FORECASTING EXCHANGE RATE CHANGE BETWEEN USD AND JPY BY USING DYNAMIC ADAPTIVE NEURON-FUZZY LOGIC SYSTEM

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ABSTRACT

Foreign exchange rate is a chaotic time series which is consistent with the Mackey-Glass equation. Fuzzy logic is an intelligent computational technique and has good potential in forecasting time-series data. This study uses fuzzy logic to study data of exchange rates and build a dynamic adaptive neuron-fuzzy logic forecasting model. The performance of the model built is compared with an autoregressive model by using the same data set.

Key Words: foreign exchange rate, fuzzy logic, chaotic time series, forecast.

JEL Code: F31, F37.

I. INTRODUCTION

Foreign exchange market is the largest and most liquid financial market. Foreign currencies are special financial assets and exchange rates are important financial indicators in the international financial market. The problem of forecasting the movement of foreign exchange rates attracts increasing attentions. Nevertheless, the prediction of foreign exchange rates poses substantial theoretical and experimental challenges. Generally speaking, exchange rates forecast models can be categorized into two classes: fundamental analysis and technical analysis.

Fundamental analysis of exchange rates is based on the information of demand and supply of domestic currency comparing with a foreign currency. While this approach is the most important tool of predicting price movement of many financial assets, it has several limitations in predicting foreign exchange rate movement. First, Exchange rates are usually determined not only by the relative supply and demand of the domestic currency and the foreign currency but also by many other fundamental and psychological factors in the market. Some factors (such as wars, strikes, political incidents) are extremely difficult to be quantified and included in the predicting models. Second, the precise timing of the impact of some factors on a currency's value is

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not known. Different factors can have different impacts on exchange rate at the different time. Coefficients derived from the regression analysis will not necessarily remain constant over time. Therefore, it is very difficult to forecast foreign exchange rate change with fundamental analysis only. Some empirical studies suggest that, for foreign exchange rates, prices and fundamentals are largely disconnected (Meese and Kenneth, 1983).

To forecast future movement of exchange rates with technical analysis, we need to study historical exchange rates data to discover the strong empirical regularities, i.e. the internal structure of these data so as to gain a better understanding of the dynamic process by which the time series data are generated. Time series data are a time-ordered sequence of observations made at equally space time interval. In finance, if we denote time at a particular point by t and the value of a particular financial asset at t by X(t), then time series values are represented as a set of discrete values X(1), X(2), X(3), … X(N). Essentially, the prediction of foreign exchange rate is using the past data, i.e. the exchange rate X(t) for $t_{-\tau} \le t \le t_0$, to solve for X(t) where $t > t_0$. In economics, if one of the variables is time-dependent, the system is called dynamic. The dynamic behavior of the system demonstrates how it performs with respect to time.

In the recent years, there has been a growing interest in using fuzzy logic to predict foreign exchange rate change. Yuize (1991) uses fuzzy logic rules to make inferences based on economic news that may affect the currency market. Tseng et al. (2001) integrate fuzzy and ARIMA models to forecast the Taiwan Dollar and US dollar exchange rate.

The reason why fuzzy logic gains popularity in foreign exchange rate change predicting is because fuzzy set theory provides a suitable framework for pattern recognition and it can deal with uncertainties of the non-probabilistic type. Fuzzy logic bridges the gap between the quantitative information (numerical data) and qualitative information (linguistic statements) (Palit and Popovic, 2005). Fuzzy logic is an intelligent computational technique of being able to find some patterns from seemingly random occurrences data and has good potential in forecasting time-series data.

Generally, the movement of the foreign exchange rates usually has two components: The first is proportionate to what has already been accumulated, i.e., the value of a particular X(t) contains a deterministic signal component. The second is affected by the whimsy in the market, i.e., the value of a particular X(t) also contains a stochastic component representing the noise interference that causes statistical fluctuations around the deterministic values. As a result, exchange rates are often fluctuating with a trend and within a limited band, and hence are often described as chaotic time series. In the last two decades, chaotic time series analysis has attracted a lot of research attention. The interests of these researches have been lately focused on the techniques of chaotic time series modeling and on prediction of future time series values.

