Paper:

Financial Institution Failure Prediction Using Adaptive Neuro-Fuzzy Inference Systems: Evidence from the East Asian Economic Crisis

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This paper introduces the use of Adaptive Neuro-Fuzzy Inference Systems (ANFIS) into the area of finance for Thai firms. This study started with collecting financial data from 82 finance companies and 15 commercial banks operating in the period 1992-1997, before the East Asian economic crisis occurred. Financial data on failed and non-failed firms were then examined to develop fuzzy rules based on CAMEL variables. ANFIS is applied to the area of finance for Thai firms for constructing failure prediction models. These models show that prediction accuracy is greater than 90 percent for one to five years prior to failure, indicating the robustness of models over time. In experiments, models yield more accurate forecasting than a logistic model that has been used in the area of finance for Thai firms. The purpose of this study is to present that models using ANFIS are better suited for financial data sets with high nonlinearity than a logistic model.

Keywords: failure prediction models, financial sector fragility, early warning systems, adaptive neuro-fuzzy inference systems (ANFIS), East Asian economic crisis

1. Introduction

Constructing sound prediction models for financial institution failures could contribute positively and significantly to the economy. Early-warning systems developed from failure prediction models, for examples, have been proven to reduce the chance that a financial institution may get into difficulty or even go bankrupt [1–8]. This should in turn prevent the systemic collapse of a country's economy.

A lack of effective early warning systems may lead to a catastrophe of economic. The collapse of the Thai financial and banking sector in 1997-1998 is a good example. Thailand was at the origin of the Asian financial crisis of 1997. During the East Asian economic crisis, 70 out of 91 finance companies closed in 1997-1998. In relation to banking, of the 15 domestic banks operating in 1994, one was closed, three merged with government-owned banks, two were taken over by the government and three became foreign-owned during the crisis.

Even though the main origin of the East Asian financial crisis was not a lack of sound early-warning systems, the adverse impact of the crisis might have been less if Thailand had such effective systems. On the bright side, the economic crisis enabled us to develop failure prediction models for financial institutions in an emerging market economy where little evidence has been provided.

Since the 1970s, models attempting to predict the difficulty and failure of individual financial institutions, i.e., early warning systems, have been developed [1, 5, 6, 9–11] that were mostly applied to banking and financial sectors in developed countries. These models emphasize identifying financial institutions early that are potentially financially troubled and may fail.

To date, several approaches based on Artificial Neural Networks (ANNs) have been proposed to predict financial difficulty and bankruptcy [12–16]. Although ANNs have proven to be a powerful general technique for classification tasks, however, the most significant shortcoming of ANNs is that a trained ANN is essentially a "black box." ANNs cannot provide a comprehensive explanation of how to relate input attributes to output prediction. After training, neural networks are often very difficult to interpret [17].

This study also relates to literature on predicting difficulty and failure/bankruptcy of financial institutions during an economy-wide crisis. The objective of this paper, using Thailand as an example, is to develop a model of predictive failure which provide a comprehensive explanation of prediction results. The purpose is to employ the technique of an Adaptive Neuro-Fuzzy Inference System (ANFIS), which is applied in the area of finance to Thai firms. The output of ANFIS is explained as rule-based systems. Although the crisis took place over a decade ago, its remaining impact is still felt in Thailand. Its implications also continue to be widely debated in the literature.

Overall, the proposed models show accuracy rates of more than 90 percent, which is explained with a set of

54 fuzzy rules at most. These results indicate that models serve as efficient early warning systems. This paper shows the development of a set of fuzzy rules based on CAMEL variables that have been widely used in prior studies. CAMEL variables are based upon five critical elements of a credit union's operations, which are (1) **C**apital, (2) **A**sset Quality, (3) **M**anagement competency, (4) **E**arnings, and (5) **L**iability. In addition, this paper has included firm size as another variable for examining the "too big to fail" effect. Last, a comparison is shown in experiments between the proposed prediction model and a logistic model [18, 19]. Comparison is based on the same variables and our resulting accuracy is better than that using the logistic model.

The paper is structured as follows. Section 2 describes related works on CAMEL and prediction models. Section 3 discusses data, variables, and methodology used in this study. Section 4 examines empirical results of proposed models. Section 5 concludes with conclusions and brief statement of future work.

2. Related Work

2.1. CAMEL

The CAMEL ranking system, commonly used for the evaluation of financial performance, uses some financial ratios to help evaluate a bank's performance. Tarawneh [20] used CAMEL the ranking system to investigate the financial performance of Omani's commercial banks. He worked on different measurable relationships among bank size, asset, management, operational efficiency and financial performance based on data for the period of 1999-2003.

Kouser et al. [21] investigated the financial performance of Islamic banks and compared this with conventional banks operating in Pakistan using results of the CAMEL method. In their study, ratios defined by the CAMEL method are analyzed by using ANOVA to investigate significant differences.

This paper aims to develop financial institution prediction models that are sets of fuzzy rules based on CAMEL-type analysis. Criteria of CAMEL variables selection are the availability of data and the statistical significance of variables.

