A COMPARISON OF TYPE-1 FUZZY AND TYPE-2 FUZZY METHODS IN ANFIS MODELLING TO ANALYZE FTSE BURSA MALAYSIA KUALA LUMPUR COMPOSITE INDEX

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BORANG PENGESAHAN STATUS TESIS

JUDUL: A COMPARISON OF TYPE-1 FUZZY AND TYPE-2 FUZZY METHODS IN ANFIS MODELLING TO ANALYZE FTSE BURSA MALAYSIA KUALA LUMPUR COMPOSITE INDEX

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A COMPARISON OF TYPE-1 FUZZY AND TYPE-2 FUZZY METHODS IN ANFIS MODELLING TO ANALYZE FTSE BURSA MALAYSIA KUALA LUMPUR COMPOSITE INDEX

LEE KIN FEI

This report is submitted in partial fulfillment of the requirements for the Bachelor of Computer Science (Artificial Intelligence)

FACULTY OF INFORMATION AND COMMUNICATION TECHNOLOGY UNIVERSITI TEKNIKAL MALAYSIA MELAKA 2013



DECLARATION

I hereby declare that this project report entitled

A COMPARISON OF TYPE-1 FUZZY AND TYPE-2 FUZZY METHODS IN ANFIS MODELLING TO ANALYZE FTSE BURSA MALAYSIA KUALA LUMPUR COMPOSITE INDEX

is written by me and is my own effort and that no part has been plagiarized without citations.

STUDENT	:		Date:	
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		DR. CHOO YUN HUOY		

DEDICATION

To my beloved parents, Lee Soon Ling and Chong Yock Cheng, your support are my greatest inspiration in accomplish this project.

To my friends, for your help, support and motivation.

To my supervisor, Dr Choo Yun Huoy for being critical and keep challenging me to be a good student.

ACKNOWLEDGEMENTS

First and foremost, I would like to thank Dr. Choo Yun Huoy for giving assistance and guidance during completion of this work.

Second, I would like to thank Dr. Sharifah Sakinah for guidance in Fuzzy Type-2.

I am heartily thankful to Dr. Wu Dong Rui for his patience and guidance to reply my email.

Furthermore, I would like to thank my parents Lee Soon Ling and Chong Yock Cheng who always give support to me.

ABSTRACT

Many investors have been using technical analysis in stock market prediction. However, technical indicators are facing difficulties in handling uncertainty and stochastic factors. This has encouraged the research of soft computing techniques in stock data analysis on the features extracted using the technical indicators. ANFIS and its variations are widely applied model in stock market prediction due to its ability in determining converge time during data learning process. Research work on Type-2 Fuzzy inference had proven to perform better than conventional Type-1 Fuzzy inference in many common dataset due to its interval membership functions can well model uncertainty than Type-1 Fuzzy. However, there is no convincing comparison on real-life stock data especially in FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLCI). Hence, a comparison of Type-1 Fuzzy and Type-2 Fuzzy in ANFIS modelling is necessary typically on the FTSE Bursa Malaysia KLCI data to provide a more in depth analysis on the different fuzzy inference method in ANFIS modelling. The project experimented on the Type-2 Fuzzy interval ranges from 0.01 to 0.10 with step size of 0.01 to demonstrate the effect of Footprint of Uncertainty (FOU) range towards prediction performance. Experiment is conducted in Matlab R2011b environment. The results are compared in terms of Root Mean Square Error and validated using two tailed t-test. Experiment results shows that overall performance of Type-2 Fuzzy are better than Type-1 Fuzzy in ANFIS modelling due to its interval membership functions to handle stock uncertainty, where the accuracy showed an increasing trend from FOU range 0.01 to 0.10. However, this experiment is not able to suggest the best FOU range. Hence, optimizing FOU range is suggested for future work to achieve better prediction accuracy.

