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A Neural Fuzzy System for Sovereign Debt Service Capacity Evaluation

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This study used neural fuzzy logic to develop models for estimating sovereign debt service capacity. These models were more robust, flexible, and economic and performed better than the models developed using the neural network method alone.

I. INTRODUCTION

When estimating a sovereign's debt service capacity (DSC hereafter), we usually use one or several variables as indicators. For instance, the debt service ratio is one of the most important and widely used indicators for predicting a sovereign's DSC. However, the debt service ratio alone is not very reliable for this purpose. There are some instances wherein a country with a high debt service ratio has resisted default while others, even with a relatively low ratio, have not.

To remedy this problem, we can use several indicators to form complex prediction models by employing either traditional statistical methods or newer techniques, such as neural networks (hereafter NN). However, neither statistical methods nor NN are ideal in optimizing the prediction model (See Parhizgari and Liu [10]).

When statistical methods are used, we can eliminate unimportant independent variables through significance tests; and the meaning of the parameters obtained can be easily interpreted. However, these methods assume that a certain functional relationship exists between the dependent variable and independent variables. This assumption may not always be true. Another disadvantage of these methods is that when some of the independent variables are highly correlated with each other (i.e., when multicollinearity exists) the parameters obtained are difficult to interpret and the resulting models are not stable.

NN are computer programs that simulate the way the human brain functions. The basic building blocks of NN are simulated neurons, which

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process a number of inputs to produce outputs. NN consist of neurons in the format of layers and nodes. The collective behavior of all these neurons demonstrates the ability to learn, recall, and generalize from training data. NN have been employed to solve a variety of financial problems (See Trippi and Turban [13]).

Although NN can remedy some of the problems of statistical methods, they have several shortcomings that have limited their applications. First, NN are often taken as a "black box": It is very difficult to determine the optimal number of hidden layers and nodes in each layer for proper learning to take place. The optimal model can be obtained only through experiments and by fine-tuning the learning parameters. Second, most NN "learn" through some form of back-propagation process, which analyzes data by the steepest descent in weight space, and thus learning may be trapped in local minima. In addition, the pattern may not be learned, and the learning can be lengthy.

Other techniques have been developed to improve model building, one of which is fuzzy logic. First proposed by Zadeh [18], fuzzy logic has gained tremendous popularity in recent years. Along with NN and genetic algorithms, fuzzy logic constitutes three stones corner of "soft computing" [19]. Unlike traditional or hard computing, soft computing strives to model the pervasive imprecision of the real world.

In real life, information available for decisions is not always a matter of black or white, true or false; it often involves gray areas. Fuzzy sets and fuzzy logic were developed to represent, manipulate, and utilize uncertain information and to provide a framework for handling uncertainty and imprecision in real-world applications. In recent years, fuzzy logic has also been applied in financial researches, such as investment (See Tanaka [12]), project cost estimation (See Turunen and Dohnal [14]), business planning (See hruschka [3]), financial ratio analysis (See Gutierrez and Carmona [2]), commercial loan analysis (See Levy and Duchessi [7]), and stock selection (See Wong, Wang and Quck [17]).

Fuzzy logic has the key advantage of being able to describe the desired system behavior with simple IF-THEN relations; however, such relations are difficult to identify by the naked eye and must be inferred from observed data. The manual derivation of fuzzy rules from large data sets is at best a time-consuming and at worst an impossible process.

Some authors (e.g., (Lin [8]) and von Altrock [16]) observe that the combination of NN and fuzzy logic can benefit from complementation where NN provide the connectionist structure (fault tolerance and distributed representation properties) and learning abilities and fuzzy logic systems provide a structural framework with high-level fuzzy IF-THEN rule thinking and reasoning. This study aims to combine the advantages of NN and fuzzy logic in developing a neural fuzzy system that can be used to evaluate the creditworthiness of sovereign borrowers.

The rest of the paper is organized as follows: Section 2 introduces the notion of fuzzy logic. Section 3 describes the data used in this study. Section 4 discusses the procedures used to develop our system. Section 5 reports the evaluation results of this system. Section 6 contains a few concluding remarks.

II. FUZZY LOGIC SYSTEMS

The term "fuzzy logic" is currently used in two different senses. In a narrow sense, fuzzy logic is a logical system that aims to formalize approximate reasoning. In a broad sense, fuzzy logic and fuzzy set are almost synonyms. Unlike a classical set that has a crisp, clearly defined boundary, a fuzzy set can contain elements with only a partial degree of membership. The elements have membership values that represent the strength of their membership in a set. Today, the growing tendency is to use the term fuzzy logic in its broad sense (See Zahedi [21]).

