained popularity in financial prediction. ANNs can also process a wide range of input data types, including numerical, categorical, and textual data, making them ideally adapted for financial forecasting tasks. In addition, ANNs have outperformed conventional statistical models in a variety of financial prediction tasks, such as stock price forecasting and credit risk assessment. (Zhang, Q. et al., 2018).

In this study, the adoption of an artificial neural network (ANN) as a model aimed to enhance the accuracy of relying exclusively on the Simple Moving Average (SMA) as a stock indicator. The study spanned from January 1, 2018, to December 31, 2022. As shown in Table 2, the output variable, denoted as *Y*, represented binary profit (1 for gain, 0 for loss), while the input variables (features) were labeled as *X*. A 5-fold cross-validation was employed for this study.

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Table 2. Input and Output variables

Input (*X*)	**Output (*Y*)**
The symbol of stock in the market	Profit (binary)
Month	
Quarter of each year	
Thailand GDP growth rate	
Thailand inflation rate	
Thailand Business sentiment index	
Thailand Private investment index	
Open price of the stock	
Open price of the stock in standard value	
Simple Moving Average 5 days	
Simple Moving Average 15 days	
Volume of the stock	

3 Results and Discussions

The dataset used to construct the neural networks model in 5-fold training validation was from the 20 Stocks (INTUCH, NEX, BDMS, KTC, ESSO, MINT, IRPC, DELTA, BTS, AP, COM7, TTB, TISCO, THG, PTT, PLANB, KBANK, CPF, BANPU, and AOT) for a period from January 2018 to December 2020. With other input variables from Table 2. The total data in this set has 357 records.

3.1 Model Performance Measures

Table 3. A confusion matrix depicting the best performance of all iterations from the proposed ANN model during 5-fold cross-validation.

	True 0	**True 1**	**Class precision**
Pred. 0	**22**	14	61.11%
Pred. 1	14	**21**	60.00%
Class recall	61.11%	60.00%	

The neural network model prediction performance is evaluated by measuring its accuracy, precision, and recall.

The result of predicting the return of stock trading using stock indicators, SMA, during the period 2018–2020, of a sample of stocks in the SET 100 index found that from running the proposed model with 5-fold cross-validation, the accuracy was 56.76% +/- 10.56% (micro average: 55.51%) calculated by the summation of Pred. 0 of True 0 and Pred. 1 of True 1 divided by the total number of the prediction in the confusion matrix, or in other words, this neural network model is able to predict the return of stock trading using SMA in the period 2018–2020, both profitable and un-profitable, representing average accuracy of 55.51%

The precision is 55.81% +/- 10.00% (micro average: 55.26%), which is to say that the neural network model can predict the profitable return of trading stocks using stock indicators during 2018–2020 was correct, accounting for 55.26 percent of the results of the prediction that all profits (Positive class: 1).

The recall is 58.82% +/- 19.15%. (micro average: 56.69%), indicating the neural network model ability to accurately predict profitable stock returns through the use of stock indicators during the period of 2018 to 2020. Given the current state of profitable trades, it can be observed that approximately 56.69% of trades are generating profit. Whereas the class recall of the negative class (label 0) is 55.88% +/- 15.16% (micro average: 54.32%) which means the model can help in avoiding losing by trading correctly at 54.32% on average.

3.2 Profit Returns Comparison

The dataset utilized to evaluate the efficacy and profitability of the proposed stock trading model encompasses all 20 stocks included in the SET100 Index: INTUCH, NEX, BDMS, KTC, ESSO, MINT, IRPC, DELTA, BTS, AP, COM7, TTB, TISCO, THG, PTT, PLANB, KBANK, CPF, BANPU, and AOT, spanning from February 2021 to December 2022. The total number of records is 357.

Table 4. Comparison table of profitable returns in Baht from using only SMA indicators versus using the artificial neural network model alongside SMA indicators.

Stock	SMA indicators	ANN model with SMA indicators
AOT	1.426	-0.07
AP	-0.013	-1.057
BANPU	-2.035	0.711
BDMS	-4.4	0.811
BTS	-1.856	0.29
COM7	18.64	10.863
CPF	-7.892	-2.82
DELTA	154.121	61.948
ESSO	3.495	-0.192
INTUCH	-8.131	-8.256
IRPC	-0.723	-0.093
KBANK	-3.177	0
KTC	-9.300	-4.323
MINT	4.608	2.75
NEX	4.956	5.8
PLANB	-9.166	-4.323
PTT	-8.322	-3.68
THG	50.396	-0.469
TISCO	-4.505	-7.29
TTB	0.068	0

As a result, the prediction model predicted that there would be a total of 66 profitable trades, so following that suggestion it would reduce the number of transactions from 357 to 66, the associated transaction costs can be significantly decreased. Table 4 compares the returns in Thai Baht currency, including transaction costs with the rate of 0.2% of values and VAT 7% of the total fee which was the minimum fee referring to Kasikorn securities service provider and InnovestX securities of SCB. Among all the stocks analyzed, ten of them (BANPU, BDMS, BTS, CPF, IRPC, KBANK, KTC, NEX, PLANB and PTT) show the advantage gains when using the proposed model over using solely SMAs indicators. However, it is worth noting that the remaining ten stocks exhibit considerable price volatility. For example, DELTA demonstrates a daily volatility value of 4.236%, whereas BDMS's volatility stands at 1.649%. This suggests that the proposed model may not be suitable for stocks with high price volatility.

4 Conclusions

The findings of this study indicate that machine learning methods have the capacity to enhance stock trading tactics and enhance the precision of trend forecasting in the Thai stock market.

