IMPROVED PARTICLE SWARM OPTIMIZATION FOR FUZZY BASED STOCK MARKET TURNING POINTS PREDICTION

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To my beloved family

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ABSTRACT

Stock prices usually appear as a series of zigzag patterns that move in upward and downward trends. These zigzag patterns are learned as a tool for predicting the stock market turning points. Identification of these zigzag patterns is a challenge because they occur in multi-resolutions and are hidden in the stock prices. Furthermore, learning from these zigzag patterns for prediction of stock market turning points involves vagueness or imprecision. To address these problems, this research proposed the swarm-based stock market turning points prediction model which is a combination of a zigzag patterns extraction method, and a mutation-capable particle swarm optimization method. This model also includes the stepwise regression analysis, adaptive neuro-fuzzy classifier, and subtractive clustering method. This study explores the benefits of the zigzag-based multi-ways search tree data structure to manage the zigzag patterns for extracting interesting zigzag patterns. Furthermore, the mutation capable particle swarm optimization method is used to optimize the parameters of subtractive clustering method for finding the optimal number of fuzzy rules of adaptive neuro-fuzzy classifier. Stepwise regression analysis is used to select the important features from the curse of input dimensions. Finally, adaptive neuro-fuzzy classifier is used for learning the historical turning points from the selected input features and the extracted zigzag patterns to predict stock market turning points. The proposed turning points prediction model is tested using stock market datasets which are the historical data of stocks listed as components of S&P500 index of New York Stock Exchange. These data are stock prices that are either moving upward, downward, or sideways. From the findings, the proposed turning points prediction model has the potential to improve the predictive accuracy, and the performance of stock market trading simulation.

ABSTRAK

Pasaran saham selalunya muncul sebagai siri dalam corak zigzag yang bergerak sama ada dalam bentuk indeks meningkat atau indeks menurun. Corak zigzag ini dikenalpasti sebagai salah satu alat untuk untuk meramal titik perubahan pasaran saham. Untuk mengenalpasti corak zigzag adalah merupakan satu cabaran kerana kerana ianya berada dalam pelbagai resolusi dan tersembunyi di dalam nilai pasaran saham. Tambahan pula, pola pembelajaran di dalam meramal titik perubahan pasaran saham melibatkan kesamaran dan ketidaketepatan terhadap corak, dan kajian ini mencadangkan teknik titik perubahan pasaran saham secara kelompok melalui kombinasi di antara kaedah pengekstrakan corak zigzag dan pengoptimuman kerumunan partikel boleh mutasi. Model ini juga merangkumi analisis regrasi berperingkat, pengkelas neuro kabur, dan juga pengklusteran penolakan. Kajian ini mengkaji kelebihan struktur data zigzag berdasarkan pelbagai kaedah carian yang mempunyai ciri-ciri yang menampung corak zigzag yang mengekstrak corak zigzag yang menarik. Kaedah pengoptimuman kerumunan partikel boleh mutasi digunakan untuk mengoptimum nilai parameter daripada kaedah pengklusteran penolakan untuk mencari nilai optimum bagi pengkelas neuro kabur. Analisis regrasi berperingkat digunakan untuk memilih ciri-ciri yang penting daripada dimensi input. Bagi pengkelas neuro kabur pula, kefahaman mengenai statistik titik perubahan pasaran saham yang di ekstrak dari corak zigzag dan ciri-ciri input yang terpilih digunakan bagi meramal titik perubahan di masa akan datang. Ramalan titik perubahan pasaran saham yang telah diuji dengan set data pasaran saham yang terdahulu yang tersenarai sebagai komponen indeks S&P500 yang terdapat dalam Bursa Saham New York di mana data pasaran saham yang diuji adalah merangkumi statistik pasaran saham yang meningkat, menurun dan pergerak sisi. Melalui kajian ini, model titik perubahan saham yang telah diusulkan mempunyai potensi bagi meningkatkan ketepatan ramalan dan juga prestasi simulasi perdagangan pasaran saham.