Fuzzy inference refers to the process of mapping from a given input to an output using fuzzy logic. This process involves membership functions, fuzzy logic operators, and IF-THEN rules.

1. Membership functions

Traditional logic programs rely on Boolean logic. Inside a program, the switch is either on or off, yes or no, or true or false. With fuzzy logic, inputs are placed into fuzzy sets with varying membership values in a step called fuzzification. Membership values are usually assigned according to knowledge or experience to denote to what degree an element belongs to a fuzzy set. Since a membership value can be any number between 1 (completely true) to 0 (completely false), fuzzy logic is also called "continuous logic." Because fuzzy logic avoids the rigidity of standard mathematical reasoning in handling ambiguous and inexact knowledge, it abridges the task of translating between human inferencing and conventional computer programs, which are characterized by stringent manipulations. This dramatically simplifies the solution of many decision support problems to which rigorous mathematical models are unavailable.

A concept that plays a central role in the application of fuzzy logic is linguistic variables, whose values are words rather than numbers. For example, debt service ratio can be defined as a linguistic variable with two possible values: high and low. A country with a debt service ratio of 50% and above can be assigned to the group of high risk countries with a membership value of 1. A country whose debt service ratio is 40% can be assigned to the same group but with a membership value of only 0.75. An element of a set is denoted by {its membership value/its value}. For example, the elements of High Risk Country Group can be denoted by:

High Risk Country Group={0/10%, 0.25/20%, 0.5/30%, 0.75/40%, 1/50%} (1)

The complement of the High Risk Country Group is denoted by:

Low Risk Country Group={1/10%, 0.75/20%, 0.5/30%, 0.25/40%, 0/50%} (2)

In this example, any element, such as a 40% debt service ratio, can be a member of both the High Risk Country Group and the Low Risk Country Group because it has nonzero membership values in both sets. Since its membership value in the first set is 0.75, compared with 0.25 in the second set, 40% debt service ratio denotes more of a high risk country than a low risk country. Thus, the fuzzy set theory codifies the way we normally address vague concepts such as risk.

2. Fuzzy Logic Operators

Fuzzy logical reasoning is a superset of standard Boolean logic. Just as classical sets can be manipulated with logical operators, fuzzy sets can be manipulated with fuzzy operators. If we keep the fuzzy values to the extremes of 1 (completely true) and 0 (completely false), standard logical operations will hold. In fact, for each logical operator, a corresponding fuzzy operator exists. Therefore, the standard Boolean logic operators, such as AND, OR, and NOT, have counterparts in fuzzy logic, which are generally defined as a minimum function, a maximum function and an additive complement, respectively.

3. IF-THEN Rules

Fuzzy or approximate reasoning is a coordinated system of inference procedures. It is characterized by fuzzy production rules of the form, “If X is A, then Y is B,” where “X is A” is called the antecedent and “Y is B” is called the consequent of the rule. A and B are fuzzy sets, or terms, of linguistic variables X and Y, respectively. Using the previous example, a fuzzy rule for DSC may be: “IF the debt service ratio is high, THEN the default risk is high."

Interpreting IF-THEN rules is a three-part process:

1. Fuzzify inputs: Resolve all fuzzy statements in the antecedent to a degree of membership between 0 and 1. For example, based on a given membership

function, a borrowing country's debt service ratio is assessed to determine to what degree it belongs to the high debt service ratio group. The membership value is known as the degree of support for the rule; i.e., the degree of truth of the rule.

2. Apply fuzzy operators: If there are multiple parts to the antecedent, apply fuzzy logic operators and resolve the antecedent to a single number between 0 and 1. For example, given another rule that "IF the debt service ratio is high AND the total debt to export ratio is high, THEN the default risk is high," two membership values would have to be determined for each borrowing country to denote to what degree it has a high debt service ratio and a high total debt to export ratio. Then, since the two parts are connected by the fuzzy operator "AND," the degree of support for the rule is the minimum of the two membership values.
3. Apply implication methods: Use the degree of support for the rule to determine the membership value of the output fuzzy set. For example, if the degree of support for the rule is 0.8 for a borrowing country, it will be assigned to the high default risk group with a membership value of 0.8.

Generally, in order to map vague concepts, such as high risk versus low risk, a fuzzy system should contain two or more rules that can play off one another. The output of each rule is a fuzzy set, but in practice the output is often required to be a single number. To distill all these fuzzy sets into a single crisp result for the output variable, the output fuzzy sets produced from individual rules are first aggregated into a single output fuzzy set and then the resulting set is defuzzified, or resolved, to produce a single number.

