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A New Approach to Modeling Early Warning Systems for Currency Crises : can a machine-learning fuzzy expert system predict the currency crises effectively?

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Abstract

This paper presents a hybrid model for predicting the occurrence of currency crises by using the neuro fuzzy modeling approach. The model integrates the learning ability of neural network with the inference mechanism of fuzzy logic. The empirical results show that the proposed neuro fuzzy model leads to a better prediction of crisis. Significantly, the model can also construct a reliable causal relationship among the variables through the obtained knowledge base. Compared to the traditionally used techniques such as logit, the proposed model can thus lead to a somewhat more prescriptive modeling approach towards finding ways to prevent currency crises.

Keywords: currency crises、neuro fuzzy, signal approach, Logit

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1. Introduction

Since the breakout of the various currency crises in the 1990s, there have been several attempts devoted to the construction of the early warning system for the currency crisis in order to avoid the recurrence of it. The European currency crises in 1992, the Mexican peso crisis in 1994, the Asian crises in 1997-98, and the Russian currency crisis in 1998 were indeed telling, as was the devastation resulting from the Argentine crisis later. In order to prevent or at least to manage better such damage to the world economy, finding an effective early warning system has become an important issue.

Basically the work done so far can be divided into four main categories. First, there are papers that emphasize the change in some important indicators before the crisis. However, these papers do not usually go into the empirical testing of these indicators (Dornbusch, Goldfajn, and Valdes, 1995; Goldstein, 1996; Krugman, 1996; Milesi-Ferretti and Razin, 1996). Second, some papers emphasize the difference in values of the variables between the crisis period and the precrisis period (Eichengreen, Rose, and Wyplosz, 1995; Frankel and Rose, 1996; Moreno, 1995). Third, some other papers predict the probability of the crisis according to a given theoretical model (Blanco and Garber, 1986). This can also be divided into two further categories, single country model (Cumby and van Wijnbergen, 1989; Kaminsky and Leiderman, 1998; and Otker and Pazarbasioglu, 1994 and 1996) and multiple countries model (Collins, 1995; Frankel and Rose, 1996; Klein and Marion, 1994; and Milesi-Ferretti and Razin, 1998), including some papers using macro economic variables to explain the contagion phenomena (Sachs, Tornell, and Velasco, 1996). Fourth, Kaminsky and Reinhart (1996) innovatively propose the signal approach to construct an early warning system. This approach looked promising at the time it was proposed. However, according to some more recent work (e.g.,Chowdhry and Goyal (2000)), the forecasting results for the out-of-sample data for Asian crisis case are disappointing for most of the theoretical models. It appears that, this problem of finding an effective early warning system remains an important issue and still needs further investigation. The possibility of extensive non-linear relationships among the variables motivates us to explore the problem from a neural network perspective.

As far as the nonlinear problem is concerned, the progress in artificial intelligence technology has provided a possible alternative that deserves further exploration. In recent years, expert systems, fuzzy logic, and neural network all have been refined in order to help managers in making real world decisions. The expert system can embed the past experience into the system; fuzzy logic can describe the problem in a way that is close to the human reasoning process and accommodate the inaccuracy and uncertainty associated with the data; the neural network can learn from historical data. However, the difficulty with the acquisition of the knowledge base for both the expert system and fuzzy logic, and the difficulty with the causal explanation through the construction of appropriate 'real'[3] relations among the variables for the neural network model have constrained the application of these three methods. A method which can combine the advantages of these three methods while avoiding some of the weaknesses, would seem to hold some promise.

In this paper, we follow this intuition and use the neuro fuzzy, a hybrid of neural network and fuzzy logic, to construct an early warning system to predict a currency crisis. In addition to providing better out-of-sample forecasting results, the proposed model can also provide a knowledge base to describe the complicated relationship among the variables. This last step can potentially provide a more concrete way to prevent a currency crisis. The paper is constructed as follows. Section 2 is the literature review. The construction of neuro fuzzy and its benchmarks are described in section 3. Section 4 describes the research methodology. The empirical results are shown in section 5. Finally we give conclusions and suggestions for further research in section 6.

2. Literature Review

2.1 Theoretical literature

The explanations for speculative attacks and balance of payments crisis were first proposed by Krugman in 1979. His model shows that, under a fixed exchange rate, domestic credit expansion in excess of money demand growth leads to a gradual but persistent loss of international reserves and, ultimately, to a speculative attack on the currency, which resulted in a persistent loss of international reserves that ultimately forced the authorities to abandon the parity. However, some papers have argued that the authorities may decide to abandon the parity for reasons other than a depletion of official international reserves. Instead, they may be concerned about the adverse consequences of policies needed to maintain the parity on other key economic variables [Agenor, Bhandari, and Flood, 1992; Blackburn and Sola, 1993; Garber and Svensson, 1994; and Flood and Marion, 1995]. While the traditional approach

[3] In the sense of being approximately true. See Khan(2004a,c;2003) and chapters 6 and 7 of Khan(2004b) for a discussion of the related philosophy of science issues.

stresses the role played by declining international reserves in triggering the collapse of a fixed exchange rate, some recent models have suggested that the decision to abandon the parity may stem from the authorities' concern about the evolution of other key economic variables—suggesting that yet another family of variables could be useful to predict currency crises [Ozkan and Sutherland, 1995; Velasco, 1987; Calvo, 1995]. Besides, recent models also suggested that crises may develop without any noticeable change in economic fundamentals. These models emphasize that the contingent nature of economic policies may give rise to multiple equlibria and generate self-fulfilling crises [Obstfeld, 1994]. Finally, some recent papers have focused on contagion effects as the spark of a balance of payments crisis [Gerlach and Smets, 1994; Calvo and Reinhart, 1996; Eichengreen, Rose, and Wyplosz, 1996]. All these models suggest the possible variables that could be used as leading indicators of crises.

2.2 Alternative Approaches

In the literature on the early warning model building, usually a multi-variate logit model or a multi-variate probit model is constructed to predict the probability of the occurrence of the crisis for the next period or the next k [4] periods. Although the explanatory variables are not exactly the same for most of the papers, the estimation technique is quite consistent. On the other hand, an alternative is to check the differences in the values of the selected variables before the crisis and during the crisis to see which variables can be helpful in predicting the crisis. Kaminsky and Reinhart (1996) have proposed the signal approach to construct a warning system by modifying this method.

The advantage of logit or probit model is to represent all the information contained in the variables by giving the probability of the crisis. The disadvantage is that it cannot gauge the precise forecasting ability of each variable though it can give the significance level of each variable. In other words, the ability of the correct signal and false alarm for each variable can not be seen exactly from the model.

On the other hand, the signal approach proposed by Kaminsky and Reinhart (1999) can show the contribution (the percentage of correct signal and the percentage of false alarm) of each variable for the crisis prediction. Besides, it can also offer a summary indicator by calculating the conditional probability given the number of indicators used for signalling. Following up on this, some researchers have studied the difference between this method (signal approach) and logit. Berg and Pattillo(1999) try to predict the currency crisis in 1997 by using

[4] 'k' is greater than or equal to 1.

the signal approach based on the work of Kaminsky; Lizondo and Reinhart(1998), the probit model based on the work of Frankel and Rose(1996), and the regression model based on the work of Sachs, Tornell and Velasco(1996). The empirical results show that the performance of all these three methods are not significantly different.