The model proposed in this study integrates simple moving averages with an artificial neural network, and exhibits superior performance compared to the simple moving average strategy. This leads to a significant increase in profits generated from stock trading. The research gathered numerical information, comprising of daily stock prices and economic indicators, and employed a cross-validation approach to authenticate the precision of the tactic.

The proposed model exhibited an average accuracy of 55.51%, signifying its capacity to forecast lucrative stock returns from 2018 to 2020. Furthermore, the aver-age class recall for predicting profitable trades of the model in forecasting profitable returns was 56.69% and the average class recall for predicting non-profitable trades was 54.32% which means this model can help in gaining profits and avoid loss in stock trading at a comparable rate. The neural network model also effectively decreases the associated transaction costs.

Nonetheless, the research discovered that the suggested framework may not be appropriate for equities exhibiting elevated levels of price volatility. In summary, this research offers significant perspectives for investors who aim to leverage prospects in the Thai stock market and underscores the significance of employing machine learning methodologies to enhance stock trading tactics.

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Application of game theory: Agricultural land fragmentation in Thailand

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Abstract. Agricultural land fragmentation (ALF) is a serious issue that has a negative impact on agricultural productivity and long-term food security in rural areas of developing countries. This study examines the decision-making of landowners and the government on ALF in Thailand using game theory. Surprisingly, landowners frequently choose fragmentation in real-life even if non-fragmentation is the optimal choice. Moreover, the findings offer insights into strategies for promoting sustainable land management and improving agricultural productivity.

Keywords: Agricultural land fragmentation · Game theory · Thailand · Land management.

1 Introduction

Agricultural land fragmentation (ALF) is the process of breaking larger areas of farmland into smaller pieces. ALF can be caused by various factors such as inheritance, split sales, and renting . ALF has many effects such as it lead to difficulties in land management, decreased agricultural productivity, and increased production costs. As a result, the ALF problem has negative impacts on food production and can contribute to food insecurity in the future. Policymakers should efficiently manage and solve this problem. In many countries, especially in developing countries, ALF can greatly affect the rural economy and community. For more information, see [?], [?], [?], and [?]. Poland has a problem with land fragmentation, which is harmful to agricultural productivity and efficiency [?]. The paper suggests that combining land can create bigger, better farms and improve productivity. In Vietnam, ALF reduces farm production because it restricts farmers from using modern machinery like tractors and harvesters. It also prevents the growth of high-profit crops that require larger land areas [?]. ALF in Thailand, as mentioned in [?], can lead to higher production costs, lower efficiency, and reduced economies of scale. As indicated in [?], it reduces vegetable production areas in the Thawi Watthana district, resulting in smaller and less productive farms with significant economic and social consequences for farmers. Additionally, ALF can also lead to smaller and less efficient farms, reduced access to resources such as water and fertilizer, and increased vulnerability to pests and diseases.

2 Methodology

To analyze agricultural land fragmentation, game theory is used, involving two key players: landowners and the government. Landowners can choose to either fragment the land or keep it non-fragmented while the government can either encourage land consolidation or implement punishments for land fragmentation. We here consider four variables that impact landowners' decision-making processes: the value of fragmented land, the value of non-fragmented land, the encouragement value, and the implementation punishment value.

3 Conclusion

The study finds that according to game theory analysis, landowners should not fragment their land as the optimal decision. However, in real-life situations, they often choose fragmentation even though it is not the best choice. To develop effective strategies, factors like agricultural product cost, agricultural product price, and agricultural land price may be taken into consideration as well.

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Team Orienteering Problem: An Arc-Based Formulation

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Abstract. This paper proposes an arc-based formulation for a team orienteering problem with three objective functions, including maximizing revenue, profit, and the ratio of revenue over cost. The performance of this model is explored through a comparison with a node-based model developed in the research literature. The node-based is modified so that it is comparable with our proposed. The comparison is carried out by using a problem instance. The results indicate that although our proposed and node-based models produce equally good solutions, the node-based model takes a longer time to produce such solutions than our proposed model. This confirms the efficiency and effectiveness of our model. In addition to the comparison result, it is observed that the solution for maximizing revenue is inferior to that for maximizing profit and the ratio of revenue over cost.

Keywords: Team orienteering problem; arc-based formulation, maximize revenue, maximize profit, maximize the ratio of revenue over cost.

1 Introduction

The orienteering problem (OP) is considered as a variant of the travelling salesman problem (TSP). It is also known as the selective TSP [1, 2]. The main objective of solving the OP and selective TSP is to identify a path that connects a collection of locations such that the total benefit gained by visiting them are maximized. The first mathematical model for the OP is presented in the studies of Tsiligirides and Golden et al. [3, 4]. Unlike traditional TSP, the OP does not require all locations to be visited. A very popular version of OP involves multiple salesmen or paths. It is named by Chao et al. [5] as the team orienteering problem (TOP). The origin of this problem is the multiple tour maximum collection problem, first proposed by Butt and Cavalier [6]. The objective of the authors is to explore its application of TOP in situations such as recruiting athletes from high schools. In this scenario, a recruiter must visit multiple schools within a specified timeframe to maximize the potential for recruitment. A TOP has three distinct characteristics: (1) each node can be visited at most once; some nodes may not be visited due to time restrictions; (2) there is no capacity constraint for a salesman; (3) it is preferred to maximize the profit or total collected scores rather than minimize the total cost or distance of travelling.

A TOP is formulated as a mixed integer programming model by using either the node-based [7-13] or arc-based [14] approach. While the former specifies a solution by the origin and destination nodes as well as the salesman, who travels through these nodes, the latter does so by using only the arcs that connect the nodes. Some studies suggest that the arc-based approach might be more efficient than the node-based approach [14, 15]. In spite of the approaches to model the TOP, most of the studies in literature focus on a problem, in which only profit is considered as the objective and the number of salesmen is pre-determined as an input parameter.