ABSTRAK

Kebanyakan pelabur telah menggunakan analisis teknikal dalam ramalan pasaran saham. Walau bagaimanapun, petunjuk teknikal menghadapi masalah dalam menangani ketidaktentuan and stokastik faktor. Ini telah menggalakkan penyelidikan teknik pengkomputeran lembut dalam analisis data saham mengenai ciri-ciri dikeluarkan dengan petunjuk teknikal. ANFIS dan variasinya secara luas digunakan dalam model ramalan pasaran saham kerana kemampuannya dalam menentukan masa penumpuan semasa proses data pembelajaran. Kerja-kerja penyelidikan dalam Jenis-2 Kabur telah dibukti prestasinya lebih baik daripada konvensional Jenis-1 Kabur dalam banyak dataset biasa kerana selangnya boleh model ketidaktentuan daripada Jenis-1 kabur. Walau bagaimanapun, tiada perbandingan yang menyakinkan pada data saham sebenar terutama FTSE Bursa Malaysia Kuala Lumpur Composite Index (KLCI). Oleh itu, perbandingan antara Jenis-1 Kabur dan Jenis-2 Kabur dalam model ANFIS perlu dilaksanakan pada FTSE Bursa Malaysia KLCI untuk menyediakan lebih banyak analisis mendalam mengenai kaedah Kabur yang berbeza dalam model ANFIS. Projeck ini akan menjalankan eksperimen pada Jenis-2 Kabur selang antara 0.01 hingga 0.10 dengan saiz langkah 0.01 untuk menunjukkan kesan "Footprint of Uncertainty (FOU)" dalam mencapai prestasi ramalan. Eksperimen dijalankan dalam Matlab persekitaran R2011b. Keputusan dibandingkan dari segi "Root Mean Square Error" dan disahkan dengan menggunakan "two tailed-t-test". Keputusan eksperimen menunjukkan bahawa prestasi keseluruhan Jenis-2 kabur adalah lebih baik daripada Jenis-1 kabur dalam ANFIS model kerana fungsi selangnya dapat mengendalikan ketidaktentuan wujud dalam saham, di mana ketepatan menunjukkan trend yang meningkat dari FOU selang 0.01 hingga 0.10. Walau bagaimanapun, eksperimen ini tidak dapat mencadangkan FOU selang terbaik. Oleh itu, mengoptimumkan FOU selang dicadangkan untuk kerja masa depan supaya dapat mencapai ketepatan ramalan yang lebih baik.

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LIST OF ABBREVIATONS

ANFIS	-	Adaptive Neuro-Fuzzy Inference System
ANN	-	Artificial Neural Network
EIASC	-	Enhanced Iterative Algorithm with Stop Condition
EMA	-	Exponential Moving Average
Eq.	-	
FOU	-	Footprint of Uncertainty
GA	-	Genetic Algorithm
HMM	-	Hidden Markov Model
KLCI	-	Kuala Lumpur Composite Index
KM	-	Karnik-Mendel
PSO	-	Particle Swarm Optimization
RMSE	-	Root Mean Square Error
SMA	-	Simple Moving Average
SVM	-	Support Vector Machine
UTeM	-	Universiti Teknikal Malaysia Melaka
WMA	-	Wilder's Moving Average

CHAPTER I

INTRODUCTION

1.1 Project Background

Stock market prediction is to predict the stock index based on existing series of stock data changes over time. Stock market prediction has begun a long time in finance area. Accurate predict of the stock index is important especially for the investors who deal with ever-increasing risks and uncertainties in future. Throughout the various literature reviews, stock market data was shown that it is highly stochastic, non-stationary, noisy and chaotic in nature. Over the years, various technical or fundamental analysis methods and soft computing techniques had been implemented on it to yield more accurate result.

Commonly, technical analysis and fundamental analysis is a traditional way applied in stock market prediction. Due to the complexity of stock market data, various soft computing techniques had been used by researchers to predict stock market returns. Among the soft computing techniques Artificial Neural Network (ANN) and Fuzzy Logic had been successfully used to modelling and forecasting financial time series data. Due to the limited of algorithmic effort prediction models in cope with uncertainties, hybrid of Fuzzy Logic and Artificial Neural Network had been used to handle uncertainties of stock market data.