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LIST OF ABBREVIATIONS

ANFC	-	Adaptive Neuro-Fuzzy Classifier
ANFIS	-	Adaptive Neuro-Fuzzy Inference System
ANN	-	Artificial Neural Networks
APSO	-	Adaptive Particle Swarm Optimization
B&H	-	Buy&Hold trading model
GA	-	Genetic Algorithms
KNN	-	K-Nearest Neighbours
MPSO	-	Mutation Capable Particle Swarm Optimization
PIP	-	Perceptually Important Point
PLR	-	Piecewise Linear Representation
PSO	-	Particle Swarm Optimization
s.t.d	-	Standard Deviation
SCG	-	Scaled Conjugate Gradient
SFTPP	-	Swarm Based Fuzzy Turning Prediction Model
VD	-	Vertical Distance
ZIP	-	Zigzag Perceptually Important Point
ZM-Tree	-	Zigzag Based Multi-Way Search Tree

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CHAPTER 1

INTRODUCTION

1.1 Overview

A large fraction of attention from the data mining community has focused on time series data. This is plausible and highly anticipated since time series data is a by-product in virtually every human endeavor, including biology (Titsias *et al.*, 2012), finance (Liu *et al.*, 2012), geology (Morton *et al.*, 2011), space exploration (Lafleur and Saleh, 2010), and human motion analysis (Akiduki *et al.*, 2011). The study of time series dates back to the 1960s, where the analysts focused mainly on financial data such as stock market movements. Common tasks on classic time series analysis include prediction, finding trends, seasonality, etc.

Financial or stock market prediction can be considered as an attractive task since it is able to gain amount of money which people who trade in financial or stock markets usually focus their determination to the market timing for taking action to buy, hold, or sell (Chang *et al.*, 2011). Unfortunately, stock market prediction is not an easy task, due to the fact that stock market is essentially dynamic, nonlinear, complicated, nonparametric, imprecise, and chaotic in nature (Jung *et al.*, 2011; Liu *et al.*, 2011; Özer and Ertokatlı, 2011; Peters, 1994).

Financial time series has high volatility, where the time series change as the stock markets move in and out of different periods, or in other words, stock market shows the variation of stock prices as upward and downward direction overtime

(Golosnoy *et al.*, 2011). In addition, stock market's movements are affected by many macro-economic factors such as political events, firms' policies, general economic conditions, investors' expectations, institutional investors' choices, movement of other stock markets, and psychology of investors (Chang *et al.*, 2009). Those factors drive stock prices moving in upward, downward, or sideways trends. Stock prices are determined solely by interaction of demand and supply. Furthermore, stock prices tend to move in trends (Edwards *et al.*, 2007b) . Shifts in demand and supply causes reversals in trends and can be detected in charts (Bauer and Dahlquist, 1999). Finally, chart patterns tend to repeat themselves (Brown, 2012; Canelas *et al.*, 2012; Edwards *et al.*, 2007a). Hence the shifts of demand and supply influence the stock and will affect the stock price. However, technical analysts believe that the market is always correct , all factors are already factored into the demand and supply curves, and, thus, the price of the company's stock (Kirkpatrick, 2007; Schwager, 2012).

As mentioned above, the stock prices often move up and down. Obviously, considering price movement behaviors after an uptrend movement, the stock often oppositely changes the trend to the down trend movement. Conversely, after the down trend ends, the stock trend often changes the direction to the uptrend again. The trends frequently change the directions to upward and downward trends sub-sequentially. The changing points of upward trends to the downward trends are known as peaks and the changing points of the downward trends to the upward trends are known as troughs. In other words, a peak will appear when the stock prices which is in an upward trend is interrupted and the stock prices start to move in the downward trend, and conversely, a trough will appear when the stock prices which is in a downward trend is interrupted and the stock prices start to move in the upward trend. The term "zigzag pattern" has been used to describe the peaks and troughs that investors can lay down on a chart that they are viewing (Edwards, *et al.*, 2007b), however, the significant zigzag patterns are unobvious, contaminated with noise, or hidden in the data and, hence, are difficult to be discovered and interpreted.

Zigzag patterns is one of stock price patterns that experts use along with some other patterns such as reversal patterns (Bouchentouf *et al.*, 2011), or Elliott waves (Brown, 2012; Richard, 2003) to predict the future price movement. Unfortunately, experts predict the stock market based on vague, imperfect and uncertain knowledge representation because they usually use the raw data which usually consist of high dimensionality, is imprecise, and uncertain, in their stock market time series. Along with the development of artificial intelligence; for example, machine learning and data mining, a number of researchers attempted to build automatic decision support systems to predict stock market (Chan and Franklin, 2011; Wen *et al.*, 2010). A number of artificial intelligent methods have been applied for stock prediction such as neural networks (Chaigusin *et al.*, 2008; Chang *et al.*, 2012; Hajizadeh *et al.*, 2012; Pino *et al.*, 2008), evolutionary methods (Hsu, 2011; Wang *et al.*, 2012), support vector machine (Wen, *et al.*, 2010; Zhao *et al.*, 2012), etc. However, as stock market prediction relates to imprecise concepts and imprecise reasoning decision (Zadeh, 1975), therefore fuzzy logic is seen as a choice for knowledge representation and is applied in stock market prediction (Atsalakis and Valavanis, 2009a; Boyacioglu and Avci, 2010a; Liu *et al.*, 2012; Wei, 2011).