As for the explanatory variables, Kaminsky, Lizondo and Reinhart(1998) divide the variables into seven categories, external, financial, real sector, fiscal, institutional/structural, political, and contagion by summarizing from 105 indicators in 17 papers. Finally 15 variables are selected to construct the warning system by using signal approach. This paper has done an excellent job in exploring the related leading indicators for the currency crisis.

From the empirical results of the above literature it can be seen that the conclusions may be inconsistent due to the presence of different explanatory variables, different data frequency (monthly data or quarterly data), and different models employed. Besides, some variables are significant for single variable model but insignificant for multi-variate model due to the possible multicollinearity. Most problematic of all, a theoretical model which can provide an effective out-of-sample prediction is still unavailable. This paper is based on an inductive learning perspective. Although based on a theory of learning, it is a data driven method to extract the relationship among the variables from the historical data. The obtained relationship can then be the reference point for theoretical modification of the existing theory. It is also an inter-disciplinary attempt to apply an artificial intelligence and fuzzy logic tool to the currency crisis problem. Empirically, our approach generates a greater forecasting accuracy for both in-sample and out-of -sample data.

3. The construction of the competitive warning models

3.1 Signal Approach

The basic philosophy of this approach is that the economy behaves differently on the eve of financial crises as compared with a more relatively ‘normal’ period. Furthermore, this aberrant behavior seems to have a recurrent systemic pattern. For example, currency crises are usually preceded by an overvaluation of the currency; banking crises tend to follow sharp declines in asset prices.

Let A and B represent respectively the number of times we observe a signal when there is really a crisis and no crisis in 24 months. Let C and D represent respectively the number of times without signaling when there is really a crisis about to happen and no crisis during 24 months. These numbers are shown in Table 2. A and D are the correct predictions, but B and C are the wrong predictions. We call B the false alarm. Let ω = [B/(B+D)]/[A/(A+C)], where B/(B+D) represents the wrong prediction rate when there is no crisis, and A/(A+C) represents the correct prediction rate when there is a crisis. ω is called noise-to-signal ratio.

The signal approach is given diagnostic and predictive content by specifying what is meant by an "early warning, by defining an "optimal threshold" for each indicator, and is decided by minimizing the ratio ω. Usually the threshold value can be located between the tenth percentile and the twentieth percentile (Kaminsky, Lizondo and Reinhart,1998) or between the first percentile and the twentieth percentile (Goldstein, Kaminsky, and Reinhart , 2000). This paper adopts the former method. Different countries can have different threshold values.

Table 1. Contingency table of the crisis

	Crisis	No crisis
Signaling	A	B
No signal	C	D

However each indicator can contribute differently to predicting a crisis. In order to take into account all the information and the different contributions among the variables at the same time, Kaminsky(1999) proposed four methods to assemble the information.

The first method records the number of indicators used in signaling. The more the number of indicators used in signaling the more likely the crisis is to occur. Let I_t^1 represent the index of method one at time t. $S_t^j = 1$ represents indicator j used in signaling at time t , and $S_t^j = 0$ otherwise. I_t^1 is calculated as follows:

$$I_t^1 = \sum_{j=1}^{n} S_t^j \tag{1}$$

where $j = 1,2...,n$ represents the number of indicators. After this, I_t^1 is viewed as another indicator. The threshold value for this indicator is found in the same way as in the case of the other indicators.

However the indicator cannot reflect the extent of the worse situation, for example, a drastic decrease of the real exchange rate would cause a different of influence on the currency crisis than just a mild decrease of the real exchange rate. Therefore, the second method will differentiate the signaling situations into tow categories, a mild one and a drastic one. Each indicator is given two threshold values (Kaminsky, 1999). Assume that SM_t^j and SE_t^j are two dummy variables, $\overline{x}_m^j$ is the mild threshold value, and $\overline{x}_e^j$ is the drastic threshold value. If $\overline{x}_m^j < x_t^j < \overline{x}_e^j$, the indicator falls within the mild signal area, $SM_t^j = 1$. If $\overline{x}_e^j < x_t^j$, the indicator falls within the drastic signal area, $SE_t^j = 1$. The second composite indicator I_t^2 is defined as follows.

$$I_t^2 = \sum_{j=1}^{n} \left(SM_t^j + 2SE_t^j \right) \qquad (3)$$

The influence of the drastic signal is twice that of the mild signal. The value of I_t^2 is between 0 and 2n.

On the other hand, the related indicators may not be signaling at the same period before the crisis due to the causal relationship among themselves. For example, the output could decrease drastic at certain month, followed by the crash of the stock market the next month, and the depletion of reserve and drastic decrease of export the following months. At last, the crisis happens. In such situation, it is inappropriate to conclude that export is the only indicator of the crisis. Therefore the third composite indicator is trying to count the signals happened in a certain period instead of certain month. Each indicator is counted only once if it sends out signals greater than or equal to once. The third composite indicator I_t^3 is defined as follows.

$$I_t^3 = \sum_{j=1}^{n} S_{t-k,t}^j \qquad (4)$$

where $S_{t-k,t}^j = 1$ if indicator j is sending out signals during the previous k periods more than or equal to once; k is set to be 8 according to Kaminsky（1999）.

However, the previous three composite indexes do not consider the different contribution of each indicator. The fourth composite index is trying to incorporate the discriminating power of each indicator by multiplying each indicator S_t^j with the reciprocal of its noise to signal ratio ω. The fourth composite index I_t^4 is defined as follows.

$$I_t^4 = \sum_{j=1}^{n} \frac{S_t^j}{\omega^j} \qquad (4)$$

where ω^j is the value of ω of indicator j. Similarly the threshold values for these composite indexes are found in the same way as the individual indicator.

3.2. Logistic Regression

Since the dependent variable, currency crisis, is a binary variable from a qualitative point of view[5], the logistic regression model is also seemingly a good candidate (Baltagi,1995). Let $Y_{it} = 1$ represent that country i has a crisis at time t, and $Y_{it} = 0$ otherwise. Let P_{it} indicate the probability of country i to have a crisis at time t, then

$$E(Y_{it}) = 1 \times P_{it} + 0 \times (1 - P_{it}) = P_{it} \quad , \tag{5}$$

which can be expanded by including n explanatory variables and can be written as the following equation.

$$P_{it} = P_r(Y_{it} = 1) = E(Y_{it} | X) = F'(\beta' X_{it}) \tag{6}$$

$$Y_{it}^* = \beta' X_{it} + \varepsilon_{it} \, , \tag{7}$$

where y_{it}^* is the actual dependent variable which cannot be observed, and X_{it} is the vector consisting of n explanatory variables, β' is the vector consisting of n unknown coefficients, ε_{it} is the error term. When I ranges over a cross section of 'N' countries, there will be naturally 'N' different probabilities--- some of which could have the same value--- for the 'N' countries. Then the log-likelihood function can be written as follows.

$$Log \quad L \sum_{t=1}^{T} \sum_{i-1}^{I} \{P_{it} \ln[F(\beta' X_{it})] + (1 - P_{it}) \ln[1 - F(\beta' X_{it})]\} \quad , \tag{8}$$

where T is the number of periods, N is the number of countries. The parameters can be obtained through the maximum likelihood method. For the details of this model construction, please refer to (Gujarati, 2003)

3.3 Neuro Fuzzy

Basically fuzzy logic deals with the extent to which an object belongs to a fuzzy set. Usually a membership function such as $\mu_A(X)$ is used to describe the extent to which an object x belongs to fuzzy set A. The difference between fuzzy logic and the traditional expert system is that the rules in fuzzy logic are described through the use of linguistic variables instead of the numerical variables. Furthermore, the linguistic variables are described by several (ordinary language) terms. For example, a simple fuzzy logic rule can be stated as follows.