III. DATA

The data used in this study were collected from the "World Debt Table" published by the World Bank. Data from 43 countries (see Table 1) during the period between 1983 and 1990 are included in the data set. There are 290 observations of which 94 have incidents purporting debt rescheduling.

Table 1
Summary of Coverage and Data Inputs

Country	Observation	Country	Observation
A. Latin America & Caribbean		C. Africa South of Sahara	

1. Argentina	1983-90	22. Congo	1986-89
2. Bolivia	1985-90	23. Gabon	1983-90
3. Brazil	1985-90	24. Ghana	1983-90
4. Chile	1985-90	25. Kenya	1985-90
5. Columbia	1983-90	26. Madagascar	1985-89
6. Dominican Republic	1983-90	27. Mali	1983-90
7. Ecuador	1985-90	28. Nigeria	1985-90
8. Honduras	1985-90	29. Senegal	1985-90
9. Jamaica	1985-90	30. Sudan	1985-90
10. Peru	1985-90	31. Tanzania	1985-90
11. Uruguay	1985-90	32. Zaire	1985-90
12. Costa Rica	1983-89	33. Zambia	1985-90
B. North Africa & Middle East		D. Asia	
13. Algeria	1983-90	34. China	1983-90
14. Cyprus	1983-90	35. India	1983-90
15. Egypt	1983-90	36. Indonesia	1983-90
16. Jordan	1983-90	37. Korea	1983-90
17. Morocco	1983-90	38. Laos	1984-90
18. Syria	1983-90	39. Malaysia	1983-90
19. Tunisia	1983-90	40. Pakistan	1983-90
20. Turkey	1983-89	41. Philippines	1983, 1985-90
21. Malta	1983-89	42. Sri Lanka	1985-90
		43. Thailand	1983-90

The determinants (i.e., the explanatory variables) of DSC used in this study include:

1. Total Debt to Export Ratio (X_1). The rationale for using this ratio is that the higher the total debt, the greater the need to increase exports in order to maintain the ability to pay the debt. If the increase in exports

does not keep up with the increase in debt, the country is more likely to default on its debt obligation.

2. Total Debt to GNP Ratio (X_2). The reason for adopting this variable is easy to understand: The higher the total debt to GNP ratio is, the more vulnerable the economy is to internal and/or external shocks.
3. Debt Service Ratio (X_3). This ratio is obtained by dividing exports of goods and services into debt service payments (including interest and principal). A shortfall in export earnings will force the government to draw upon exchange reserves or cut down imports in order to accommodate debt service payments. Thus, an increase in this ratio is expected to increase the risk of debt rescheduling.
4. Interest Payment to Export Ratio (X_4). This ratio is similar to the debt service ratio.
5. Interest Payment to GNP (X_5). While the above variables demonstrate primarily the impact of exports on a country's DSC, this ratio is expected to capture the pure burden of interest payments. In this regard, a high ratio would tend to increase the need for painful domestic adjustments, thereby causing a higher probability of rescheduling.
6. International Reserves to Total Debt Ratio (X_6). The effect of this variable is easy to understand: If a sovereign has a large reserve of foreign exchanges, it would be in a strong position to deal with financial shocks; thus, the risk of debt rescheduling is lower.
7. International Reserves to Imports Ratio (X_7). A high ratio of international exchange reserves (such as foreign exchange, SDR, gold, etc.) to import indicates that the country would have a strong ability to maintain the level of imports even if its exports decrease; thus, the likelihood of default will decrease.
8. Short-term Debt to Total Debt Ratio (X_8). If a sovereign secures some short-term debt, the country would have more cash in hand to pay back the interest of long-term debt. Thus, debt rescheduling is less likely to occur.
9. Concessional to Total Debt Ratio (X_9). If large chunks of the debt are concessional, the probability of debt rescheduling will be small.
10. Multilateral to total debt ratio (X_{10}). If a country has multilateral resources, it would have more flexibility in dealing with financial shocks.

Until now no economic theory has identified a unique set of indicators with which to build an optimal prediction model. The above specification can only be taken as a plausible choice among many alternatives.

To facilitate the evaluation of the models built, we randomly split the data set into two sub-samples of training and checking under three different sizes: 60 percent and 40 percent, 70 percent and 30 percent, and 80 percent and 20 percent of the total sample. These arbitrary ratios were selected for the sake of model building and performance comparisons. The training sub-samples were employed to build models while the checking sub-samples were used to evaluate the predictions made by the models developed.

IV. DEVELOPMENT OF A NEURAL FUZZY SYSTEM

In this study, we integrated fuzzy logic with NN and developed a neural fuzzy system to predict the DSC of borrowing countries. The system was created in two steps.

