Hybrid Intelligence Approaches for Designing a Dynamic Financial Time-series Predictive Model Based on Web-Architecture Home Finance Learning Environment

Hsio-Yi Lin[1],
[1)] *Department of Finance, Ching-Yun University, Jung-Li, Taiwan 320*
hylin@cyu.edu.tw

Hsiao-Ya Chiu[2], Chieh-Chung Sheng[2],
[2)] *Department and Graduate Institute of Information Managment, Yu Da College of Business, MiaoLi, Taiwan 361*
kates.chiu@msa.hinet.net
samuel@ydu.edu.tw

An-Pin Chen [3]
[3)] *Institute of Information Management, National Chiao-Tung University, HsinChu, Taiwan 300*
apc@iim.nctu.edu.tw

Abstract

This study proposes design concepts for a comprehensive home financial learning environment that individual investors can use as a reference in establishing web-based learning and investment platforms. This study also introduces a hybrid approach that demonstrates a data mining function of the financial learning environment. Known as Fuzzy BPN, this approach is comprised of backpropagation neural network (BPN) and fuzzy membership function. This membership function takes advantage of the nonlinear features of artificial neural networks (ANNs) and the interval values as a means of overcoming the inadequacy of single-point estimation of ANNs. Based from these characteristics, a dynamic and intelligent time-series forecasting system will be developed for practical financial predictions. In addition to this, the experimental processing can demonstrate the feasibility of applying the hybrid model-Fuzzy BPN. The empirical results of the study show that Fuzzy BPN provides an alternative data mining tool for financial learning environment to investment forecasting.

1. Introduction of Home Financial Investment

"*Those who ignore the rules of finance are more likely to lose their money*" is a well-known financial management concept and stresses the importance of good financial management to individual investors. However, individual investors face considerable disadvantages in comparison to institutional investors, and thus, the greatest concern of individual investors is how to enhance the searching and anglicizing ability of investment information.. Technologies such as computer-assisted instructions (CAI), virtual instrument technology, and integrated interactive learning environment have recently been discussed in relation to financial knowledge education for individual investors[18][41][45]. In line with the growing popularity of Internet-based learning and knowledge-gained applications, individual investors are attempting to upgrade their investment-knowledge environments to meet their financial requirement, which is to earn profit. Although several investment simulation websites offer virtual stock trading exercises, there are only a few studies which explain to investors the applications of macroscopic, real-time, and learning investment environment.

This study proposes designs for Integrated Home Financial Investment Learning Environment (IHFILE) which includes a basic web-based environment, investment modules, virtual trading center, and scenario generator. In addition to this study, a dynamic financial time-series predictive model with illustrations to support data mining system of IHFILE was suggested and was applied to a study of the New Taiwan Dollar exchange rate for purposes of trend forecasting. The following sections demonstrate the architecture of IHFILE and the dynamic financial time-series predictive model proposed in this study.

1.1. IHFILE System Framework

IHFILE focuses primarily on providing a financial and investment learning environment in which individual investors can improve their investment skills. This paper develops an educational platform that offers an interactive financial learning environment with five investment modules that will satisfy different investment needs.

1.2. Web-Based Learning Environment

The bottom level of IHFILE is a web-based financial education platform that provides an interface which facilitates fundamental learning and research. It also has a virtual trading center that provides trading exercises without requiring real money. Individual investors can login to this website and learn via online programs and materials.

The website is comprised of the following web pages:

(1) Virtual classroom- includes financial learning platform and online chat room where users/ individual investors are taught financial knowledge.
(2) Virtual Financial Building- integrates real-time quoting system to respond to users' online inquiries regarding stocks, funds, derivatives, bonds, international markets, and financial news.
(3) Virtual Trading Center- originally designed for virtual trading based on real-time data produced by actual financial markets. It also archives transaction records of individual users in their historical database.
(4) E-Library- provides a learning database and other learning resources.
(5) Database Renewal and Maintenance E-office- helps the IHFILE system to enhance and renew investment knowledge and regularly upgrade the functions of IHFILE.
(6) Users Forum: a web-based forum system through which users can freely share opinions regarding investments.

Figure1 shows the financial education platform provides the fundamental framework of the IHFILE system, while the various financial investment modules serve as venue for simulated trading through the virtual trading center.

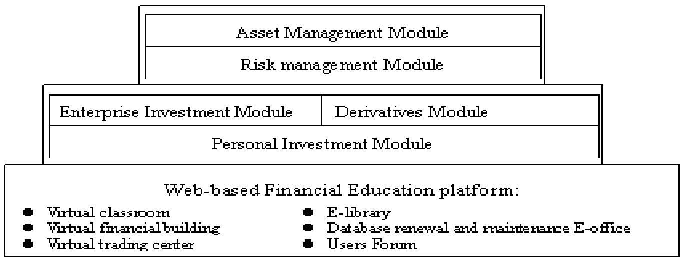

Figure 1. The framework of IHFILE includes a web-based financial education platform and five modules based on the *Fundamentals of Investments* learning path.