Chaotic behavior can be described as bounded fluctuations of the output of a non-linear system with high degree of sensitivity to initial conditions (Casdagli, 1992).

To put it in another way, the volatility of foreign exchange rates displays considerable persistence. Thus current and past volatility can be used to predict future volatility. However, trajectories with nearly identical initial conditions can differ a lot from each other (Rasband, 1999).

One of the mathematical descriptions of chaotic behavior is the delay differential equations (DDEs). A time-dependent solution of a system of DDE is not uniquely determined by its initial state at a given moment; instead the solution profile on an interval with length equal to the maximal delay has to be given. That is, we need to define an infinite dimensional set of initial conditions between t=-τ and t=0. Thus, DDEs are infinite-dimensional problem, even if we have only a single DDE. One of the most commonly used DDE is the Mackey-Glass model (Glass and Mackey, 1988) which was proposed as a model for the production of white blood cells but now is quite frequently used in other time series problems. The model is given by the following equation:

$$\frac{dx}{dt} = Ax_\tau \frac{\theta^n}{\theta^n + x_\tau^n} - Bx$$

where A, θ and n are parameters. For τ >17, this equation is known to exhibit chaos. The Mackey-Glass model has become one of the benchmark problems for time series prediction in fuzzy logic.

In this study we use the exchange rates between US dollar and Japanese yen[2] as sample data. The principles and methods used in this study, however, can generally be applied to other currency pairs. The software used in this study is MATLAB Fuzzy Logic Toolbox developed by MathWorks (Matlab, 2001).

The rest of the paper is organized in the following way. Section 2 describes the data used in this study and discusses the methods of model building. Section 3 is a performance comparison of the model built with fuzzy logic and model built with AR method with the same date set. Section 4 contains some conclusion remarks.

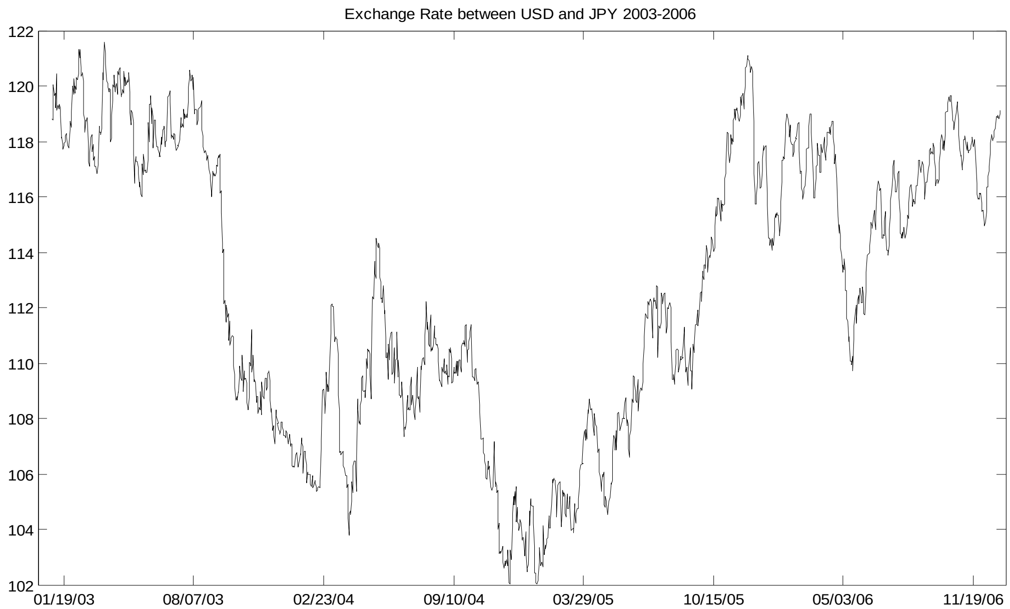
II. DATA AND MODEL BUILDING

Data of exchange rates of USD/JPY between January 1, 2003 and December 31, 2006 were collected. Therefore, this series of exchange rates has 1461 observations. The following graph shows the exchange rates between Euro and US dollar during this period of time.