To address this research gap comprehensively, this paper introduces a mathematical formulation of the TOP that includes three distinct objectives: maximizing the profit, the ratio of revenue over cost, and the revenue. By using this approach, the impact of various objective functions on the solution of the TOP is investigated. Traditionally, the TOP focuses only on maximizing the total profitability. However, the existing literature lacks an exploration of scenarios where TOP's objective involves striking a balance between revenue generation and cost efficiency, which is represented in this paper as an objective function of maximizing the ratio of revenue over cost. Furthermore, this paper also introduces the maximization of total revenue in TOP. This objective focuses on achieving the highest revenue by choosing a sequence of visiting locations and disregarding the consideration of associated costs.

Our model, similar to that of Deryaa et al. [14], is formulated by using the arc-based approach. Apart from exploring different objective functions with our model, the number of salesmen is also optimized. In other words, an optimal number of salesmen is determined by the proposed model and is no longer an input parameter as other models in the literature. The performance of our proposed model is investigated by comparing it with a model developed by Vansteenwegen et al. [12]. For ease of exposition, the model of Vansteenwegen et al. [12] is referred to as the node-based model. Moreover, this node-based model is modified to have similar capabilities as our model for comparison purposes. The comparison in terms of solution quality and solving time is conducted via a ten-customer problem instance. The results demonstrate that despite comparable solutions with respect to each objective function, our model considerably outperforms the node-based model in terms of solving time. This indicates the competence of our model. In addition, it is found that while maximizing revenue is not a good objective, maximizing profit and the ratio of revenue over cost are comparatively effective under different circumstances.

In the remainder of this paper, section 2 presents the arc-based mathematical formulation. Section 3 provides a performance analysis of a numerical experiment. The conclusion and potential further directions for research are discussed in section 4.

2 Arc-based formulation

This section presents the new arc-based model formulation for the team orienteering problem. While the term “node-based” is used to describe the mathematical formulation where decision variables are defined on nodes of the graph, the “arc-based” refers to the mathematical formulation where these decision variables are defined on arcs of the graph instead. This model aims to find the solution to maximize the profit, maximize the ratio of revenue over cost, maximize the revenue, and satisfy the requirements: (1) some customers may not be visited because of the time limit; (2) the optimal number of paths or routes is determined by the model; (3) each path or route begins and finishes at a dummy depot; (4) the total time including transportation and service time at each customer node by a salesman must be within a limit, regarded as the route time window.

The sets and parameters of the model are presented as follows.

Sets

$C = \{1,2, \dots, n\}$	set of customer nodes
$N = \{0\} \cup C$	set of all nodes including the dummy customer as node 0

Parameters

n	the number of customers
m	the number of routes/salesmen
d_{ij}	the distance from node i to node j (km)
c_{ij}	the cost from node i to node j (baht)
r_j	the revenue of customer node j (baht)
$p_{ij} = r_j - c_{ij}$	the profit from node i to node j (baht)
$rc_{ij} = r_j / c_{ij}$	the ratio of revenue over cost from node i to node j
t_{ij}	the travel time between node i and node j (hrs)
h_i	the service time at node i (hrs)
T_{max}	the maximum route time-window excluding dummy node (hrs)

Let x_{ij} be binary variable that indicates the traveling from node i to node j, and T_{ij} be the continuous variable that represents the total time from the origin to node j when a salesman travels from node i to node j. A mixed integer linear programming model (MILP) is formulated as follows.

$$Max \sum_{i \in N} \sum_{j \in N} p_{ij} \times x_{ij} \tag{1}$$

$$Max \sum_{i \in N} \sum_{j \in N} rc_{ij} \times x_{ij} \tag{2}$$

$$Max \sum_{i \in N} \sum_{j \in N} r_j \times x_{ij} \tag{3}$$

$Subject\ to$:

$$\sum_{i \in C} x_{0i} \geq 1 \tag{4}$$

$$\sum_{i \in C} x_{i0} \geq 1 \tag{5}$$

$$\sum_{i \in C} x_{0i} \leq m \tag{6}$$

$$\sum_{i \in C} x_{i0} \leq m \tag{7}$$

$$\sum_{i \in C} x_{0i} = \sum_{i \in C} x_{i0} \tag{8}$$

$$\sum_{i \in N} x_{ij} \leq 1;\ \forall j \in C \tag{9}$$

$$\sum_{j \in N} x_{ij} \leq 1;\ \forall i \in C \tag{10}$$

$$\sum_{j \in N, j \neq i} T_{ij} - \sum_{j \in N, j \neq i} T_{ji} = \sum_{j \in N, j \neq i} (t_{ij} + h_j) \times x_{ij}\ ;\ \forall i \in C \tag{11}$$

$$T_{ij} \leq T_{max} \times x_{ij};\ \forall i \in C, \forall j \in N \tag{12}$$

$$T_{0i} = h_i \times x_{0i};\ \forall i \in C \tag{13}$$

$$T_{ij} \geq \left(T_{0i} + T_{ij}\right) \times x_{ij};\ \forall i, j \in N \tag{14}$$

$$x_{ij} \in \{0,1\};\ \forall i, j \in N \tag{15}$$

The objective functions (1), (2) and (3) are to maximize the overall profit, the ratio of revenue over cost, revenue, respectively. It should be noted that in the numerical experiment in the next section, one objective function is optimized at a time. Constraints (4)-(8) are flow balance, ensuring that the number of routes departing from equals the number of routes returning to the dummy node. Constraints (9) and (10) specify that some customers may not be visited due to time limit of a salesman. Constraint (11) eliminates the subtour and keep track of the cumulative time of a salesman on a route. Constraints (12) and (14) provide the upper and lower bounds for T_{ij} of the salesman traveling from node i to node j, and from node i to the dummy node, respectively. Constraint (13) presents the total time T_{ij} from the dummy node to node i. Constraints (15) is the binary constraint.