Fuzzy logic, introduced by Zadeh (1965, 1975), is a form for reasoning method with vague knowledge. A fuzzy based model is known as a preferable approach among a number of available models for making prediction. It is essential for the prediction model that closely corresponds to the way experts work like interactive problem solving and explanation facilities to justify the decision making.

However, among above approaches, using a single method for stock market prediction may produce the poor result with low accuracy or high error comparing to the actual values. Obviously, by nature, the stock market prediction problem requires the combination of a number of techniques together instead of exclusive single technique to increase the prediction performance (Atsalakis and Valavanis, 2009b; Wang, *et al.*, 2012). Recently, researchers combined fuzzy logic technique with neural networks (Agrawal *et al.*, 2010; Boyacioglu and Avci, 2010b), particle swarm optimization (Liu, *et al.*, 2012) , genetic algorithms (Chang, *et al.*, 2012) etc. in order to improve the prediction performance. The results reported that, obviously, the hybridizations of fuzzy logic with other methods produce better prediction performance than their basic single methods. However, in the fuzzy based methods, the appropriate number of generated fuzzy rules is important because it affects the prediction performance, thus the optimal number of fuzzy rules is still an issue and required to be improved.

Searching for the appropriate number of fuzzy rules has been widely studied. However, a number of researchers used the subtractive clustering method (Chiu, 1994) to solve the problems (Esfahanipour and Mardani, 2011; Torun and Tohumoğlu, 2011; Zanaganeh *et al.*, 2009) because it is able to find an appropriate number of clusters which correspond to a number of fuzzy rules. However, the subtractive clustering method requires some predetermine parameters to search a number of clusters. Some optimization methods; e.g. particle swarm optimization, and genetic algorithm were used to find the optimal values of these parameters (Chen *et al.*, 2008; Shahram, 2011; Zanaganeh, *et al.*, 2009).

1.2 Background of Problem

Prediction of stocks is generally believed to be a very difficult task. There are several attempts to predict stock market in order to help investors to make decision of buying a stock at the bottom and selling it at the top in the range. The points where stock prices change their trend directions are called turning points (Bao and Yang, 2008). The turning point of changing the trend direction from an upward trend to the downward trend is called the peak, and the turning point of changing the trend direction from a downward trend to an upward trend is called the trough point (Siegel, 2000). Predicting price behaviors on the financial market such as trends and turning points have been considered as important tasks and have been widely discussed (Bao and Yang, 2008; Chang, *et al.*, 2012; Li and Deng, 2008; Ni *et al.*, 2011; Poddig and Huber, 1999).

In general, the markets do not exclusively move in one direction, but they move in upward and downward directions sub-sequentially by a series of zigzag directions (Edwards, *et al.*, 2007b). These zigzag directions form a series of consecutive zigzag waves which represent the obvious peaks and troughs. The direction of each pair of a peak and a trough constitutes a market trend of upward, downward, and sideways trends. An upward trend is a series of consecutively higher peaks and troughs; a downward trend is a series of consecutively lower peaks and troughs; finally, a sideways trend is a series of horizontal peaks and troughs (Edwards, *et al.*, 2007b; Siegel, 2000).

Naturally, the prediction of financial time series trends relies on the discovery of strong empirical turning points in observations of the system (Li, 2009; Liu and Kwong, 2007). Turning points, obviously, position nearby or at the peaks and troughs of the time series (Bao and Yang, 2008). Nevertheless, since these turning points are often masked by noise, and hidden in the price movement, thus, the accurate prediction of trends and turning points is very difficult. Many researchers have attempted to predict stock market based on learning from turning points, which the experimental results showed that learning from the historical turning points affected the stock market prediction performance (Bao, 2007; Bao and Yang, 2008; Chang, *et al.*, 2012; Li, 2009). In order to predict the stock market in the accurate way, discovery and learning from the zigzag patterns are very important since the zigzag patterns represent the zigzag moving trends of prices consisting of the sharp top points or "peaks" and the deep bottom points or "troughs". Peaks and troughs are cooperated as patterns that are developed by the price action of all securities. The straight line connecting between a pair of a peak and a trough or a trough and a peak represents a trend (Kirkpatrick, 2007). Peaks bring an appreciation on stocks, consumer-spending surges, and there is obviously high consumption. When a series of rising or falling of peaks and troughs is interrupted, it is a signal that a trend reversal may be taking place, or in other words, a turning point occurred (Lan *et al.*, 2011; Siegel, 2000). The example of demonstration of peaks, troughs, trends, and turning points are shown in Figure 1.1.

