International Journal of Innovative Computing, Information and Control
Volume **8**, Number **9**, September **2012**

ICIC International ©2012 ISSN 1349-4198
pp. 6173–6190

EVOLUTIONARY FUZZY STOCK PREDICTION SYSTEM DESIGN AND ITS APPLICATION TO THE TAIWAN STOCK INDEX

Hsuan-Ming Feng[1] and Hsiang-Chai Chou[2]

[1]Department of Computer Science and Information Engineering
[2]Graduate Institute of Electrical Engineering and Computer Science
National Quemoy University
No. 1, University Road, Kin-Ning Vallage Kinmen 892, Taiwan
hmfeng@nqu.edu.tw

Received May 2011; revised September 2011

Abstract. *The study develops fuzzy stock prediction system that integrates the novel computer technologies of stepwise regression analysis (SRA), auto-clustering analysis, recursive least-squares (RLS) and particle swarm optimization (PSO) learning schemes. The SRA methodology serves as a data filtering channels to select two primary technical indexes from the training dataset. The selected items are then assigned as input variables of the fuzzy prediction system to simplify the modeling architecture. An efficient evolutionary clustering algorithm can then determine the available centers positions of the membership functions. It is proposed to exploit appropriate behaviors of the identified stock dataset. In addition, the initial architecture of fuzzy prediction system is represented with the trained clusters information. The proposed evolutionary-based learning scheme with its evolutionary hybrid particle swarm optimization (PSO) and recursive least-squares (RLS) technologies can extract the appropriate parameters for the fuzzy stock prediction system. The proposed fuzzy stock prediction systems are implemented as necessary data acquirement, feature description and time serious stock prices and trends forecasting stages in the real financial environment. The objective of this study is that it is not only capable of automatically initializing and creating the appropriate fuzzy architecture, but it can also develop the stock model to accurately simulate the actual trading of the Taiwan stock indexes (TAIEX). This study develops various stock predictions examples for daily and weekly approximations for the training and testing phases based on historical TAIEX data. A comparison with other learning methods shows that the proposed approach offers improved forecasting accuracy. The generated fuzzy stock model can help traders achieve the greatest rewards in real TAIEX trading applications.*
Keywords: Auto-clustering analysis, Fuzzy stock prediction system, Particle swarm optimization, Recursive least-squares, Taiwan stock indexes

1. **Introduction.** Forecasting stock prices and their trends are important factors in achieving significant gains in financial markets. Behavior descriptions in the historical collection of financial time series data are that it faces a big challenge to recover the tremendous sudden variation, complex and non-linear dimensionality. However, stock markets exhibit dynamic, nonlinear, chaotic, nonparametric, and complicated features [20,30]. Predictions stock market prices and movements is a difficult task because of the significant influence of several macro-economical factors, including political events, general economic conditions, investors' expectations, institutional investors' choices, and unexpected situations in other stock markets, and psychology of investors [31]. In general, there are two main catalogues (i.e., fundamental econometrics and technical indexes analysis) for stock forecasting procedures. Thus, the best trading time is when the stock price is approaching the acceptable range [6]. Fundamental econometrics analysis is based

on collected macroeconomics data and their tendency in the world. The most command factors in a stock forecasting system are interest rates, money supply, inflationary rates, national income accounting, foreign exchange rates, and industrial production rates [2]. These indexes are the main factors affecting the gross domestic product (GDP). Great investors first obtain required financial historical and real-time macroeconomics data. They then apply the reliable financial analysis methods to forecast the possible high and low movement range of the stock market before making decisions about buying or selling actions. The technical analysis method uses this stock index information, tighter with the calculation of trading prices, volumes size and moving time, to deliver useful information for choosing the available stratagies (i.e., buy, sell, or wait actions) [26]. Generating a stock forecasting model system with technical indexes has been a major concern in economic fields. Fazel Zarandi et al. selected several technical indices to form a multiple-input-single-output type 2 fuzzy model system to perform stock price forecasting task [17]. Chun and Park collected four technical indexes to derive the nearest training case for predicting the real stock price movements with a dynamic adaptive ensemble case based reasoning in the Korean sock exchange market [14]. Atsalakis and Valavanis used the neuro-fuzzy methodology to predict the next day's stock market trend [2]. Several studies use the historical stock trading price, volume and other datasets in the past thirty years [1,4,8,24,29]. In reality, their approach attended to model the framework of historic serial data for nonlinear stock price representation, prediction, and decisions in resolving stock problems. Previous experiments indicate that a fuzzy model system can accurately predict the accurate time-series future of stock behavior based on the observations of collected past and current technical input datasets.

Fuzzy logic and fuzzy inference engines are an inherently non-linear way to be considered as a universal function approximation [34]. Therefore, fuzzy model systems cannot only reconstruct well to approximate the complex non-linear financial time-series data, but can also deal with the well-known variations condition in stock price. Over the last few decades, many artificial fuzzy model systems have used a valid learning machine to obtain the human-type linguistic fuzzy rules, which in turn play important roles in solving the system identified problems [34]. Several clustering algorithms use different measures, and have also been adopted to particular purposes and engineering applications. For example, the fuzzy c-means (FCM) algorithm introduced by Bezdek [5] and the K-means algorithm presented by Anderberg [3] are both the most popular known clustering algorithms that divide a collected dataset into several groups, and then calculate the cluster centers for the selection of the related data groups. The drawback of using the FCM and K-means algorithms is that a suitable number of the cluster centers must be given manually in advance. Despite traditional electrics measure, the proper reorganization in cluster centers number has been developed substantially by the efficient validity functions to yield [13,35]. Based on the concept of fuzzy logic and inference theory, and first introduced by Zadeh in 1965 [36], Song and Chissom applied the MAX-MIN operation to generate the linguistic fuzzy rules for forecasting enrollment at the University of Alabama [27]. Other researchers solved temperature prediction and the Taiwan features exchange (TAIFEX) forecasting problems use forecasting methods with a two-factor high-order fuzzy time series to achieve great forecasting accuracy [11,12]. Wang and Chen [32] used an automatic clustering algorithm to divide the collected dataset and forecast the temperature and the Taiwan Futures Exchange (TAIFEX) with the high-order fuzzy time series technology. Lai et al. used an evolutionary genetic algorithm and fuzzy decision tree to decide the best time to buy or sell on the trends of a stock prediction model [26]. To approximate the purpose of the stock price function approximation, appropriate validity functions can improve the quality to evaluate the structure of training data and detect the reasonable cluster centers number. Based on Chou's study [13], selecting a better validity function should simultaneously consider compact and shell properties to separate various complex datasets. One of the main objectives of the fuzzy prediction model system is to approach an exact characterization of the expected model for rebuilding the non-linear behavior in the collected time serial data. The commonly used fuzzy inference engine requires three categorized parameters (i.e., the centers, the widths of membership functions, and connection weights of consequent parts) to reproduce the primary behavior of the discussed time serial data. In practicality, a suitable membership function is first determined based on the consideration in covering the scatter-typed region of the training data. In general, the number of fuzzy rule is determined by experience, and is often derived in time-consuming, trial-and-error way. This manual approach is too imprecise to predict complex and uncertain time series data. Other gradient descent type learning machines also have difficultly solving complex, higher dimensional data modeling and prediction problems. To construct an initial fuzzy model system, this study uses a clustering-based algorithm with a well-defined cluster validity measure to assess the interaction among patterns. This approach ensures that training data are similar to the selected cluster centers. Therefore, the study uses Chou's CS measure to build the initial fuzzy model system in the structure identification step. The secondary step involves generating a flexible learning algorithm to acquire the desired parameters. Because of the adoption of universal functional approximation, fuzzy model systems with various learning schemes approximate nonlinear time series data and solve complex prediction problems [2,10,16,18,32].

The two main types of learning scheme include local and global type parameters learning algorithms. The gradient descent type algorithm can be considered as a typical local learning stratagem that obtains an accurate system curve from the identified dataset [33]. However, the actual derived results are most likely to encounter local optimal problems and may cause unacceptable modeling outcomes for complex and high-dimensional dataset problems with some variances in initial conditions. Several global learning algorithms can improve the performance of the fuzzy rules-based systems when the traditional local type optimal learning algorithm falls into local optimal solutions. For examples, the genetic algorithms (GA) [21], and the particle swarm optimization (PSO) [9,19,22] are the popular evolutionary learning algorithms that acquire the appropriate parameters of fuzzy systems. Kenney and Eberhart first introduced the Evolutionary PSO-based learning methods in 1995 through a simplified social sharing model [25]. The swarm-like PSO learning algorithm simulates the manner of bird flocking or fish schooling, and automatically generates the initial architectures and extracts the proper parameters of the fuzzy stock prediction system. Because of the actuation of the specific fitness function, the PSO can efficiently identify the best parameters in the search space. If the initial architecture of the fuzzy model system is set correctly, the proposed PSO-RLS learning scheme can combine the global PSO learning algorithm with recursive least-squares (RLS) technology to solve stock prediction problems.