1.3. Module Design

To design a learning environment that effectively supports the real investment needs of individual investors, the IHFILE design group first examined several popular textbooks[46][2][48]. The design group also developed the following modules based on learning paths related to financial investment:

(1) *Personal Investment Module*- familiarizes users with securities and trading operations.
(2) *Enterprises Investment Module*- simulates a professional investment institute.
(3) *Derivatives Module*- teaches users how to control risk by using derivatives.
(4) *Risk Management Module*- helps users improve their skills in risk control and profiting by illustrating numerous financial skills and quantitative models.
(5) *Asset Management Module*- helps users build their capabilities in dynamic asset allocation, investment efficiency evaluation and asset portfolio optimization.

The software systems used in IHFILE modules are enhancements of popular financial industry packages developed by software vendors adapted for more specialized learning purposes.

1.4. The Virtual Trading Center

The learning software used in IHFILE is connected to real-time market data sources and scenario generators, while practice orders are transmitted to a virtual trading center via a web interface to provide real world exchanges between buyers and sellers. The virtual trading center is designed to meet educational requirements by reproducing trading centers in real financial markets, effectively permitting users to learn how to make investment decisions. Figure 2 illustrates the software component and operating flows of the IHFILE virtual trading center.

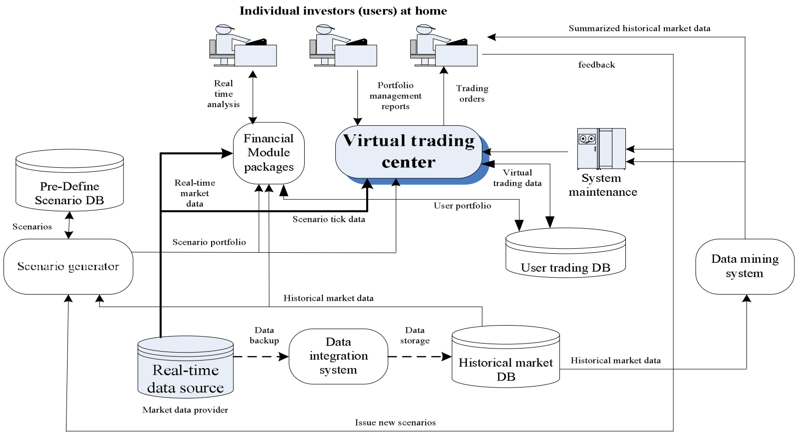

Figure 2. System components and operating flows of the virtual trading center in IHFILE

1.5. Financial Market Scenario Generator

One of the objectives of IHFILE is to allow users to practice trading exercises under various market situations. IHFILE applied scenario-based technology which aims to support these learning needs. Scenario-based learning[35] is defined as learning that occurs in a context, situation, or social framework, and, thus, is based on the concepts of situated cognition[9][14] and constructivist learning[8][19][40]. This study focuses on designing a financial market scenario generator (FMSG) system to support scenario-based learning.

Real world investment decisions are correlated to real-time market behaviors that happened only once. Furthermore, the application of financial models is adjusted to fit changing market situations. To increase instruction effectiveness, an ideal financial investment learning system should accommodate repetitive practice exercises, allowing users to compose various investment strategies and apply them in different financial models in each specific scenario.

Section 1 has summarized the framework of IHFILE. In the following sections, this paper elucidates on an improved neural network method to establish a dynamic financial time-series predictive model which can support data mining for IHFILE.

2. Preliminary Description of Dynamic Financial Time-series Predictive Model for Exchange Rate forecast

Recently, international investment activities have become more frequent while global trades have become more liberal. This makes floating time-series foreign exchange rate (FX rate) environments risky in terms of the international trade and investments. Thus, for FX time-series trend forecasting, the high accuracy of FX rate prediction has become an important issue in business trade and financial investment. This also makes selecting an appropriate model for a given time-series data a rather difficult task. At present, linear time series techniques, non-linear time series techniques, and artificial intelligence techniques have been proposed as formal tools to forecast time-series movement and have been a recurrent subject of research in the last two decades. Meese and Rogoff[32] demonstrated the forecasts of exchange rate predictability from structural model based on monetary and asset pricing theories of exchange rate determination. According to their study, the forecasts did not perform better than the ones generated by the simplest of all models in terms of out-of sample forecasting ability. Furthermore, many literatures[1][10][38][44] have also pointed out that econometric methods are, in general, unable to produce significantly better forecasts than the random walk model and are supportive of the efficient-market hypothesis.

