An Application of Neural Network on Early Warning System by Rating for the Credit Department of Fishermen Association in Taiwan

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This paper applies the Back-Propagation Network (BPN) to build the financial distress prediction models. Empirical results show that the effect of BPN on crisis management mechanisms towards communities' financial institutions in Taiwan is doing quite fine. In addition, the predictability comparison indicates that the highest accuracy is the Primitive BPN (81.1%) in the surveillance system, followed by the Factory BPN (77.85%) and the Ordered Logit (75.9%). Damages and impacts to the fishing community and industry are always far more serious when financial crises occur in the community's financial institutions. Thus, a more accurate financial warning system for governing these financial institutions is needed more than ever. The artificial neural network (ANN) suggested in this study can provide a bankruptcy predictor of financial distress among credit unions.

Keywords: *Early Warning System, Credit Department of Fishermen Association, Artificial Neural Network*

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I. Introduction

Due to financial liberalization, credit departments for farmers and fishermen associations have been on the downgrade for the past few years in Taiwan.　The crisis in operations emerged from a defective financial frame, especially in the credit departments such as the cooperative association of credit and the credit departments of farmers and fishermen.　For proper management, financial institutions with signs of crisis need to be detected and addressed with the effective measures if possible at an early date.

In the pioneering work of classifying the financial distress of a firm, Altman (1968) uses multiple discriminate analysis (MAD) to identify financial distress.　Since 1968, this has been commonly used as the accounting and financial tool for estimating the future fiscal health of a corporation.　However, the MAD technique has limitations based on its assumptions of linear separability, multivariate normality, and independence of the predictive variables.　This results in the fact that most financial ratios violate the MAD assumptions (Ohlson, 1980; Karels and Prakash, 1987; Odom, 1990).　Therefore, the efficiency of MAD for financial ratios analysis is conservative. Until the recent developments in Artificial Neural Networks (ANN), MAD has been used most frequently among the statistical approaches in bankruptcy prediction (Pompe and Bilderbeek, 2005).　Currently, there has been a considerable interest in ANN because it has performed well in business classifications including bankruptcy (Tam and Kiang, 1992; Flecther and Goss, 1993; Lacher *et al.*, 1995; Lee, Han, and Kwon, 1996; Leshno and Spector; 1996; Shi, Xu, and Liu, 1999; Zhang *et al.*, 1999).　In fact, since 1990, related literature examines the viability of the analysis of financial distress based on Artificial Neural Network that focused on the applicability of ANN as a bankruptcy predictor of financial distress among credit unions (Han, Jo, and Shin,1997; Alataris, Berger, and Marmarelis, 2000; Randall and Dorsey, 2000; Siermala and Vihinen, 2001; Bongini, Laeven, and Majnoni, 2002; Verikas and Bacauskiene, 2002; Waszczyszyn and Bartczak, 2002; Alessandri, 2003; Chen, Leung, and Daoukc,2003; Chen and Leung, 2004). In this paper, the ANN-based model, the Back Propagation Network (BPN) in particular is compared with the Ordered Logit Model.

The objective of this paper is to construct an early warning system for the credit department of fishermen association in Taiwan to detect potential financial problems. The paper uses BPN to build the financial distress prediction models for the credit departments for fishermen associations. The CAMELS (C-capital adequacy, A-asset quality, M-management capability, E-earnings ability, L-liquidity and S-sensitivity to market risks) guidance indicators were used to do quantitative data analysis. The remaining sections of this paper include: Section II discusses the models used in the paper. Section III presents the data and describes the financial risk index variables. Section IV shows the empirical results. Finally, Section V summarizes the findings.

II. Methodology

2.1 Ordered Logit Model

In order to solve the limits of regression analysis while discrete independent variables exist, the Ordered Logit Model forms by cumulative distribution function with standard logistic distribution is used; this results in a value between zero to one (Foka and Franses, 2002). The Logit model can be expressed as follows:

$$Y = \beta_0 + \sum_{j=1}^{k} \beta_j X_{ij} + e_i \,, \quad \text{i} = 1, 2 \ldots \text{n} \tag{1}$$

where X_{ij} are the explanatory variables, β_j is the parameter, and e_j is the error term with zero mean. To show how the model specified in above equation can be estimated, both sides of the equation need to be represented by the expected value,

$$E(Y_i) = X_i\beta$$

where $X_i = (1, X_{i1}, X_{i2}, \cdots X_{ik})$ and $\beta = (\beta_0, \beta_1, \cdots \beta_K)$