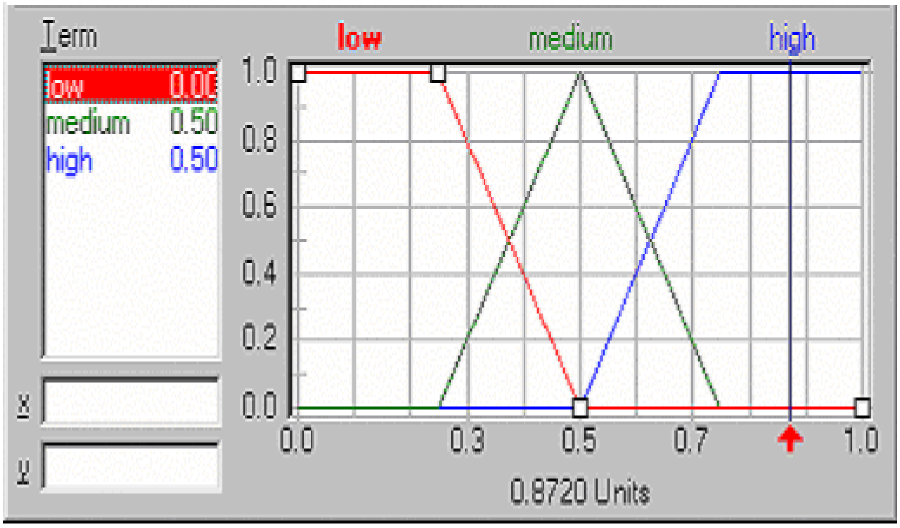
[5] That is, the dependent variable, currency crisis, either occurs or it does not occur.

IF exports are low and reserves are medium,
then chance of a currency crisis is high (17)

where export, reserve, and currency crisis are called linguistic variables; low, medium, and high are the so called terms.[6] Each term has a corresponding membership function. A fuzzy logic model is constructed by a set of "IF-THEN" rules as equation (15) to describe the relationship among the input and output variables. The process to construct a fuzzy logic model generally consists of three major steps, fuzzification, inference, and defuzzification, which are described briefly as follows.

3.3.1. fuzzification

The first step in constructing a fuzzy logic is to clearly define the linguistic variables which are stated in the "if-then" rules. A linguistic variable can be described by several terms. For example, we can use three terms, high, medium, and low to describe exports and reserves. Each term has a corresponding membership function as shown in Figure 2a and 2b. There are four commonly used membership functions, Z , Λ, Π, and S type (Von Altrock, 1996)。 Since there is no rule available to decide which type to choose, and the preliminary experiment shows that there is no significant difference for these four different membership functions, we choose the most commonly used one, namely, the Λ type membership function.



[6] Notice that the consequent part of the 'if…then' statement here does not give probabilities, or at least the standard Kolmogorov-type probabilities on the measure space with the range of probabilities on the closed interval between 0 and 1. It could be interpreted as 'qualitative' probabilities under some axiomatic systems.

Figure 2a. Membership function of exports

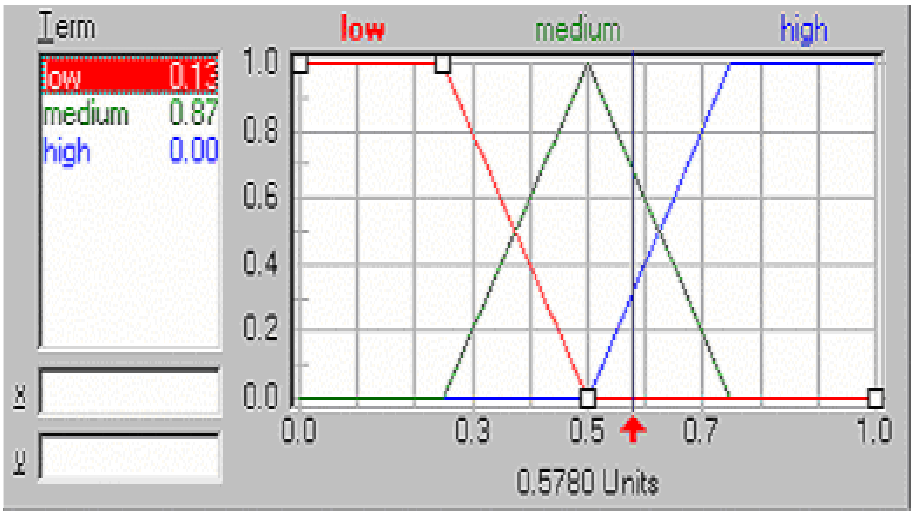


Figure 2b. Membership function for reserves.

Assume there is a country with exports and reserves equal to 0.872 and 0.578, respectively. The values for each term can be obtained from figure 2a and 2b as follow.

Export : μlow(0.872)=0、μmedium(0.872)=0.5、μhigh(0.872)=0.5

Reserve : μlow(0.578)=0.13、μmedium(0.578)=0.87、μhigh(0.578)=0.00

The above process is what we call fuzzification. Since a linguistic variable can be described by several terms, this method has broken out of the binary logic constraint.

3.3.2. Inference

The knowledge base of fuzzy logic is constructed by a series of 『If–Then』 rules. Each rule consists of two parts, the "if" part and the "then" part. The "If" part measures the extent of how the condition is satisfied and the "then" part describes how the model responds to the input. Therefore, each inference consists of two calculations. The extent of the validity for the 'then'part depends on the extent to which the "if" part is satisfied. According to Thole (1979), the extent to which the "if" part is satisfied is determined as the minimum value of the membership functions in the "if" part. In other words, $\mu_{A\cap B} = \min\{\mu_A, \mu_B\}$. Take the above rule for example. Since μhigh(0.872) = 0.5, and μmedium(0.578) = 0.87, the validity of the "if" part is min{0.8720, 0.5780} = 0.5780. Therefore, the output for this rule is that the chance of a currency crisis is low with validity equal to 0.578.

3.3.3. Defuzzification

After the fuzzification and the inference step, each rule will obtain an output like equation (15), e.g., that the chances of a currency crisis is low with validity equal to 0.578. Assume that we have the other outputs as currency crisis is medium with validity equal to 0.23 and currency crisis is high with validity equal to 0.97. The process to transform these linguistic results into a numerical value is called defuzzification. Usually it entails two steps. First, we need to find the proxy value for each term. Second, we have to combine these proxy values. Usually the proxy value is determined as the value with the maximum membership function value. Then we calculate the weighted value of the proxy value of each term with its membership function value as its weight. For example, if the proxy value for each term is {0.2,0.5,0.7}, then the weighted average is 0.5780* 0.2 + 0.2300*0.5 + 0.9700*0.7 = 0.8236。 In other words, in the language of probability calculus, the probability for currency crisis is 0.8236. This commonly used method is called gravity method(Von Altrock, 1996)。

The process is what we have called the inference mechanism of fuzzy expert system. The problem with this inference mechanism of fuzzy expert system is that the influence of each rule should be different. The way to improve this is to assign a certain weight (DOS, degree of support) to each rule, representing the relative importance of each rule compared to the other rules. Then the calculation for the "then" part should be modified as the validity of the "if" part multiplied the corresponding weight. However, how can the correct knowledge base be obtained? How to decide on the weight for each rule? Among all the possible alternatives, the learning ability of neural network holds out the greatest promise. It has been known for some time that the learning ability of neural network can be used to solve this problem. Therefore, the hybrid modeling approach of neural network and fuzzy logic can be a good prospective methodological solution, hence, our choice of neuro fuzzy modeling.