2.2. Prediction Models

Most previous research on the causes and origins of the East Asian crisis and other economic crises has studied macroeconomic factors that may help predict financial and/or currency crises [4, 22–26]. Although early warning systems using macroeconomic variables were effective in the timely detection of systemic crises, they did not recognize the contribution of firm-level weakness to the incidence of the crisis. In other words, macroeconomic analysis is "unlikely to be able to discriminate between the view that distressed financial institutions were hit by exogenous shocks and the view that many weaknesses before the crisis may have led to systemic financial distress" [27]. Hence, early warning systems using firm-level or microeconomic data are worth developing.

2.2.1. Linear and Nonlinear Regression Models

Aminian et al. [28] forecast economic data by comparing linear and nonlinear regression techniques. For the purpose of generality, the nonlinear regression technique outperforms the linear regression technique since economic data analyzed often exhibit some nonlinearity that cannot be captured by a linear model. Their work employs neural networks to forecast macroeconomic behavior based on financial data.

Zopounidis and Doumpos [29] presented the application of the UTilitès Additives DIScriminantes (UTADIS) method in forecasting bankruptcy risk and business failure prediction. Their results showed that the UTADIS method performed better than linear discriminant analysis.

2.2.2. Soft Computing Models

Olmeda [30] and Sookhanaphibarn et al. [31] compared the accuracy of parametric and nonparametric classifiers in the problem of bankruptcy prediction. They proposed a combination of decision support systems as an optimal system for bankruptcy risk rating. Their hybrid classifier consists of a neural network and logit. For comparison, their neural networks outperformed regression models and showed good performance for modeling nonlinear systems, but they suffered from an inability to explain the steps used to make decisions and to incorporate rules in their architecture.

Ravikumar and Ravi [32] developed a set of ensemble classifiers using a simple majority voting scheme consisting of ANFIS, SVM, Linear RBF, semionline RBF1 and semionline RBF2, Orthogonal RBF, and MLP. The authors conducted experiment on Spanish and US bank data. Models ANFIS, semionline RBF2 and MLP emerged as the most important models because they figured in the best ensemble combinations. The above study showed that ANFIS is advantageous in applications to the area of finance. For comparison with neural networks, resulting rules of ANFIS can be further adjusted without retraining a new data set.

2.3. Studies of Finance in Thai Firms

After the East Asian economic crisis of 1997, most studies of Thai firms investigated the impact of bankruptcy as addressed by Reynolds et al. [33] and Urapeepatanapong et al. [34]. Tirapat and Nittayagasetwat [35] focused on the analysis of financial variables in bankruptcy. Pongsatat et al. [36] examined the use of Ohlson's logit model and Altman's four-variance model for predicting the bankruptcy of large and small firms in Thailand. Charumilind et al. [37] conducted empirical analysis using univariate analysis by comparing patterns of financing structures and firms characteristics to discover the important factors determining access to long-term bank debt prior to the East Asian economic crisis.

Polsiri and Sookhanaphibarn [38] developed distress prediction models incorporating both governance and financial variables by using both logit and neural network approaches, and their studies show that using neural network approaches is more effective for dealing with financial data of Thai firms.

2.4. Contributions of this Paper

Compared with conventional approaches, i.e., regression models, ANFIS models are suitable for financial data sets with high nonlinearity. To build failure prediction models, ANFIS also yields results comparable with neural networks from the aspect of prediction accuracy. The advantage of ANFIS is in extracting the fuzzy rules that are adaptive. Specifically, in the area of finance in Thai firms, this paper presents the use of ANFIS for building failure prediction models. The contributions of this paper are as follows:

1. Applying ANFIS with high nonlinearity to finance data of Thai firms.
2. Combining CAMEL models for selecting financial variables.
3. Utilizing statistical analysis (ANOVA) to optimize the number of considering variables.

3. Data and Methodology

3.1. Study Sample

The sample for this study includes all banks and finance companies in Thailand during the East Asian economic crisis period of 1992-1997 for which relevant data are available. In total, there are 97 financial institutions in the sample, 63 of which had closed or had merged with other institutions. In models, a financial institution is considered as failed when it has been ordered by the Bank of Thailand to close or merge with another institution.

The list of failed banks and finance firms is provided on the websites of the Bank of Thailand and the Stock Exchange of Thailand. The SETSMART database produced by the Stock Exchange of Thailand and the Finance Companies Handbook produced by the Association of Finance Companies are the main data sources for listed and non-listed financial institutions, respectively.

3.2. Variables

Variables used to develop financial institution prediction models are based on CAMEL variables.

A ratio of equity to assets is used as a proxy for "capital adequacy." It is expected that the greater the ratio of equity to assets, the lower the likelihood of financial institution failure due to greater ability to absorb loss. Loan growth is used as a proxy for "asset quality." This is expected to have a positive effect on the probability of failure since it leads to greater credit risk exposure. The ratio of operating expenses to total revenue is used as a financial variable related to "management quality." It is expected that the higher the ratio, the greater the likelihood of failure.