Although these findings are strongly advocating that FX rates trend are random walk, many researchers have attempted to search various alternative to modeling of FX rates forecasting. One of the first studies which dismissed the random walk model is the proposal made by MacDonald and Taylor[30]. Many literatures have proposed several proofs explaining that FX rates belong to nonlinear behavior. In addition, Kilian and Taylor[25] also signified that the forecast efficiency of exchange-rate econometric models was not able to achieve its optimum potential because it was constrained by the linear quality of the traditional statistics models. Then, the FX rates time-series property was proven to exist in the family of autoregressive conditional heteroskedasticity (ARCH)[16] effect. Among the members of ARCH family, GARCH(Generalized Auto Regressive Conditional Heteroscedasticity) model proposed by Bollerslev[6] is the most representative application and most widely used model to forecast the time-varying volatility seen in many financial data. This is because it can effectively remove the excess kurtosis in return series and be adapted to the feature of heavy-tailed distribution and volatile clustering in financial data such as stock indexes, interest rates, exchange rates and futures[27]. Park[34] proposes a robust GARCH model using the least absolute deviation estimation and the empirical applications with Jananes Yen-US and British Pound-US FX rates favored that the RGARCH model over other competitive models. Elyasiani and Mansur[17] used a multi-factor GARCH model to estimate the market, interest rate, and exchange rate sensitivities (betas) of Japanese banking institutions. The investigation also pointed out that financial rations for FX beta model forecasting has higher explanatory power of market beta model. Nakatsuma and Tsurumi[33] applied Markov chain, Monte Carlo, Laplace approximation and quadrature formula to estimate the parameters of GARCH model integrated with ARMA property (called ARMA-GARCH) for forecasting British, Canadian, Deutsche, Japanese, and Swiss weekly FX rate. The results showed that their stochastic volatilities are determined by the posterior probabilities of those in stationary. In the later section, this study employs the GARCH model of predicting Taiwan FX rates for a comparison with a novel intelligence approach suggested by this study.

In the past ten years, following rapid technological advances and, in particular, the widespread application of artificial intelligence, researchers have increasingly applied artificial neural network (ANN) as an alternative method of FX rate forecasting, and backpropagation neural networks (BPNs) have become one of the most popular ANN being applied to numerous financial time-series problems. Refenes[36] used BPN together with a constructive learning algorithm to forecast currency exchange rates, and also detailed a technique for constructing and training a hidden unit using network architecture. De Matos[15] Compared BPN strength with recurrent network strength based on forecasting of the future of the Japanese yen. In addition, Kuan and Liu[28] presented a comparative evaluation of the performances of the BPN and other ANN models in predicting commonly traded exchange rates, and found that BPN performed well in all cases. Furthermore, Lisi and Schiavo[29] used BPNs and also applied chaotic models in FX rate prediction, and found that in both cases the results were better than the random walk hypothesis. Funahashi[20] and Hornik et al.[23] believed that ANN is more suitable for time series prediction. Most of the studies done recently hybridize several artificial intelligence techniques, or integrate ANN statistics methods[22][43]. Chen and Leung[12] used the General Regression Neural Network(GRNN) to predict foreign FX rates and through actual proofs discovered that GRNN approach not only produced results better FX rate forecasts but also results in higher investment returns than the single-stage model.

However, the predictive outputs of ANN are generally single-point values. It seems unreasonable that single-point values surpass an interval for forecasting certain financial predicting problems such as stock prices indexes, returns, and FX rates. A single-point value, indeed, has more difficulty than an interval value in forecasting a target value. In order to take advantage of BPNs' non-linear feature and improve the single-point values problems in BPNs, this paper attempts to propose BPNs which utilize a fuzzy set architecture, and modified neural network designed to combine the non-linear learning characteristic of BPNs and the interval estimation of statistics. This can be an active model to recognize the financial time series patterns and to forecast the FX rate trend. This dynamic time-series intelligence system of FX rate not only decreases the uncertainty of profits which will be gained by multinational corporations, but also enables global investors to adjust and diversify the ratio of FX in through the purchase of foreign dollars.

The remaining parts of the study have five sections. Section 3 introduces the basic concept of BPN and GARCH models. Section 4 describes a fuzzy set interval approach based on the BPN model for forecasting FX rates movement. In this section, a case study of the US /New Taiwan Dollar FX rates is also designed to examine the influence of the predictive performance of the modified BPNs (Fuzzy BPNs) suggested by this study, and a comparison is drawn between the traditional BPN model, Fuzzy BPNs and AR-GARCH model. Subsequently, the empirical results are presented and discussed in section 5. Finally, the concluding remarks are presented in section 6.