Essentially, the neuro fuzzy modeling uses the learning ability of neural network to find the parameters in the fuzzy logic system. In this paper, we adopt the fuzzy associate memory model proposed by Kosko (1992) in order to implement the learning process. Each rule is seen as the neuron in the neural network and the procedure relies upon an updating of the weight of each rule by using the back propagation. The knowledge base is obtained when the training stopping criteria is satisfied. Usually the stopping criterion is set as follows.

$$E = \sum_j \frac{1}{2}(Y_j - O_j)^2 \le \xi \qquad (4)$$

where Y_j is the actual probability of the crisis, O_j is the predicted chance of the crisis for month j, and ξ is the threshold value. Due to its simplicity with regards to implementation and its recursive learning ability, this method has been applied in many fields (Stoeva, 1992). The neuro fuzzy model building process is as follows.

Step 1. Divide the data set into training data set and testing data set.

Step 2. Construct the complete knowledge base and set all the weights (DOS) equal to 0 as the initial solution.

Step 3. Use the learning ability of neural network to update the weight of each rule. If the relationship described in some rules really exists in the data set, the weight of these rules will be strengthened, otherwise the weights will remain 0. The training process stops when the stopping criterion is satisfied. All the rules with weight value less than a predetermined threshold value will be eliminated, the remaining rules are what we obtain to describe the data set.

Step 4. Use the testing data set to validate the obtained model. If the out-of-sample observations can be predicted within an acceptable range of accuracy, the model building process stops. Otherwise, repeat step 3 and step 4.

4. Methodology

4.1 Data Set

The data set comes from the work of Kaminsky and Reinhart(1999), including 20 countries from 1970 June to 1998 June. It is divided into two parts, training data set and testing data set. Training data set goes from 1970 through 1995, used for model building. Testing data set goes from 1996 through 1998, used for model validation.

4.2 Definition of Crisis

According to Eichengreen-Rose-Wyplosz(1996), currency crisis can be measured through the EMP, which is calculated as follow.

$$EMP_{i,t} = \left\lfloor(\alpha\%\Delta e_{i,t}) + (\beta\%\Delta(i_{i,t} - i_{USA,t})) - (\gamma\%\Delta r_{i,t})\right\rfloor, \tag{18}$$

where $(\%\Delta e_{i,t})$ is the deflation rate of nominal exchange rate of country i at time t,$\%\Delta(i_{i,t}-i_{USA,t})$ is the difference of interest rate between country i and America, $(\%\Delta r_{i,t})$ is change rate of foreign reserve, α,β,γ are the weights to make sure that the variances are equal among these three parts. A currency crisis can then be defined as follows.

$$Crisis_{i,t}\begin{cases}=1 \ \ if \ \ EMP_{i,t}>1.0\sigma_{EMP,i}+\mu_{EMP,i} \\ =0 \qquad\qquad\qquad\qquad otherwise\end{cases} \tag{19}$$

where $\mu_{EMP_{i,t}}$ and $\sigma_{EMP_{i,t}}$ represent the mean and variance of EMP respectively. This way to define currency crisis was proposed by Sachs-Tornell-Velasco (1996) first, and used later by many others. Goldstein、Kaminsky, and Reinhart(2000) modified this formula as follows.

$$EMP=(\Delta e/e)\text{-}(\sigma_e/\sigma_R)*(\Delta R/R), \tag{20}$$

where $\Delta e/e$ is the rate of change of exchange rate, $\Delta R/R$ is the rate of change of foreign reserves, σ_e is the standard deviation of $\Delta e/e$, and σ_R is the standard deviation of $\Delta R/R$. The reason to remove the interest rate change part is that some countries adopt interest rate control which forces this variable to have no significant explanatory role for the currency crisis. The function of σ_e/σ_R is similar to the function of α,β,γ to make the variances of each part equal. We will follow the practice of Goldstein、Kaminsky, and Reinhart(2000)to define the currency crisis as the situation when the EMP is greater than the average of more than at least 3 standard deviations, otherwise no currency crisis is said to have happened.

4.3 The Selection of Indicators

Among the 15 indicators obtained in Kaminsky and Reinhart(1996), we choose 13 indicators due to the availability of the data set. They are M2 multiplier, Domestic Credit/GDP、real interest rate、Lending-deposit rate ratio、M2/reserves、Bank Deposits、export、Terms-of-Trade、real exchange rate、Imports、Reserves、output、and Stock Prices. The sources of these data are listed in Appendix 1.

4.4 Performance Indicators

To compare the performance among the models, we use the accuracy rate and type I error as the criteria. The accuracy rate is defined as the ratio of the number of the correct predictions divided by the total number of predictions. The higher the accuracy rate the better the model. Type I error is defined as the percentage that number of times that there is no signal sent out when there is a crisis divided by the number of times that there is a crisis. The smaller the type I error the better the model is. We now turn to our empirical analysis.

5. Empirical Results

5.1 Results of the signal approach

The results of the signal approach for the variables are shown in table 2. The second column is the noise to signal ratio from this study. The third column is the rank of the variables according to the noise to signal ratio, from small to large of this study. Besides, we put the empirical results from KLR (1996) at the right hand side for comparison. The fourth column is the noise to signal ratio from KLR (1996). The fifth column is the rank of the variables from KLR (1996). Basically, the order of the rank is similar, except for some variables. This result is similar to that of Edison (2000). The difference of the results may come from the data modification every two years, the ways in which data are transformed, and the ways to deal with missing values (Edison, 2000).

Table 2. Comparisons between this research and KLR

Variables	Results of this study		Orignal KR Results	
	Noise/Signal Ratio	Rank	Noise/Signal Ratio	Rank
Real Exchange Rate	0.1602	1	0.14	1
Exports	0.4539	2	0.40	3
M2/reserves	0.4762	3	0.52	5
Reserves	0.5048	4	0.55	6
Real Interest Rate	0.5433	5	0.75	10
Stock Prices	0.6151	6	0.38	2
Domestic Credit/GDP	0.6736	7	0.64	7
M2 Multiplier	0.6936	8	0.67	8
Terms-of-Trade	0.7599	9	0.70	9
Imports	0.8143	10	1.10	11
Output	1.2167	11	0.46	4
Bank Deposits	1.2298	12	0.67	8
Lending-deposit rate ratio	1.8112	13	1.52	12

5.2 Results of the Logit model

Due to the availability of the data set in the out sample, only four indicators are incorporated into the logit models. The empirical results are shown in table 3, 4, 5, and 6 for Indonesia, Malaysia, Philippine, and Thailand respectively. It can be seen that the real exchange rate has the same significantly negative influence on the currency crisis for all these four countries, which is consistent with the empirical results of Kaminsky and Reinhart (1999). Most often the drastic real exchange rate change (decrease) is the leading indicator of the currency crisis. As for the negative influence of the decrease of export, the significant evidence can be found in Indonesia and Thailand. However, as far as M2/reserves and Reserves are concerned, these two variables have different influence on currency crisis in Philippine and Thailand. Calvo (1996) claims that M2/reserves is positively related to the currency crisis, which can be found in Thailand. However, it has significantly negative influence on currency crisis in Philippine. On the other hand, reserve is supposed to be negatively related to the currency crisis, which can be found in Philippine, but it is opposite in Thailand. This result could imply that the relationship among the variables could be different in different country due to the different environment, and also that the relationship among the variables may be much more than just the linear one.