3 Numerical Experiments

In this experiment, the effectiveness of our proposed model is evaluated against a node-based model developed by Vansteenwegen et al. [12] through a problem instance consisting of ten customers. The details are presented in Tables 1 – 7. The maximum route time-window in this instance is 55 hours.

The purpose of the numerical experiment is to illustrate the proposed model with three objective functions. To achieve this, we adapted a problem instance with 33 customers from the dataset known as TS33-p3, which is first introduced by Tsiligirides [3]. For the purpose of demonstrating our model, the original problem instance is scaled down to 10 customers to make the solving time manageable using a standard solver. Specially, the customer locations and the expected amount used to compute the revenue (Table 1), the service time (Table 2), the travel cost (Table 4), the travel time (Table 5), the profit (Table 6), and the ratio revenue over cost (Table 7) are from the original problem instance. The latitude and longitude are then used to generate the distance matrix by the Euclidean distance equation (Table 3). With a unit travel cost, a vehicle velocity, a unit price, and a unit service time, we can construct the data based on the expected amount in Tables 1-2 and Tables 4-7 to be used for three objective functions, respectively. Note that this problem instance could be generalized to other datasets for TOP with the same problem settings by updating the number of customers, customer locations, the expected amount, unit travel cost, vehicle velocity, and unit price.

Table 1. The revenue (baht).

Node	1	2	3	4	5	6	7	8	9	10
Revenue	24,000	24,000	24,000	24,000	24,000	24,000	24,000	36,000	36,000	36,000

Table 2. The service time (hrs).

Node	1	2	3	4	5	6	7	8	9	10
	5	5	5	5	5	5	5	7.5	7.5	7.5

Table 3. The distance matrix (km).

Node	1	2	3	4	5	6	7	8	9	10
1	0.00	3.58	5.36	8.75	1.70	9.51	2.30	12.67	12.30	10.07
2	3.58	0.00	2.50	6.30	2.36	7.43	5.72	13.66	14.12	12.91
3	5.36	2.50	0.00	3.80	4.65	4.96	7.04	12.43	13.44	13.15
4	8.75	6.30	3.80	0.00	8.35	1.42	9.93	11.34	13.22	14.33
5	1.70	2.36	4.65	8.35	0.00	9.33	4.00	13.86	13.76	11.75
6	9.51	7.43	4.96	1.42	9.33	0.00	10.42	10.32	12.45	14.02
7	2.30	5.72	7.04	9.93	4.00	10.42	0.00	11.46	10.61	7.87
8	12.67	13.66	12.43	11.34	13.86	10.32	11.46	0.00	3.28	7.83
9	12.30	14.12	13.44	13.22	13.76	12.45	10.61	3.28	0.00	5.00
10	10.07	12.91	13.15	14.33	11.75	14.02	7.87	7.83	5.00	0.00

Table 4. The travel cost matrix (baht).

Node	1	2	3	4	5	6	7	8	9	10
1	0.00	21.51	32.16	52.48	10.22	57.05	13.81	75.99	73.80	60.40
2	21.51	0.00	15.01	37.82	14.16	44.60	34.35	81.96	84.69	77.46
3	32.16	15.01	0.00	22.81	27.89	29.79	42.26	74.60	80.63	78.92
4	52.48	37.82	22.81	0.00	50.13	8.53	59.58	68.06	79.35	85.96
5	10.22	14.16	27.89	50.13	0.00	55.96	24.00	83.17	82.56	70.49
6	57.05	44.60	29.79	8.53	55.96	0.00	62.52	61.94	74.68	84.10
7	13.81	34.35	42.26	59.58	24.00	62.52	0.00	68.77	63.65	47.25
8	75.99	81.96	74.60	68.06	83.17	61.94	68.77	0.00	19.68	47.00
9	73.80	84.69	80.63	79.35	82.56	74.68	63.65	19.68	0.00	30.01
10	60.40	77.46	78.92	85.96	70.49	84.10	47.25	47.00	30.01	0.00

Table 5. The travel time matrix (hrs).

Node	1	2	3	4	5	6	7	8	9	10
1	0.00	0.09	0.13	0.22	0.04	0.24	0.06	0.32	0.31	0.25
2	0.09	0.00	0.06	0.16	0.06	0.19	0.14	0.34	0.35	0.32
3	0.13	0.06	0.00	0.10	0.12	0.12	0.18	0.31	0.34	0.33
4	0.22	0.16	0.10	0.00	0.21	0.04	0.25	0.28	0.33	0.36
5	0.04	0.06	0.12	0.21	0.00	0.23	0.10	0.35	0.34	0.29
6	0.24	0.19	0.12	0.04	0.23	0.00	0.26	0.26	0.31	0.35
7	0.06	0.14	0.18	0.25	0.10	0.26	0.00	0.29	0.27	0.20
8	0.32	0.34	0.31	0.28	0.35	0.26	0.29	0.00	0.08	0.20
9	0.31	0.35	0.34	0.33	0.34	0.31	0.27	0.08	0.00	0.13
10	0.25	0.32	0.33	0.36	0.29	0.35	0.20	0.20	0.13	0.00

Table 6. The profit matrix (baht).

