Forecasting Exchange Rates: A Neuro-Fuzzy Approach

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***Abstract**—This paper presents an adaptive neuro-fuzzy inference system (ANFIS) for USD/JPY exchange rates forecasting. Previous work often used time series techniques and neural networks (NN). ANFIS can be used to better explain solutions to users than completely black-box models, such as NN. The proposed neuro-fuzzy rule based system applies some technical and fundamental indexes as input variables. In order to generate membership functions (MFs), we make use of fuzzy clustering of the output space. The neuro-fuzzy model is tested with 28 candidate input variables for both currencies. For the purpose of comparison, Sugeno-Yasukawa model, feedforward multi-layer neural network, and multiple regression are benchmarked. The comparison demonstrates that the presented algorithm shows its superiority in terms of prediction error minimization, robustness and flexibility.*

Keywords— ANFIS Network, Exchange Rates, Forecasting, Neuro-Fuzzy Systems, Nonlinear Identification.

1 Introduction

The Efficient Market Hypothesis ([1], [2], [3]) states that one cannot predict the behavior of efficient markets, as the markets follow a random walk. However, other studies ([4], [5]) found evidences against the Efficient Market Hypothesis. Exchange rate prediction is one of the most challenging applications of modern time series forecasting. To become an efficient dealer in foreign exchange market, one must be conversant with the factors that are responsible for a currency to appreciate or depreciate.

Methods that have been proposed for currency exchange rates forecasting fall into three categories: (i) econometric methods, (ii) time series methods, and (iii) soft computing methods. The difficulty in predicting currency exchange rates, due to their high volatility and complexity, has long been a concern in international financial markets, as many econometric methods are unable to produce significantly better forecasts than the random walk model [6]. Time series methods have their limitations for multidimensional time series with mutual non-linear dependencies. Most recently, researchers have applied soft computing tools such as multilayer Artificial Neural Networks (ANN), Fuzzy Logic (FL), and their hybrids to exchange rate forecasting.

ANN support time-series analysis and forecasting and multivariate analysis. Medeiros et al [7] presented and compared alternatives to model and forecast monthly exchange rates time series. Medeiros et al [7] simulated ANN, neuro-coefficient smooth transition autoregressive, linear autoregression, and random walk models. Kamruzzaman and Sarker [8] have investigated ANN modeling of foreign exchange rates using three learning algorithms, namely, Standard Back Propagation, Scaled Conjugate Gradient, and Back Propagation with Bayesian Regularization. Majhi et al [9] proposed two low complexity ANN exchange rate prediction models for US Dollar to British Pound, Indian Rupees, and Japanese Yen exchange rates.

The literature has shown fuzzy sets as a superior modeling tool for many problems. The statistical fuzzy interval NN is proposed by [10] to perform knowledge discovery and predict currency exchange rate. To overcome the difficulty in finding matching rules for forecasting in the fuzzy time series model, [11] proposed to use the Euclidean distance between two fuzzy logic relationships as a metric for selecting matching rules and applied their model to exchange rate time series prediction.

At the computational level, a fuzzy system is a layered structure, similar to an ANN of the radial basis function type [12]. In order to optimize parameters in a fuzzy system, ANN learning algorithms can be employed. This neuro-fuzzy modeling approach can be better used to explain solutions to users than completely black-box models, such as ANN [13].

For the sake of clarity and completeness, section 2 gives a brief overview of the adaptive neuro-fuzzy inference system (ANFIS) approach. Section 3 systematically discusses neuro-fuzzy systems modeling. Section 4 carefully applies neuro-fuzzy modeling to US Dollar to Japanese Yen exchange rate forecasting. Finally, conclusions are given in Section 5.

2 Adaptive Neuro-Fuzzy Inference System

The Takagi-Sugeno-Kang (TSK) model uses fuzzy logic with crisp functions in consequent that is convenient for complex applications [14]. TSK systems are widely used in the form of a neuro-fuzzy system called Adaptive Neuro-Fuzzy Inference System (ANFIS). The structure of ANFIS and its learning algorithms are described in the following:

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2.1 ANFIS Structure

An ANFIS is a fuzzy inference system that can be trained to model some collection of input/output data. The training module allows the system to tune its parameters to learn the input/output relationships hidden in the data set. ANFIS uses two approaches: ANN and fuzzy modeling. By composing these two approaches, a suitable reasoning in quality and quantity might be achieved [15]. In ANFIS fuzzy logic is used to determine decision surfaces rather than to determine uncertainty associated with particular linguistic terms [16]. The rule-based representation of neuro-fuzzy systems offers transparency.