Two proxies are used for the "earning ability" variable. First, Return On Assets (ROA) is used and its interpretation is unambiguous. It is expected to have a negative impact on the probability of failure. For the alternative variable ratio of interest income to total income, however, this is not the case. The volatility hypothesis predicts that a higher ratio of interest income to total income may increase the volatility of income if service income is more stable, thereby increasing the probability with which a financial institution will fail. Conversely, it may also reduce the probability of failure if focusing on the core business entails a better allocation of resources or if service income is actually more volatile in the face of economic shock [27]. A financial institution with high liquidity risk is, finally, more likely to fail. Hence, the ratio of total loans to total assets as a proxy for a "liquidity position" is expected to have a positive effect on the probability of failure.

Initially, there are numerous sets of variables to choose from. The criteria employed here are the availability of data and the statistical significance of variables. Accordingly, the financial variables used in this study include Equity to Assets, Loan Growth, Operating Expenses to Revenue, Return on Assets, Interest Income to Total Income, and Loan to Assets, which are all proxies for Capital, Asset, Management, Earnings, and Liquidity components of CAMEL, respectively.

Although it is not considered a CAMEL variable, firm size has frequently been included in early warning and failure/bankruptcy prediction studies as a proxy for "too big to fail" situations. Since large firms tend to have a great impact on a country's economic performance, they may be more likely to receive government support when confronted with financial distress. Such situations are widely known, especially in the case of emerging market economies. Larger intermediaries are more inclined to be subject to political intervention, and regulators may consider large financial institutions to be "too big to fail" [27].

For the above reason, this paper includes the variable Size, which is measured by the log of total assets having investigated. The expected effects of variables on the likelihood of financial institution failure are summarized in **Table 1**.

3.3. Adaptive Neuro-Fuzzy Inference Systems (ANFIS)

Failure prediction models are equivalent to classification problems, which are used to partition a given set of financial data into two clusters – failed and non-failed. A fuzzy inference system is the process of formulating mapping from given input to output using fuzzy logic. Mapping then provides a basis from which decisions can be made or patterns discerned. The process of fuzzy inference involves membership functions, logical opera-

Table 1. Explanatory variables and their expected effects on the likelihood that a financial institution fails.

Variables	Expected effect on failure likelihood
CAMEL	
Equity to Assets	(−) Ability to absorb losses
Loan Growth	(+) Credit risk
Operating Expense to Revenue	(+) Inefficiency
Return on Assets	(−) Profitability
Interest Income to Total Income	(+/−) Less volatility / More volatility of income
Loans to Assets	(+) Liquidity risk
NOT CAMEL	
Size	(−) Too big too fail

tions, and if-then rules. ANFIS includes a neuro-adaptive learning method that works similarly to that of neural networks. Neuro-adaptive learning techniques provide a method for a fuzzy modeling procedure to learn information about a data set.

In this paper, a dataset is a set of input-output data whose input data are CAMEL-based variables normalized in unit interval $x_p \in [0,1]^n$ and one output is a crisp value in the interval. Let input data x_p on the n-dimension be represented by the following vector:

$$\mathbf{x}_p = [x_{p1}\ x_{p2}\ \dots\ x_{pn}]^T \quad p = 1,\dots,M \quad . \quad . \quad . \quad . \quad (1)$$

where M is the number of data vectors. ANFIS used in this paper is a Takagi-Sugeno model [39–41] as given by

$$\left.\begin{array}{ll} R_i & : \textbf{if } x_{p1} \text{ is } A_{i1} \text{ and } \dots \text{ and } x_{pn} \text{ is } A_{in} \\ & : \textbf{then } y_i = a_{i1}x_{p1} + \dots + a_{in}x_n + b_i; \\ & \ \ i = 1,\dots,K \end{array}\right\} \quad (2)$$

which are given as rules in fuzzy sets denoted by $A_{i1},\dots,A_{in}$. K and n are the numbers of rules and variables, respectively. y_i is output for the i^{th} rule. $a_{i1},\dots,a_{in}$ are weights and b_i is bias.

Given two-dimensional data $\mathbf{x_p} = [\mathbf{x_{p1}}\ \ \mathbf{x_{p2}}]^{\mathbf{T}}$, for instance, fuzzy sets in the first and second dimension are A_1, A_2 and B_1, B_2, respectively. As a result, there are four rules, as follows:

if (x_{p1} is A_1) and (x_{p2} is B_1) **then** $y_1 = q_1x_{p1} + r_1x_{p2} + s_1$
if (x_{p1} is A_1) and (x_{p2} is B_2) **then** $y_2 = q_2x_{p1} + r_2x_{p2} + s_2$
if (x_{p1} is A_2) and (x_{p2} is B_1) **then** $y_3 = q_3x_{p1} + r_3x_{p2} + s_3$
if (x_{p1} is A_2) and (x_{p2} is B_2) **then** $y_4 = q_4x_{p1} + r_4x_{p2} + s_4$