Node	1	2	3	4	5	6	7	8	9	10
1	24,000	23,978	23,968	23,948	23,990	23,943	23,986	35,924	35,926	35,940
2	23,978	24,000	23,985	23,962	23,986	23,955	23,966	35,918	35,915	35,923
3	23,968	23,985	24,000	23,977	23,972	23,970	23,958	35,925	35,919	35,921
4	23,948	23,962	23,977	24,000	23,950	23,991	23,940	35,932	35,921	35,914
5	23,990	23,986	23,972	23,950	24,000	23,944	23,976	35,917	35,917	35,930
6	23,943	23,955	23,970	23,991	23,944	24,000	23,937	35,938	35,925	35,916
7	23,986	23,966	23,958	23,940	23,976	23,937	24,000	35,931	35,936	35,953
8	23,924	23,918	23,925	23,932	23,917	23,938	23,931	36,000	35,980	35,953
9	23,926	23,915	23,919	23,921	23,917	23,925	23,936	35,980	36,000	35,970
10	23,940	23,923	23,921	23,914	23,930	23,916	23,953	35,953	35,970	36,000

Table 7. The ratio of revenue over cost.

Node	1	2	3	4	5	6	7	8	9	10
1	-	1,116	746	457	2,349	421	1,737	474	488	596
2	1,116	-	1,599	635	1,695	538	699	439	425	465
3	746	1,599	-	1,052	860	806	568	483	446	456
4	457	635	1,052	-	479	2,814	403	529	454	419
5	2,349	1,695	860	479	-	429	1,000	433	436	511
6	421	538	806	2,814	429	-	384	581	482	428
7	1,737	699	568	403	1,000	384	-	524	566	762
8	316	293	322	353	289	387	349	-	1,829	766
9	325	283	298	302	291	321	377	1,829	-	1,200
10	397	310	304	279	340	285	508	766	1,200	-

While the node-based model requires the number of routes/salesmen to be pre-specified, our proposed model does not require so. To guarantee a fair comparison, the node-based model is solved iteratively by changing the number of routes/salesmen with an upper bound is the number of customers. The time limit for a salesman is assumed to be 10,800 seconds. The proposed and node-based models are implemented in Python with CPLEX as the solver. The experiment is conducted on a machine equipped with an Intel Core i7-8565U processor and 8GB of memory.

The experimental results are presented in Table 8. The table summarizes the performance of the proposed model compared to that of the node-based model with respect to solution quality and solving time.

For solution quality, it is observed that with maximizing revenue as the objective, the solution of the node-based model is slightly better than that of the proposed model in terms of total profit. On the contrary, our proposed model provides a better solution than the node-based model if the profit is taken as the objective. Moreover, when the revenue is maximized, both models provide the same solution with the least number of routes than the other two objective functions. Regardless of the model, maximizing revenue produces an inferior solution to maximizing profit and the ratio of revenue over cost. Therefore, maximizing revenue is not recommended for the problem with characteristics like ours. Despite having lower profit than maximizing profit, maximizing the ratio of revenue over cost remains an effective objective function, especially in situations where the number of routes/salesmen is an additional concern.

Table 8. Performance summary of the node-based and proposed.

Model	Objective function	Total profit (baht)	No. of routes	Solving time (seconds)
Node-based	Maximize profit	275,910	4	0.98
	Maximize revenue/cost	275,866	2	4.22
	Maximize revenue	275,774	4	1.14
Proposed	Maximize profit	275,919	4	0.06
	Maximize revenue/cost	275,866	2	0.24
	Maximize revenue	275,691	4	0.16

With solving time, Table 8 indicates that across the three objective functions, the proposed model outperforms the node-based model by a large margin. This is attributed to the fact that our proposed model can provide the optimal solution in a single run, while it takes the node-based model several runs before the best solution can be identified.

In summary, while the proposed model is on par with the node-based model with respect to solution quality, it takes a shorter time to run that its counterpart. In fact, our proposed model can also solve larger problem instances (e.g., up to 40 customers) with which the node-based model is struggling to find solutions. This implies the effectiveness and efficiency of our proposed model.

4 Conclusion

In this study, a team orienteering problem with different objective functions, consisting of maximizing revenue, profit, and ratio of revenue over cost, is formulated using the arc-based model. Instead of taking the number of salesmen as a given input, our proposed model can determine this value in its solution. To demonstrate the performance of our model, it is compared with a node-based model, which is tweaked for comparison purposes. The results from the comparison validate the ability of our model in terms of solution quality and solving time. Specifically, our model is capable of generating solutions as good as those of the node-based model in a short time. With the promising outcomes, this paper lays the groundwork for future exploration. For example, one may consider the inclusion of additional constraints in the model to reflect aspects of practical problems. Another direction worth exploring is to develop heuristic algorithms to solve large-size problem instances.

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A Measure of Similarity for Reference Class Forecasting in Projects

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Abstract. Literature and practice show the benefits of Reference Class Forecasting (RCF) for forecast generation. It is generally accepted that forecast generation is subject to considerable uncertainty. Project management literature lacks a quantitative method that captures the level of uncertainty in forecast generation using RCF. This paper argues that the level of similarity between the projects in a reference class and the project at hand can be used as a proxy to capture the degree of uncertainty in forecast generation. Accordingly, it employs a distance-based statistical measure, called the radius of gyration, to measure of similarity between the focal problem and the source cases. Empirical data from a reference class of 8 real-life projects are used to demonstrate the proposed method. The proposed method enables the selection of highly comparable reference class to the project at hand, thereby reducing uncertainty in forecast generation.

Keywords: Outside view, Projects, Reference class forecasting, Uncertainty.