For pedagogical purposes, one can imagine a fuzzy inference system with two inputs *x* and *y* and one output *z*. The equivalent ANFIS architecture (Type-3 ANFIS) is shown in Fig. 1. The node functions in the same layer are from the same function family. The first layer implements a fuzzification, the second layer executes the T-norm of the antecedent part of the fuzzy rules, the third layer normalizes the membership functions, the fourth layer calculates the consequent parameters, and finally the last layer computes the overall output as the summation of all incoming signals. The feed forward equations of this ANFIS are as follows:

$$w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \tag{1}$$

$$\overline{w}_i = \frac{w_1}{w_1 + w_2}, i = 1,2. \tag{2}$$

$$\begin{cases} f_i = p_1 x + q_1 y + r_1 z \\ f_2 = p_2 x + q_2 y + r_2 z \end{cases} \Rightarrow \tag{3}$$

$$f = \frac{w_1 f_1 + w_2 f_2}{w_1 + w_2} = \overline{w}_1 f_1 + \overline{w}_2 f_2 \tag{4}$$

where,

- x is the input to node i,
- $\mu_{A_i}(x)$ is the node i node function,
- A_i is the linguistic label associated with node functions,
- w_i is the firing strength of the ith rule,
- $\overline{w}_i$ is the ratio of the ith rule's firing strength to the sum of all rules' firing strength,
- $\{p_i, q_i, r_i\}$ is the parameter set, and
- f_i is the consequent value.

Note that the network's output y is nonlinear in the weights $\mathbf{w}$. The training of this ANN is thus a *nonlinear optimization problem* to which various methods can be applied [13].

2.2 Learning Algorithms

The neuro-fuzzy inference system is optimized by adapting the antecedent parameters and consequent parameters so that a specified objective function (usually a difference between the model output and the actual output) is minimized. A number of methods have been proposed for learning rules. For example, Mascioli, Varazi, and Martinelli [17] have proposed merging of Min-Max and ANFIS models to determine the optimal set of fuzzy rules. Jang and Mizutani [18] have presented an application of the Lavenberg-Marquardt method, which is essentially a nonlinear least-squares technique, for learning in an ANFIS network. Tang, Quek, and Ng [19] proposed a hybrid system combining a Fuzzy Inference System and Genetic Algorithms to tune the parameters in the TSK fuzzy ANN.

Jang [20] proposed methods to update the ANFIS parameters involving gradient descent and Least Square Error (LSE). High complexity is one of these methods' features. Several popular training algorithms for tuning parameters of ANFIS membership functions are compared in [21]. In this paper we use the hybrid learning algorithm proposed in [20] which is a combination of least square estimation and backpropagation algorithms.

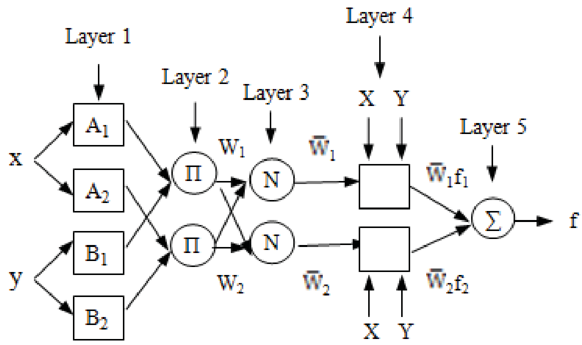

Figure 1: The equivalent ANFIS structure

3 Designing a Systematic Neuro-Fuzzy System

The two basic steps in neuro-fuzzy systems modeling are *system identification* and *fuzzy reasoning*. In the system identification stage, the significant input variables are determined, the fuzzy if–then rules are generated, and the parameters of the model, such as the number of clusters, the level of fuzziness, and the operators to be used in the reasoning, are selected. The second, *fuzzy reasoning*, is used to infer new knowledge from the identified rule base [22].

In fuzzy system modeling, the relationships between variables are represented with *if-then* rules with imprecise predicates. The basic steps are:

1) Fuzzy clustering of the output,
2) Input selection,
3) Rule base construction,
4) Tuning the parameters of membership function of input and output variables, and
5) Inference.