Step I. Training data were utilized to develop a fuzzy model.

A fuzzy system can be built if human expertise or experience is available for the definition of membership functions. If such knowledge is not available, sample data can be used to derive membership functions, using techniques known collectively as fuzzy clustering. The purpose of fuzzy clustering is to identify the number of clusters that exist in a given data set. As with traditional clustering procedures, a user can specify the expected number of clusters or let the system “find” the likely number of clusters from input data.

In this study, we used the GENFIS2 function of the Fuzzy Logic Toolbox [1]. This function can extract a set of rules by clustering the training data to generate an initial fuzzy model that describes the data behavior. The general format of the GENFIS2 function is:

$$\text{Fismat} = \text{genfis2 (Xin, Xout, radius)} \tag{3}$$

where Fismat is the fuzzy model estimation, Xin is the input data set, Xout is the output data set, and radius specifies a cluster center’s range of influence on each variable. A large radius results in fewer rules and clusters, whereas a small radius results in more rules and clusters.

Since, ideally, the data should form two clusters (default versus non-default countries), different radii were tried, and eventually a large radius (1.5) was selected for the final specification of the GENFIS2 function. The resulting fuzzy model includes two membership functions for each input variable. The third input variable, Debt Service Ratio (DSR hereafter), for example, has two membership functions that may be labeled as small DSR and large DSR.

The fuzzy model also includes two fuzzy rules that take the following form:

$$\text{If } x \text{ is A and } y \text{ is B, then } z = p*x + q*y + r, \tag{3}$$

where A ar zy sets (of input variables); p, q, and r are constants estimated by the model; and z is the output variable; i.e., the default risk. The consequent of the rules is a linear function rather than a fuzzy set. A fuzzy model that of fuzzy rules is known as a Sugeno fuzzy model (See Sugeno [11 fuzzy model is easier to work with than the other type, the Mamdani fuzzy model (See Mamdani and Assilian [9]), because the defuzzification process is simplified.

Figure 1 depicts the fuzzy system derived from the fuzzy clustering procedure described previously. Each input variable had two membership functions that contributed to the classification of cases according to the fuzzy rules mentioned above.

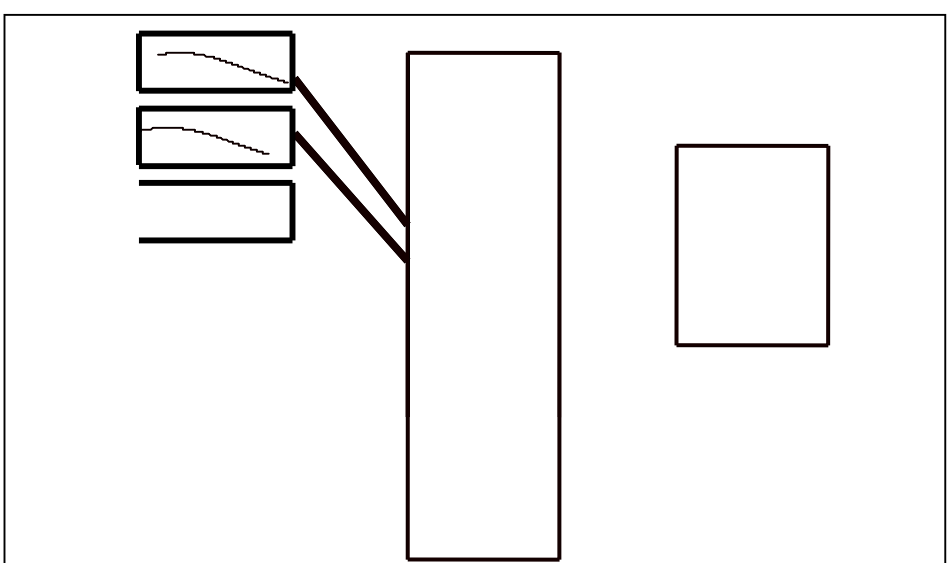
Figure 2 is an enlargement of the membership functions for the third input variable, debt service ratio, depicted in Figure 1. The membership functions for other input variables had similar forms as can be seen in Figure 1.