3. Artificial Neural Network and GARCH Model

3.1. Artificial Neural Network Model

Earlier studies on financial time-series prediction using ANN have been widely adopted by BPN. Therefore, this study uses BPN, which uses backpropagation influenced by gradient descent algorithm. This algorithm supposes that the j^{th} neuron of the hidden layer receives that activation function:

$$H_j = \sum_i x_i w_{ij}^h \qquad \textbf{(1)}$$

where x_i is the signal to the input neuron i and w^h_{ij} is the weight of the connection between the i th input neuron and the he j th neuron of the hidden layer., then this activation function produces output by a transfer function f of the hidden layer

$$h_j = f_j (H_j) = f^h_j \tag{2}$$

Then each output neuron k receives as input from the output of the previous layer (hidden layer) and produces the final result

$$O_k = \sum_j w^o_{jk} \times h_j \tag{3}$$

where w^o_{jk} is the weight of the connection between hidden neuron j and output neuron k, and it is transformed again to

$$o_k = f_k (O_k) = f^o_k \tag{4}$$

The goal of the learning process is to determine a set of weights when the actual output y_k by the network given x_i as input be as close as possible to the desired output o_k, the function of square of the errors for each neuron which is minimized,

$$E = \frac{1}{2} \sum_k (y_k - o_k)^2 , \tag{5}$$

The data fed to an input node are multiplied by a set of weights; all such weighted inputs are totaled using an activation function that depends on the learning algorithm at each node of the next layer. The output of the activation function then transforms the raw input for a node in the next layer, this process is called “feed-forward.”

In addition, the weights are modified to reduce the squared error. The change in weights,

$$\Delta w_{kj} = -\eta \frac{\partial E}{\partial w_{kj}} \tag{6}$$

where η is the learning rate, $0 < \eta < 1$, Rumelhart et al.[37] introduced a momentum term α in (6), thus obtaining the following learning rule,

$$\Delta w_{kj} (t+1) = -\eta \frac{\partial E}{\partial w_{kj}} + \alpha \Delta w_{kj} (t) \tag{7}$$

The momentum α is usually set in the interval [0,1] and it can also be helpful to keep the learning process from falling to the local minima.

That is, in the final layer, the predictive values of the output nodes may differ from the target values owing to the weights being randomly initialed. The error between the predictive and the target values can be adjusted by adjusting the weights of learning epochs, using a delta rule derived from a cost function of the error. This process is termed “backward”.

3.2. GARCH Model

The GARCH model of Engle and Bollerslev requires joint estimation of the current conditional mean model as formula (8) and the past conditional variance (9) in order to capture the non-linearity involved the distribution of financial data is leptokurtic. The GARCH (p,q) model can be represented by the following model:

$$E_t = a_0 + \sum_{i=1}^{m} a_i E_{t-i} + \sum_{j=1}^{n} b_j \varepsilon_{t-j} \tag{8}$$

where E_t is a series of continuous FX rate (normalized), the a_0, a_i and b_j are the constant parameters, $\varepsilon_t \sim N(0,h)$ and the conditional variance of errors, h_t is given by:

$$h_t = \alpha_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j h_{t-j} \tag{9}$$

where $\alpha_0 > 0, \alpha_i, \beta_j \geq 0$ and $\sum_i \alpha_i + \sum_j \beta_j < 1$. These restrictions on the parameter prevent negative variances and the GARCH(1,1) was found to be the most popular.

4. The Hybrid Methodology and Research Design

4.1. Fuzzy BPNs

Modeling the financial data using normal distributions was common method until Mandelbrot[31]. Mandelbrot observed the presence of leptokurtosis in the empirical distribution of price changes and also proposed the use of symmetric stable distribution to capture this excess kurtosis, and moreover developed methods of financial data model building using various non-normal distributions[5][3][26][7][4]. Although non-normal distributions, the noticeable contribution characterizing financial data, were explored, no techniques exist to explain the distribution of financial data up to the present. Consequently, this paper proposes fuzzy-interval architecture using fuzzy set in improving the single-point shortcoming of BPNs which are termed, Fuzzy BPN. Further, a fuzzy set is completely characterized by its membership function (MF), the MF of fuzzy-interval approach defined by Gaussian MF is a normal distribution of common assumption used in this paper and specified by two parameters {c, σ}:

$$f(x;c,\sigma) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{1}{2}(\frac{x-c}{\sigma})^2} \tag{10}$$

where c is the Gaussian MF's center and σ determines the MFs width. In this paper, the c indicates the mean of weekly FX rates and the σ intents the standard deviation of weekly FX rates, the MF of fuzzy-interval is also decided completely by c and σ. Note that Gaussian MF is a direct generalization of the normal distribution used in probability theory, when fuzzy-interval MF is centered on c and the extent to which it spreads out around c is added and subtracted 1σ, 2σ and 3σ(± 1σ, ± 2σ and ± 3σ) of interval that mends the traditional BPN's single-point defect. (see Figure 3).