1 Introduction

Forecast generation is extensively used for decision making across different phases of projects. However, errors in forecasting occur because considerable uncertainty is presented in various aspects of projects [1]. Consequently, the literature acknowledges the need for accommodating uncertainty associated with unforeseen events in forecast generation [2].

To reduce uncertainty and increase the reliability of forecasts, an outside view, also known as Reference Class Forecasting (RCF), is widely employed [3]. RCF is founded on theories of decision making in the face of uncertainty that won its originator, Daniel Kahneman, a Noble Prize in economics in 2002. A bibliometric analysis, using the *Bibliometrix-R Package* [4], reveals that 354 papers on the applications of RCF and outside view have been published from 1929 to May 2023. Fig. 1 illustrates the annual scientific production of the published papers in the contexts of RCF and outside view. As can be seen from this figure, RCF and outside view have become increasingly utilized in various fields. Particularly, a large body of literature (320 papers) has been published since 2000, which signifies the level of attention that RCF has received.

In the project management context, RCF examines the actual performance of a reference class of similar past projects to statistically predict the future of the project at hand [5]. To reduce uncertainty in forecast generation, several studies have provided guidelines to select a suitable reference class by emphasizing the significance of the similarity between the selected reference class and the new project [6]. Despite this, there is a knowledge gap surrounding quantifying the extent to which a reference class is similar to the new project [7].

This paper sets out to fill this gap by developing a novel quantitative method that measures the degree of similarity between the project at hand and the projects in the reference class. In doing so, it builds on the concept of the iron triangle, and subsequently, adopts a distance-based statistical measure, called the radius of gyration, to quantify how far the projects in a reference class are distributed from the project at hand [8]. More specifically, to develop a measure of similarity, this paper examines the dispersion of the values of budget, planned duration, and the number of similar activities for the projects in the reference class from their corresponding values for the project at hand. The proposed method enhances learning from experience because it enables the selection of highly comparable reference class to the project at hand. Further, to the best of the author's knowledge, this paper is the first that develops a quantitative method to measure the degree of similarity between the focal problem and the source cases.

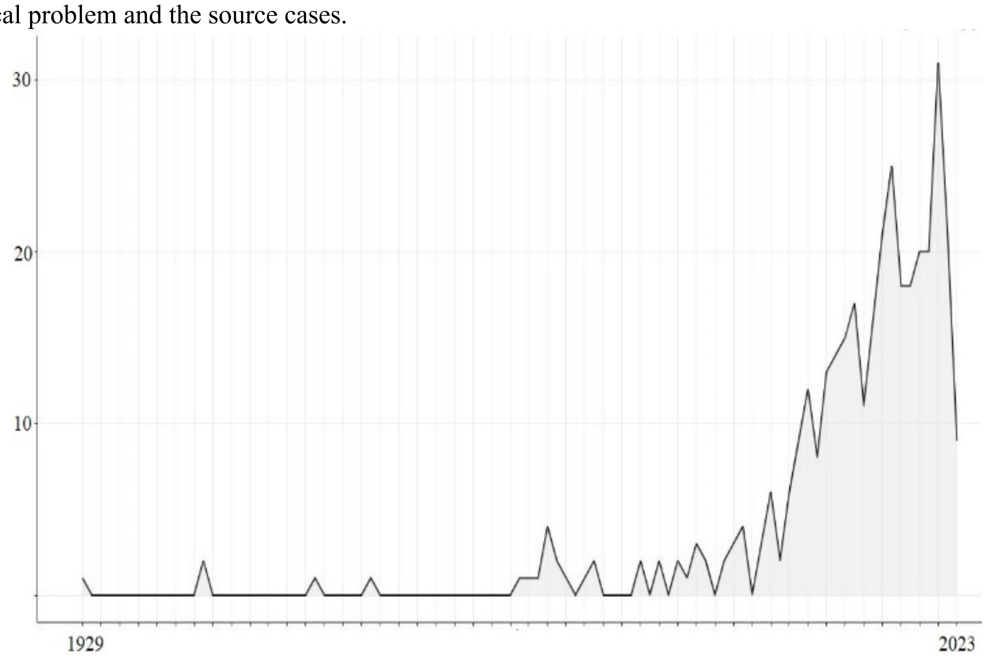

Fig. 1. Annual scientific production of studies on RCF and outside view

This paper unfolds as follows. Section 2 outlines how artificial intelligence has been used for forecast generation. It also reviews the literature on the applications of RCF in different domains. Section 3 discusses the development of the proposed method. Section 4 selects a reference class of real-life projects to demonstrate the development of the proposed method. The paper discusses potential areas for future research in Section 5.

2 Literature Review

Literature and practice widely suggest RCF as a complementary approach to improve the accuracy of traditional forecast generation tools [9]. It is widely recognized that decision makers tend to overestimate positive events [6], which results in honest mistakes or delusions, known as optimism bias [10]. RCF has been widely used to not only improve the reliability of forecasts but also temper the problem of optimism bias. Fig. 2 presents the word cloud of the most frequent terms that appeared in the title and abstract of studies on applications of RCF and outside view published between 1929 and 2023. As shown, RCF has been used in a diverse range of fields as diverse as project management, decision making, aviation, and risk management.

Fig. 2. The word cloud of the literature on RCF and the outside view

In the project management context scholars have employed RCF for forecast generation of various aspects of projects such as project costs, schedule, and risk management. For example, Bayram and Al-Jibouri [11] employed RCF to forecast the actual cost of construction projects by taking into account various risk factors affecting projects. Zhou et al. [12] adopted RCF for the planning evaluation of large-scale urban projects in the appraisal process. Building on RCF, Natarajan [13] proposed a machine learning model to estimate the cost and schedule performance of oil and gas megaprojects. Zarghami and Zwikael [14] used a reference class of 43 construction projects to develop a mathematical model for measuring the level of resilience in similar projects.