2. Evolutional Fuzzy Structure Auto-Learning Scheme.

The primary purpose of creating the initial architecture of the fuzzy model system is to extract the important input factors from the collected training dataset. The proposed configuration stage applies the dynamic regression concept and stepwise regression analysis (SRA) [26] to simplify the system model and reduce the complex computation when initializing the fuzzy model. Therefore, the SRA method in this study selects only two technical indexes. It can be considered as the primary factors to provide the most appropriate information on how to predict the variant stock price in the discussed TAIEX dataset. This is an important theme because it allows traders to efficiently track the actual stock-price trends and movements to obtain the big benefits. The training process of the stepwise regression analysis (SRA) allows it to gradually add the principal technical indices or delete the lower priority technical indices after several regression steps. This is a great way to choose the principal indices by sorting the priority of the technical stock indices from the complicated stock database. Therefore, this method choose only the most two important items as the input variables in this way to generate the architecture of the fuzzy stock prediction system. Training samples include 18 indices from the technical stock indices dataset including 6 period moving average (5 MA, 10 MA, 20 MA, 60 MA, 120 MA, 240 MA), 3 period bias indicator (6 BIAS, 12 BIAS, 24 BIAS), stochastic line (K and D values), 3 relative strength indicator (6 RSI, 12 RSI, 24 RSI), 1 moving average convergence and divergence (MACD), 1 William indicator(14 WMS), and 4 volume of transaction (1 VOL, 4 VOL, 8 VOL, 15 VOL), samples. Detailed definitions of these different MA, BIAS, K, D, RSI, MACD and WMS indexes are available in the other references [7,15].

To select the proper number of fuzzy rules, the developed evolutional auto-clustering algorithm with the available measuring function can be manipulated to self-determine the clustering numbers, and their related center positions. An automatic clustering-based algorithm with flexible validity function, called the CS measuring function, is used to identify the distribution of the trained stock dataset. It is feasible to attempt a real cluster number from the discussed time-series stock dataset. The most similar data will be collected as one group and removed the dissimilar data point into the other cluster areas.

In a fuzzy model system, the n-inputs-single-output model contains several fuzzy IF-THEN rules. The proposed whole input variables are determined by an n-dimensional pattern as the vector form $X = (x_1, x_2, \ldots, x_n)$. The developed fuzzy inference engine chooses the specific hyper-ellipsoid membership functions (HE_k) to define the input fuzzy space and a single value y_k is bound to achieve the system output. The fuzzy rules-base can be described as follows:

$$\text{RULE}^{(i)}: \text{ IF } X \text{ is } MB_i \text{ THEN } Y \text{ is } y_i, \quad i = 1, 2, \ldots, \text{Num}, \tag{1}$$

where Num is the total number of fuzzy rules and y_i denotes a real value of the corresponding ith rule. The mathematical formula of Membership function MB_i is defined as follows:

$$MB_l(X) = \exp\left(-\left(\sum_{l=1}^{n} \frac{(x_l - a_l^i)^2}{(b_l^i)^2}\right)\right) \tag{2}$$

where a_l^i and b_l^i represent the center and length of the lth principal axis for the related ith hyper-ellipsoid function, respectively. Both required parameters a_l^i and b_l^i approach the better region of fuzzy set in the premised part. The value of y_i is denoted as the consequent part of the fuzzy system's parameters set. The study uses a simplified fuzzy inference engine and the weighted average defuzzifier method. When the input vector is applied to the fuzzy system, the output value (Y) can be derived as

$$Y = \frac{\sum_{i=1}^{Mun} MB_i(X) \bullet y_i}{\sum_{i=1}^{Mun} MB_i(X)} \tag{3}$$

Here, the defined contour of the ith membership function $MB_i(X)$ is derived by combining parameters $\{a_1^i, b_1^i, a_2^i, b_2^i, \ldots, a_n^i, b_n^i\}$ and the real parameter value y_i. Free parameters selection from the combinations of R $(a_1^i, a_2^i, \ldots, a_n^i, b_1^i, b_2^i, \ldots, b_n^i, y_i,\ 1 \le i \le Mun)$ significantly affects the evaluation of final fuzzy prediction model.

This study uses the evolutionary PSO learning algorithm, combined with the validity function (CS), to determine approximate number of fuzzy rules and the initial center positions of the membership function in the structure identification stage.

This study also uses the structure learning algorithm to construct the initial architecture of the fuzzy model. Their detail learning stages are discussed as follows:

Structure learning 1) Randomly generate the initial populations $IP = [X_1, X_2, \ldots, X_{pop\_size}]$, the definition of X_p is presented by

$$X_p = [RULE_p, \gamma_p] = [RULE_{1,i}^p, RULE_{2,i}^p, \ldots, RULE_{\Gamma,i}^p, \gamma_1^p, \gamma_2^p, \ldots, \gamma_\Gamma^p], \quad i = 1, 2, \ldots, n, \\ p \in \{1, 2, \ldots, pop\_size\}. \tag{4}$$

The possible positive number is selected as by the designer; this number represents as the maximal bound of cluster centers for the individual pth particle, and pop_size means the population size in this training cycle. The prepared interval in the selected cluster centers number is between 2 and Γ, so $j \in \{1, 2, \ldots, \Gamma\}$. Notes that $\gamma_j^p \in [0,\ 1]$ represents as the indexes values, and can be used to evaluate which candidates of the cluster centers must be selected.

Structure learning 2) The IF-THEN rules are proposed to choose the active cluster centers by γ_j^p value as follows:

$$\begin{aligned} &IF \gamma_j^p \ge 0.5\ \textit{THEN the jth candidate cluster center}\ R_{j,i}^p\ \textit{is SELECTED} \\ &\textit{ELSE IF}\ \gamma_j^p < 0.5\ \textit{THEN the jth candidate cluster center}\ R_{j,i}^p\ \textit{is REMOVED} \end{aligned} \tag{5}$$

This example is assumed that the initial possible solutions $X_p = [RULE_p, \gamma_p]$ are randomly created, where $RULE_p = [RULE_{1,i}^p, RULE_{2,i}^p, \ldots, RULE_{j,i}^p, \ldots, RULE_{10,i}^p]$, $i = 1, 2, \ldots, n$ and $\gamma_p = [0.82, 0.27, 0.55, 0.27, 0.66, 0.17, 0.42, 0.91, 0.21, 0.49]$. An evaluation of the previous IF-THEN rules shows that the active cluster centers are selected as $\left\{R_{1,i}^p, R_{3,i}^p, R_{5,i}^p, R_{8,i}^p\right\}$. The previous defined formula indicates that the selection of clustering number is 4. Thus, the membership functions are sett at the same 4 value and the initial center positions of their related membership functions are located at the cluster centers.

Structure learning 3) Replace the cluster center positions with the following formula

$$z_l = \frac{1}{N_l} \sum_{x_j \in C_l} x_j, \quad l = 1, 2, \ldots, K \tag{6}$$

where C_i is the collected data point for the associated lth cluster, N_l denotes the element number of C_l, and K is the possible maximal number of cluster centers.

Structure learning 4) Compute the related CS values of the selected kth clustering group by the following Formula (7):

$$CS(K) = \frac{\frac{1}{K} \sum_{l=1}^{K} \left\{ \frac{1}{N_l} \sum_{x_j \in C_l} \max_{x_k \in C_l} \{d(x_j, x_k)\} \right\}}{\frac{1}{K} \sum_{l=1}^{K} \left\{ \min_{j \in K, j \ne l} \{d(z_l, z_j)\} \right\}} = \frac{\sum_{l=1}^{K} \left\{ \frac{1}{N_l} \sum_{x_j \in C_l} \max_{x_k \in C_l} \{d(x_j, x_k)\} \right\}}{\sum_{l=1}^{K} \left\{ \min_{j \in K, j \ne l} \{d(z_l, z_j)\} \right\}} \tag{7}$$

where z_l and z_j are the related lth and jth cluster center for data groups C_l and C_j, respectively. The determined distance between the grouped dataset z_l and z_j is denoted as d. The fundamental concept of the CS measure is not only to achieve this value in the ratio of sum of within-cluster scatter, but also to obtain the minimal distance between the cluster separations. Previous research discusses the clusters in different densities and various groups sizes [13].