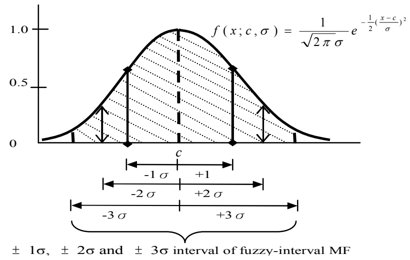

Figure 3. Gaussian MF of fuzzy-interval approach

According to the assumption of the MF mentioned above, this research tried to learn the parameter c and σ using BPN. Figure 4 shows the BPNs frame for producing the fuzzy-interval MF, then used c and σ to find the fuzzy-interval MF, in this way, not only can it maintain the BPNs' non-linear feature, at the same time, it can improve the single-point values problems in BPNs. Here, the above framework is called Fuzzy BPNs, as seen in Figure 5.

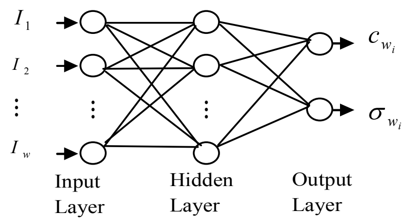

Figure 4. BPNs frame for producing the fuzzy-interval MF

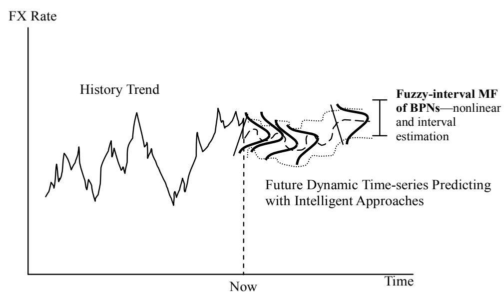

Figure 5. The property of fuzzy BPNs in this paper

To build an interval of Fuzzy-BPN, this study proposed a k -lag output vector to determine the values of c and σ, where c denotes the mean of the next k -lag -day values and σ presents the standard deviation of the next k -lag -day values. This study presented a dynamic time-series predictive model for forecasting the interval value using weekly (k =5, five trading days per week) data instead of single-point data ("daily price" or "daily return" as used in the most investigations of ANNs discussed in Section 2), and a more practical application involving c and σ was illustrated using formula (12) and (13) in Section 4.2

4.2. Data and Experimental Design

The data sets were bilateral FX rates between New Taiwan Dollar and US dollar (NTD/USD), and composed of daily rates covering almost 14-year period from the beginning of Central Bank of China, Republic of China (Taiwan), on January 3, 1993 to October 14, 2006 and including 3425 observations.

This study tries to take w days to predict the succeeding weekly (5 trading days) FX rate. To put it plainly, when we want to forecast the next unknown weekly FX rate, we can use the past w days ahead of the succeeding weekly days to training model to get predicted values. Consequently, a "sliding window" was proposed as shown in Figure 6 with different window width $w + 5$ moving from the first period to the last period of the entire data set labeled by S_i (i is from one to $N-w-4$) resulting in all N (N =3425) observations being divided again into $N-w-4$ samples. Consulting Chen and Tsao[11] and Tay and Cao[42], there are five different w, their being 5,10,15,20 and 25, considered in this paper. Many investigations have used a convenient ratio to separate in-samples from out-of samples ranging from 70%:30% to 90%:10%[47]. Hence, approximately 25% of the samples are used for test, 75% for training in this paper and every sample comprises a time series data containing $w + 5$ FX-rate observations.

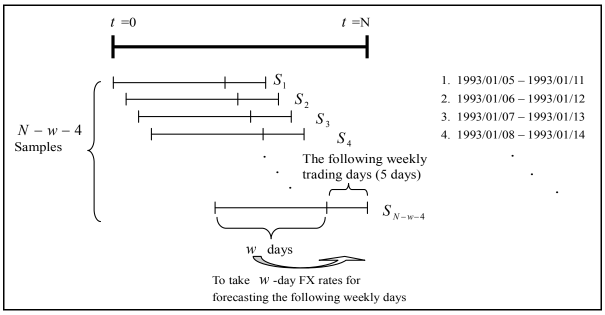

Figure 6. Sliding window

For effective predictive performance of BPN and GARCH processing, this paper takes the natural logarithmic transformation to stabilize the time series of FX rate via normalization. The normalizations of w-input and two-output variables of the FX rates in this paper are

$$I_k = \ln\left(\frac{P_k}{P_{0,w}}\right) \tag{11}$$

$$mean_{S_i} = \frac{1}{5}\sum_{j}^{5} \ln\left(\frac{P_{w+j}}{P_w}\right) \tag{12}$$

$$SD_{S_i} = \sqrt{\frac{\sum_{j}^{5}\left(\ln\left(\frac{P_{w+j}}{P_w}\right) - mean_{S_i}\right)^2}{4}} \tag{13}$$

where $P_{0,w}$ is the normalized basic day of input variables, k is from 1 to w, P_w denotes the normalized basic day of the following weekly FX rates for the previous w days, while $mean_{S_i}$ and SD_{S_i} represents the mean and standard deviation for the following week FX rates during period S_i .