Hence, total rules are the numbers of combinations of fuzzy sets. A_1, A_2 and B_1, B_2 can be any appropriate fuzzy sets in parameter form. In this study, fuzzy sets are computed by using two Membership Functions (MFs): Gaussian curve built-in MF and generalized bell-shaped built-in MF. The Gaussian MF is written as follows:

$$\left.\begin{array}{l} \mu_{A_1} = \exp\left(-\left(\dfrac{x_{pk}-v_1}{2\sigma_1}\right)^2\right) \\ \mu_{A_2} = \exp\left(-\left(\dfrac{x_{pk}-v_2}{2\sigma_2}\right)^2\right) \end{array}\right\} \quad . \quad . \quad . \quad . \quad . \quad . \quad (3)$$

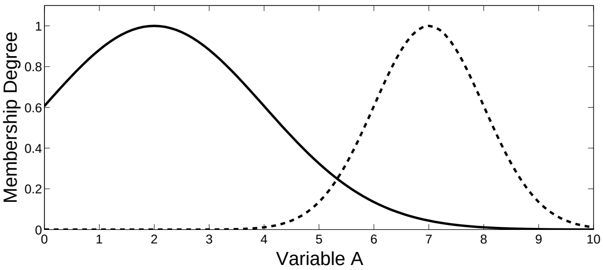

Fig. 1. Example of Gaussian curve built-in membership function (Gaussian curve MF) μ_{A_1} and μ_{A_2}.

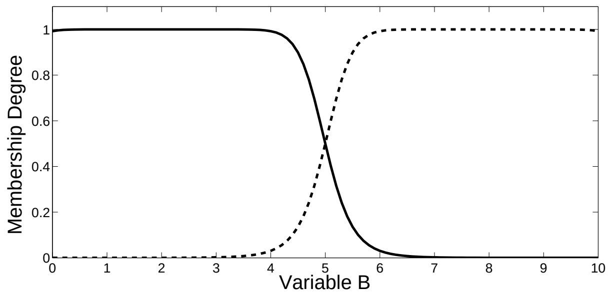

Fig. 2. Example of generalized bell-shaped built-in membership function (bell-shaped MF) μ_{B_1} and μ_{B_2}.

where v_1 and v_2 are mean values of fuzzy sets. σ_1 and σ_2 are standard deviations of fuzzy sets. The bell-shaped MF is written as follows:

$$\left.\begin{array}{l} \mu_{B_1} = \dfrac{1}{1+\left(\dfrac{x_{pk}-c_1}{a_1}\right)^{2b_1}} \\ \mu_{B_2} = \dfrac{1}{1+\left(\dfrac{x_{pk}-c_2}{a_2}\right)^{2b_2}} \end{array}\right\} \quad . \quad . \quad . \quad . \quad . \quad . \quad . \quad (4)$$

where a_1, a_2, b_1, b_2, c_1, and c_2 are parameters the same as for the Gaussian MF. **Figs. 1** and **2** show examples of Gaussian and bell-shaped MF, respectively.

4. Empirical Analysis

In this section, the development and evaluation of failure prediction models are explained in detail. The description is divided into five subsections: data sets, failure prediction models, experiment settings, variable analysis, and comparison with logistic models. The aim of experiments is to evaluate the proposed models of failure prediction and to compare their performance with logistic models. For evaluating the proposed models, experiment settings are explained in detail because parameters in ANFIS, a supervised learning method, have to be defined beforehand. Defined parameters were carefully selected from the variables that are significantly impact to failure. Experiments show the performance of models of

Table 2. Numbers of bankruptcy-classified data points for five data sets during 1992-1997.

	t-1		*t*-2	*t*-3	*t*-4	*t*-5
	1997	**1996**	**1995**	**1994**	**1993**	**1992**
Bankruptcy	9	36	61	61	59	45
Non bankruptcy	23	46	66	66	64	30
Total	32	82	129	129	123	75

Table 3. ANOVA difference test at 0.05 in bankruptcy classification. See Section 4.4 for details.

VARIABLES	***t*-1**	***t*-2**	***t*-3**	***t*-4**	***t*-5**	**ALL**
Equity to Assets						s
Loan Growth	s	s	s	s	s	
Operating Expense to Revenue						
Return on Assets	s					s
Interest Income to Total Income		s	s	s	s	s
Loans to Assets	s	s				s
Size	s	s	s	s	s	s

Note: A letter ‘s’ indicates significance.

failure prediction up to five years ahead. The comparison to logistic models, is done because they have been widely used in the area of finance in Thai firms as addressed in [35–38]. The advantages of using logistic models are not only the resulting models for failure prediction but also the analysis of the impact of variables on failure.