Usually the first step is to build a model by using the past data of time series. The second step is to use the model to forecast the future time series values at various time distances. Of course, the forecasting does not deliver the exact future values of data that the given time series will really have, but rather their estimates.

[2] . In this paper, the symbols of currencies used follow the convention of the SWIFT (Society for Worldwide Interbank Financial Telecommunications). The currency before the slash is the base currency, the currency after the slash is the counter currency. The exchange rate is shown as one unit of base currency equals to how many units of counter currency, e.g. USD/JPY 115 indicates one US dollar equals to 115 Japanese yen.

Figure 1 Exchange Rates of USD/JPY (1/1/2003-12/31/2006)



In this study, the past values of this time series, x(t-18), x(t-12), x(t-6) and x(t), are used to build a model to predict the value of x(t+6). Thus, data is a matrix with N+1 columns where the first N columns, i.e. x(t-18), x(t-12), x(t-6) and x(t), are data for each fuzzy inference system input, and the last column, i.e., x(t+6) is the output data. From t = 51 to 1350, we collect 1300 data pairs of the above format. The first 650 are used for training while the second 650 are used for checking.

When a mathematical model of the process is unknown, fuzzy technology has several advantages. First, this method is in the form of approximate reasoning and can easily represent analog processes on a digital computer. Second, fuzzy logic can be used when dealing with continuous and imprecise variables. Third, fuzzy inference system (FIS) employing fuzzy if-then rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analyses. Fourth, fuzzy logic can easily deal with situations when the input-output relationship is non-linear.

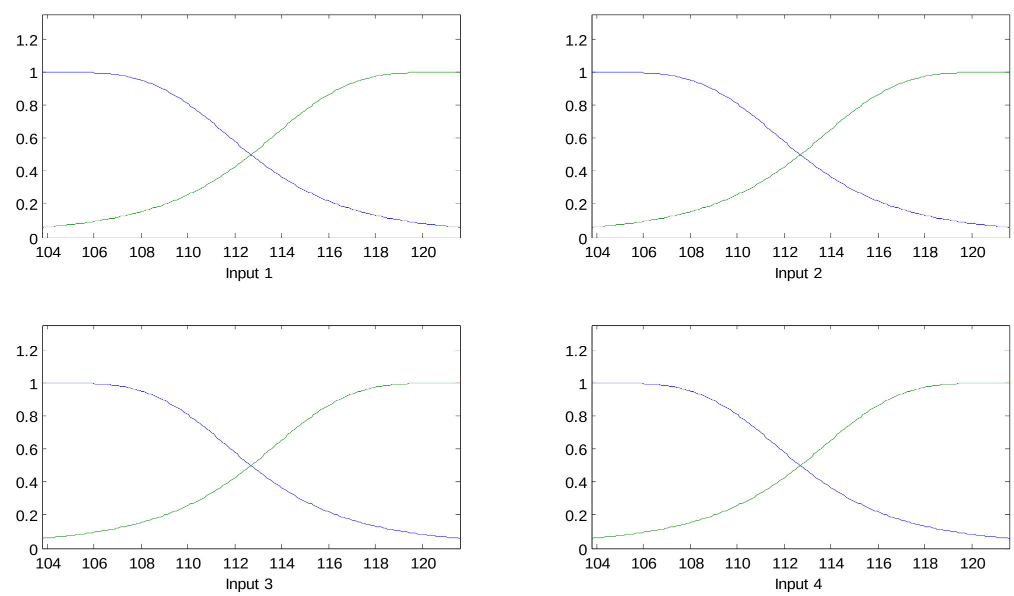
The first step of model building is to construct a set of initial membership functions (MFs henceforward). One of the drawbacks of fuzzy logic is the lack of a learning capability. The development of a Fuzzy Logic System (FLS) can be done in a trial-and-error style, i.e., the initial MFs can be set up manually by using existing human knowledge about the movement of foreign exchange rates. However, this method is time-consuming and unreliable. A more promising approach is to use the adaptive neuron-fuzzy inference system (ANFIS) developed by Jang (1993). ANFIS uses a hybrid learning algorithm to identify parameters of Sugeno-type fuzzy inference systems, whose output MFs are only linear or constant (Sugeno, 1985).