Although researchers and practitioners have widely used RCF in the project management context, there is a dearth of methods that measure the similarity of projects in the reference class with the project at hand [7]. The literature raises concerns about the biased selection of reference classes [15]. This, in turn, elevates the need for a method that evaluates the degree of similarity of the selected reference class to ensure its accuracy.

3 Method

This section draws on the concept of the "iron triangle" to develop a measure of similarity between the project at hand and the projects in the reference class. The concept of the iron triangle is a cornerstone of project management. It describes the three key components of project management, namely, budget, schedule, and scope, which affect the success and failure of a project [16]. Indeed, the concept of the iron triangle states that the success of the project is highly impacted by its time, cost, and scope. These elements frame a project by determining the quality and quantity of the project scope, schedule, and budget. It is therefore sensible that a project can learn from the experience of another project with similar scope, budget, and schedule. This can eliminate flawed judgments in forecast generation by shifting from "learning too late to learning before doing" [17, p. 29].

Let c_i, s_i, and w_i be respectively project budget, planned duration, and the number of similar activities for project i in a reference class of n projects. Clearly, the sets containing the elements of the iron triangle can be expressed as follows:

$$C = \{c_i \mid i = 1,2, \dots, n\} \tag{1}$$

$$S = \{s_i \mid i = 1,2, \dots, n\} \tag{2}$$

$$W = \{w_i \mid i = 1,2, \dots, n\} \tag{3}$$

The following measures of similarity are now defined for these sets:

$$RG_C = \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{c_i}{c_P} - 1\right)^2}{n}} \tag{4}$$

$$RG_S = \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{s_i}{s_P} - 1\right)^2}{n}} \tag{5}$$

$$RG_W = \sqrt{\frac{\sum_{i=1}^{n} \left(\frac{w_i}{w_P} - 1\right)^2}{n}} \tag{6}$$

where c_P, s_P, and $w_P$are respectively the project budget, planned duration, and the number of activities for the project at hand, and RG_C, RG_S, and RG_W denote the radius of gyration for data points in sets C, S, and W.

The radius of gyration of a set describes how far the elements of the set are distributed from a given point [8]. For example, RG_S measures how far the planned durations of the projects in the reference class are distributed from the planned duration of the project at hand. In other words, it measures the dispassion of the planned duration of the reference class from the project at hand. Thus, the radius of gyration can be interpreted as a measure of similarity between the projects in the reference class and the project at hand. That is, the smaller value of the radius of gyration indicates a lower level of dispersion, thereby the higher level of similarity between the projects in the reference class and the new project.

4 Case Study

The case study for this research is a reference class of 8 construction projects that have been already completed. The data for the reference class were obtained from Batselier and Vanhoucke [18], which can be publicly procured from (https://www.projectmanagement.ugent.be). The average budget and completion time of the projects in the reference class are respectively €6’150’486 and 303 days. Table 1 provides an overview of projects in the reference class.

Suppose that the project at hand is the construction of an apartment residential building involving 25 main activities. The project completion time and the project budget are estimated to be 365 days and €3,900,000, respectively.

Table 1. An overview of the project in the reference class

i	Project Type	s_i (day)	c_i (€)	w_i
1	Mixed-Use Building	474	38,697,822	20
2	Apartment Building 2	547	3,486,375	20
3	Apartment Building 4	233	1,992,222	20
4	Railway Station	417	1,121,317	15
5	Social Apartment Ypres 3	358	2,509,031	20
6	Ijzertoren Square	50	214,418	8
7	Roadworks Poperinge	120	511,326	9
8	Railway Bridge 1	225	671,383	14

Let us assume that the baseline measurements, representing the maximum acceptable values of the radius of gyration corresponding to the project budget, planned duration, and scope, are respectively$(RG_C)_{max} = 1.0$, $(RG_S)_{max} = 1.0$, and $(RG_W)_{max} = 1.0$. Using Eqs. 4, 5, and 6, we obtain $RG_C = 3.218$, $RG_S = 0.478$, and $RG_W = 0.416$. Fig. 3 depicts a radar chart comparing the results of similarity measures with the baseline triangle in which the values of the radius of gyration are assumed to be 1.0.

As shown in Fig. 3, the results demonstrate relatively high similarities between the projects in the reference class and the project at hand using the schedule and scope elements of the iron triangle. This is because $RG_S < (RG_S)_{max} = 1.0$ and $RG_W < (RG_W)_{max} = 1.0$. However, an obvious concern emerges from the relatively high value of RG_C. This can be ascribed to the considerable difference between the budget of the first project in the reference class. That is, $RG_C > (RG_C)_{max} = 1.0$. This observation implies that the exclusion of this project from the reference class increases the reliability of forecast generation.