4.1. Data Sets

Proposed ANFIS failure prediction models are built by using feed-forward architecture and trained with a hybrid optimization method. Hybrid optimization is a combination of least-squares and back-propagation gradient descent methods. To teach ANFIS, the training set consists of 91 financial institutions for six years, which is equivalent to 566 data points. These data points are classified into two groups: failure and non-failure. **Table 2** shows the number of data points in dimensions of year and data set. As noted, a failed financial institution is one that was ordered to close or to merge with another institution in 1996 or 1997. Data sets are assigned to different time-to-failure periods as follows: t-1, t-2, t-3, t-4, and t-5. The i-year-ahead prediction model is denoted by t-i, $(i = 2,3,4,5)$. Data used for t-i, $(i = 2,3,4,5)$ were observed in 1995, 1994, 1993, and 1992, respectively.

To select variables significantly different from bankruptcy-classified groups, ANOVA technique is applied prior to the ANFIS. Using the ANOVA tool, we tested significant difference on failure-classified groups at 0.05. In five data sets, we found that two variables, Equity to Assets and Operating Expense to Revenue, are not statistical significance at level 0.05. Equity to Assets is, however, significant in testing against all data sets. There are five variables, i.e., Equity to Assets, Loan Growth, Interest Income to Total Income, Loans to Assets, and Size, considered in our experiments. **Table 3** shows statistically significant variables denoted by s.

4.2. Failure Prediction Models

The training phase begins with the initialization of membership functions and then uses the hybrid optimization method. The procedure of selecting a training set is repeated until optimal values of learning parameters are found and then training sets are determined. Here, the maximum number of iterations is set at 200 in experiments. The whole data set is divided into training and the test sets, based on the K-fold cross-validation technique. The ratio of training and test data points is 90 : 10. The advantage of the K-fold cross-validation technique is that all data in the dataset are eventually used for both training and test sets.

4.3. Experiment Settings

For using ANFIS, number of memberships and type of their functions are a key factor in the design. The number of memberships is 2. Membership functions are Gaussian and bell curve built-in MF. To validate the proposed prediction model, we carry out three experiments as follows:

1. Experiment I: The data set is from data on all years (ALL) for generalization.
2. Experiment II: The five data sets are t-1, t-2, t-3, t-4, and t-5.
3. Experiment III: Comparison is conducted with a logistic model.

Table 4 reports results obtained for ANFIS prediction models using the Gaussian MF and the bell curve MF, respectively, categorized in five different experiments as explained in the next section in detail. The table shows that the prediction accuracy as shown by the increasing MAE is in decreasing order according to time to failure. These results are consistent with those documented in [12]. Results of logistic models are shown in **Table 5**. In **Tables 4** and **5**, a Type I error is misclassification of failed financial institutions as non-failed and a Type II error is misclassification of non-failed financial institutions as failed. The sample consists of financial institutions operating between 1991 and 1998. The dependent variable is the incidence at which a financial institution was ordered to close or merge with another institutions during the East Asian economic crisis. The model uses explanatory variables of one to five years prior to the failure.

4.4. Variable Analysis of Number of Membership Functions

In this section, training errors of ANFIS varied by the number of membership functions are examined to specify the failure-classified denominator for each experiment,

Table 4. Results of ANFIS failure prediction models with two memberships per variable using Gaussian and bell MF.

TTF		Results of failure prediction models in 30-fold cross validation (%)											
		Overall Accuracy				Type I error[d]				Type II error[e]			
		Mean	Min	Max	Std	Mean	Min	Max	Std	Mean	Min	Max	Std
All Years	Gaussian	90.68	89.39	91.94	0.71	9.29	7.78	11.19	0.72	9.32	6.93	10.97	1.00
	Bell	91.14[c]	89.00	94.11	10.80	9.22	6.96	11.11	1.04	8.42[a]	4.66	11.49	1.42
t-1	Gaussian	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	Bell	100.00	100.00	100.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
t-2	Gaussian	99.56[a]	98.25	100.00	0.55	0.53[a]	0.00	1.90	0.77	0.28[b]	0.00	1.82	0.64
	Bell	98.13	94.74	100.00	1.26	2.47	0.00	5.71	1.48	0.98	0.00	6.35	1.62
t-3	Gaussian	86.31	81.58	90.35	1.97	11.45	6.67	19.30	2.68	15.70	9.52	20.41	2.55
	Bell	86.93	84.11	89.47	1.31	11.38	6.52	15.49	2.60	14.38[a]	9.52	22.22	2.38
t-4	Gaussian	87.87	80.18	95.50	3.11	12.00	3.33	21.62	4.96	11.92	4.35	17.78	3.11
	Bell	87.45	81.98	90.99	2.38	13.25	5.66	18.31	3.76	11.24	4.44	18.60	4.42
t-5	Gaussian	93.88	88.06	97.01	2.58	4.07	0.00	11.11	3.36	7.16[c]	2.70	12.5	2.78
	Bell	92.74	85.07	97.05	3.18	4.33	0.00	10.00	2.99	8.83	0.027	18.60	3.81

a: Denotes statistical significance at the 1% level.
b: Denotes statistical significance at the 5% level.
c: Denotes statistical significance at the 10% level.
d: Is the misclassification of failed financial institutions as non-failed (so-called false positives).
e: Is the misclassification of non-failed financial institutions as failed (so-called false negatives).