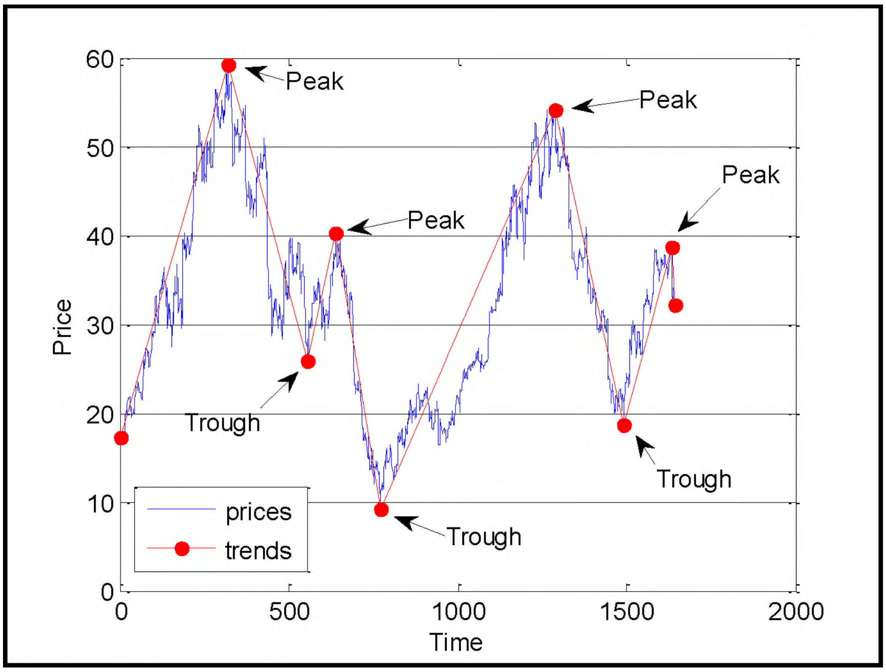

Figure 1.1: Plot of stock prices with trends and points of peaks and troughs which represent the turning points for stock of Akamai Technologies Inc. (AKAM)

Points of changing of trends which are called peaks and troughs, can be generally called as turning points. If the stock price is at the trough turning point, good investors need to buy the stock, but, conversely, if the stock price is at the peak turning point, good investors need to take profits by selling that stock. The example representing of selling/buying points is shown in Figure 1.2. As mention above, the identification of the turning points is a challenge of stock market prediction.

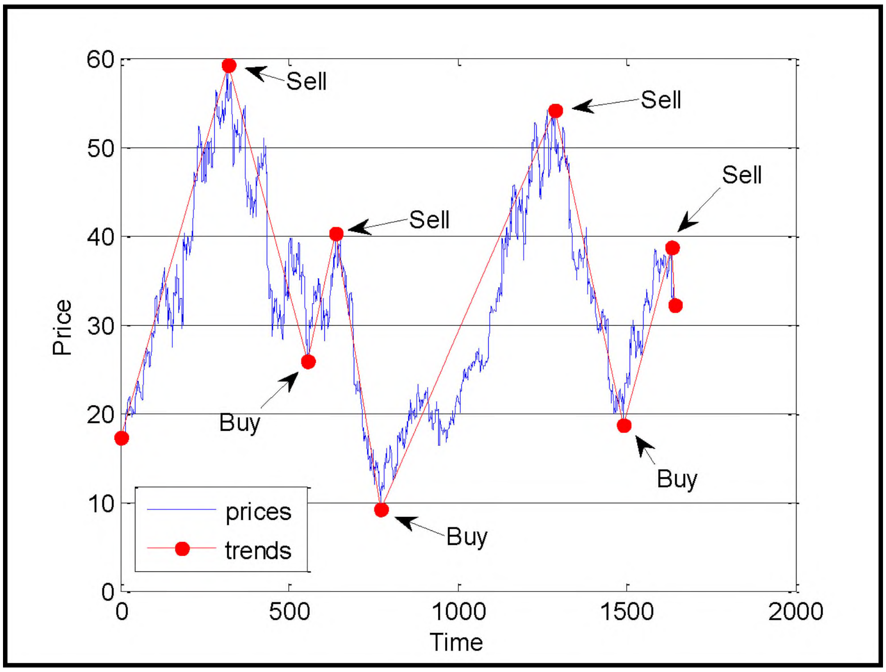

Figure 1.2: Plot of stock prices and trends representing of buying/selling points for stock of Akamai Technologies Inc. (AKAM)