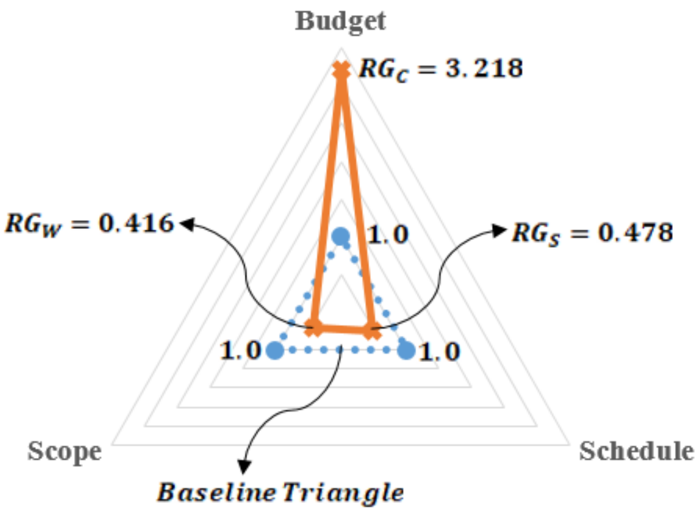

Fig. 3. The radar chart comparing the results of similarity measures with the baseline measurement

5 Practical Implications

In the following, two practical implications of this research are discussed. First, the proposed method allows for de-biasing the selection of a reference class of similar projects. Quite often, decision makers select a reference class of past similar projects intuitively. Using the proposed measure of similarity, decision makers can make informed decisions about the inclusion of projects in the reference class based on numerical values, rather than drawing on their intuition.

Second, the proposed method can be used to select an optimal set of projects among several projects for inclusion in the reference class. This can be accomplished by eliminating outliers in the reference class, and accordingly, selecting the projects that satisfy the following inequality:

$$\begin{gathered} RG_{ave}(x) \leq 1 \\ x \in \Omega \end{gathered} \tag{7}$$

where Ω is a set that includes the projects that their inclusion will satisfy Eq. 7, and $RG_{ave}(x)$ is given by:

$$RG_{ave}(x) = \frac{RG_C(x) + RG_S(x) + RG_W(x)}{3} \tag{8}$$

6 Concluding Remarks

Answering the question “To what extent is a reference class of past projects similar to the new project?” presents a challenge to researchers despite the widespread use of RCF in various domains. This paper attempted to find an answer to this question by developing a measure of similarity between the projects in the reference class and the new project.

A real-life reference class of 8 construction projects was selected to demonstrate the proposed method. The results showed how the elements of the iron triangle could be used to assess the level of similarity between the 8 projects in the reference class and the new project.

The proposed measure of similarity is built on the elements of the iron triangle in isolation. It does not provide a unifying basis for measuring the degree of similarity by joint consideration of all elements of the iron triangle. Future research is required to develop an integrative measure of similarity that concurrently captures the overall level of similarity between the focal problem and the source cases.

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An Evidential Reasoning Approach to Evaluating Health-care Waste Treatment Technologies

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Abstract

This paper addresses the problem of evaluating treatment technologies in health-care waste management that is typically considered as a multi-criteria decision making problem with linguistic assessments. Due to the qualitative nature of evaluation criteria and subjectivity of expert judgments, various uncertainties are inherently introduced in the evaluation process, making the problem complicated and difficult to model. In this paper, an evidential reasoning based multi-criteria evaluation method for HCW treatment technologies is developed in which expert judgments are used to define mass functions representing individual criteria assessments and multi-criteria aggregation is performed by means of Dempster's rule of combination for the overall assessments of alternative technologies. A case study taken from the literature is used to illustrate the efficiency and applicability of the proposed method.

Efficiency of the ASEAN-5 Stock Markets: A Markov-switching Model Estimation using Adjusted Market Inefficiency Magnitude

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Abstract. The effectiveness of spreading stock market information in the ASEAN-5 financial stock markets including Thailand, Malaysia, the Philippines, Singapore, and Indonesia is examined in this study. For this investigation, we used the Adjusted Market Inefficiency Magnitude (AMIM) measure to determine market efficiency in terms of information distribution in different market states such as the lower and the higher fluctuating stock returns periods. Therefore, we extended the autoregressive model into Markov Switching Model to incorporate both the higher and lower regimes for stock market returns, then we calculated the AMIM value for each regime to confirm market efficiency for different market states. The empirical findings from AMIM based Markov Switching Model indicate that the stock markets of Thailand and Singapore are efficient in the lower volatile period only, showing that the stock information of both countries is well distributed during the comparatively lower stock-return fluctuating time. Moreover, The Philippines and Indonesia stock markets are efficient in the higher fluctuating regime, meaning that the market information properly spreads during high volatile period. In addition, Malaysia's stock market is the only stock market in which the market information reveals the fact of the stocks very well in both lower and higher fluctuating markets, meaning that whatever the states of market the Malaysian stock market has, the Malaysian stock indexes reflect the information effectively.

Keywords: Efficiency, ASEAN-5 Stock Markets, Markov Switching Model, AMIM

Can Monetary Policy Uncertainty Predict Exchange Rate Volatility? New Evidence from Hybrid Neural Network-GARCH Model

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Abstract. This paper aims to examine the capacity of the US Monetary Policy Uncertainty (MPU) Index in forecasting accurately the volatility of foreign exchange rates for the Dollar Index, Euro/US Dollar, and Yen/US Dollar. To achieve this, we introduce several hybrid Artificial Neural Networks (ANN)-GARCH models, namely GARCH, ANN-EGARCH, and ANN-GJR-GARCH, which incorporate MPU as the exogenous variable (X). However, a significant challenge in ANN modeling is choosing the appropriate activation function. Therefore, we consider and compare various forms of activation functions, including logistic, Gompertz, Tanh, ReLU, and leakyReLU. Our results demonstrate that incorporating MPU improves the forecasting performance of the benchmark ANN-GARCH-type models both in- and out-of-sample. In particular, we find that incorporating MPU into the ANN-EGARCH model yields the largest forecasting gains compared to all other variants of the ANN-GARCH-type models. Additionally, our findings reveal that ReLU is the best activation function for predicting Dollar and Yen volatility, while Gompertz performs the best for predicting Euro volatility.

Keywords: Activation functions, Foreign exchange rates, Hybrid Artificial Neural Networks (ANN)-GARCH models, Volatility forecasting