$E(Y_i)$ is between 0 to 1. The Logistic distribution is used to transfer $X_i\beta$ into F (Z) such that

$$F(Z) = \frac{1}{1+e^{-z}} \tag{2}$$

Therefore, we can write

$$F(E(Y_i)) = \frac{1}{1+e^{-xi\beta}} \tag{3}$$

Let $P_i = F(E(Y_i))$, we write (3) as

$$P_i = \frac{\exp(\beta_0 + \beta_i X_{i1} + \cdots + \beta_k X_{ik})}{1+\exp(\beta_0 + \beta_1 X_{i1} + \cdots + \beta_k X_{ik})} \tag{4}$$

Thus, the Ordered Logit model can be established through Maximum Likelihood Estimation, and explanatory variables are substituted into the sample regression to get the estimates of scoring of credit departments. Then, the goodness of fit for the Ordered Logit Model is tested by -2 Log Likelihood Ratios, and if $\lambda(\beta) > X^2$ then it indicates the significance of the model. Finally, the effective level is measured with standard estimate modulus; bigger modulus means stronger effective levels.

2.2 BPN Model

Using the ANN to the early warning system is a breakthrough approach to solve the nonlinear model, which is superfluous when used in the traditional hypothesis. One of the most popular activation functions for ANN is the Back Propagation

Network, which is capable of handling large learning problems. A group of BPN is connected by many artificial neurons, where several layers containing some processing elements are found. A completed BPN framework can be classified into three layers: input layer, output layer and hidden layer as shown in Figure1.

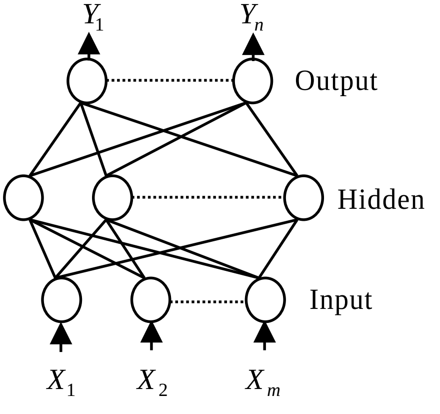

Figure 1. Completed framework of BPN

Source: This study.

The input layer processing elements deal with the external information where the numbers of elements differ from the issues. Here, the linear transfer function is applied. The interactive effect and the capability of internal structure are shown in the hidden layer, where input variables through the input layer are weighed and transferred and then compared with the expected output value. The weights can be adjusted according to delta until the difference between the estimated and the expected value converge to the minimized value. Normally, more processing elements in the hidden layer will slower the convergence process and lessen delta, but too many processing elements increase the training time only and do not reduce delta. In general, the suggested numbers of processing elements is between the means of numbers of the input and output layers. Processing elements of the output layer represent the output variable of the network and the numbers of elements also differ from the issues. The nonlinear transfer function and the gradient steepest method are used to understand the BPN rule on how to minimize the energy function.

III. Description of the Data and Variables

The principle of variables selection and model set-up are established for early warning system in this section. Financial data for 1997 to 2002 were collected from the Taiwan provincial fishermen associations. The financial risk indexes, including capital adequacy (C), asset quality (A), management capability (M), earnings ability (E), liquidity (L) and sensitivity to market risks (S) (CAMELS), were extracted by Kslomogorov-Smirnov test (K-S test) and factor analysis where twenty-five significant financial ratios were selected (see Table 1). The financial ratios and the rating mechanism of the Central Deposit Insurance Corp. to the financial institutions were then treated as the input variables to establish the crisis-warning models included in the Ordered Logit Model, the factor analysis BPN and the primitive BPN. The credit departments for fishermen associations in respective regions are rated into A, B, C, D and E rates. The results of the credit rating were taken as dependent variables, where rate A refers to the best operation with minimum probability of crisis and rate E refers to the worst operation with maximum probability of crisis. Finally, the prediction capacities of various models were tested.

3.1 Ordered Logit Model

The Ordered Logit Model applies the ratings resulting from cluster analysis and uses factor analysis to transfer the variable indexes into a few independent common factors which are used to classify samples. Then, those credit departments with similar overall financial characteristics are categorized into the same group, and a performance rating is conducted in accordance with the financial attributes of various groups. This rating result is used in the Ordered Logit Model to obtain the rated credit departments of fishermen association's probability of falling into each rating group, which determines the annual credit rating of credit departments.