3.1 Fuzzy Clustering of the Output

To determine the number of rules of the initial ANFIS, one should choose the optimum number of clusters. For this purpose, a validity index which is proposed by [23] and modified by [24] is used. In other words, one minimizes:

$$V_{FNT}(U,V;X) = \frac{2}{c(c-1)} \sum_{p \neq q}^{c} S_{rel}(A_P, A_q) \tag{5}$$

The optimal number of clusters is obtained by minimizing V_{FNT} $(U, V; X)$ over the range of c values: 2, …, $c_{\max}$; where

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$S_{rel}(A_P, A_q)$ is the relative similarity between two fuzzy sets A_p and A_q and is defined as:

$$S_{rel}(A_P, A_q) = \sum_{i=1}^{n} S_{rel}(x_j : A_p, A_q) h(x_j) \tag{6}$$

where,

$$h(x_j) = -\sum_{p=1}^{c} u_{A_p}(x_j) \log(u_{A_p}(x_j)) \tag{7}$$

And $S_{rel}(x_j : A_p, A_q)$ is the relative similarity between two fuzzy sets A_p and A_q at x_j which is defined as:

$$S_{rel}(x_j : A_p, A_q) = \frac{f(x_j : A_p \cap A_q)}{f(x_j : A_p \cap A_q) + f(x_j : A_p - A_q) + f(x_j : A_q - A_p)} \tag{8}$$

Here, $h(x_j)$ is the entropy of datum x_j and $u_{A_p}(x_j)$ is the membership value with which x_j belongs to the cluster A_p.
After determining the optimum number of clusters, Gustafson-Kessel (GK) clustering algorithm is used for generating membership functions.

3.2 Input Selection

The performance of non-linear identification techniques is often determined by the appropriateness of the selected input variables and the corresponding time lags. High correlation coefficients between candidate input variables in addition to a non-linear relation with the output signal induces the need for an appropriate input selection methodology [25].
For variables selection, the Sugeno and Yasukawa [26] method is used. They proposed a combinatorial approach in which all possible combinations of input candidates are considered. For each combination, they built two fuzzy models based on two separated sets of data and calculated a performance index called "Regularity Criterion" (RC). After that a combination of input variables is chosen which has the minimum value of the performance index.

3.3 Rule Base Construction

There are three alternative strategies for incorporating the fuzzy clustering during rule base construction; cluster the:

1. output space and obtain the fuzzy membership functions based on the projections of the output clusters onto the input space [26].
2. input space, relating the output variables to each input cluster based on the degree of possibility [27].
3. joined input and output spaces and then project these multidimensional clusters to the separate input and output spaces [28].

Kilic, Uncu, and Turksen [22] compared these three approaches. This paper uses the first approach.

3.4 Membership Parameters Tuning

ANFIS has two kinds of parameters that needed to be trained: the antecedent parameters and the premises parameters. In this study, Gaussian membership functions are located in the antecedent part:

$$\mu_{A_i}(x) = \exp\left\{ -\left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i} \right\} \tag{9}$$

It has three types of parameters: $\{a_i, b_i, c_i\}$, where a_i is the variance, b_i is the crossover slop and c_i is the center of MFs.

4 Exchange Rates Forecast Modeling

The authors used ANFIS in forecasting US Dollar/Japanese Yen exchange rates. While other researchers primarily used a few technical inputs ([8], [9], [10], [29], [30], [31]), (see Table 1) this work uses significant fundamental and technical inputs.

Table 1: List of some previous inputs data used in exchange rate forecasting

Authors	Model	Inputs
Tenti (1996)	Recurrent Neural Network	Compound returns of the last n periods (n=1, 2, 3, 5, 8) The running standard deviation of the k last periods (k=13, 21, 34) Average directional movement index (ADX) Trend movement index (TMI) Rate of change (ROC) Ehlers leading indicator (ELI)
Lisi and Schiavo (1999)	Chaotic models and NN	Monthly exchange rate of Franc, Deutschmark, Lira, and Pound- all against US Dollar
Kamruzzaman and Sarker (2004)	ANN	Moving average of one week, two weeks, one month, one quarter, half year closing rate Last week's closing rate
Preminger and Franck (2007)	Regression	Monthly exchange rate of Yen and Pound against the US dollar
Zhang and Wan (2007)	Fuzzy interval NN	Three, two, and one weeks ago rate of exchange
Majhi, Panda, and Sahoo (2009)	ANN	Normalized rate on the first day of a month Mean of the monthly rate Variance of the monthly rate