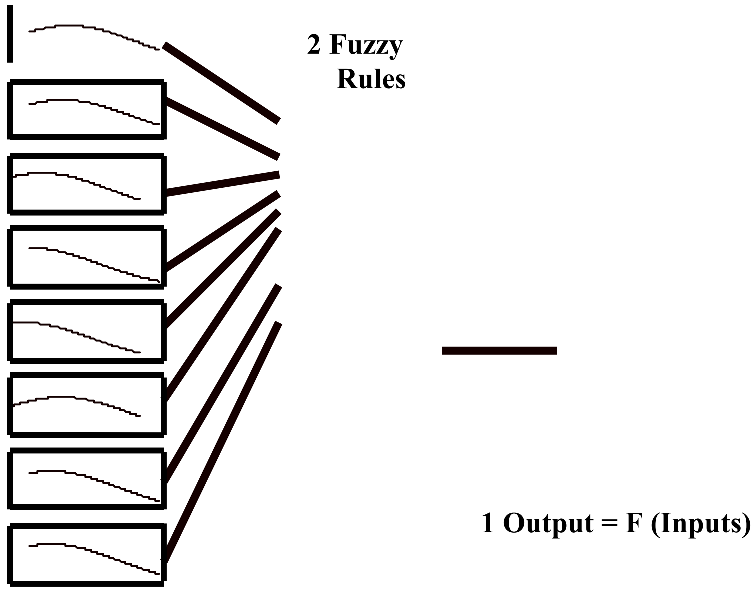
Step II. The was refined using NN techniques.

Even though many alternative ways of integrating fuzzy logic and NN have been propos actually been implemented [16]. The fuzzy model developed from the first step was improved through an iterative adaptive learning process implemented in Fuzzy Logic Toolbox [1]. The training algorithm was developed by Jang [5] and termed Adaptive Neuro-Fuzzy Inference System, or ANFIS. Basically, ANFIS takes a fuzzy model and tunes it with a back propagation algorithm. During each epoch, an error measure, usually defined as the sum of the squared difference between the actual and desired output, is reduced. Training stops when the predefined epoch number or error rate is obtained.

Figure 1

Neural fuzzy system





The ANFIS technique is implemented in Fuzzy Logic Toolbox as a function with the following format:

Fismat1, TrnErr, StepSize, Fismat2, ChkErr=Anfis (TrnData, Fismat, ChkData)

10 Inputs (5)

where Fismat is the fuzzy model to be trained, TrnData is the training data set, and ChkData is the checking data set. Fismat1 is the resulting fuzzy model that records the minimum training error, and Fismat2 is the resulting fuzzy model that records the minimum checking error.

Figure 2

Membership functions for debt service ratio

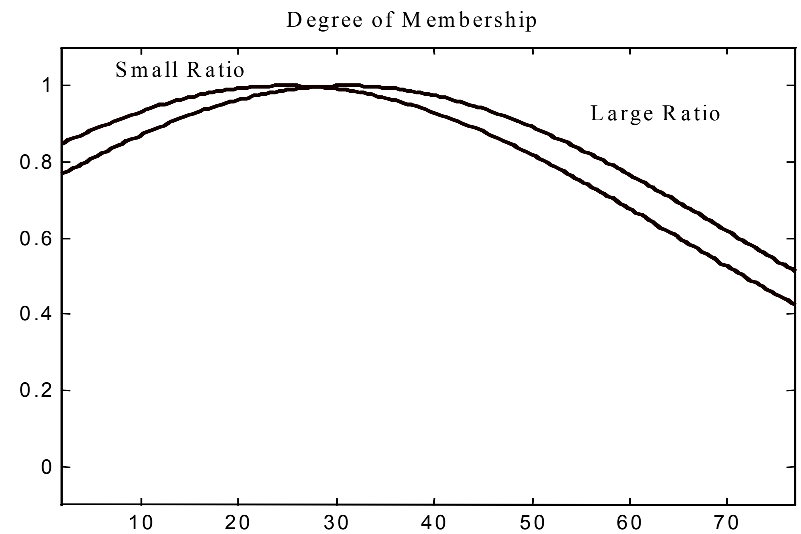
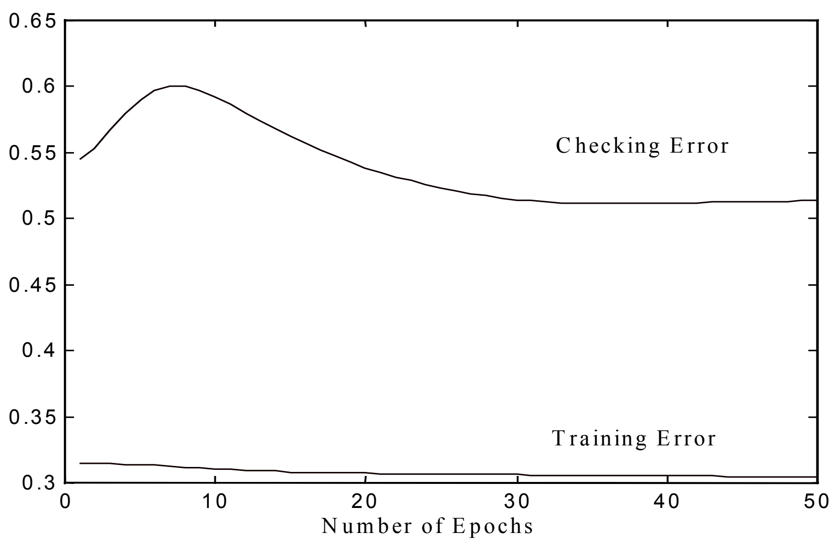