1.3 Problem Statement

In the few past decades, a number of scholars studied and looked at stock price movement direction or trend by using various kinds of data mining techniques (Atsalakis and Valavanis, 2009a; Chang, *et al.*, 2012; Dai *et al.*, 2012; Edwards, *et al.*, 2007b). In general, the trend is the direction of the market of moving up, or down. The trend always moves upward and downward directions subsequently. Or in other words, after the market moves in one direction e.g. upward direction the markets change its direction to opposite direction like downward direction and after a period it move upward gain (Edwards, *et al.*, 2007b).

Identification of zigzag patterns is a challenge since zigzag patterns usually hide in the high dimensions of stock prices. The high dimensions of stock prices indicate as the frequently changing of stock prices over time. Moreover, the zigzag patterns also usually occur in multi-resolutions, or in other words, the zigzag patterns occur in either short or longer time frames. Fu et al (Fu *et al.*, 2008) used the perceptually important points (PIPs) identification method to collect important points and used the specialize binary tree (SB-Tree) to structurally index those collected PIPs. SB-Tree is a kind of multi-way search tree (M-Tree) or a tree with maximum available having M children where M is two. However, the retrieved patterns do not exactly form zigzag patterns. The patterns that characterize the behavior of stock prices always form a series of consecutive zigzag waves which clearly represent the peaks and troughs. For stock trading activities, early detection of turning points is the key of success. Investors decide to buy a stock if it is at a trough turning point and they decide to sell a stock if it is at a peak turning point.

However, if the stock is along in an upward trend investors need to decide to hold the stock and wait for the price movement until the stock price reaches the peak turning point, oppositely, if the stock is along in a downward trend investors surely do not enter to buy the stock but they have to wait for the price moving until reaches the trough turning point. Such that, the way how to identify the turning point is a challenge because the turning points usually occur in multi-resolutions and hide in the high dimensionality of stock prices. Many attempts have been used to identify or predict the turning points by using statistical approaches (Giot and Petitjean, 2011; Marsh, 2011), or artificial intelligent (AI) approaches (Chang, *et al.*, 2011; Li, 2009). However, the statistical approaches like autoregressive model, it is limited to only single predictor, in the real world, there are many factors affect the stock price movement.

AI methods are widely used to improve the prediction performance such as neural networks (Asadi *et al.*, 2012; Dai, *et al.*, 2012) and fuzzy logic (Atsalakis *et al.*, 2011; Liu, *et al.*, 2012). Neural networks represent their remarkable feature to learn how to work with tasks based on the given training data (Gallant, 1993; Rao and Cecchi, 2011). On the other hand, fuzzy logic is known as the technique that can solve the problems with imprecise data and linguistic concepts like the ones generated from stock markets (Atsalakis *et al.*, 2012; ElAal *et al.*, 2012). Stock prediction involves vagueness or imprecision of concepts and reasoning. However, although fuzzy logic can uncover the imprecise problem, fuzzy logic does not have a learning ability.

Recently, a number of researchers introduced hybrid methods of neural networks and fuzzy logic (Jang, 1993; Sun and Jang, 1993). Jang (1993) introduced an Adaptive Network based-Fuzzy Inference System (ANFIS) which is a hybridization of neural networks and fuzzy inference system. ANFIS learns from a given training data by using the hybrid of gradient descent and least-squares method for parameters updating. Sun and Jang (1993) proposed adaptive neuro-fuzzy classifier (ANFC) to solve the fuzzy classification problem. ANFC learns patterns from data by using gradient descent based method.

Since the prediction of turning points is a classification of the trend for future trading day as upward or downward trend thus ANFC based techniques can be suitably employed to solve turning points prediction with imprecision problem.

Although the networks concept in ANFC can be used for tuning the parameters of membership functions and other parameters of the fuzzy rule base of the learning process, however a number of fuzzy rules which related to the performance of ANFC is still the issue. The appropriated number of fuzzy rules can lead to the higher performance of fuzzy classification problem. A critical problem is how to find an appropriate number of fuzzy rules. Clustering based method is frequently used to determine a number of fuzzy rules. The number of clusters which are found by the subtractive clustering method indicates a number of fuzzy rules.