The candidate inputs are shown in Table 2. Similar to [32] the inputs are divided into categories. However, in each category, this study used some other indices than [32]. Additionally, some of the most popular technical input variables are used. As a result, 28 fundamental and technical candidate input variables, among which there exist 20 fundamental indices for both countries and the remaining ones have been allocated to technical indices, are fed to ANFIS. The full sample compromises daily observation for the Jan-2001 to Aug-2008 period from the Reuters 3000 Xtra Hosted Terminal Platform, where 60% of data points are used for training and the rest for testing the model.
After collecting candidate input data, the Sugeno-Yasukawa [26] input selection method is used. The method selected the following input variables:

- US Federal Reserve Bank interest rate,
- US M2 Money Supply: it technically defined as sum of M1, savings deposits, small denomination time

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deposits (where small is less than $100,000), and retirement account, where M1 is the sum of the tender that is held outside banks, travelers checks, checking accounts (but not demand deposits), minus the amount of money in the Federal Reserve float,

- West Texas Intermediate oil price,
- Rate of Change (10 days) of the USD/JPY time series,
- Momentum (5 days) of the USD/JPY time series, and
- Stochastic K% (5 days) of the USD/JPY time series.

Table 2: Candidate Input Data

No.	Factor	Indexes
1	Economic Activities	Gross domestic product, Industrial Production
2	Price	Consumer price index, Producer price index
3	Interest Rates	Short term interest rate (overnight, 1 week), Federal rate
4	Money Supply	M1, M2, M3
5	Trade Balance	Trade balance, BOP
6	Employment	Unemployment rate, Nonfarm payroll
7	Personal Consumption	Retail sale, Personal income
8	Oil	Brent, WTI oil
9	Stock	Dow Jones, Nikkei
10	Technical Indexes	Stochastic K%(5, 10 days), ROC(5, 10 days), Momentum(5, 10 days), William R%(5, 10 days)

The corresponding RC values are shown in Fig. 2. Next, based on an introduced Cluster Validity Index, we determine that the optimum number of clusters is 7 (see Fig. 3). GK fuzzy clustering algorithm is applied for initialization of antecedent membership functions. Then ANFIS with hybrid learning algorithm (combination of least square estimation and backpropagation algorithms) is used for parameters tuning. We use Mamdani-style inference, min–max operators, and centroid defuzzification method. The rules that ANFIS generated make sense relative to the economics of the foreign exchange market, as shown in Fig. 4.

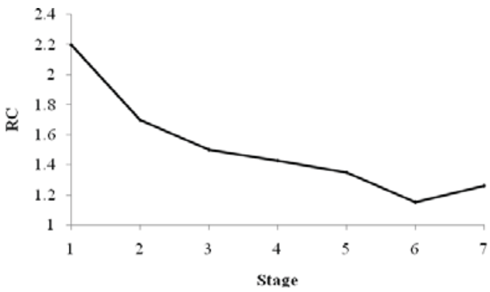

Figure 2: Behavior of RC in proposed model

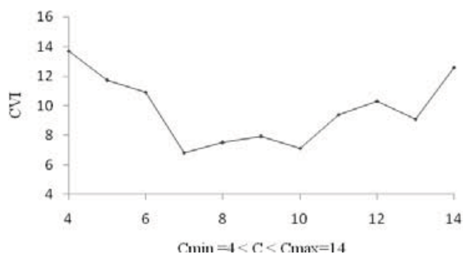

Figure 3: Identification of the optimum number of clusters

To further validate this approach for currency exchange rates forecasting, the results were compared to the results with a) the Sugeno-Yasukawa [26] approach, b) a feedforward multi-layer neural network, and c) multiple regression. The comparison uses the root mean square of the prediction error (RMSE) and mean error of the prediction (BIAS). The comparison results for training and testing dataset are shown in Table 3, 4, 5, and 6. The characteristics of the mentioned test models are described next.