Structure learning 5) Compute the individual fitness value of related particle using the following calculation:

$$F = \frac{1}{CS_i + eps} \tag{8}$$

where the CS_i represents the CS measure value for the ith particle, and eps is a very small positive value. The purpose of this evolutionary clustering algorithm is to find the correct clustering results from the possible existed clustering groups that contain the smallest CS value.

Structure learning 6) Determine the personal best solution (pbest) in every individual particle using the following formula

$$pbest_p(t+1) = \begin{cases} X_p(t+1) & \text{if } F(X_p(t+1)) \geq F(pbest_p(t)) \\ pbest_p(t) & \text{if } F(X_p(t+1)) < F(pbest_p(t)) \end{cases} \tag{9}$$

Here $pbest_p(t)$ and $pbest_p(t+1)$ are denoted as the th-p particle's best solutions at the current and next time step, respectively.

Structure learning 7) Obtains the global best (pbest) solution using Equation (10),

$$gbest(t+1) = \begin{cases} pbest_p(t+1) & \text{if } F(pbest_p(t+1)) \geq F(gbest(t)) \\ gbest(t) & \text{if } F(pbest_p(t+1)) < F(gbest(t)) \end{cases} \tag{10}$$

From the previous formula, it is determined by choosing the better one based on a comparison of the individual particle's personal best value ($pbest_p(t+1)$) with the previous global best solution ($gbest(t)$). If the current fitness value of this particle is better than the previous global best solution, the $gbest(t)$ will be replaced by the current particle's solution.

Structure learning 8) Run the simple PSO learning using Equations (11) and (12):

$$V_n^p(t+1) = \tau \cdot V_n^p(t) + \alpha_1 * rand() * (pbest_n^p(t) - X_n^p(t)) + \alpha_2 * rand() * (gbest_n(t) - X_n^p(t)) \tag{11}$$

$$X_n^p(t+1) = X_n^p(t) + V_n^p(t+1) \tag{12}$$

where m is the dimensional number, i can be considered as the particle's number, V is called the velocity vector, and the generated parameters in this fuzzy model system are denoted as X, which is the particle's position vecto τ of the inertia factor. These α_1 and α_2 values are parameters of cognitive and social learning rates in the social leaning model, respectively. Note that $gbest$ is called the global best particle and consists of the highest fitness value among the entire PSO running cycle. The term $pbest$ means the personal best particle that has been found so far.

Structure learning 9) Repeat the learning cycle from (Structure learning 1) to (Structure learning 8) until the running iteration is terminated.

Real clusters number and their related positions of individual cluster centers are determined after the PSO learning cycles are complete. The acquired clusters numbers are assigned to ensure the fuzzy rules number. The position of cluster center is utilized to initialize the membership function of the fuzzy stock prediction system. The motivation of the evolutionary clustering-type algorithm is to obtain the primary feature from the given stock database. Therefore, the fuzzy stock prediction system, with a set of proper membership functions, attempts to actually approximate the nonlinear time-series stock curve by using proposed learning machine.

In this literature, the whole parameters set (R) is achieved by the efficient learning strategy of particle swarm optimization (PSO). The recursive least-squares (RLS) is embedded into the PSO to form the PSO-RLS learning algorithm, which is used to derive the near optimal fuzzy stock prediction systems.

3. **Evolutionary PSO-RLS Parameters Learning Algorithm.** Kenney and Eberhart first introduced the simplified social learning models-based PSO algorithm is in 1995 [25]. The parameters learning cycle uses the evolutionary PSO algorithm and the adaptive recursive least-squares (RLS) method to acquire the proper parameters for fuzzy stock prediction systems. It derives the initial particles to arrive at the near optimal areas based on the guide of the global best and the personal best solutions in the population-based PSO learning machine. Every particle evaluated with its own fitness evaluation helps direct the particle's movement in a self-heuristic learning way to approach the desired solutions. After completing the previous clustering-based learning cycle, the information of the fuzzy rules number and the related membership function centers is used to organize the architecture of fuzzy sock prediction systems. After obtaining the number of fuzzy rules, suitable center positions of fuzzy membership functions are sequentially assigned by the selected cluster center values. Based on the previous initial organization, the evolutionary-based PSO combined with the RLS, called the PSO-RLS learning scheme, is applied to recurrently achieve the optimal parameters of fuzzy stock prediction systems. The evolutionary PSO-RLS parameters learning strategy uses the PSO and valid RLS [19] learning methods to achieve the best parameter values for fuzzy stock prediction systems. Simulations result demonstrates that this approach can recursively regulate the systems parameters and achieve the desired stock forecasting curve. The designed PSO-RLS parameters learning algorithm is expressed in the following PSO-RLS parameter learning steps:

Parameter learning 1) As in the previous auto-clustering learning algorithm, construct the initial fuzzy stock prediction system by selecting real membership functions number and their associated center positions. Set the maximal iteration number (G) and running from initial number $g = 0$ to G.

Parameter learning 2) Calculate the PSO learning formulas using Equations (11) and (12).

Parameter learning 3) Compute each particle's fitness value by the formula

$$FIT = \exp^{-RMSE}$$

where

$$RMSE = \left(\frac{1}{M} \sum_{k=1}^{N} \left(y^d(k) - \frac{\sum\limits_{i=1}^{m} MB_i(x(k)) \cdot y_i}{\sum\limits_{i=1}^{m} MB_i(x(k))} \right)^2 \right)^{0.5} \tag{13}$$

and y^d is denotes as the desired training value.

Parameter learning 4) Derive the personal best particle (*pbest*) and global best (*gbest*) values using Equations (9) and (10), respectively.

Parameter learning 5) Regulate the parameters of fuzzy systems by the PSO learning formulas, i.e., run Equations (11) and (12).

Parameter learning 6) Tune the parameter of fuzzy stock prediction systems to help transform the output (Y) to the RLS learning method,

$$Y(k+1) = Y(k) - \frac{Y(k) \cdot Q^T(k+1) \cdot Q(k+1) \cdot Y(k)}{1 + Q(k+1) \cdot Y(k) \cdot Q^T(k+1)}, \quad k = 1, \cdots, N \tag{14}$$

$$\boldsymbol{\omega}(k+1) = \boldsymbol{\omega}(k) + Y(k+1) \cdot Q^T(k+1) \cdot \left(y^d(k) - Q(k+1) \cdot \boldsymbol{\omega}(k)\right), \quad k = 1, \cdots, N \quad (15)$$

where the initial value $\boldsymbol{Q}(1)$ is determined in the zero vector form. The initial $Y(1) = \eta \mathrm{I}$ and its related learning constant are defined by the positive value $\eta = 100$, the term N is the number of the collected training data, and the identity matrix I is denoted as an $m \times m$ matrix. The adopted RLS learning scheme can manipulate the proper parameters of a fuzzy stock prediction system to approximate the desired output (y^d). Let $\boldsymbol{\omega}$ be the consequent part of the fuzzy inference engine displayed in the vector form $\boldsymbol{\omega} = [\omega_1, \omega_2, \ldots, \omega_m]$. The vector Q is the normalized activation of the membership functions, shown as $\boldsymbol{Q} = [q_1, q_2, \ldots, q_m]$. In this study, q_i represents the ith membership functions (HE_i) with the input vector $\boldsymbol{x}$, and its value is calculated by

$$q_i = \frac{HE_i(x)}{\sum_{i=1}^{m} HE_i(x)} \quad (16)$$

Parameter learning 7) Set $g = g + 1$.

Parameter learning 8) If $g = G$, then stop, otherwise return to the Parameter learning 2 step.

Parameter learning 9) Generate the desired fuzzy prediction system from the selected gbest parameters.

The objective of the proposed evolutionary PSO-RLS parameters learning algorithm is to achieve the smallest root mean square error (*RMSE*) efficiently. In a word, a greater fitness value leads to best parameter selections for fuzzy stock prediction systems, ultimately achieving better forecasting results. This study uses two types of stock prediction examples, i.e., the collected daily and weekly dataset, to present the adaption of the proposed evolutionary algorithm.