ANFIS can find parameters of a model through training rather than to set them up arbitrarily. In another word, ANFIS can serve as a basis for constructing a set of fuzzy if-then rules with appropriate membership functions to generate the stipulated input-output pairs (Jang, 1993). Once the initial MFs are found, it is straightforward to improve them through training. This is a significant advantage of ANFIS over its neural network counterpart. The most important advantage of using ANFIS is that all its parameters can be trained like a neural network, but with its structure in a fuzzy logic system (Kodogiannis and Lolis, 2002).

ANFIS applied a combination of the least-squares method and the back-propagation gradient descent method for training. In this study, we use GENFIS1, a commonly used function, to generate an initial single-output FIS matrix from training data. This FIS is used to provide initial conditions for ANFIS training. Default values for MFs number "2" and membership function type "gbellmf" (generalized bell MFs) are used.

These defaults provide two generalized bell MFs on each of the four inputs, eight altogether. The generated fuzzy inference system structure contains $2^4 = 16$ fuzzy rules. Each rule generated by GENFIS1 has one output MF, which is of type "linear" by default. The following figure shows the initial MFs:

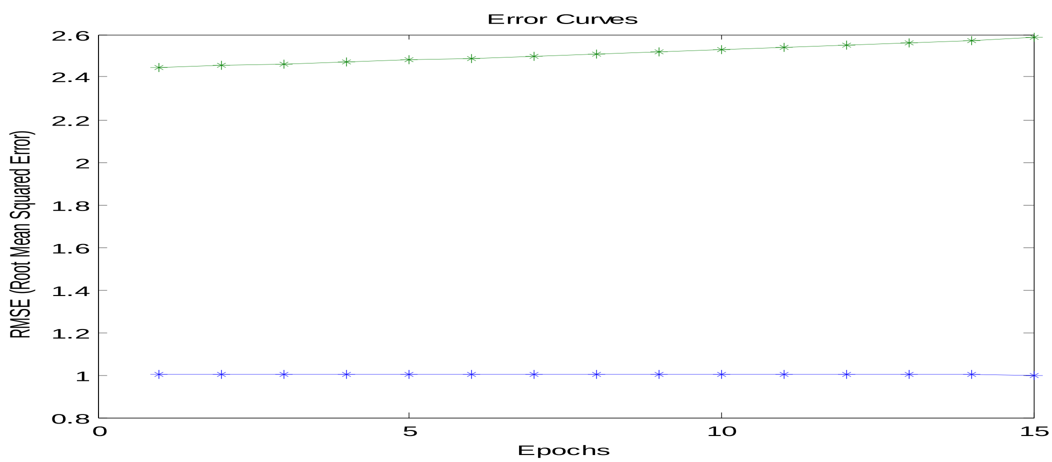
Figure 2 Initial Membership Functions



The initial MFs need to be trained by several epochs. The trained ANFIS model has 104 fitting parameters (see Appendix for details), including 24 nonlinear parameters which are optimized via back-propagation (3 parameters for each premise MF) and 80 linear parameters which are optimized via linear least-squares estimation (five parameters for each consequent equations). In order to achieve good generalization capability, it is important to have the number of training data points be several times larger than the number of parameters being estimated. In this case, the ratio between data and parameters is roughly six (650/104). This is a proper balance between number of fitting parameters and number of training data.