Table 5. Logistic regression models: coefficients of explanatory variables on likelihood of financial institution failure. The i-year-ahead prediction model is denoted by t-i, $(i = 2,3,4,5)$. Data used for t-i, $(i = 2,3,4,5)$ were observed in 1995, 1994, 1993, and 1992, respectively. Numbers in parentheses are t-statistics.

Explanatory variables	*All Years*	t-1	t-2	t-3	t-4	t-5
Intercept	0.09 (0.38)	−1.05 (−0.80)	1.35 (1.54)	−0.05 (−0.08)	−0.00 (−0.01)	−0.25 (−0.42)
Financial variables						
Equity to Assets	−0.12 (−0.79)	1.09 (0.76)	−1.81[b] (−2.40)	0.12 (0.28)	0.08 (0.21)	−0.65 (−1.20)
Loan Growth	−0.07[a] (−3.32)	0.77[b] (−2.34)	−0.18[b] (−2.18)	−0.12[c] (−1.84)	−0.09[b] (−2.12)	−0.02 (−0.87)
Operating Expense to Revenue	0.69[b] (2.01)	1.00 (0.92)	2.01[b] (2.03)	0.54 (0.87)	0.89 (1.11)	−0.57 (0.70)
Return on Assets	0.29 (0.64)	2.79 (1.49)	12.80[b] (2.14)	0.98 (1.03)	−0.93 (−0.59)	0.04 (0.02)
Interest Income to Total Income	0.37[b] (02.22)	0.35 (0.71)	−0.02 (0.02)	0.32 (0.66)	0.78[b] (2.11)	0.74[c] (1.68)
Loans to Assets	−1.06[a] (−4.65)	−0.28 (−0.26)	−1.17[c] (−1.78)	−0.73 (−1.56)	−1.45[a] (−3.17)	−1.12[c] (−1.89)
Size	0.19[a] (4.55)	0.29[b] (2.11)	−0.03 (−0.31)	0.18 (1.63)	0.21* (2.29)	0.29* (2.54)
No. of observations	570	114	129	129	123	75
Overall prediction accuracy(%)	18.72	73.68	77.95	66.14	69.91	80.27
Type I error[d](%)	0.00	29.72	24.61	36.36	29.73	22.22
Type II error[e](%)	64.28	24.67	19.35	31.14	24.67	4.28
Precision[f](%)	100.00	70.27	75.38	63.63	67.74	77.77
Recall[g](%)	0.36	57.77	80.32	68.85	71.18	93.33

a: Denotes statistical significance at the 1% level.
b: Denotes statistical significance at the 5% level.
c: Denotes statistical significance at the 10% level.
d: Is the misclassification of failed financial institutions as non-failed (so-called false positives).
e: Is the misclassification of non-failed financial institutions as failed (so-called false negatives).
f: Is the probability that failed financial institutions are predicted as failed (so-called sensitivity).
g: Is the probability that financial institutions predicting as failed are corrected.

i.e., time-to-failure. Overall performance between the bell-shape MF and the Gaussian MF is significantly different. Specifically, for all-year data sets, the membership function built by the bell shape yields a better result in terms of higher accuracy and lower variance. Hence, the membership function is defined by using a bell shape. Let $MFs(A,B,C) = (1,2,3)$ be the number of membership functions corresponding to variables A, B, and C that are

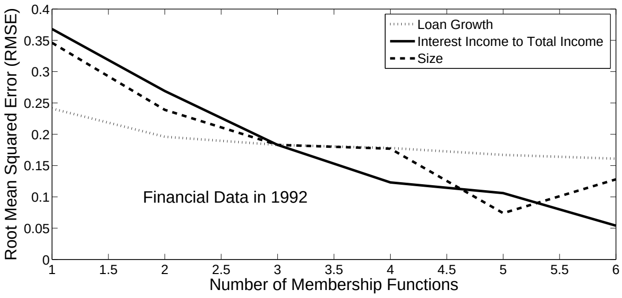

Fig. 3. RMSE of ANFIS training with three variables: (1) Loan Growth, (2) Interest Income to Total Income (IITI), and (3) Size. For example, IITI denoted by a solid line is examined for an MF number from one to six. The number of MFs of loan growth and size are three each, respectively. The minimum RMSE equal to 0.054 at $MFs(LoanGrowth, IITI, Size) = (3,6,3)$, i.e., the number of fuzzy rules is 54.