5. Empirical Results

This section interprets and presents the best specifications of Fuzzy BPNs, traditional BPNs and GARCH model for daily NTD/USD FX-rate series.

5.1 BPNs Model

The BPNs model used in this study is a three-layer feed forward network, and is developed to map the next weekly-day mean and standard deviation for the coming w days using a backpropagation algorithm. This study used various numbers of nodes in the hidden layer and stopping criteria for training. Table 1 is the parameters setting list and Matlab7.0 program language was run for the experiments of BPNs in this study.

Table 1. BPNs parameters setting in this study

parameters	setting value
Hidden layer	1 layer and 2 layers
Hidden nodes	$\begin{cases} \text{1 layer : 5, 15, 30, 50, 100} \\ \text{2 layers : 5, 15, 30} \end{cases}$
Learning epochs	10000
Learning rate	0.1, 0.3, 0.5, 0.7, 1.0
Momentum term	Defaulted by Matlab program language
Total number of trial-and-error	350 $\begin{cases} \text{1 layer : } 5 \times 5 \times 5\ (w) = 125 \\ \text{2 layers } 3 \times 3 \times 5 \times 5\ (w) = 225 \end{cases}$

Several performance criteria are used to model BPNs. This study included the mean squared error (MSE) suggested by Coakley et al.[13] to determine the point at which the training stops and assess the forecasting performance.

$$MSE = \frac{\sum_{i}^{n_w} (F_i - O_i)^2}{n_w - 1} \tag{14}$$

where n_w is the number of the example sequences, $n_w = N - w - 4$, O_i is the target value, F_i is the predicted value, the final determined parameters of each w-days BPNs are based on the smallest converged MSE their own respectively. Since the major purpose of this paper is to investigate the effects of BPNs parameters on the modeling and forecasting performance of BPNs, the values of MSE between training set (in-sample) and testing set (out-of-sample) will be compared, with the emphasis put on the out-of-sample analysis, because it is only using the testing data that the BPN parameter setting with the best forecasting capability can be proven and found.

All the set parameters, after passing trial and error, are then based on the smallest MSE value of the five different w, the MSE value is chosen as its first measurement standard. If the training data MSE value is the same, then the training data becomes the second screening standard. Table 2 is the best parameter setting model (the best performance) chosen and arranged as follows.

Table 2. BPNs best parameter setting model

w	training data MSE	testing data MSE	Hidden	learning rate
5	0.000010357	0.000010723	30	0.5
10	0.000009428	0.000009566	15×15	0.3
15	0.000005957	0.000008403	30×30	0.7
20	0.000007632	0.000012630	15	1.0
25	0.000008058	0.000010245	5×15	0.5

5.2. GARCH Model

Various goodness-of-fit statistics are used to compare the all estimated GARCH model in this paper, the diagnostics are the MSE, the likelihood-ratio tests, tests for the standard residuals, Schwarz's Bayesian information criterion (SBC) by Schwarz[39] and Akaike's information criterion (AIC)[24].The GARCH models were tried for $p = 1,2,\Lambda ,5$ and $q = 1,2,\Lambda ,5$ using SAS 9.1 program software. Table 3 shows that the statistically significant parameters for every AR(w)-GARCH(p,q) model and the last results were listed, the estimated values of parameters α_0, α_1 and β all satisfy $\alpha_0 > 0,\ \alpha_1 \geq 0,\ \beta \geq 0$ and $\alpha + \beta < 1$. This indicates the weaknesses of imposing the parameter estimates of a GARCH model to certain constraints such as stationary.

Table 3. Estimation results of GARCH models for NTD/USD FX rates

Model	$\alpha_0(\times 10^{-6})$	t-value	α_1	t-value	β_1	β_2	β_3	β_4	β_5	t-value				
										β_1	β_2	β_3	β_4	β_5
AR(5)GARCH(1,4)	4.5487	17.5	0.001401	0.03**	0.0421	0.0276	0.0231	0.0281	-	27.95**	7.07*	4.24**	6.72*	-
AR(10)GARCH(1,4)	4.5564	17.21	0.001382	0.03**	0.0421	0.0275	0.0229	0.0278	-	27.13**	6.69*	3.98**	5.67*	-
AR(15)GARCH(1,5)	4.5185	13.35	0.001567	0.02**	0.0423	0.0256	0.0183	0.0171	0.0228	25.64**	5.23*	2.83**	2.95**	5.39*
AR(20)GARCH(1,5)	5.9404	9.55	0.0172	0.17**	0.0399	0.0256	0.0186	0.0182	0.0212	20.59**	3.73**	2.3**	2.23**	3.44**
AR(25)GARCH(1,3)	0.67168	13.51	0.4395	14.28**	0.1156	0.0804	0.0907	-	-	24.38**	4.67**	3.86**	-	-

* : at 5% significant level
** : at 1% significant level

Table 4 indicates all final AR(w)-GARCH(p,q) models that their own MSE values, Log L values, the lowest AIC and SBC, dividedly. In the next section, the Fuzzy BPNs and traditional BPNs models will be compared the forecasting performance with final AR-GARCH models.