4. **Illustrated Simulations in TAIEX.** The first case involves data collected from the daily TAIEX dataset from January 2000 to December 2004. This stock data was divided into the training and testing patterns in 8 different individual periods to test the self-tuning ability of the proposed fuzzy stock prediction system. In the second case, the weekly dataset is summarized 5 daily load dataset as 1 weekly data point. Unlike the daily data in the previous case, weekly data is suitable for forecasting the middle-term stock trends. Note that the period of training data ranges from January 1995 to December 2004 and testing phase ranges from January 2003 to the December 2004.

The whole evolutionary learning cycle prescribes the parameters setting for the developed auto-clustering and PSO-RLS parameter learning schemes. The population size (P) is 20 and the maximal generated iteration (G) is 50. The learning rates for global and personal learning formulas are setting as $\alpha = 1.2$ and $\beta = 1.2$, respectively. The simulations in this study normalize the original stock index within the range $[0, 1]$. The normalization is formulated by

$$\overline{O}_i = \frac{O_i - O_{\min}}{O_{\max} - O_{\min}} \quad (17)$$

where $\overline{O}_i$ is called the normalized data, O_i denotes the original data value, and $O_{\min}$ and $O_{\max}$ represent the lower and upper bounds, respectively.

Example 4.1. Daily Fuzzy Stock Model Generation and Tracking Curve Response. *In this simulation of the daily curve, the active period of training data ranges from January 2000 to December 2002, and the testing phase ranges from the January 2003 to the December 2004. The proposed evolutionary fuzzy stock prediction system can approximate the trading curve of the stock price. In the system variables selection process,* *SAR regressing method extracts two primary technical indexes from the stock training dataset. Two daily primary technical indexes, 5 MA and 6 RSI, were selected to form the input variables of the simplified fuzzy stock prediction system in this literature. Based on the normalized procedure of Equation (17), the 5 MA and 6 RSI were transformed into the range of* $[0, 1]$*. Therefore, the historical stock data, that is 5 MA, 6 RSI and stock price, where collected in the form of sequent vector. These values where respectively assigned as two input and one output variables to form the fuzzy stock prediction system. The evolutionary auto-clustering algorithm with CS measure was utilized to recognize the initial architecture of fuzzy modeling system. 4 cluster centers constructed in this experiment, together with their related positions, were automatically determined to build the initial architecture of the fuzzy stock prediction model. Figure 1 and Figure 2 show the distributed clustering centers and their related grouping-dataset in the form of 2D and 3D plots, respectively. In these two simulation results, the auto-clustering algorithm can achieve the best classifications to obtain the connoting feature of the training dataset. Results features show that 4 fuzzy rules are sufficient to build an accurate fuzzy stock model. Figures 3 and 4 present computer simulations in training and testing cycles for the stock curves predictions based on the evolutionary PSO and adaptive RLS learning algorithms, respectively. In these two experiments, the desired output from the collected historical dataset appears as the solid curve. The actual output of the fuzzy stock prediction system appears as a dotted-type line. The stock tracking curve of the run-time response shows that it is accurately approaching toward the desired stock prices by the evolutionary PSO-RLS learning algorithm. The best objective of the proposed evolutionary learning scheme is that it can efficiently generate the whole fuzzy system to approximate toward the nonlinear behavior of the time-series stock trend. The forecasting curve of the stock price produces by the evolutionary learning-based fuzzy stock prediction system actually follows on the desired stock trend. Evaluated performance comparison with the other learning methods is illustrated in Table 1. These numerical results confirm that the adaptive SAR learning methodology is apparently better than the random selection method. Comparison results with the other learning systems indicates that the evolutionary auto-learning fuzzy stock prediction system can obtain the smallest RMSE value to actually approximate to the stock price curves of TAIEX in the testing phase.*

TABLE 1. Performance comparisons of different methods for Example 4.1

Learning machine	**RMSE (testing phase)**
The Fuzzy Model with random selection	52.85
The Fuzzy Model with SAR selection	27.02
Chen's System [10]	119
Huarng's System [23]	187
Chu's System [15]	84

Example 4.2. Daily Stock Forecasting Performance Analysis. *The objective of trading in the stock market is to obtain the best return. This study builds efficient fuzzy rules to configure the stock prediction models for accurately forecasting the stock price. The developed model is a big help to traders because it increase their changes of making correct buying/selling decisions. To evaluate the adaptive quality of the proposed decision-making machine, several error-type and trend-type measuring items can be considered together to*