ANFIS is the hybrid of Artificial Neural Network and Fuzzy Logic which contain strength of two techniques in a single framework. It acquires a good result in stock market prediction (Yunos, Z.M. et al., 2008), (Boyacioglua, M.A. & Avci, D., 2010) and (Banik, S. et al., 2007). Recently, there exists of many researchers was doing research on Type-2 Fuzzy due to its capability to model uncertainty well than Type-1 Fuzzy. So in this project, Type-1 Fuzzy and Type-2 Fuzzy in Adaptive Neuro-Fuzzy Inference System (ANFIS) are compare in order to find out one technique can model well FTSE Bursa Malaysia KLCI stock market.

1.2 Problem Statement

Many investors has been using technical analysis in stock market prediction However, technical indicators are facing difficulties in handling uncertainty and stochastic factors. This has encouraged the research of soft computing techniques in stock data analysis on the features extracted using the technical indicators. ANFIS and its variations are widely applied model in stock market prediction due to its ability in determining converge time during data learning process. In (Castillo, O. et al., 2013), an Interval Type-2 Fuzzy had been hybrid with Neural and it is performed better than ANFIS. The difference between two techniques used in (Castillo, O., 2013) is the type of fuzzy inference and it showed that potential to use Type-2 Fuzzy inference in predict chaotic data. In addition regard Type-2 Fuzzy, Mendel (2001) had proved that Type-2 Fuzzy can perform better than Type-1 Fuzzy because the membership function of Type-1 Fuzzy set is crisp number, while Type-2 Fuzzy set is an interval. With the interval fuzzy sets in Type-2 Fuzzy, it is able to model uncertainties well than Type-1 Fuzzy. Hence, a comparison of Type-1 Fuzzy and Type-2 Fuzzy in ANFIS modelling is necessary typically on the FTSE Bursa Malaysia Kuala Lumpur Composite Index data to provide a more in depth analysis on the different fuzzy inference method in ANFIS modelling.

1.3 Objective

The objectives of project are as follows:

- To implement the Type-1 and Type-2 ANFIS modelling to predict FTSE Bursa Malaysia KLCI data value.
- Select suitable technical indicators as features input for data training and testing.
- To analyse the experimental results of Type-1 Fuzzy and Type-2 Fuzzy ANFIS modelling for FTSE stock market data.

1.4 Scope

This scope of this project:

- Focuses mainly on modelling FTSE Bursa KLCI stock market.
- A total of 10 years historical daily data are collected.
- Convert the raw input into technical indicators and using Type-1 Fuzzy and Type-2 Fuzzy ANFIS for modelling.
- FOU ranges of Type-2 Fuzzy from 0.01 to 0.10 with step size 0.01.
- Run the experiment using Matlab R2011b.
- 10-fold cross validation use for evaluates the performance of both techniques.

1.5 **Project Significance**

FTSE Bursa Malaysia KLCI market is the Malaysia Capitalization Market and the growth of it has the great impact to Malaysia Economy. Since (Jerry M. Mendel & Robert I. Bob John, 2002) said that Type-2 Fuzzy had a good result in capture chaotic and uncertainty data, so it was proposed to use it in ANFIS and to compare with Type-1 Fuzzy in ANFIS to model FTSE Bursa Malaysia KLCI stock market. In this project, performance of both techniques in modelling FTSE Bursa Malaysia KLCI market will be evaluated and provide an analysis for 10 years of FTSE Bursa Malaysia KLCI stock market.

1.6 Expected Output

In order to handle chaotic and uncertainties, many researchers are focusing on fuzzy model. By using the Type-2 Fuzzy in ANFIS in this project, it will successful to modelling the FTSE Bursa Malaysia KLCI stock market than Type-1 Fuzzy in ANFIS in term of accuracy.