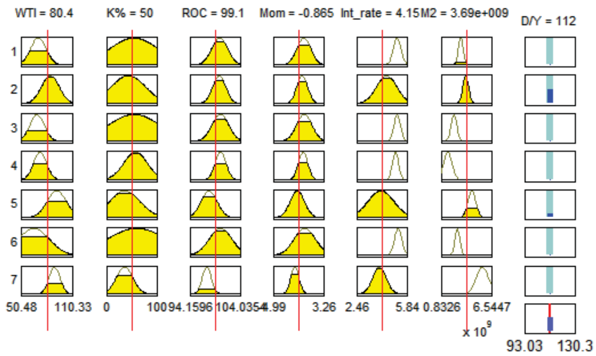

Figure 4: Fuzzy rule base of USD/JPY exchange rates forecasting

4.1 *Sugeno-Yasukawa Approach*

This Sugeno-Yasukawa [26] approach produces a fuzzy model with 6 rules, 6 inputs, and 1 output. The inputs are the same as with the ANFIS model. Other aspects of the approach include a Mamdani-style inference, min–max operators, and centroid defuzzification.

4.2 *Feedforward Multi-layer Neural Network*

A 10×5×1 feedforward multi-layer network with gradient descent learning algorithm is used to forecasting US Dollar against Japanese Yen currency exchange rates. A tangent sigmoid activation function is used in each node. The tests were performed for a maximum iteration number of 500.

4.3 *Multiple Regression*

The multiple regression analysis with Matlab ® is used for prediction. The regression equation is:

$$y = 1.9164\, x_1 - 0.00001\, x_2 - 0.0602\, x_3 + 1.7423\, x_4 - 0.2103\, x_5 - 0.0208\, x_6 \quad (10)$$

The output is computed by the above equation and the modeling performance measure is obtained.

Table 3: RMSE of different models for training set

Model	# Rules	# Runs	RMSE		
			Min.	Max.	Ave.
Multiple regression	-	10	6.1002	9.1770	7.2391
Neural network	-	10	1.3055	2.7595	2.1306
Sugeno-Yasukawa	6	10	3.1397	5.6691	3.8723
ANFIS	7	10	1.3805	2.4980	1.7447

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Table 4: RMSE of different models for testing set

Model	# Rules	# Runs	RMSE		
			Min.	Max.	Ave.
Multiple regression	-	10	6.3060	9.4483	7.9221
Neural network	-	10	1.3820	4.9647	2.8082
Sugeno-Yasukawa	6	10	3.9835	8.2009	4.8290
ANFIS	7	10	1.9284	5.4007	2.6301

Table 5: BIAS of different models for training set

Model	# Rules	# Runs	BIAS		
			Min.	Max.	Ave.
Multiple regression	-	10	1.7193	2.0918	1.7201
Neural network	-	10	0.5311	0.8375	0.7611
Sugeno-Yasukawa	6	10	0.8129	1.1602	0.9069
ANFIS	7	10	0.5591	0.7190	0.6207

Table 6: BIAS of different models for testing set

Model	# Rules	# Runs	BIAS		
			Min.	Max.	Ave.
Multiple regression	-	10	1.7660	2.2183	1.9219
Neural network	-	10	0.5005	1.1020	0.9011
Sugeno-Yasukawa	6	10	0.6291	1.5918	1.4820
ANFIS	7	10	0.5197	0.9518	0.8526

5 Conclusions

The average RMSE and BIAS results are better for the ANFIS approach than for the Sugeno-Yasukawa, ANN, or multiple regression approaches. However, the difference between the ANFIS and ANN average RMSE and BIAS does not appear significant. One might say that the performance of ANFIS and ANN was comparable as regards accuracy. However, with ANN one does not gain the benefit of the semantically meaningful presentation of rules that is possible with ANFIS. Given the choice between two computer systems that produce comparable test accuracies, humans are likely to prefer the system whose logic is transparent.

Future work would explore refined hypotheses in various directions. One hypothesis is that by taking advantage of further information about currency exchange rates, we can improve the initialization of antecedent membership functions and the clustering technique. Another hypothesis is that the application of other learning or optimization algorithms, such as genetic algorithms and particle swarm optimization, would demonstrate interesting variations on the representation and reasoning for the currency exchange problem. By implementing new hybrid learning programs, researchers might gain further insights about how to solve the currency exchange problem. Vast amounts of available data, clear definitions of success in testing, and practical importance are hallmarks of this problem. The problem of forecasting currency exchange rates provides a valuable test bed for soft computing methods, and researchers can thus elaborate the merit and the shortcomings of each method.

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