Most recent studies used subtractive clustering method to determine the number of clusters of the input space because it can automatically determine a number of clusters. However, subtractive clustering method requires the user to set some optimal parameters of input space radii and a squash factor. Many researchers used the optimization techniques, e.g. Genetic algorithm (GA) (Zanaganeh, *et al.*, 2009) or particle swarm optimization (PSO) (Chen, *et al.*, 2008) to optimize these parameters. Nevertheless, these powerful optimization methods have their inherent shortcomings and limitations (Wang *et al.*, 2007).

GA is known as the chromosome encoding based global optimization method developed by Holland (1975). GA can improve its performance by performing its operators e.g. selection, reproduction, mutation, and crossover. However, GA usually delays convergence speed and it may destruct good gene in a chromosome (Yang *et al.*, 2007). PSO is a population based stochastic optimization technique developed by Kennedy and Eberhart (Kennedy *et al.*, 2001). In PSO, each potential solution is assigned to a particle. PSO, as a relative new evolutionary algorithm has been successfully applied to unconstrained and constrained optimization with fast convergence. However, PSO may easily be trapped into local optimum (Hu *et al.*, 2004).

As can be seen, the combination of the computational intelligence methodologies can usually provide superior performances over employing them individually (Olmeda and Fernández, 1997). A hybrid method of two single methods like PSO and GA are widely used for optimization problems (Alireza, 2011; Kuo and Han, 2011). However, these hybrids are done with different techniques. Aireza (2011) used adaptive mutation of GA method for combining to PSO algorithm while Kuo and Han (2011) integrated the mutation mechanism of GA to PSO then used elitist policy to enhance the evolutionary performance.

However, to integrate the mutation mechanism to PSO method is an issue since in each iteration process, PSO produces a global best particle which behaves the best performance among the swarm in the iteration. If the global best particle is mutated this may bring the global best particle lost the chance of getting better position based on current position updating in the next iteration. Thus, it is a better idea to prevent the global best particle from mutation operation in the iteration for keeping the best position of the particle.

In this research, the fuzzy based stock market turning points prediction is focused. The idea of the prediction is since the stock markets always move upward and downward subsequently, or in other words, they always move in zigzag patterns, the identification of these zigzag patterns can benefit in the future movement prediction. However, the zigzag patterns consist of two major parameters to be specified; the oscillation size and the trading time frame. These two parameters are hidden in the stock prices and difficult to specify. Next, performance of the fuzzy based prediction method relates to a number of used fuzzy rules. A number of fuzzy rules can be specified by the subtractive clustering method. However, the subtractive clustering method requires the optimal parameters specification. The global optimization method is needed to search for optimal number of clusters in subtractive clustering method. The particle swarm optimization method (PSO) is known as a fast convergence optimization method, but it is easily be trapped in local optima. Additionally, the mutation operation in genetic algorithm (GA) is known as the global optimization operation, thus it is the good idea to incorporate the mutation operation into the PSO method. However, in PSO, each iteration of searching the global best particle (gBest) is found. The gBest particle is the best performance particle in PSO, it should be protected from the mutation operation during the PSO flying in the searching space. Finally, the stock market turning points prediction based on the learning from zigzag patterns and the fuzzy concept data is the major techniques used in this research.

The proposed framework for stock market turning points prediction can benefit for stock market investors to take actions in stock market trading strategy. Furthermore, if investors want to buy a stock, the investors are advised to wait until the stock price reaches the trough turning points and then they are advised to hold the stock until the stock price reaches the peak turning point, the investors are then advised to sell that stock. This aims to gain the high profit in stock market trading strategy. Although there are several stock market prediction models exists but the proposed model shows it's excellent in the benefit of fuzzy based prediction since the used stock market data are imprecise and vague to interpret. Furthermore, the proposed model can learn from the historical turning points in order to predict the future turning points.

As described above, the main solved and unsolved issues are categorized and displayed in Table 1.1.

Table 1.1 : Issues in turning points prediction with solved and unsolved issues

Main Issue	Solved Issue	Unsolved Issue
Zigzag pattern extraction from stock time series	Collecting the important points and indexing them structurally (Fink and Pratt, 2003; Fink *et al.*, 2003; Fu, *et al.*, 2008)	The retrieved patterns do not behave in the zigzag manner with specific of oscillation size and the trading time frame.
Global optimization method of hybrid PSO and GA	The mutation mechanism of GA is combined to all particles in PSO process (Alireza, 2011; Kuo and Han, 2011; Premalatha and Natarajan, 2009).	The global best particle in PSO of the iteration is not kept for the next iteration but it is still be mutated.
Turning points prediction based on imprecise data and learning from zigzag patterns.	- Turning points prediction without supporting imprecise data problem (Bao and Yang, 2008; Li, 2009) - Turning points with supporting imprecise data but not supporting learning from zigzag patterns (Atsalakis, *et al.*, 2011; Hsu, 2012)	Turning points prediction learning from imprecise data and learning from zigzag patterns.