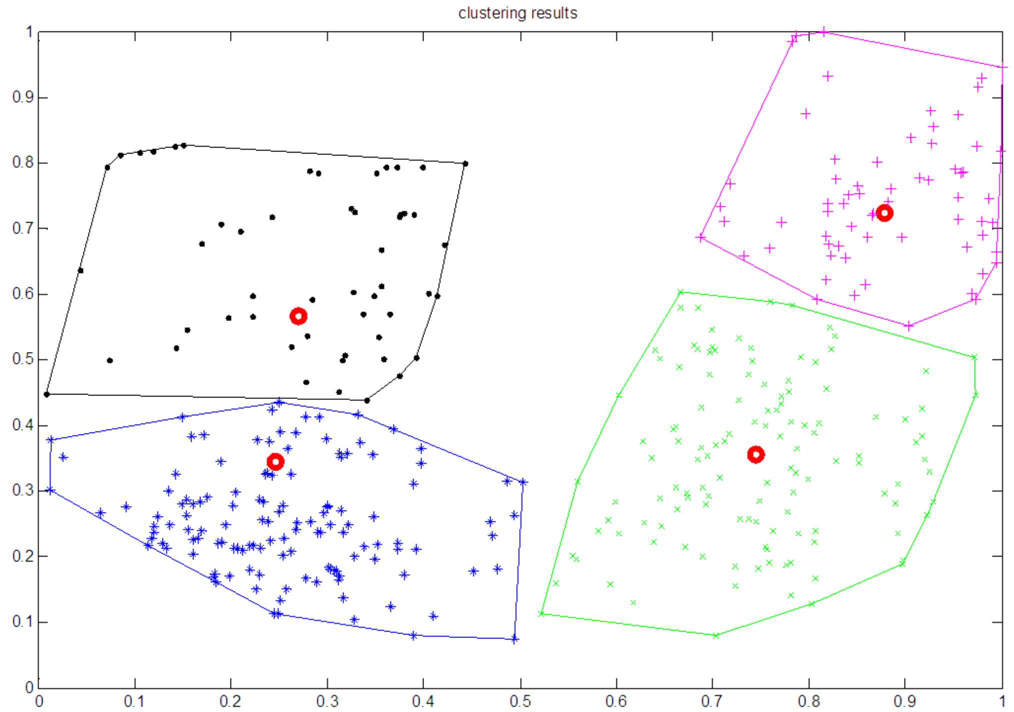

FIGURE 1. Clustering 2D results of the evolutionary-clustering based algorithm

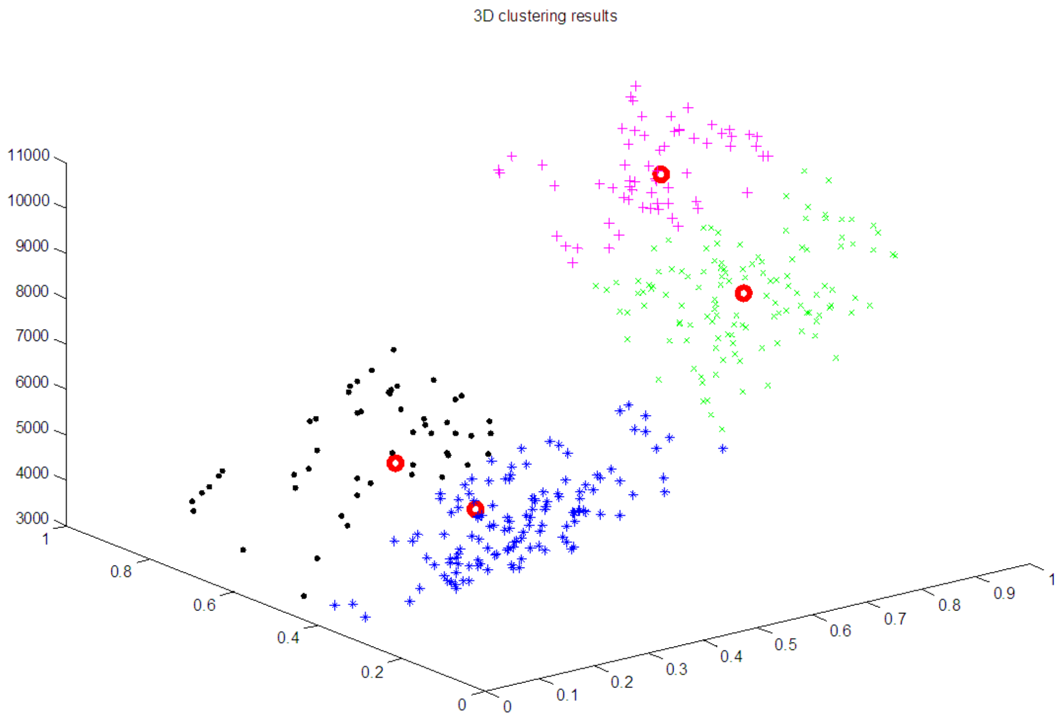

FIGURE 2. Clustering 3D results of the evolutionary-clustering based algorithm

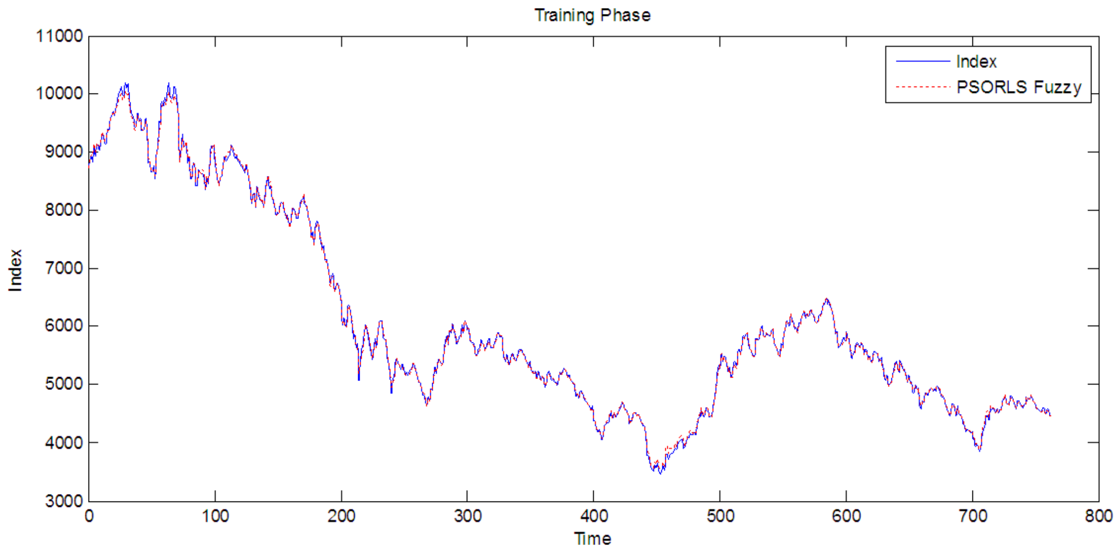

FIGURE 3. Simulation results of the training phase for Example 4.1. Actual (solid) and fuzzy models (dashed).

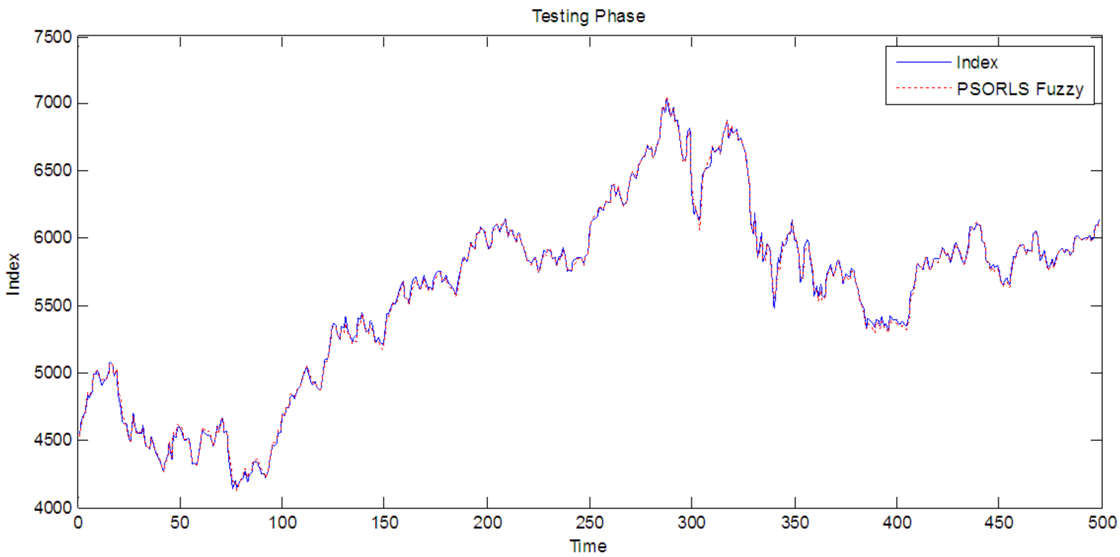

FIGURE 4. Simulation results of the testing phase for Example 4.1. Actual (solid) and fuzzy models (dashed).

provide affluent trading information in the real stock market applications. The root mean squared error (RMSE), mean absolute deviation (MAD) and mean absolute percentage error (MAPE) are error-type measures used to estimate the forecasting accuracy in the stock market. In addition, the directional symmetry (DS), correct up-trend (CP) and correct down-trend (CD) are the trend-type performance measures of the stock trends, and are used to check the correct trending rate of the practical stock movement. These formulas *are presents as follows:*

$$MAD = \frac{\sum_{i=1}^{N} |T_i - Y_i|}{N} \tag{18}$$

$$MAPE = \frac{\sum_{i=1}^{N} \left| \frac{T_i - Y_i}{T_i} \right|}{N} \tag{19}$$

$$\text{DS} = \frac{100}{N} \times \sum_{i=1}^{N} d_i,\ d_i = \begin{cases} 1 & \text{If } (Y_i - Y_{i-1})(T_i - T_{i-1}) \geq 0 \\ 0 & \text{Otherwise} \end{cases} \tag{20}$$

$$\text{CP} = \frac{100}{N} \times \sum_{i=1}^{N} d_i,\ d_i = \begin{cases} 1 & \text{If } (T_i - T_{i-1}) \geq 0 \text{ and } (Y_i - Y_{i-1})(T_i - T_{i-1}) \geq 0 \\ 0 & \text{Otherwise} \end{cases} \tag{21}$$

$$\text{CD} = \frac{100}{N} \times \sum_{i=1}^{N} d_i,\ d_i = \begin{cases} 1 & \text{If } (T_i - T_{i-1}) \leq 0 \text{ and } (Y_i - Y_{i-1})(T_i - T_{i-1}) \geq 0 \\ 0 & \text{Otherwise} \end{cases} \tag{22}$$

where Y is the output of the proposed fuzzy prediction system and T denotes the actual stock price of the Taiwan stock indexes. The collected data in the training and testing phase are denoted as N. The purpose of the developed fuzzy stock prediction system is to obtain the smallest error based on the calculations of error-type indexes, including RMSE, MAD and MAPE. In the other type of performance evaluation, the trend type indexes, i.e., DS, CP, CD, need to be increased the winning rate by the evolutionary learning scheme as high as possible.