Table 3. Logit model for Indonesia

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	4.6932	1.5132	3.1014	0.0019
Real Echange Rate	-7.5940	1.0351	-7.3368	0.0000***
Exports	-4.1750	0.7902	-5.2832	0.0000***
M2/reserves	-0.7025	1.3548	-0.5185	0.6041
Reserves	-0.9442	1.4748	-0.6402	0.5220

***: 1% significance level, ** 5% significance level, * 10% significance level

Table 4. Logit model for Malaysia

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-2.9926	2.2518	-1.3290	0.1839
Real Echange Rate	-9.2291	1.9709	-4.6827	0.0000***
Exports	-0.0075	0.8641	-0.0087	0.9930
M2/reserves	3.3164	2.2325	1.4855	0.1374

Reserves	2.5788	1.8691	1.3797	0.1677

***: 1% significance level, ** 5% significance level, * 10% significance level

Table 5. Logit model for Philippine

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	11.3975	2.0530	5.5517	0.0000
Real Echange Rate	-1.2774	0.6876	-1.8577	0.0632*
Exports	-1.0510	0.6421	-1.6369	0.1017
M2/reserves	-10.3316	1.9254	-5.3661	0.0000***
Reserves	-14.6079	2.1211	-6.8869	0.0000***

***: 1% significance level, ** 5% significance level, * 10% significance level

Table 6. Logit model for Thailand

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-9.5888	3.0092	-3.1865	0.0014
Real Echange Rate	-7.1775	1.1217	-6.3987	0.0000***
Exports	-1.0325	0.5802	-1.7796	0.0751*
M2/reserves	13.1513	3.0762	4.2752	0.0000***
Reserves	9.1546	2.8940	3.1633	0.0016***

***: 1% significance level, ** 5% significance level, * 10% significance level

5.3、Neuro Fuzzy model

To make the comparison fair, we include the same four variables in the neuro fuzzy model as input variables. BOP is the output variable representing the probability for a currency crisis to occur. If the probability is greater than a threshold value, it is interpreted as signaling a warning that a currency crisis is to happen. Otherwise, there is no currency crisis predicted.

We adopt the approach of describing these four independent variables by using three ordinary language terms, low, medium, and high. We describe the dependent variable BOP by using 5 terms, very low, low, medium, high, and very high. This model consists of four input variables, one output variable, and one knowledge base. The model is listed as Figure 2. Part of the knowledge base obtained through the training process for Thailand is shown in Table 7.

Table 7. Knowledge base for Thailand

	IF				THEN	
	Exports	M2/reserves	Real Exchange	Reserves	DoS	BOP
1	low	Low	low	low	1	Low
2	low	Medium	low	high	1	High
3	low	High	low	medium	1	very_high
4	low	High	medium	high	1	very_low
5	low	Low	high	high	1	very_low
6	low	Medium	high	medium	1	Low
7	medium	Low	high	high	1	very_low
8	medium	Medium	high	low	1	very_low
9	medium	Medium	high	medium	1	very_low
10	medium	High	high	low	1	very_low
11	high	High	low	high	1	very_high
12	high	Low	medium	medium	1	very_low
13	high	High	medium	low	1	very_low
14	high	low	high	medium	1	very_low
15	high	low	High	high	1	Low
16	high	medium	High	high	1	very_low

To see the influence of exports on BOP, we try to sort the rules according to M2/reserves, real exchange rate, and reserves. Five rules are filtered and listed in table 7a for clear demonstration. For the first three rules, the m2/reserves, real exchange, and reserves are same. Only the exports are different. Although the difference between rule 2 and rule 3 (exports is medium for rule 2 and export is high for rule 3) cause the positive influence on BOP from very low to low. However the difference between rule 1 and rule 2 does not cause any difference on BOP. On the other hand, m2/reserves, real exchange, and reserves are the same for rule 4 and rule 5. However the difference of exports causes the negative influence on BOP from low to very low. In other words, the influence of export on BOP can be nothing like rule 1 and rule 2, positive one like rule 2 and rule 3, and negative one like rule 4 and rule 5.

Table 7b. The rules to see the influence of exports on BOP

	IF				THEN	
	Exports	M2/reserves	Real Echange Rate	Reserves	DoS	BOP
1	low	low	high	high	1	very_low
2	medium	low	high	high	1	very_low
3	high	low	high	high	1	low
4	low	medium	high	medium	1	low
5	medium	medium	high	medium	1	very_low

Similarly we sort the rules according to exports, m2/reserves, and real exchange rate to see the influence of reserves on BOP. Four rules are filtered and listed in table 7b as follows. The variables, exports, m2/reserves, and real exchange rate are the same for rule 1 and rule 2, and rule 3 and rule 4. However the difference for reserves from low to medium does not cause difference on BOP, which can be seen from rule 1 and rule 2. On the other hand, the difference for reserves from medium to high cause a positive influence on BOP, which can be seen from rule 3 and rule 4.

Table 7b. The rules to see the influence of reserves on BOP

	IF				THEN	
	Exports	M2/reserves	Real Echange Rate	Reserves	DoS	BOP
1	medium	medium	high	low	1	very_low
2	medium	medium	high	medium	1	very_low
3	high	low	high	medium	1	very_low
4	high	low	high	high	1	low

Contrast to the results just obtained from table 7a and 7b, the influence of independent variables on BOP is either positive or negative or no influence for each logit function. The difference between these two methods somehow reminds us to reconsider the possible relationship among the variables.

In addition to the detailed relationship described in the knowledge base to help explain the causal relationship among the variables, this knowledge base can also be used to do the diagnosis, to see what reactions need to be taken to avoid the crisis more efficiently. Take the example of Thailand on May 1997. After the related data being input to the neuro fuzzy model, the relationship among the variables is shown in table 8 with BOP equal to 0.75, which means that the currency crisis is very likely to happen given the situation on May 1997. It can also be seen that the rule with the highest validity is rule 5 as follows.

『IF Exports is low and M2/reserves is high and Real Echange Rate is low and Reserves is low, THEN BOP is very high』 (A)

In order to improve the situation to avoid the crisis, we can find a rule similar to rule 5 but with BOP is low from the obtained knowledge base. The following one is one example.

『IF Exports is low and M2/reserves is low and Real Exchange Rate is low and Reserves is low, THEN BOP is low』 (B)

If m2/reserves can be controlled to be low, the probability of crisis can be reduced a lot. Similarly we can find some other rules to find out some possible ways to improve the situations. In other words, contrast to logit, neuro fuzzy can somehow really provide some more concrete ways to avoid the crisis in addition to the much more complicated relationship among the variables than that shown by the logit.

Table 8. The relationship among the variables for Thailand on May 1997.