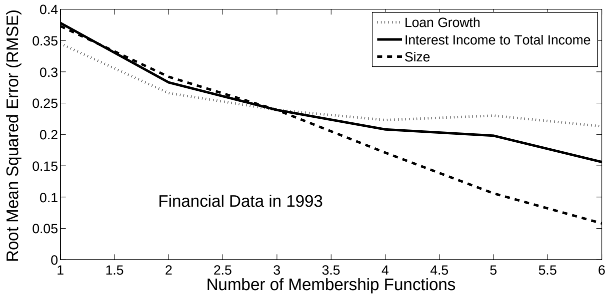

Fig. 4. RMSE of ANFIS training with three variables: (1) Loan Growth, (2) Interest Income to Total Income (IITI), and (3) Size. For example, size denoted by a dash line is examined for an MF number from one to six. The number of MFs of loan growth and IITI are three each, respectively. The minimum RMSE equal to 0.058 at $MFs(LoanGrowth, IITI, Size) = (3,3,6)$, i.e., the number of fuzzy rules is 54.

equal to 1, 2, and 3, respectively. For variables exhibited in **Table 4**, numbers of membership functions are considered independent of each other. In this section, considering variables of each data set are based on the ANOVA difference test from **Table 3**, and the list of variables is shown as follows:

1. t-1: 4 variables : Loan Growth, Return on Assets, Loans to Assets, and Size.

2. t-2: 4 variables : Loan Growth, Interest Income to Total Income, Loans to Assets, and Size.

3. t-3: 3 variables : Loan Growth, Interest Income to Total Income, and Size.

4. t-4: 3 variables : Loan Growth, Interest Income to Total Income, and Size.

5. t-5: 3 variables : Loan Growth, Interest Income to Total Income, and Size.

Figs. 3–7 illustrate Root Mean Squared Error (RMSE) of ANFIS training with significant variables obtained from the ANOVA method for prediction models categorized by time to failure.

Using financial data in 1992, i.e., the t-5 model, **Fig. 3** shows that Interest Income to Total Income (IITI) is considered to be a failure-classified denominator because of its steepest slope. Contrary to IITI, Loan Growth marginally affects the classification. For ANFIS with 54 fuzzy rules, the minimum RMSE is investigated at $MFs(LoanGrowth, IITI, Size) = (3,6,3)$. The denominator of year 1993, i.e., the t-4 model, becomes Size and the least influential factor of failure prediction remains Loan Growth as shown in **Fig. 4**. Minimum classification error equals 0.058 calculated by using $MFs(LoanGrowth, IITI, Size) = (3,3,6)$ with 54 fuzzy rules. Unlike the previous two years, **Fig. 5** shows graphs of three significant variables in 1994, i.e,

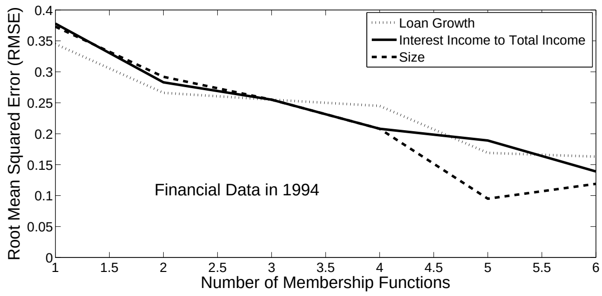

Fig. 5. RMSE of ANFIS training with three variables: (1) Loan Growth, (2) Interest Income to Total Income (IITI), and (3) Size. For example, size denoted by a dash line is examined for an MF number from one to six. The number of MFs of loan growth and IITI are three each, respectively. The minimum RMSE equal to 0.095 at $MFs(LoanGrowth, IITI, Size) = (3,3,5)$, i.e., the number of fuzzy rules is 45.

the t-3 model, that illustrate mostly the same behavior. In other words, we cannot discern these three variables in 1994. Minimum training error is 0.095 at $MFs(LoanGrowth, IITI, Size) = (3,3,5)$ with 45 fuzzy rules.

As for 1995 data, i.e., the t-2 model, **Fig. 6** suggests that Size is the denominator that achieves minimum error at 0.042 by using $MFs(LoanGrowth, IITI, LoanToAssets, Size) = (2,2,2,6)$. The Loan to Assets graph showing the gradually decrease is the least influential. Finally, we examine four significant variables during 1996 and 1997, i.e., the t-1 model, as presented in **Fig. 7**. The experimental result shows that the variables with the greatest impact on failure classification are Loan Growth and Size, respectively, whereas Return on Assets has the least impact. Minimum classification error is 0.025 by using $MFs(LoanGrowth, ReturnOnAssets, LoanToAssets, Size) = (6,2,2,2)$.

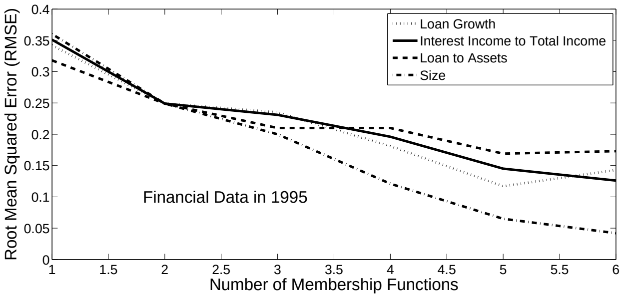

Fig. 6. RMSE of ANFIS training with four variables: (1) Loan Growth, (2) Interest Income to Total Income (IITI), (3) Loan to Assets, and (4) Size. For example, size is examined for an MF number from one to six. Each variable has the number of MFs equal to two. The minimum RMSE equal to 0.042 at $MFs(LoanGrowth, IITI, LoantoAssets, Size) = (2,2,2,6)$, i.e., the number of fuzzy rules is 48.