Figure 3
Checking and training error



For the first sub-sample (60% training, 40% checking), the fuzzy system was trained with 50 epochs. Figure 3 shows the training errors and checking errors during different epochs. The initial training error was 0.3152, which was reduced through each epoch; and the minimum of 0.3045 was reached at epoch 50. The system's performance using the training data could be improved further; however, it would be at the expense of higher checking errors. The initial checking error was 0.5452; and the minimum checking error of 0.5117 was reached at epoch 36, suggesting that the optimal performance of the neural fuzzy system in DSC prediction using the checking data had been achieved. Because we were interested in developing a model that would minimize checking errors, Fismat2 was used to calculate the predicted output of the system. A similar procedure was applied to the second and the third sub-sample to obtain a separate neural fuzzy system with minimum checking error.

V. RESULTS

The performance of the improved neural fuzzy models was then evaluated by applying the models to the checking data. As discussed earlier, the output of the models was a crisp number denoting the default risk of each borrowing country. In order to evaluate the creditworthiness of borrowing countries, one needs to establish a cutoff point so that the countries can be assigned to default or non-default group based on their default risk. Since no standard cutoff point exists, we will present our results based on different cutoff points.

Like any classification model, a neural fuzzy model will commit some errors. When a model predicted a borrowing country would not default on the debt obligation but in actuality default took place, the model committed "default errors." On the other hand, if the model predicted that a country would default on the debt obligation but actually the country did not, "non-default errors" were committed.

Table 2 reports the performance of these models when the cutoff point was set at 0.5. From the data shown in table 2, we can see that Model 1 (60% training and 40% checking) committed 8 default errors, resulting in a 7.27% default error rate and 12 non-default errors, resulting in a 10.91% non-default error rate. The total error rate of this model was 18.18%. The other two models had similar results. Among these rates, the most important should be the default error rate. A lending institution may lose not only the interest it could have earned but also part of or even the entire investment when a default error is made. Consequently, a model with a low default error rate is valuable to a lender.

Table 2

Prediction results of neural fuzzy system with a 0.5 cutoff point

Model 1	Predicted Case

			Non-default	Default	Total
	Actual Case	Non-default	70	12	82
		Default	8	20	28
		Total	78	32	110
Model 2			Predicted Case		
			Non-default	Default	Total
	Actual Case	Non-default	54	10	64
		Default	7	21	28
		Total	61	31	92
Model 3			Predicted Case		
			Non-default	Default	Total
	Actual Case	Non-default	35	4	39
		Default	8	11	19
		Total	43	15	58

Table 3
Performance comparison between neural fuzzy models and NN models

		Neural Fuzzy Models	NN Models
1	Default Error Rate	7.27%	8.56%
	Non-default Error Rate	10.91%	14.51%
	Total Error Rate	18.18%	23.07%
2	Default Error Rate	7.61%	8.92%
	Non-default Error Rate	10.87%	14.99%
	Total Error Rate	18.48%	23.91%
3	Default Error Rate	13.79%	15.43%
	Non-default Error Rate	6.90%	6.99%
	Total Error Rate	20.69%	22.41%

To evaluate the performance of the obtained models, we compared the error rates with those of NN models developed in a previous research that used the same data set [10]. As shown in Table 3, neural fuzzy models achieved better prediction performance than the NN models did.