	IF				THEN	
	Exports	M2/reserves	Real Echange Rate	Reserves	validity	BOP
1	low	high	Low	low	0.30	very low
2	low	high	Low	low	0.00	low
3	low	high	Low	low	0.01	medium
4	low	high	Low	low	0.89	high
5	low	high	Low	low	0.98	very high

The relationship among the variables obtained can also be described through the 3-D graphs in addition to the knowledge base. Figure 3 and 4 describes the influence of exports and m2/reserves on BOP and the influence of real exchange rate and exports on BOP respectively. Basically these graphs can enhance the understanding of the relationship among the variables which are described in the knowledge base. These graphs at least demonstrate that the relationship should be much more than just the linear one.

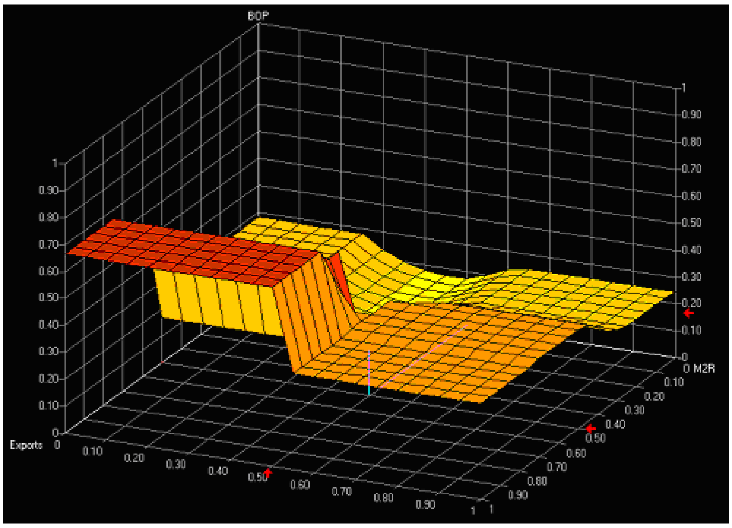


Figure 3. The influence of exports and m2/reserves on BOP

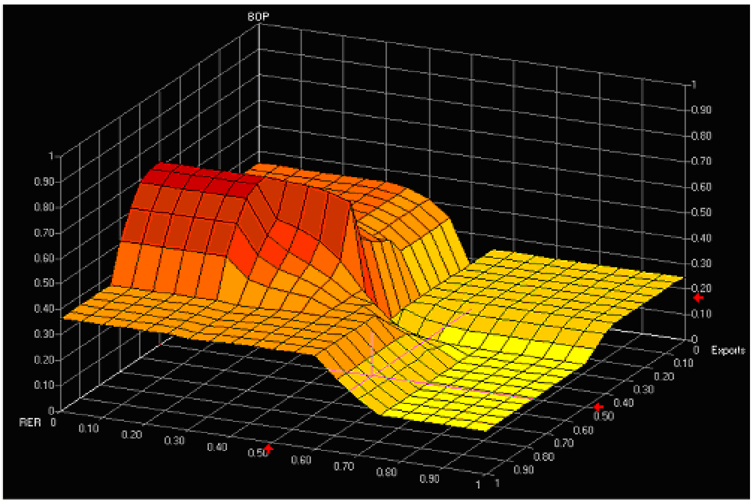


Figure 4. The influence of real exchange rate and exports on BOP

5.4 The comparisons among the models

Due to the nature of the data set and availability, we use Indonesia, Malaysia, Philippine, and Thailand as the data set for testing. We divide the data set of each country into two parts, training data set and testing data set. The training data set is used for the model construction, and the testing data set is used to test the validity of the obtained model from the training data set. The threshold value is decided based on the total accuracy rate with the premise that both the type I and type II error are less than 20%.

The empirical results are shown in Table 7, 8, 9, and 10 for Indonesia, Malaysia, Philippine, and Thailand respectively for both in-sample and out-sample data. Column 3 and 5 represent the rank for each method based on accuracy rate and type I error respectively for in-sample data. Similar information are shown for out-sample data. Basically the training process for the neural network and neuro fuzzy model will not be stopped until the accuracy rate is better than that of the benchmark logit. Therefore, the accuracy of neural network and neural fuzzy is definitely better than that of logit. However, we use the out-sample data to validate the performance. It can be seen that neuro fuzzy has the best performance for these four countries no matter in terms of accuracy rate of type I error.

In addition to the type I error and the accuracy rates of each model, we also show the signals given by each model during the crisis period and during the normal period based on the out-of-sample data. The grey area in Figure 5 represents the crisis periods, when the model must give a signal to indicate the crisis. In other words, according to our definition it represents the previous 24 months before the crisis. We use 1 to represent the signal and 0 to represent non-signal. In other words, during period depicted by the grey area, if there is a signal, it is a correct signal. If the signal happens outside the grey area, it is a false alarm. Figure 5, 6, 7, and 8 shows the signals given by each model for Indonesia, Malaysia, Philippine, and Thailand respectively.

Table 9. Forecasting results given by each model for Indonesia

Indonesia								
	In-sample				Out-sample			
	Accuracy rate	Rank	Type I error	Rank	Accuracy rate	Rank	Type I error	Rank
CI 1	0.8333	4	0.2250	4	0.2667	4	1.0000	3
CI 2	0.7917	6	0.5000	5	0.3333	3	1.0000	3
CI 3	0.6979	7	0.8250	7	0.3333	3	1.0000	3
CI 4	0.8264	5	0.6125	6	0.3333	3	1.0000	3
Logit	0.8403	3	0.1250	2	0.8667	2	0.2000	2
Neural Network	0.8576	2	0.1500	3	0.8667	2	0.2000	2
Neuro Fuzzy	0.9549	1	0.0375	1	0.9000	1	0.1500	1
CI 1 : Composite Indicator 1 (Signal Approach); CI 2 : Composite Indicator 2 (Signal Approach) CI 3 : Composite Indicator 3 (Signal Approach); CI 4 : Composite Indicator 4 (Signal Approach)								