This case uses the same historical stock dataset for training and testing data. The difference is that the PSO-RLS algorithm was used to identify various properties divided in 8 different training periods. In these illustrated experiments, 8 training datasets were collected at each one-year interval, and the following 6 months of collected data were defined as the testing dataset. Different performance evaluation index in various 8 regions for the training and testing dataset are presented in Table 2. These training and testing examples illustrate the stock accuracy and tendency with 6 measure-types under 8 prediction period regions. The constructed evolutionary clustering-based fuzzy stock prediction systems have the ability to choose the proper fuzzy rules. In the testing phase, the presented PSO-RLS

Table 2. Proposed learning algorithm results for different performance evaluation indices in 8 regions

Region	**Clusters**	**Training Phase**		**Testing Phase**					
		RMSE	**Run time**	**RMSE**	**MAD**	**MAPE**	**DS**	**CP**	**CD**
1	9	37.10	14.96	33.89	27.40	0.50%	94.07	96.08	92.54
2	6	34.20	13.27	105.05	73.14	1.86%	96.77	95.31	98.33
3	8	20.87	13.10	30.67	25.14	0.43%	93.16	90.74	95.24
4	7	26.40	12.94	20.26	15.89	0.34%	93.80	96.23	92.11
5	9	23.10	13.52	17.38	13.84	0.31%	85.59	93.22	77.97
6	13	24.82	15.96	198.61	163.70	2.79%	87.60	89.86	85.00
7	5	17.67	11.95	55.19	41.84	0.67%	88.43	86.76	90.57
8	8	22.83	13.00	11.94	9.66	0.17%	94.49	95.16	93.85
Average		25.83	13.58	59.12	46.32	0.88%	91.74	92.91	90.70

TABLE 3. Performance comparisons of 3 different methods in 8 time periods for Example 4.2. (Bold form is the best data)

Region	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**
Training period	2000/01 ↓ 2000/12	2000/07 ↓ 2001/06	2001/01 ↓ 2001/12	2001/07 ↓ 2002/06	2002/01 ↓ 2002/12	2002/07 ↓ 2003/06	2003/01 ↓ 2003/12	2003/07 ↓ 2004/06
Testing period	2001/01 ↓ 2001/06	2001/07 ↓ 2001/12	2002/01 ↓ 2002/06	2002/07 ↓ 2002/12	2003/01 ↓ 2003/06	2003/07 ↓ 2003/12	2004/01 ↓ 2004/06	2004/07 ↓ 2004/12
Chen [10]	134	105	103	94	76	78	117	81
Huarng and Yu [24]	418	823	264	237	150	459	534	166
Chu et al. [15]	97	**98**	97	86	70	**72**	115	59
Fuzzy Model	**33.89**	105.05	**30.67**	**20.26**	**17.38**	198.61	**55.19**	**11.94**

learning fuzzy model machine has the great ability to approximate the better average values, that is RMSE = 59.12, MAD = 46.32, MAPE = 0.88%, DS = 91.74, CP = 92.91, and CD = 90.70. Table 3 presents a compression of these software simulations with the other stock prediction systems in the same stock prediction problems. After the whole testing cycle is completed, the proposed learning algorithm can ensure to efficiently achieve the feature of stock prediction data algorithm to approach the fuzzy prediction model. This comparison data indicates that the developed fuzzy prediction model generates more accurate forecasting results than other learning schemes except for the discussed 2 and 6 regions. Therefore, the trader can obtain the best return by the proposed learning scheme.

Example 4.3. Weekly Stock Forecasting Model Generations and Performance Analysis. *This case uses the weekly stock prediction system to give investors more trading information in the middle-term period. The period of training data for this case ranges from January 1995 to December 2004, and the testing phase ranges from the January 2003 to the December 2004. Eighteen weekly technical stock indices were filtered into 2 primary factors by stepwise regression analysis (SRA) to form the input variables of fuzzy stock prediction system. Two selected weekly technical indices, that is, the highest value and the MACD, and one forecasting TAIEX stock quote were assigned as input and output variables for the fuzzy stock prediction system, respectively. In this case, 8 clusters and their related positions were determined by the evolutionary auto-clustering algorithm. Figures 5 and 6 represent simulation results for these 2D and 3D plots, respectively. The feature of this weekly training data is scattered over a wide training area. Even under unfavorable conditions, the proposed auto-clustering algorithm can achieve the appropriate classifications to obtain the proper connoting characteristic from the training dataset Based on this initial configuration, the PSO-RLS learning algorithm was applied to efficiently rebuild the accurate fuzzy stock prediction model for approaching the desired Taiwan stock quotes. Software simulations in forecasting the Taiwan's stock quotes on the training and testing cycles are illustrated in Figure 7 and Figure 8, respectively. Simulation result presents that the created fuzzy stock prediction system obtains the great stock price forecasting curve. To verify the correct fuzzy number selection using the proposed auto-clustering algorithm, the fuzzy C-means (FCM) learning algorithm was applied to obtain the initial fuzzy structure* *while the clustering number was manually increased from 2 to 10. The parameter learning algorithm and the standard PSO learning algorithm were then applied to construct the fuzzy stock prediction system. Table 4 shows a comparison of the performance of various approaches. These experiments use the correct 8 cluster number determined by the auto-clustering algorithm and the PSO-RLS learning to achieve the best performance in this weekly stock trading decision. Because of the superior performance measure for the testing cycle produced by the proposed evolutionary learning algorithm, the selected values included RMSE = 240.12, MAD = 116.7, MAPE = 2.315%, DS = 74.51, CP = 82.37, and CD = 70.89. The developed fuzzy stock prediction system in the weekly period can provide sufficient information to help traders earn higher profits in investment market in the future middle-term.*

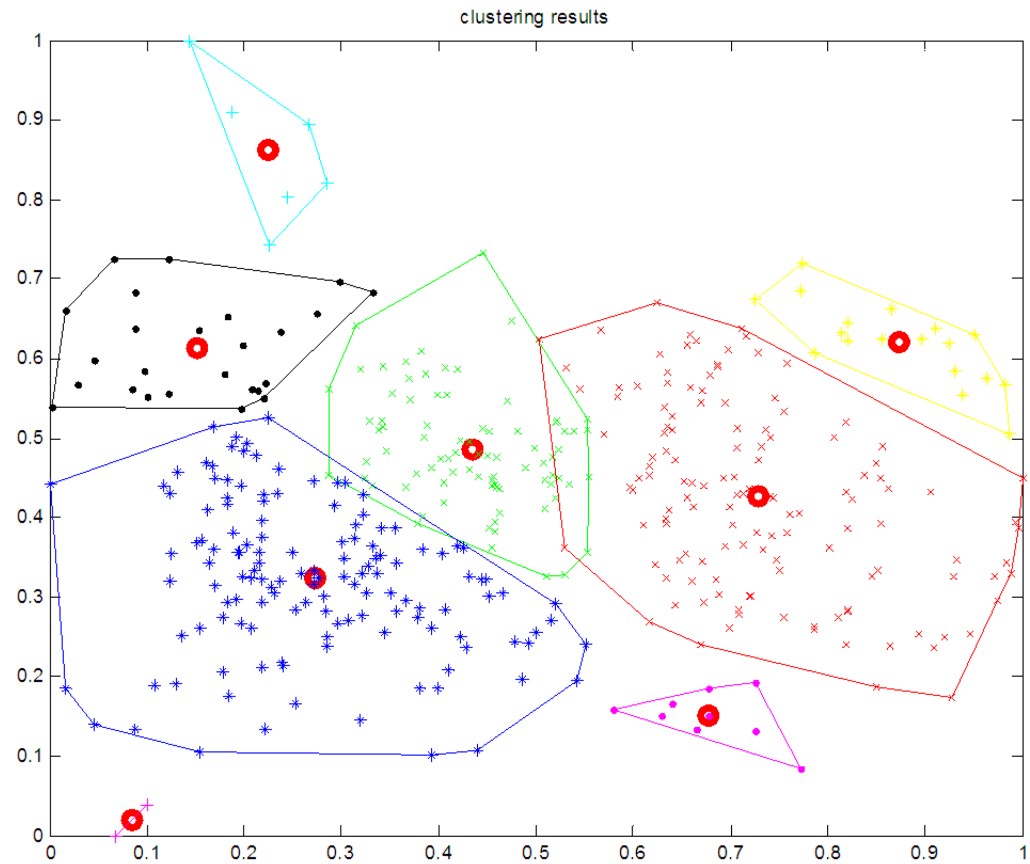

FIGURE 5. Clustering 2D results of the evolutionary auto-clustering algorithm for Example 4.3

5. **Conclusion.** The evolutionary auto-clustering learning machine in this study was applied to automatically, quickly and accurately construct a feasible architecture of fuzzy stock prediction system. After the initial configurations of the fuzzy stock prediction system, a set of flexible membership functions was tuned to form an adaptive behavior fuzzy stock model by the evolutionary PSO-RLS learning algorithm in the discussed TAIEX applications.