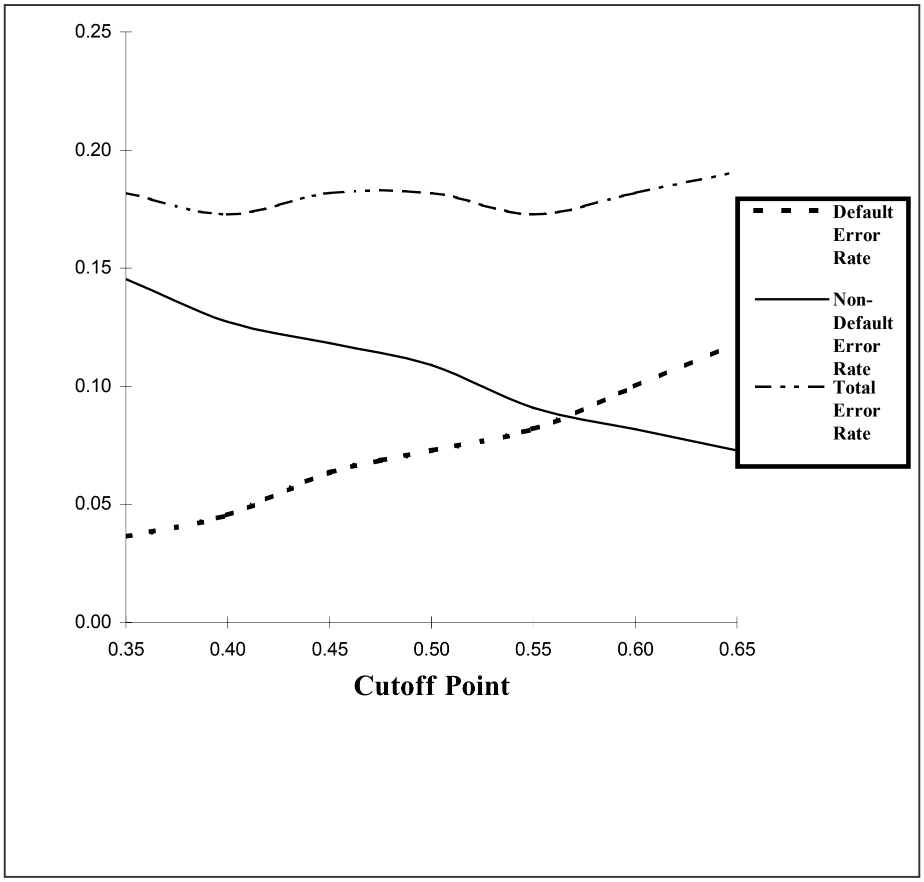
However, it must be pointed out that minimizing the default error rate is not the only consideration in model building because a decrease of default error rate is usually accompanied by an increase of non-default error rate. We did some experiments to find an optimal cutoff point. Table 4 reports the different default error rates, non-default error rates and total error rates of the three models at different cutoff points. Figure 4 plots these rates for model 1 at different cutoff points.

Table 4
Error rates of neural fuzzy system

	Model 1						
Cutoff Point	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Default Error Rate	0.04	0.05	0.06	0.07	0.08	0.10	0.12
Non-Default Error Rate	0.15	0.13	0.12	0.11	0.09	0.08	0.07
Total Error Rate	0.18	0.17	0.18	0.18	0.17	0.18	0.19
	Model 2						
Cutoff Point	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Default Error Rate	0.00	0.03	0.03	0.08	0.10	0.12	0.13
Non-Default Error Rate	0.16	0.14	0.12	0.11	0.07	0.04	0.04
Total Error Rate	0.16	0.17	0.15	0.18	0.16	0.16	0.17
	Model 3						
Cutoff Point	0.35	0.40	0.45	0.50	0.55	0.60	0.65
Default Error Rate	0.02	0.03	0.09	0.14	0.16	0.17	0.17
Non-Default Error Rate	0.16	0.12	0.10	0.07	0.05	0.03	0.03
Total Error Rate	0.17	0.16	0.19	0.21	0.21	0.21	0.21

Figure 4

Error rates based on different cutoff points (Model 1)



From Figure 4, we can see that lower cutoff points resulted in lower default error rates but higher non-default rates. It means that if a lending institution lowers the cutoff point, it would have to reject more applications; and thus, the volume of transactions would be lower. Consequently, the lender would lose the opportunity to make more profit. This implies that lenders should weigh the different misclassification costs of default errors and non-default errors and choose a suitable cutoff point.[1] For instance, if a bank uses model 1 and accepts a 5% default rate, then it should use 0.4 as the cutoff point for assessing the risk of new loans.

VI. CONCLUSION

Various modeling approaches have been developed over the years to estimate sovereign debt service capacity. In this study, estimation models were developed by combining fuzzy logic with NN techniques. These models were found to achieve better prediction results than did previously developed NN models.

In addition to performance advantage, several other strengths are present in neural fuzzy systems. First, their explicit membership functions (e.g., High Risk Country Group in our system) are meaningful to users. In comparison, the discriminatory capability of NN is difficult to express in symbolic forms. In the case where models are built mainly for prediction purposes, this may not constitute a serious drawback. However, in most studies, we want to know the significance of all input variables. Since most NN systems do not have explanation facilities, justification for results is difficult because the connection weights do not usually have obvious interpretations.