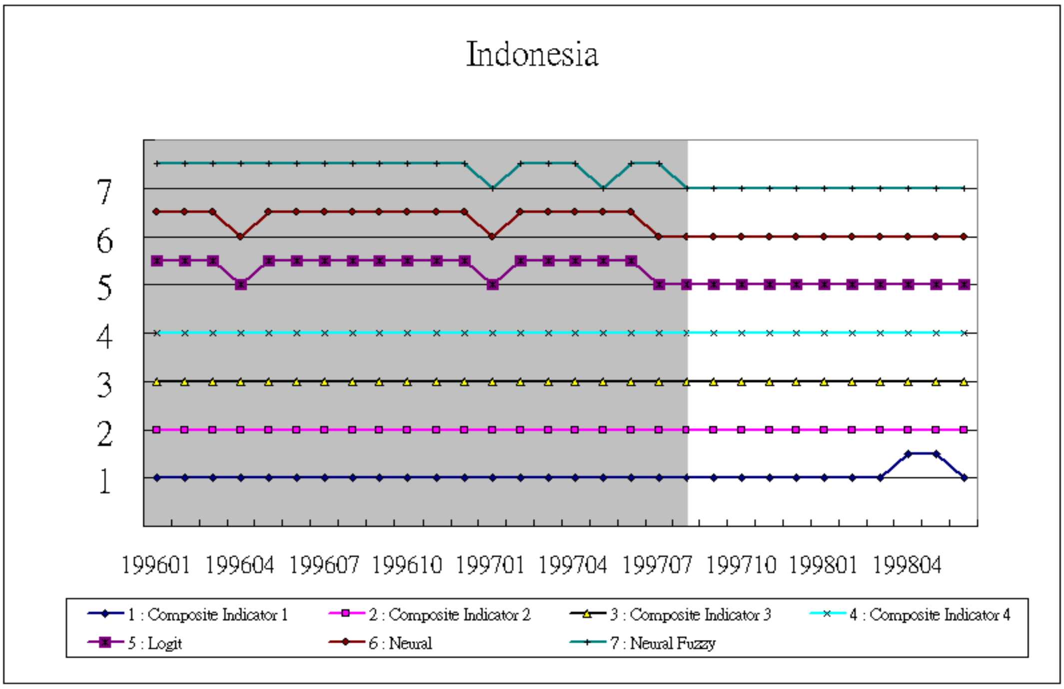


Figure 5. The signals given by each model for Indonesia

Table 10. Forecasting results given by each model for Malaysia

Malaysia								
	In-sample				Out-sample			
	Accuracy rate	Rank	Type I error	Rank	Accuracy rate	Rank	Type I error	Rank
CI 1	0.7244	7	0.2667	3	0.4000	6	0.3684	3
CI 2	0.8397	5	0.5000	6	0.2000	7	0.8421	7
CI 3	0.7532	6	0.6000	7	0.4667	5	0.4211	4
CI 4	0.9038	1	0.4667	5	0.5000	4	0.7895	6
Logit	0.8526	4	0.1667	2	0.8667	2	0.2000	2
Neural Network	0.8942	2	0.4000	4	0.5333	3	0.7000	5
Neuro Fuzzy	0.8622	3	0.0667	1	0.9000	1	0.1500	1
Philippines								
CI 1 : Composite Indicator 1 (Signal Approach), CI 2 : Composite Indicator 2 (Signal Approach)								
CI 3 : Composite Indicator 3 (Signal Approach), CI 4 : Composite Indicator 4 (Signal Approach)								

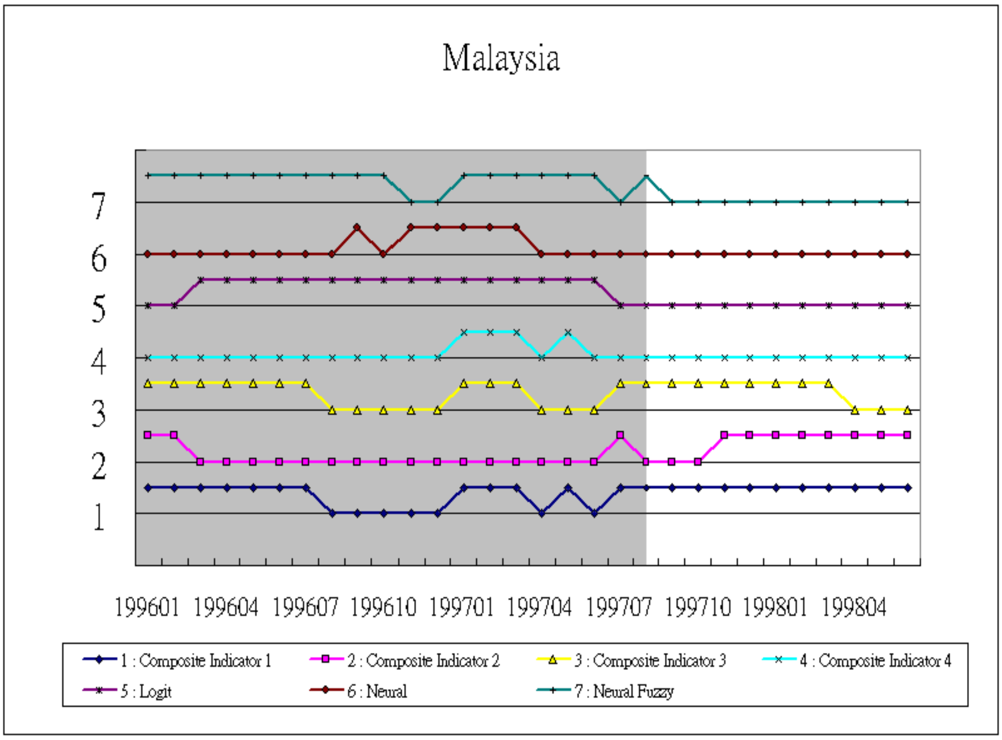


Figure 6. The signals given by each model for Malaysia

Table 11. Forecasting results given by each model for Philippine

Philippines								
	In-sample				Out-sample			
	Accuracy rate	Rank	Type I error	Rank	Accuracy rate	Rank	Type I error	Rank
CI 1	0.8397	6	0.5574	6	0.3667	2	1.0000	2
CI 2	0.8494	4	0.6066	7	0.3667	2	1.0000	2
CI 3	0.8141	7	0.1967	2	0.3667	2	1.0000	2
CI 4	0.8462	5	0.4918	5	0.2333	3	1.0000	2
Logit	0.8878	3	0.2951	3	0.0000	5	1.0000	2
Neural Network	0.9071	1	0.3934	4	0.0667	4	1.0000	2
Neuro Fuzzy	0.8910	2	0.1148	1	0.4667	1	0.4737	1
CI 1 ： Composite Indicator 1 (Signal Approach), CI 2 ： Composite Indicator 2 (Signal Approach) CI 3 ： Composite Indicator 3 (Signal Approach), CI 4 ： Composite Indicator 4 (Signal Approach)								