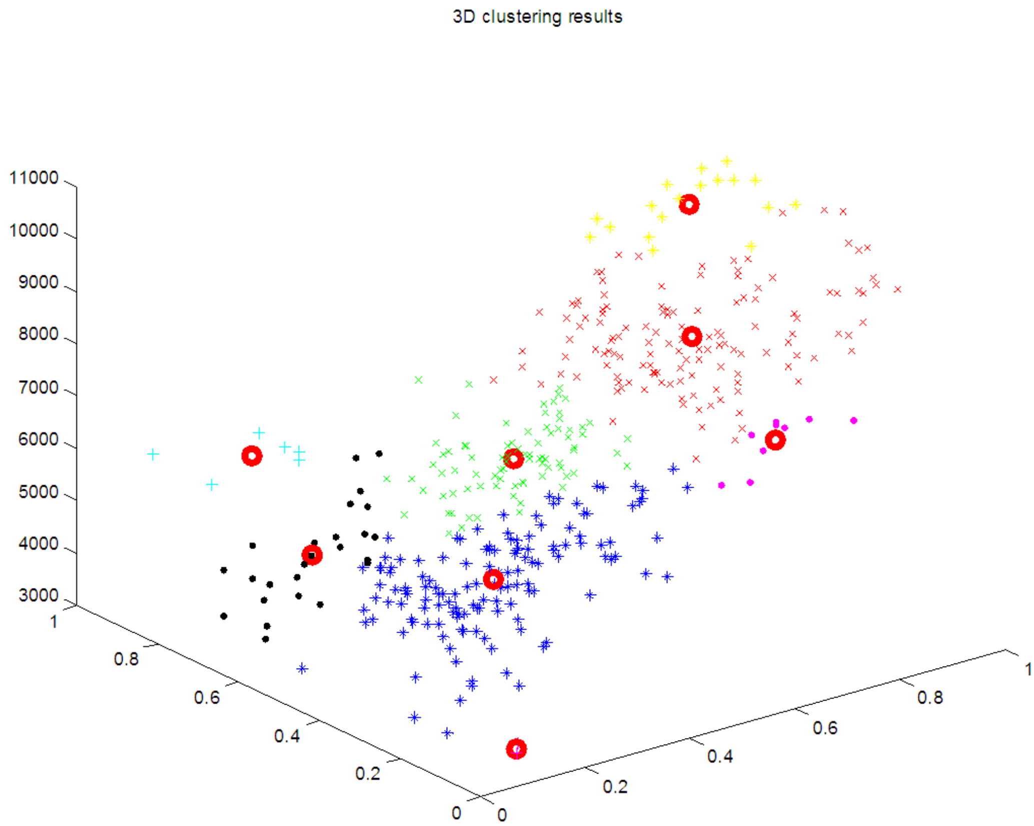

FIGURE 6. Clustering 3D results of the evolutionary auto-clustering algorithm for Example 4.3

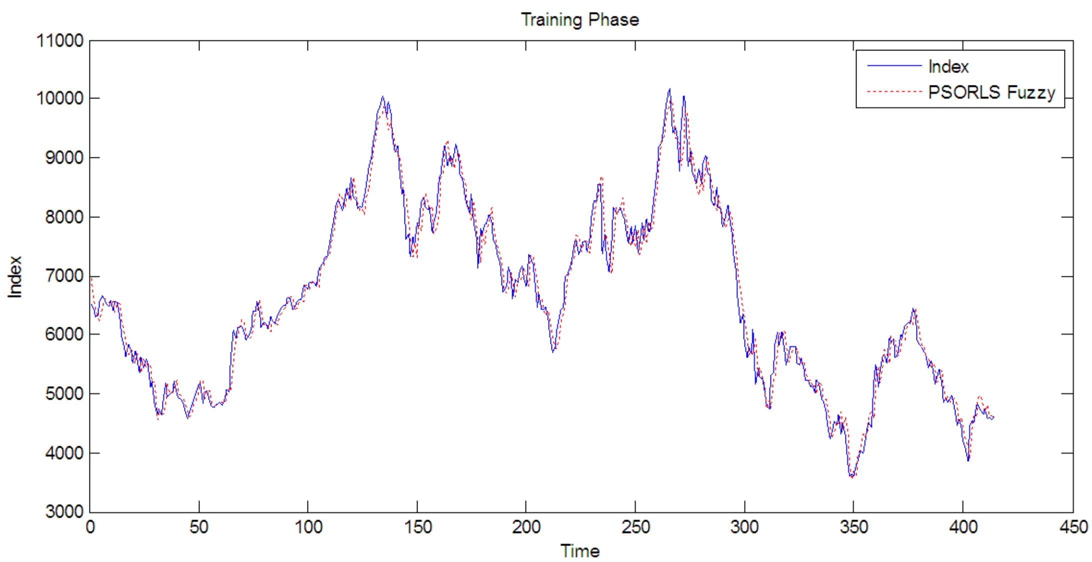

FIGURE 7. Simulation result of the training phase for Example 4.3. Actual (solid) and fuzzy models (dashed).

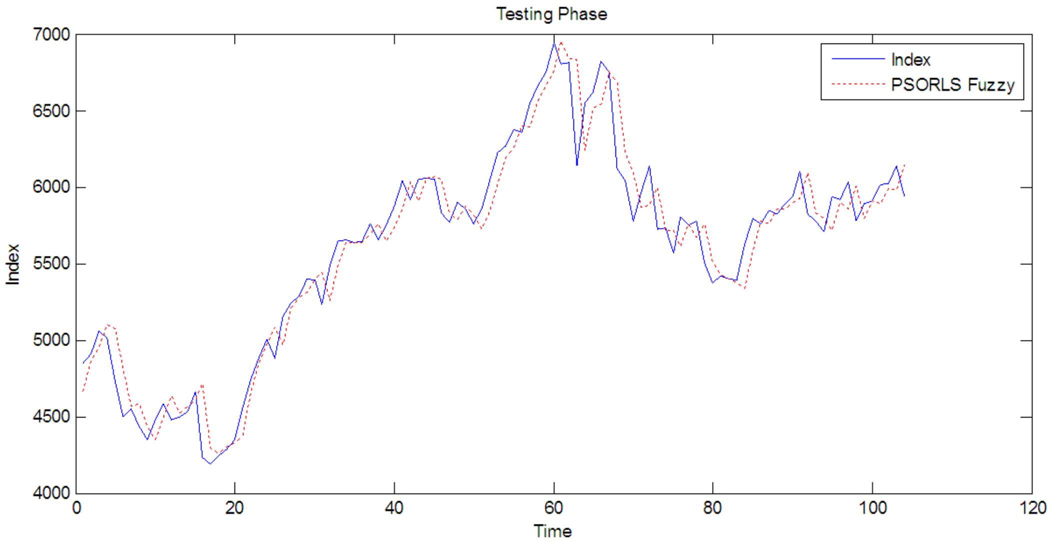

FIGURE 8. Simulation result of the testing phase for Example 4.3. Actual (solid) and fuzzy models (dashed).

TABLE 4. Performance comparisons of different clustering numbers conditions for Example 4.3

Training Phase					Testing Phase					
Testing Cycle	Clustering Number	RMSE	DS	Run Time	RMSE	MAD	MAPE	DS	CP	CD
FCM & PSO learning algorithm										
1	2	179.49	72.30	12.83	271.71	131.16	2.37%	70.49	76.45	61.46
2	3	180.11	72.30	14.09	268.33	131.38	2.38%	70.49	76.45	61.46
3	4	180.19	73.51	15.58	257.49	135.11	2.43%	71.46	76.45	63.90
4	5	177.19	73.03	16.54	262.65	128.90	2.31%	70.49	76.45	61.46
5	6	178.10	73.03	17.78	257.23	132.69	2.39%	71.46	76.45	63.90
6	7	177.03	73.51	19.45	257.36	131.30	2.36%	72.43	76.45	66.34
7	8	176.17	74.72	20.38	255.85	130.16	2.34%	71.46	76.45	63.90
8	9	176.20	73.51	21.66	256.24	127.19	2.28%	71.46	78.06	61.46
9	10	183.11	73.27	23.46	260.76	134.95	2.43%	70.09	74.84	63.90
The proposed evolutionary learning algorithm										
10	8	169.21	75.12	22.72	240.18	116.7	2..315%	74.51	82.37	70.89

In the proposed fuzzy structure learning procedure, the SRA method first extracts the two most important technical indexes as the input variables of fuzzy model to reduce the complexity of the fuzzy system. An evolutional auto-clustering algorithm with the CS validity function then determines the proper fuzzy number to quickly initialize the organization of fuzzy stock prediction system. The parameters learning procedure uses the evolutionary PSO with the specific fitness function and the adapted RLS learning methods to create the required fuzzy parameter values. The developed evolutionary structure and parameter learning schemes can fit the desired stock tracking curve to accurately present the nonlinear behavior of the time-series daily and weekly stock datasets.