Second, unlike previous statistic or NN models, which all use quantified values, neural fuzzy systems use linguistic values that may be viewed as a form of data compression [20]. This process is often referred to as granulation. The most important advantage of granulation over quantization is that it mimics the way in which humans interpret linguistic values.

Another advantage of neural fuzzy systems is that the transition from one linguistic value to another is gradual rather than abrupt, resulting in continuity and robustness. Thus, neural fuzzy systems can be more general than previous NN models or statistic models.

On the other hand, a major limitation of fuzzy logic is that the fuzzy rules are often unknown beforehand and thus have to be derived from large data sets. NN can be utilized to improve the derived rules until a desired performance level is achieved. This research has shown that the integration of fuzzy logic and NN is an effective solution to the sovereign debt service capacity problem. The application of the same approach to other financial problems should be equally promising.

NOTES

1. More detailed discussions about the relationship between misclassification costs and cutoff point can be found in Koh (1992) and Hsieh (1993).

REFERENCES

[1] Gulley, N. and R. Jang. (1996). *Fuzzy Logic Toolbox User's Guide*, The

Math Works.
[2] Gutierrez, I. and S. Carmona. (1988). "A Fuzzy Set Approach to Financial Ratio Analysis," *European Journal of Operational Research,* 36, 78-84.
[3] Hruschka, H. (1988) "Use of Fuzzy Relations in Rule-Based Decision Support Systems for Business Planning Problems," *European Journal of Operational Research*, 34, 326-33.
[4] Hsieh, S.J. (1993). "A Note on the Optimal Cutoff Point in Bankruptcy Prediction Models," *Journal of Business Finance & Accounting,* 20, (3), 457-464.
[5] Jang, J.S.R. (1993). "Self-Learning Fuzzy Controllers Based on Temporal Back Propagation," *IEEE Transactions on Neural Networks*, 3, (5), 714-723.
[6] Koh, H.C. (1992). "The Sensitivity of Optimal Cutoff Points to Misclassification Costs of Type I and Type II Errors in the Going-Concern Prediction Context," *Journal of Business Finance & Accounting,* 19, (2), 187-197.
[7] Levy, J., E. Mallach, and P. Duchessi. (1991). "A Fuzzy Logic Evaluation System for Commercial Loan Analysis," *Omega*, 19, (6), 651-669.
[8] Lin, C.T. and C.S. Lee. (1996). *Neural Fuzzy Systems*, Prentice Hall.
[9] Mamdani, E.H. and S. Assilian. (1975). "An Experiment in Linguistic Synthesis with a Fuzzy Logic Controller," *International Journal of Man-machine Studies*, 7, (1), 1-13.
[10] Parhizgari, A. and W. Liu. (1997). "Debt Service Capacity Revisited: A New Approach," *Journal of Transnational Management Development,* 3, (1), 25-38.
[11] Sugeno, M. (1985) *Industrial Applications of Fuzzy Control*, Elsevier Science.
[12] Tanaka, H. (1975). "A Formulation of Fuzzy Decision Problems and Its Application to an Investment Problem," *Kybernetes,* 5, 25-30.
[13] Trippi, R.R. and E. Turban. (1995). *Neural Networks in Finance & Investing: Using Artificial Intelligence to Improve Real-world Performance*, 2/e, Irwin.
[14] Turunen, I., M. Jarvelainen, and M. Dohnal. (1984). "Fuzzy Approach to Factorial Cost Estimation of Chemical Plants," *Engineer Costs Production Economics,*7, (4), 279-272.
[15] von Altrock, C. (1995). *Fuzzy Logic and NeuroFuzzy Applications Explained*, Prentice Hall.
[16] von Altrock, C. (1997). *Fuzzy Logic & NeuroFuzzy Applications in Business & Finance*, Prentice Hall.

[17] Wong, F.S., P.Z. Wang, T.H. Goh, and B.K. Quek. (1992). "Fuzzy Neural Systems for Stock Selection," *Financial Analysts Journal,* January-February.
[18] Zadeh, L.A. (1965). "Fuzzy Sets," *Information and Control*, 8, (3), 338-353.
[19] Zadeh, L.A. (1988). "Fuzzy Logic," *Computer,* April, 83-93.
[20] Zadeh, L.A. (1994). "Fuzzy Logic, Neural Networks and Soft Computing," *Communication of the ACM,* 37, (3), 77-84.
[21] Zahedi, F. (1993). *Intelligent Systems for Business: Expert Systems with Neural Networks*, Belmont, CA: Wadsworth.