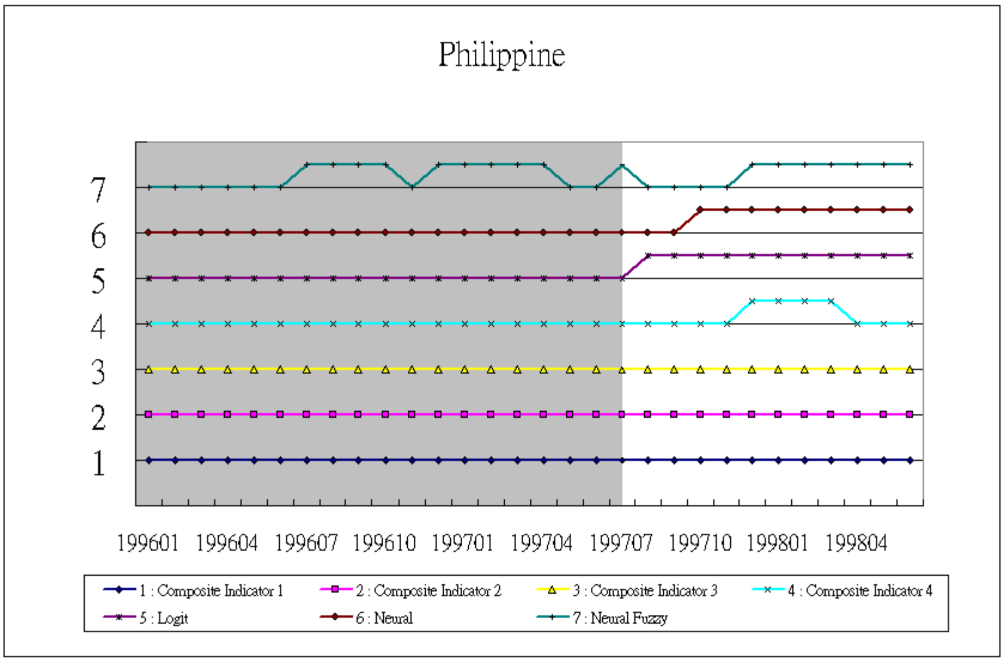


Figure 7. The signals given by each model for Philippine

Table12. Forecasting results given by each model for Thailand

Thailand								
	In-sample				Out-sample			
	Accuracy rate	Rank	Type I error	Rank	Accuracy rate	Rank	Type I error	Rank
CI 1	0.7853	5	0.6543	6	0.7000	2	0.4211	2
CI 2	0.7788	6	0.7284	7	0.4667	5	0.7895	5
CI 3	0.7500	7	0.4815	5	0.2333	6	0.8421	6
CI 4	0.8462	4	0.4691	4	0.9000	1	0.1579	1
Logit	0.8750	2	0.1975	3	0.6333	4	0.5789	4
Neural Network	0.8654	3	0.1605	2	0.6667	3	0.5263	3
Neuro Fuzzy	0.9006	1	0.1235	1	0.9000	1	0.1579	1
CI 1 ： Composite Indicator 1 (Signal Approach), CI 2 ： Composite Indicator 2 (Signal Approach)								
CI 3 ： Composite Indicator 3 (Signal Approach), CI 4 ： Composite Indicator 4 (Signal Approach)								

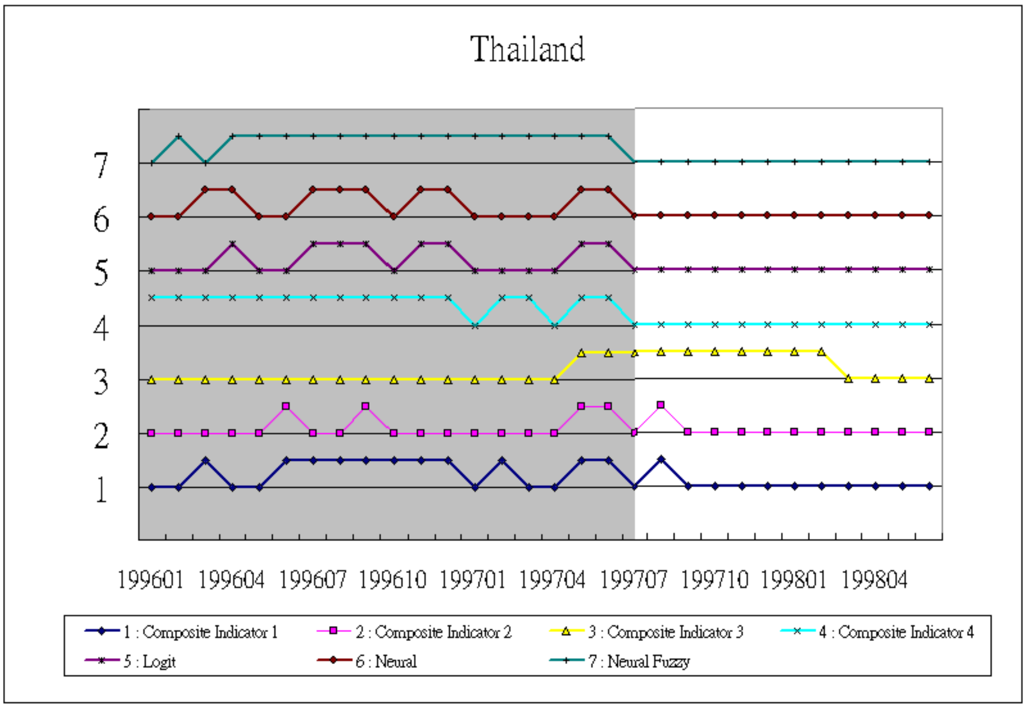


Figure 8. The signals given by each model for Thailand

6. Conclusions

There is wide agreement among financial economists and policy makers that in order to avoid the devastating damage on the economy due to the currency crisis, we need an effective early warning system as a necessary tool[7]. We have constructed in this paper such an early warning system by using the neuro fuzzy technique. We have compared its forecasting performance with those of signal approach and logit models. The empirical results show that neuro fuzzy model can provide as high an accuracy rate as 80.62% for the out-sample data set. Besides, the knowledge base provides a more detailed relationship among the variables, suggesting concrete policies for increasing the chances of avoiding the crisis. The 3-dimensional graphics can also show a more clear relationship and the interaction effects between the variables. These relationships can also be the basis for theoretical modifications of the modeling approach for further research.

In summary, then, our work makes the following main contributions: First, we try to explain the relationship between chances of a currency crisis and the explanatory and policy variables through the construction of a knowledge base. This illustrates the value of a more detailed cognitive approach to rational decision making. Second, we provide an alternative to deal with the inherent nonlinearities of this problem. Finally, our general approach to uncovering the relationships among the variables inductively be the base for further hypothesis testing regarding important explanatory factors for currency crises. Another important area of future application could be banking and even broader financial crises.

[7] Clearly, this may not be sufficient if for example, there is not sufficient flexibility to change existing policies and implement the necessary safeguards. Both financial and administrative resources may be lacking in some cases. However, without an effective early warning system, even a capable administrative authority may be unable to act in time to prevent a crisis.

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Appendix 1. The souces of the indicators.

Indicators	Sources
M2 multiplier	The ratio of M2 (IFS lines 34 plus 35) to base money (IFS line 14)
Domestic credit/GDP	IFS line 52 divided by IFS line 64 to obtain domestic credit in real terms, which was then divided by IFS line 99b.p. (interpolated) to obtain the domestic credit/GDP ratio. Monthly real GDP was interpolated from annual data.
Real interest rate	Deposit rate (IFS line 60) deflated using consumer prices (IFS line 64). Monthly rates expressed in percentage points. In levels.
Lending-deposit rate ratio	IFS line 60p divided by IFS line 60 was used in lieu of differential to ameliorate the distortions caused by the large percentage point spreads observed during high inflation. In levels.
M2/reserves	IFS lines 34 plus 35 converted into dollars (using IFS line ae) divided by IFS line 1L.d.
Bank deposits	IFS line 24 plus 25 deflated by consumer prices (IFS line 64).
Exports	IFS line 70.
Terms of trade	The unit value of exports (IFS line 74) over the unit value of imports (IFS line 75). For those developing countries where import unit values (or import price indices) were not available, an index of prices of manufactured exports from industrial countries to developing countries was used.
Real exchange rate	The real exchange rate index is derived from a nominal exchange rate index, adjusted for relative consumer prices (IFS line 64). The measure is defined as the relative price of foreign goods (in domestic currency) to the price of domestic goods. The nominal exchange rate index is a weighted average of the exchange rates of the 19 OECD countries with weights equal to the country trade shares with the OECD countries. Since not all real appreciations reflect disequilibrium phenomena, we focus on deviations of the real exchange rate from trend. The trend was specified as, alternatively, log, linear, and exponential; the best fit among these was selected on a country-by-country basis. In level.
Imports	IFS line 71.
Reserves	IFS line 1L.d.
Output	For most countries, the measure of output used is industrial production (IFS line 66). However, for some countries, (the commodity exporters) an index of output of primary commodities is used (IFS lines 66aa) if industrial production is not available.
Stock prices	IFC global indices are used for all emerging markets; for industrial countries the quotes from the main boards are used. All stock prices are in US dollars.