Table 4. The goodness-of-fit statistics values of all final AR(w)-GARCH(p,q) models

Model	Goodness-of-Fit Statistics				
	MSE-Train data	MSE-Test data	Log L	SBC	AIC
AR(5)-GARCH(1,4)	0.0000204	0.0000318	11061.0956	-22028.009	-22098.191
AR(10)-GARCH(1,4)	0.0000204	0.0000318	11045.7559	-22057.512	-21958.113
AR(15)-GARCH(1,5)	0.0000203	0.0000319	11044.3184	-22042.637	-21908.183
AR(20)-GARCH(1,5)	0.0000199	0.0000284	11031.2324	-22006.465	-21842.826
AR(25)-GARCH(1,3)	0.0000198	0.0000293	11739.1774	-23416.355	-23235.244

5.3. Forecasting Performance

This paper also apply three evaluative criteria used to compare the fitness and the forecasting performance to appraising traditional BPNs, Fuzzy BPNs, and AR-GARCH models, the root mean squared error, the mean absolute percentage error, and correct rate between the target and the predicted value as following.

$$MAE = \frac{\sum_{i=1}^{n_w} |O_i - F_i|}{n_w - 1} \quad \textbf{(15)}$$

$$MAPE = \frac{\sum_{i=1}^{n_w} |(O_i - F_i) / O_i)|}{n_w - 1} \quad \textbf{(16)}$$

$$Correct\ Rate = \frac{\#\text{ of correct examples}}{\#\text{ of total training/ testing examples}}, \quad \textbf{(17)}$$

where n_w is the number of the example sequences, $n_w = N - w - 4$, O_i is the target value calculated by formula (12). Also F_i is the predicted value by traditional BPNs and Fuzzy-BPNs according to formula (12). The "# of correct examples" indicates the numbers of target values inside the forecasting intervals with Fuzzy BPNs, traditional BPNs and AR-GARCH models; the "# of total Training/testing examples" denotes all the training/testing in each w-day models of Fuzzy BPNs, traditional BPNs and AR-GARCH models in this study.

From Table 2 and Table 4, the effect can be known that the MSE values of different w BPN models are all lower than those with AR-GARCH models, and the MAE and MAPE values of BPN models also lesser than AR-GARCH models in Table 5 except that only the MAE value of 5-day AR-GARCH is higher than 5-day BPNs. To eliminate the irrational MAPE because its values of testing are all soaring more than training values in AR-GARCH models, i.e., the results of Table 2, Table 4 and Table 5 show that the forecasting ability of the BPNs models are mainly better than the AR-GARCH models. In this study, the training and testing processing are the same between traditional BPNs and Fuzzy-BPNs, the only difference between the two methods is the traditional BPNs single-point value is for forecasting the FX rate. Fuzzy-BPNs uses an interval estimation skill which consists of means and standard deviations to forecast the FX rate. Therefore, traditional BPNs and Fuzzy-BPNs proposed by this paper have the same results of MAE and MAPE.

Table 5. Performance comparison of Traditional BPNs, Fuzzy BPNs and AR-GARCH models: MAE and MAPE

w-day	MAE				MAPE			
	Traditional/Fuzzy BPNs		AR-GARCH		Traditional/Fuzzy BPNs		AR-GARCH	
	training	testing	training	testing	training	testing	training	testing
5	0.001684421	0.003148663	0.002352434	0.002814610	9.737909617	18.2029289	13.59980343	11.1617253
10	0.001414663	0.002804992	0.002349419	0.002807887	9.722758056	19.62191452	16.14719056	12.13520911
15	0.000833325	0.002564620	0.002358323	0.002817249	5.385533308	16.57438146	15.24114364	15.54229985
20	0.001141500	0.002835546	0.007856785	0.002855237	4.080694045	10.85162898	28.08684814	18.86375352
25	0.001205216	0.002462325	0.009775209	0.002611541	3.398369982	16.94306407	27.56333817	13.03262841

In addition, from the point of view of correct rate as the judgment criterion, the correct rates of the Fuzzy BPNs are the maximum values than conventional BPNs and AR-GARCH, totaled. Besides, the correct rates of testing data in AR-GARCH models are a little higher than Fuzzy BPNs (see Table 6) and all of the correct rates of the traditional BPN models are 0% because it cannot forecast the precise values of target data. However, it seems to be rational that the correct rates of testing data should be lower than training data, thus, the Fuzzy BPNs have better forecasting ability than the AR-GARCH models. It also rid of the illegitimate correct rates of testing data in AR-GARCH models, the study made use of the interval characteristic of fuzzy MF to improve the single point forecasting shortcoming of the traditional BPN models.