A common problem in ANFIS model building is the so-called "overfitting", which occurs when we fit the fuzzy system to the training data so well that it no longer does a very good job of fitting the checking data. The result is a loss of generality (Chiu, 1994). However, optimal number of epochs can only be found through experiments. To find the optimal number of epochs, the error curve is plotted.

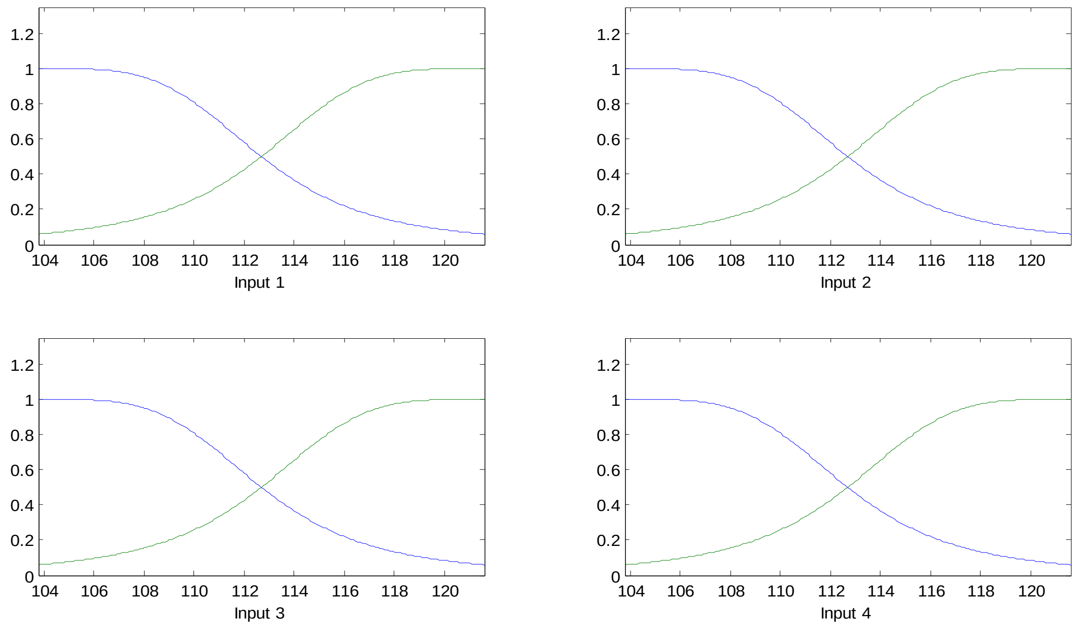
Figure 3 Error Curve



From this graph, it can be seen that the Root Mean Squared Error (RMSE) increases when epoch increases. To avoid overfitting problem, we set training epoch equals to twelve.

The following graph shows the final MFs after twelve epochs of training. It can be seen that after training, the final MFs shown in the plots is significantly different from the initial MFs.

Figure 4 Final Membership Functions



III. PERFORMANCE EVALUATIONS

There is no consensus on the most appropriate measure to assess the performance of a forecasting technique. In this study, a mean-based performance measure, RMSE (Root Mean Square Error) is used, which can be defined as:

$$RMSE = \sqrt{\frac{1}{N}\sum_{j=1}^{N}(\hat{\theta}_j - \theta_j)^2}$$

Where N is the total number of prediction, $\hat{\theta}_j$ is the predicted time series and θ_j is the original series.

Figure 5 shows the original time series (solid) and the one predicted by ANFIS (dotted). It can be seen that FIS model generally has very good prediction ability and RMSE of the model is 2.55, which is very encouraging. However, the performance of the model is not ideal in the fourth quarter of 2004 and first quarter of 2005. During this period of time, the movement of exchange rates between USD and JPY demonstrates an abnormal volatility. Figure 6 shows that the ANFIS prediction error and confirms what we observed in Figure 5.