1.7 Conclusion

During past decades, there are many researchers put effort in time series stock market prediction desire to get more accurate predict values. Hence, many techniques had been implemented in stock market prediction in order to yield an accurate result. Among those techniques, soft computing techniques was famous used to implemented in it. Type-1 Fuzzy and Type-2 Fuzzy in ANFIS was chosen to implement in this project. By compare it two, the most accurate one can further code into expert system in further research.

CHAPTER II

LITERATURE REVIEW

2.1 Introduction

Nowadays, there are a lot of researches had been done in analysing the behaviour of stock market. Successful prediction of stock index is important especially for those investors who deal with ever-increasing risks and uncertainties in future. Throughout the various literature reviews, stock market data was shown that it is highly stochastic, non-stationary, noisy and chaotic in nature. It also will affect by economic conditions, political events and other factors. So, the prediction of stock index will become very tough and difficult.

Various techniques have been carried out to predict stock index ranging from statistical analysis, technical analysis, fundamental analysis and soft computing. Among of this techniques, soft computing currently are widely using in stock market prediction. Compared to traditional methods, soft computing are acquire more accurate and less time in stock market prediction.

2.2 Stock Market Prediction

Stock market also known as equity market for the company's trading stock or shares. It is different from stock exchange which is an entity in business and participants in the stock market can be range from stock investors to the large of fund traders in the world. Trading in the stock market is through buying and selling activities. The buying and selling in the stock market means the person will accept any bid price for the stock.

Stock market is an important part in economy growth of a country. It plays a pivotal role in the growing of company and industry which eventually affect the country's economy. That is the reasons why industry, government, banks of country are keep watch what happening in stock market. Therefore, predict the index of the stock market can yield the money. The major prediction method using in the financial area was either technical or fundamental analysis. Other from that, soft computing is popular applying on it.

2.3 Technical Analysis

A method of evaluated the securities through analyzing statistics generated by stock market activity are called technical analysis. It analyzing the market based on past historical data such as past prices and volume. Technical analysts are believed that prediction of future movements of stock market can be indicated by historical stock data, because of that technical analysts are widely using chart and statistical tools to identify the pattern of stock movements so that can predict the future movement of stock.

There are three assumptions of technical analysis field (Smolennikov, D.O. et al.):

1. The market discounts everything

There is criticism about technical analysis is focuses on price movement which ignoring the company's fundamental factors. Technical analysis assumes that at any given time, stock prices will reflects everything that could affect company which include the fundamental factors.

2. Price moves in trends

It believe that price movements in technical analysis is follow the trends which means when a trend has been established, future price movement are like in the same direction as the trend.

3. History tends to repeat itself

They believed that pattern in price movements always repeat at a certain time.

Technical analysis technique:

- 1. Moving Average
- 2. Channels
- 3. Oscillating Indices

2.4 Fundamental Analysis

A method that used to estimate the value of a stock by examining the financial data that is fundamental to the company is called fundamental analysis. It does not analyse at the overall state of market but it determines the stock should be bought or sold by focusing the exclusive on the company's business. That mean it is estimates the stock value based on companies' its earnings, its earnings per share, its price to earnings ratio, its dividend and others.

i. Earning

Earning is how much is the profit of a company after subtract the expenses, it is important to investors in determine whether the stock should bought or not. Because it gives the indication of company's potential for growth and expected dividends. Low or negative earning usually indicates that is bad stock.

ii. Earnings per Share (EPS)

It is not good in comparing the total net earnings for different company, because it does not take into account of how many shares of stock are outstanding.

$$EPS = \frac{company's net earning}{company'number of outstanding shares of stock}$$

iii. Price to Earnings Ratio (P/E ratio)It is how much the market willing to pay a company's earning.

$$\frac{P}{E} = \frac{Price \ per \ Share}{EPS}$$