Mainly from the issues state above, the primary research question is:

"How to extract zigzag patterns from stock market time series, next, how to design the hybrid global optimization method in order to search for the optimal parameter of subtractive clustering method which are used for identifying the appropriate number of fuzzy rules, and finally, how stock market data can be classified using fuzzy based classifier with a number of fuzzy rules which are initialized by the subtractive clustering method, and the extracted zigzag patterns, in order to identify the stock market turning points which are used for trading decision."

The secondary research questions that need to be addressed in order to complement the primary research questions and the solutions are given below:

Problem 1: How to structurally extract the zigzag patterns from stock market time series with specific interest size of oscillation and trading time frame?

Solution 1: Propose algorithm for zigzag patterns extraction which comprises of three sub-solutions; zigzag-perceptually important points (ZIP) identification method, zigzag based multi-way search tree (ZM-Tree), and zigzag patterns retrieval from the ZM-Tree based on the specifications of percentage of oscillation size and interest trading time frame.

Problem 2: How to design the hybrid global optimization method that meets the global convergence?

Solution 2: Construct the mutation capable particle swarm optimization (MPSO) which is a hybrid method of PSO and GA by incorporating the mutation operation of GA into the particles of PSO. Each particle in MPSO normally operates its velocity and position then the consideration of performing the mutation operation to the particle position. The consideration is done by determining whether each particle is a global best particle or not. If it is the global best particle, the mutation operation is prohibited otherwise the mutation operation is performed.

Problem 3: How to uncover the hidden patterns of stock market time series for stock market turning points prediction which are used to conduct the trading strategy?

Solution 3: The swarm based fuzzy turning points prediction (SFTPP) model is constructed in order to learn the zigzag patterns and predict the turning points for conducting the trading strategy. SFTPP model is created based on adaptive neuro-fuzzy classifier which learns the historical information from the selected features and the extracted zigzag patterns. A number of the generated fuzzy rules of the ANFC is determined by the subtractive clustering method with the parameters optimization based on MPSO method. The learned model is used to predict the future turning points, and then these turning points are converted to trading signals and the trading strategy is conducted based on the generated trading signals.

1.4 Objectives of Research

The main objective of this research is to propose an approach in order to predict the stock turning points based on the extracted zigzag patterns by using the adaptive neuro-fuzzy classifier (ANFC) which the fuzzy rule generation technique is improved by applying the subtractive clustering method and the improved hybrid PSO and GA method. Therefore, this study investigates the hypothesis "zigzag pattern extraction method and fuzzy rules generated from the hybrid optimization method of PSO and GA can produce high accuracy of stock turning points prediction". To achieve this goal, the following objectives have been set:

1. To develop a method for identifying zigzag perceptually important points that can be used to construct the zigzag based multi-way search tree which are essential to extract zigzag patterns from stock price time series.

2. To investigate the performance of the mutation capable particle swarm optimization method for the global optimization problem.

3. To develop Improved Particle Swarm Optimization for Fuzzy Based Stock Market Turning Points Prediction method based on the extracted zigzag patterns, mutation capable particle swarm optimization, and adaptive neuro-fuzzy classifier.

1.5 Scopes of Research

The previous section has stated the objectives of this study which focuses on how to improve the stock turning points prediction problem. The following aspects are the scope of research for those objectives.

1. The study focuses on automatic stock turning points prediction through the zigzag patterns extracted from zigzag based multi-way search tree (ZM-Tree), and the retrieved zigzag patterns from the ZM-Tree are learned through adaptive neuro-fuzzy classifier (ANFC) which a number of fuzzy rules are generated by subtractive clustering method with the mutation capable particle swarm optimization (MPSO).

2. The study uses historical data of 9 stocks which are selected from stocks listed in S&P500 index of New York Stock Exchange (NYSE) since it is well-known and large in size stock market. The data covers the basic information of open, high, low, close and volume values which 500 trading days during November 19, 2008 until November 14, 2010 are used as training set, and 150 trading days during November 15, 2010 until June 22, 2011 are used as testing set. However, for the selected stocks, the testing period must meet these constraints, the first three stocks must be in the upward trend, the next three stocks must be in the sideways trend, and finally, the last three stocks must be in the downward trend. The length of training period is 500 trading days and the testing period is 150 trading days. These are enough for using in training and testing processes because the trading time frames used in this research are in the short term periods. Thus the training and testing data above are enough for using in the

model. The details of these time frames are explained in Chapter 3. All datasets are available to download from Yahoo finance (2012).