A 764-item dataset was collected in the interval between January 2000 and June 2004 for the daily type stock optimization problem. Simulation result indicates that the two primary technical indexes derived by the SRA selections achieve better forecasting outcomes in various testing regions. It can be proved that the constructed fuzzy prediction system can actually represent the feature of the TAIEX. Simulation comparisons with other various leaning machine in 8 different periods shows that the fuzzy prediction system contains the better prediction results. A 260-item dataset was derived from the interval of January 1995 to October 2004 for the weekly type stock prediction problem. Forecasting results in improving the stock price accuracy and wining rate indicates that the novel evolutionary learning algorithm achieves better performance than the FCM + PSO learning scheme.

The adapted capability of the evolutionary learning algorithm is not only suitable for daily stock prediction, but also available for the weekly stock prediction problems. In a word, the developed evolutionary algorithm is capable of making good decisions in the short-term and middle-term stock markets. The self-learning schemes in this study can be improved to apply to hourly (i.e., real-time) data applications, such as forecasting application in forward price markets.

REFERENCES

[1] S. S. Alexander, Price movements in speculative markets: Trends or random walks, *Industrial Management Review*, vol.2, no.2, pp.7-26, 1961.

[2] S. A. George and P. V. Kimon, Forecasting stock market short-term trends using a neuro-fuzzy based methodology, *Expert Systems with Applications*, vol.36, no.7, pp.10696-10707, 2009.

[3] M. R. Anderberg, *Cluster Analysis for Application*, Academic Press, New York, 1973.

[4] H. Bessembinder and K. Chan, The profitability of technical trading rules in the Asian stock markets, *Pacific-Basin Finance Journal*, vol.3, no.2-3, pp.257-284, 1995.

[5] J. C. Bezdek, Numerical taxonomy with fuzzy sets, *J. Math. Biol.*, vol.1, no.1, pp.57-71, 1974.

[6] P.-C. Chang and C.-H. Liu, A TSK type fuzzy rule based system for stock price prediction, *Expert Systems with Applications*, vol.34, no.1, pp.135-144, 2008.

[7] P.-C. Chang, C.-H. Liu, J.-L. Lin and C.-Y. Fan, Celeste S.P. Ng: A neural network with a case based dynamic window for stock trading prediction, *Expert Systems with Applications*, vol.36, no.3, pp.6889-6898, 2009.

[8] J.-F. Chang, L.-Y. Wei and C.-H. Cheng, ANFIS-based adaptive expectation model for forecasting stock index, *International Journal of Innovative Computing, Information and Control*, vol.5, no.7, pp.1949-1958, 2009.

[9] C.-Y. Chen, H.-M. Feng and F. Ye, Automatic particle swarm optimization clustering algorithm, *International Journal of Electrical Engineering*, vol.13, no.4, pp.379-387, 2006.

[10] S.-M. Chen and J.-R. Hwang, Temperature prediction using fuzzy time series, *IEEE Trans. on Systems, Man, and Cybernetics, Part B: Cybernetics*, vol.30, no.2, pp.263-275, 2000.

[11] S.-M. Chen, Forecasting enrollments based on high-order fuzzy time series, *Cybernetics and Systems*, vol.33, no.1, pp.1-16, 2002.

[12] S.-M. Chen and N.-Y. Chung, Forecasting enrollments using highorder fuzzy time series and genetic algorithms, *International Journal of Intelligent Systems*, vol.21, no.5, pp.485-501, 2006.

[13] C.-H. Chou, M.-C. Su and E. Lai, A new cluster validity measure and its application to image compression, *Pattern Analysis and Applications*, vol.7, no.2, pp.205-220, 2004.

[14] S.-H. Chun and Y.-J. Park, Dynamic adaptive ensemble case-based reasoning: application to stock market prediction, *Expert Systems with Applications*, vol.28, pp.435-443, 2005.

[15] H.-H. Chu, T.-L. Chen, C.-H. Cheng and C.-C. Huang, Fuzzy dual-factor time-series for stock index forecasting, *Expert Systems with Applications*, vol.36, no.1, pp.165-171, 2009.

[16] A. Esfahanipour and W. Aghamir, Adapted neuro-fuzzy inference system on indirect approach TSK fuzzy rule base for stock market analysis, *Expert Systems with Applications*, vol.37, no.7, pp.4742-4748, 2010.

[17] M. H. Fazel Zarandi, B. Rezaee, I. B. Turksen and E. Neshat, A type-2 fuzzy rule-based expert system model for stock price analysis, *Expert Systems with Applications*, vol.36, no.1, pp.139-154, 2009.

[18] M. Fasanghari and G. A. Montaze, Design and implementation of fuzzy expert system for Tehran stock exchange portfolio recommendation, *Expert Systems with Applications*, vol.37, no.9, pp.8138-8147, 2010.

[19] H.-M. Feng, Self generation fuzzy modeling systems through hierarchical recursive-based particle swarm optimization, *Cybernetics and Systems: An International Journal*, vol.36, no.6, pp.623-639, 2005.

[20] H.-M. Feng and H.-C. Chou, Evolutional RBFNs prediction systems generation in the applications of financial time series data, *Expert Systems with Applications*, vol.38, pp.8285-8292, 2011.

[21] H.-M. Feng and C.-C. Wong, Fewer hyper-ellipsoids fuzzy rules generation using evolutional learning scheme, *Cybernetics and Systems: An International*, vol.39, no.1, pp.19-44, 2008.

[22] H.-M. Feng, Hybrid stages particle swarm optimization learning fuzzy modeling systems design, *The Tamkang Journal of Science and Engineering*, vol.9, no.2, pp.167-176, 2006.

[23] Y. S. Huang, The trading performance of filter rules on the Taiwan stock exchange, *Applied Financial Economics*, vol.5, no.6, pp.391-395, 1995.

[24] K. Huarng and H.-K. Yu, A type 2 fuzzy time series model for stock index forecasting, *Physica A: Statistical Mechanics and its Applications*, vol.353, pp.445-462, 2005.

[25] J. Kennedy and R. C. Eberhart, Particle swarm optimization, *Proc. of IEEE Int. Conf. Neural Networks*, Perth, Australia, pp.1942-1948, 1995.

[26] R. K. Lai, C.-Y. Fan, W.-H. Huang and P.-C. Chang, Evolving and clustering fuzzy decision tree for financial time series data forecasting, *Expert Systems with Applications*, vol.36, pp.3761-3773, 2009.

[27] Q. Song and B. S. Chissom, Forecasting enrollments with fuzzy time series – Part I, *Fuzzy Sets and Systems*, vol.54, no.1, pp.1-9, 1993.

[28] Q. Song and B. S. Chissom, Forecasting enrollments with fuzzy time series – Part II, *Fuzzy Sets and Systems*, vol.62, no.1, pp.1-8, 1994.

[29] R. J. Sweeney, Evidence on short-term trading strategies, *Journal of Portfolio Management*, vol.17, no.1, pp.20-26, 1990.

[30] T. Z. Tan, C. Quek and G. S. Ng, Brain inspired genetic complimentary learning for stock market prediction, *Proc. of the IEEE Congress on Evolutionary Computation*, vol.3, pp.2653-2660, 2005.

[31] Y. Wang, Predicting stock price using fuzzy grey prediction system, *Expert System with Applications*, vol.22, pp.33-39, 2002.

[32] N.-Y. Wang and S.-M. Chen, Temperature prediction and TAIFEX forecasting based on automatic clustering techniques and two-factors high-order fuzzy time series, *Expert Systems with Applications*, vol.36, pp.2143-2154, 2009.

[33] Y.-F. Wang, S. Cheng and M.-H. Hsu, Incorporating the Markov chain concept into fuzzy stochastic prediction of stock indexes, *Applied Soft Computing*, vol.10, no.2, pp.613-617, 2010.

[34] C.-C. Wong and C.-C. Chen, A hybrid clustering and gradient descent approach for fuzzy modeling, *IEEE Trans. Systems, Man and Cybernetics*, vol.29, pp.686-693, 1999.

[35] X.-L. Xie and G. Beni, A validity measure for fuzzy clustering, *IEEE Trans. Pattern Analysis and Machine Intelligence*, vol.13, no.8, pp.841-847, 1991.

[36] L. A. Zadeh, Fuzzy sets, *Information and Control*, vol.8, pp.338-353, 1965.