Figure 5 Comparisons of Original Time Series and Time Series Predicted by ANFIS

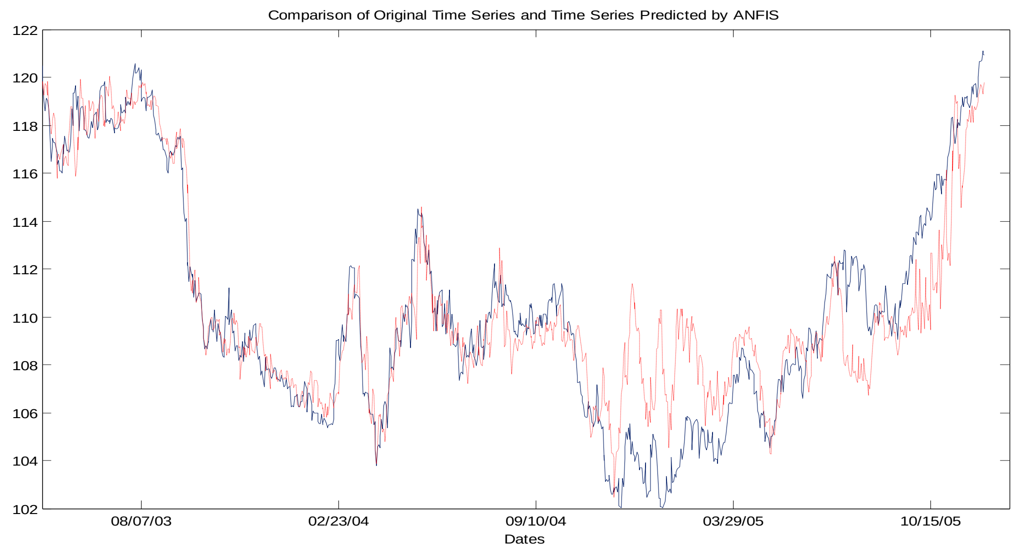
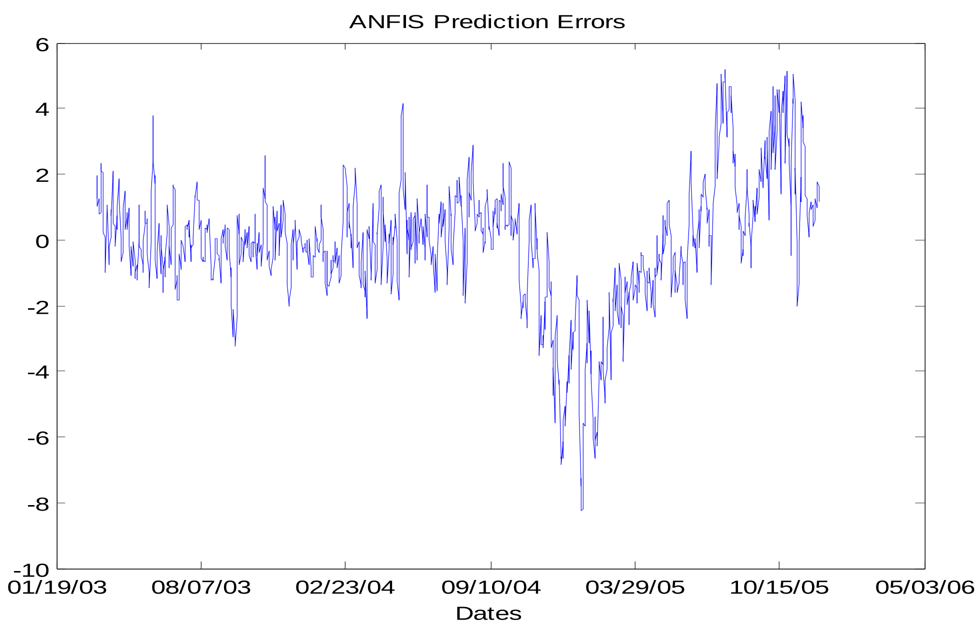


Figure 6 ANFIS Prediction Error



Actually to forecast the future values of a time series, a wide spectrum of methods is available. The traditional method of predicting time series data is autoregression method (AR), which expresses the current value of a time series by a finite linear aggregate of previous values and by a shock. The definition the AR is as follows:

$$X_t = \sum_{i=1}^{N} a_i X_{t-i} + \varepsilon_t$$

where a_i are the autoregression coefficients, X_t is the series under investigation, and N is the order. The noise term or residual ε, is almost always assumed to be Gaussian white noise.