Table 6. Performance comparison of Fuzzy BPNs, Traditional BPNs and AR-GARCH models: Correct Rate

W-day	Correct Rate of NTD/USD Exchange-rate Prediction			
	Fuzzy BPNs*		AR-GARCH**	
	training	testing	training	testing
5	83.3669%	70.6909%	71.8579%	72.8337%
10	83.1798%	68.1455%	72.2048%	73.2708%
15	82.4129%	70.2941%	70.2935%	71.5629%
20	83.8702%	60.9482%	67.5813%	70.7059%
25	83.5577%	63.7264%	68.8261%	78.2097%

* Assumption of 95% probability in Gaussian distribution , the Fuzzy-interval MFs were extended based on 1.96 σw
**In order to compare Fuzzy BPNs with AR-GARCH, the intervals of AR-GARCH also were assumed 1.96 σw

6. Conclusion

This study demonstrated IHFILE, which provides an integrated learning environment comprised of various topics such as module design, virtual trading center, and financial scenario generator which were never previously discussed in similar studies. This study also administered questionnaires to individual investors, and the results stated that an integrated learning environment such as IHFILE can help individual investors increase their interest in learning and improve their trading skills.

In addition to IHFILE, a dynamic, intelligent and predictive time-series model called Fuzzy BPNs consisting of fuzzy-interval MF was suggested for the purpose of improving the shortcomings of single-point estimations in conventional artificial neural networks, and still possess the ANNs' nonlinear capabilities. Nevertheless, designing a system of ANNs for forecasting time series data is still a daunting problem. This paper also provides evidence for the forecast performance of Fuzzy BPNs in terms of interval evaluation. Fuzzy BPNs are not only much better than traditional BPNs in terms of single-point evaluation, but also better than AR-GARCH models. To conclude, this contribution presents that a combination of BPNs with Fuzzy membership function proposed by this research which offers a useful approach in predicting time series patterns in FX market data. Based on the evolution of paradigms such as the AR-GARCH method, the future research considerations could include (1) assessing the ability of Fuzzy BPNs to deal with financial time-series problems (for instance, stock price returns) or related to other areas (for example, forecasting the webpage-view flows for business websites, applications that can enhance the functions of IHFILE); (2) applying other artificial intelligence or statistical tools to determine superior parameter setting for Fuzzy BPNs.

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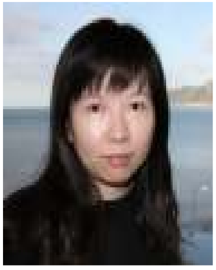
Authors

Hsio-Yi Lin received the B.S. and M.S. degree in Risk Management and Insurance from National Kaohsiung First University of Science and Technology, Kaohsiung, Taiwan, in 1999 and 2001, respectively. She is currently working toward the Ph.D. degree in the Institute of Information Management, National Chiao-Tung Universit y, Hsin-Chu, Taiwan. She is also an instructor in the Department of Finance, Chin g-Yun University, Jung-Li, Taiwan. Her current research interests focus on soft co mputing and finance domain, including neural network, fuzzy set theory and applic ation, financial behavior and investment analysis.



Hsiao-Ya Chiu is an Associate Professor at Department and Graduate Institute of In formation Management, Yu Da College of Business. She received her M.S., in 199 6, and Ph.D. degree, in 2006, in the Institute of Information Management, National Chiao-Tung University. Previously, her interests focus on E-commerce, Database A pplication and Financial Information System.

Chieh-Chung Sheng received the M. S. and Ph. D. degree in the Institute of Inform ation Management, National Chiao-Tung University, in 1994 and 2007, respectivel y. He is now an Associate Professor at Department and Graduate Institute of Inform ation Management, Yu Da College of Business. His present research interests focus on Financial Information Systems, Numerical Methods and Database Programmin g.

An-Pin Chen is currently a professor at the Institute of Information Management, n ational Chiao-Tung University. After graduated from the National Taiwan Universi ty in 1978, he continued his further learning in U.S. In 1983, he received his master' s degree in Industrial & Systems Engineering from Ohio University. Then he receiv ed his Ph.D. in Industrial & Systems Engineering from University of Southern Calif ornia in 1988. His major research focuses on artificial intelligence applications, we b-base finance investment strategy, stock behavior and technical analysis. At preset, he is on of the chief consultants of Polaris Security Group, as well as a well-known expert of Taiwan E-Commerce market in information technology field.