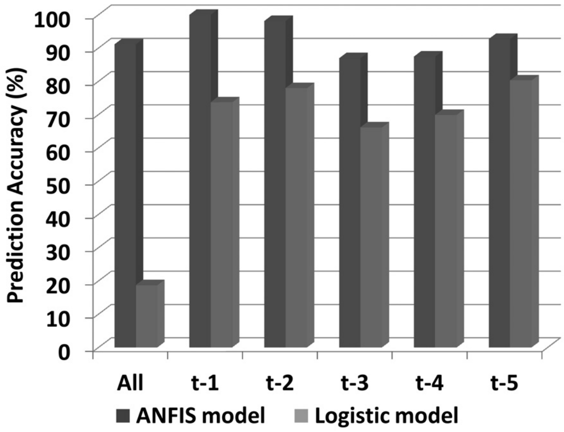

Fig. 8. Experiment III: comparison between the proposed model and the logistic model.

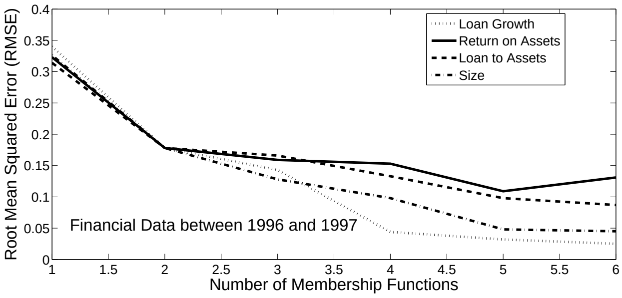

Fig. 7. RMSE of ANFIS training with four variables: (1) Loan Growth, (2) Return to Assets, (3) Loan to Assets, and (4) Size. For example, loan growth is examined for an MF number from one to six. Each variable has the number of MFs equal to two. The minimum RMSE equal to 0.042 at $MFs(LoanGrowth, ReturntoAssets, LoantoAssets, Size) = (6,2,2,2)$, i.e., the number of fuzzy rules is 48.

4.5. Comparison with Logistic Models

We ran logistic models against six data sets (ALL, t-1, t-2, t-3, t-4, t-5) using the same variables as our models. Results are shown in **Table 5**, which are coefficient of variables, accuracy, Type I error, Type II error, precision, and recall. For the model built specifically for each year, overall accuracy is approximately 70% to 80%. For the data set of ALL years, precision is 100% but the recall rate is very low at 0.36%. For comparison with the proposed model, prediction accuracy in **Table 4** is plotted together with that of **Table 5** as shown in **Fig. 8**.

5. Conclusions and Discussion

To serve as an efficient early warning signal, the accuracy of a failure prediction model is as important as its robustness over time to failure. This study has considered financial data for 82 finance companies and 15 commercial banks operating in Thailand during the period of 1992-1997. Consistent with existing research, financial factors help predict the probability of corporate failure. CAMEL variables regarding capital adequacy, management quality, asset quality, and earnings ability appear to be significant factors determining failure probability. Based on CAMEL and firm size variables, this paper has shown the development of failure prediction models using ANFIS for Thai financial institutions during the East Asian economic crisis. The proposed models for all data tests have yielded minimum and average MAE in 10-fold cross validation lower by 10.04 and 11.41 percent, respectively. Using rule-based bankruptcy analysis, resulting ANFIS models extract 45–54 rules with an accuracy rate greater than 90 percent. A comparison between ANFIS models and logistic models has shown that ANFIS models outperform logistic models for all data sets, especially for data set "All."

In future work, the goal is investigating the application of the proposed model to other data sources, for example, the financial crisis in 2008. Note that the recent crisis of 2008 is different from the crisis in 1997 in several ways. First, the 1997 crisis originated in Thailand, whereas the 2008 crisis started in the U.S. The impact of the 1997 crisis on Thai financial institutions was therefor much more devastating. Second, the 1997 crisis was triggered by attacks on the baht, the national currency of Thailand, while the 2008 crisis began when large financial firms in the U.S. started to collapse due to poor-quality subprime loans. Third, the consequences of the two crises also differ markedly. The 1997 crisis resulted in closures of a large number of financial institutions in Thailand. Although the impact of the 2008 crisis was also felt by financial institutions in Thailand, the effect was only indirect and relatively mild. In addition, in 2008 in Thailand, the spotlight was much more on ongoing internal political conflict and street protests rather than on the indirect impact of the U.S.-based crisis. In summary, as far as Thailand is concerned, the 1997 crisis was much more relevant and far more devastating than the recent 2008 crisis.

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