3. The performance of the proposed optimization method is compared to the standard particle swarm optimization (PSO) (Kennedy and Eberhart, 1995), standard genetic algorithms (GA) (Goldberg, 1989; Holland, 1975), and a novel adaptive particle swarm optimization (APSO) (Alireza, 2011).

4. The performance of the proposed prediction model which is based on learning from the zigzag patterns is evaluated in terms of prediction accuracy. The model evaluation compares to some existing similar prediction models e.g. k-nearest neighbor classification (KNN) (Teixeira and de Oliveira, 2009), adaptive neuro-fuzzy inference system (ANFIS) (Esfahanipour and Mardani, 2011), and artificial neural networks (ANN) (Enke and Thawornwong, 2005).

5. The performance of trading results following up the prediction results by conducting the simple stock trading strategy. The performance evaluations are measured based on their rate of return (ROR) and rate of success trades (ROS). The comparisons are made to the results of the proposed model and the results of models based on KNN (Teixeira and de Oliveira, 2009), ANFIS (Esfahanipour and Mardani, 2011), and ANN (Enke and Thawornwong, 2005) as described above. Next, the trading results are also compared to the trading results generated from the technical analysis technique e.g. moving average convergence/divergence (MACD) which the trading signals are generated by Expert Advisor of MetaStock ® 10.1 (MetaStock, 2012). Finally, the comparison is made to the buy and hold (B&H) trading strategy as found in (Li, 2009).

1.6 Contributions of Research

In this section, the research contributions those lead to philosophy of the study in the problem domain perspective are highlighted. The contributions ordered by the related problems are stated as follows:

Problem 1: How to structurally extract zigzag patterns from stock market time series?

Contribution 1: Identification of zigzag patterns which is able to collect the zigzag patterns from stock time series and is able to specify the percentage of oscillation and the interest trading time frame for retrieval.

Problem 2: How to construct the global optimization algorithm for the global optimization problems?

Contribution 2: More effective global optimization method based on the hybridization of particle swarm optimization and genetic algorithms.

Problem 3: How to uncover the hidden patterns of stock market time series for prediction of stock market turning points which are further used to conduct the trading strategy?

Contribution 3: More effective stock turning points prediction for stock trading strategy based on the combination of the zigzag patterns extraction method, hybrid of particle swarm optimization method and genetic algorithms, and the adaptive neuro-fuzzy classifier.

1.7 Thesis Organization

This thesis is structured into seven chapters as described follows:

Chapter 1, Introduction: this chapter presents the introduction of the research and the research background including discussion on the issues that need to be solved in this research area by stating the problems, the objectives, the scopes and contributions of this thesis.

Chapter 2, Literature Reviews: this chapter provides the literature and information of related area that leads to the problem statement and solution of this research. This chapter is covered by an overview of the survey in the research areas, some information and issues that related to stock turning points prediction, adaptive neuro-fuzzy classifier with learning algorithms, fuzzy rules generation methods, the global optimization methods and stock trading strategies.

Chapter 3, Methodology: This chapter describes the research methodology and justification for the solution approach to achieve the objectives of this research. The approach including zigzag patterns extraction, the design of hybrid particle swarm optimization and genetic algorithms for global optimization problem, and the swarm based fuzzy turning points prediction model are briefly presented.

Chapter 4, Zigzag Patterns Extraction: this chapter describes algorithm of extracting stock zigzag patterns based on the identified zigzag-perceptually important points and zigzag based multi-way search tree (ZM-Tree).

Chapter 5 A hybrid particle swarm optimization and genetic algorithms method for global optimization problems: this chapter introduces the proposed mutation capable particle swarm optimization (MPSO) method for global optimization problems.

Chapter 6, Swarm based fuzzy turning points prediction model: this chapter represents the stock turning points prediction model which is mainly constructed based on the zigzag patterns extraction method, the mutation capable particle swarm optimization method, and the adaptive neuro-fuzzy classifier. The stock turning points prediction results are converted to trading signals for simulating simple trading decision.

Chapter 7, Conclusion and future work: this chapter discusses and highlights the contributions and findings of the research work, and presents suggestions and recommendations for future study.

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