The aim of AR analysis is to derive the best values for a_i given a series X(t). These methods usually assume that the series X(t) is linear and stationary. AR can provide a general framework for forecasting time series in which the specification of a model within the class is determined by the data. This may be quite advantageous in certain situations, particularly when it is difficult to identify the main components in a series and to construct suitable models for them. However, the very flexibility of AR is also its disadvantage. Unless one has some experience in time series analysis, such models may not yield sensible forecasts. The main problem of AR is that it performs piece-wise linear approximation, and it is difficult to model "volatile" time series. Such a model is likely to break down when it is used for forecasting (Harvey, 1989).

To compare the performance, a model using the traditional autoregressive method is also built with the same data set. In this case, the autoregressive equation is as follows:

$$X(t+6) = a_0 + a_1 X(t) + a_2 X(t-6) + a_3 X(t-12) + a_4 X(t-18) + \varepsilon$$

The resulted regression coefficients are reported in the following table:

Table 1 Coefficients Obtained through Autoregression Method

		Estimates	Std Error	t	Approx Sig
Rho (AR1)		.994	.005	208.635	.000
Regression Coefficients	-18	.016	.045	.363	.717
	-12	-.029	.044	-.663	.507
	-6	-.009	.044	-.199	.842
	-0	.015	.045	.343	.732
Constant		1.237	.115	10.752	.000

From this table we can see that all parameters obtained are insignificant. This shows the problem of AR method: it is difficult to deal with the non-probabilistic type uncertainties in time-series data.

Therefore, in this case it is meaningless to compare RMSE of the model built with the traditional autoregressive method and that of the Fuzzy Logic Model. Nevertheless, it shows that the dynamic adaptive neuron-fuzzy logic system proposed in this study is more powerful and flexible in pattern recognition when time-series data are used.

IV. CONCLUSION

In this study, a rule-based fuzzy logic combined with an adaptive neuron-fuzzy inference system is used to build a model to forecast the movement of foreign exchange rates. Even though FIS models trained usually have very good forecasting ability, their performance is not ideal when the exchange rate dramatically changes. This raises the possibility that fuzzy logic models could be further improved so they should not only be able to represent frequently occurring relationship but also be able to update itself in view of new data. Some researchers (e.g. Michalski, 2003) suggests that the system needs background knowledge that will allow it to reinterpret and/or combine concepts in the data into new concepts that can lead to more accurate and/or simpler patterns. That might be the direction for the soft-computing study.

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Appendix: ANFIS info:

Number of nodes: 55
Number of linear parameters: 80
Number of nonlinear parameters: 24
Total number of parameters: 104
Number of training data pairs: 500
Number of checking data pairs: 500
Number of fuzzy rules: 16

```
  1     1.00371     2.44393
  2     1.00348     2.45278
  3     1.00325     2.46167
  4     1.00301     2.4706
  5     1.00278     2.47955
Step size increases to 0.011000 after epoch 5.
  6     1.00254     2.48854
  7     1.00228     2.49845
  8     1.00201     2.5084
  9     1.00175     2.51837
Step size increases to 0.012100 after epoch 9.
 10     1.00149     2.52836
 11     1.00119     2.53937
 12     1.0009      2.5504
```

Designated epoch number reached --> ANFIS training completed at epoch 12.

```
trn_fismat =
         name: 'anfis'
         type: 'sugeno'
    andMethod: 'prod'
     orMethod: 'max'
  defuzzMethod: 'wtaver'
    impMethod: 'prod'
    aggMethod: 'max'
        input: [1x4 struct]
       output: [1x1 struct]
         rule: [1x16 struct]
```