Table 1. Selection of financial risk index variables

CAMELS	Financial risk index variables	operation performance
Capital adaptability	X_1 self-owned capital ratio	+
	X_2 self-owned venture capital ratio	+
Assets quality	X_3 dunning and loan ratio	-
	X_4 bad debt allowance and loan ratio	-
	X_5 bad debt and total assets ratio	-
Management performance	X_6 revenue and capital ratio	+
	X_7 operating expenses and assets ratio	-
	X_8 operating expenses and revenue ratio	-
	X_9 interest exchange and savings ratio	-
	X_{10} interest exchange and interest return	-
Earnings	X_{11} rate of return on assets	+
	X_{12} rate of return on net value	+
	X_{13} profit margin	+
	X_{14} interest return and loan ratio	+
Liquidity	X_{15} liquidity ratio	+
	X_{16} liquidity preparation ratio	+
	X_{17} loans and deposits ratio	-
Sensitiveness to market risks	X_{18} interest sensitiveness	*
	X_{19} interest sensitiveness gap	+
	X_{20} deposit interest rate discrepancy	-
	X_{21} ratio of assets and risks	-
	X_{22} asset growth rate	+
	X_{23} deposit growth rate	+
	X_{24} loan growth rate	+
	X_{25} pre-tax net profit growth rate	+

Source: This study.

Note: The mark "*" means it depends upon the changing direction of interest rate.

3.2 Factor-BPN Model

Simulating and learning basis is constructed in this model. Sample design and statistics of grades are established after factor and cluster analysis. The input layer includes factors in six groups that indicate six input variables. In the single hidden layer, the learning cycle and Root of Mean Square (RMS) from the number of processing elements in each network structure are compared, and then six processing elements are selected. The output layer with five grades indicates five output variables, so the Factor-BPN model is with a structure of 6-6-5.

3.3 Primitive-BPN Model

In the Primitive-BPN model, the input layer includes twenty-five financial ratios that indicate twenty-five input variables. In a single hidden layer, fifteen processing elements are selected, which as suggested, are the mean numbers of input and output layers. They are also consistent with the learning cycle and RMS from the number of processing elements in each network structure. The output layer with five grades indicates five output variables, so the Primitive-BPN model is with a structure of 25-15-5.

Generally, the optimal framework of artificial neural network can be tested and learned via experience. The momentum term of the network parameter in this study is set at 0.4 and the learning speed is 0.5 after the repeated learning exercises and tests. The learning rule employs the Delta Rule and the transfer function is the Sigmoid Function. When the model is complete, all sample data are put into the model to obtain various credit departments' of fishermen associations' probability of credit ratings.

IV. Analysis and Results

4.1 Ordered Logit Model

Table 2 lists the relevant results of the Ordered Logit Model, and shows that its Log-Likelihood is significant (p=0.001), which shows that the model fits well except for factor 4. The other five factors, under the 5% significant level, demonstrate statistical significance. According to Table 1, the importance of significant variable factors resulting from the Ordered Logit Model can be ordered as follows: Factor 1: earning ability (E), managerial capability (M) and assets quality (A); Factor 3: assets adaptability (C) and Liquidity (L); Factor 6: sensitiveness to market risks (S); Factor 2: liquidity (L), managerial capability (M) and sensitiveness to market risks (S); and Factor 5: earning ability (E) and managerial capability (M).

4.2 Factor-BPN Model

The model produces variable indexes by means of factor analysis to analyze interdependent common factors and ranks the credit ratings according to various groups' financial attributes, which are used to execute the artificial neural network. The framework of Factor-BPN is 6-5-5, in which the hidden level decides the number of process elements from one to seven in this level by gradual increase. When the number reaches seven, the RMS is highest and the convergent speed is slower than when the number is six. Therefore, the hidden level takes six process elements and the training circle and the RMS are shown in Figure 2.

Table 2. Evaluated results of the Ordered Logit Model and their sequence of importance

Variables	Factor	Chi-square	P value	Standardization	Sequence
Intercepts	-9.366	26.551	0.001	-	-
Factor 1 Earning ability(E) Managerial capability(M) Assets quality(A)	8.898	44.775	0.001*	3.179	1
Factor 2 Liquidity (L) Managerial capability(M) Sensitiveness to market risks(S)	4.224	18.488	0.001*	1.085	4
Factor 3 Assets quality(A) adaptability(C) Liquidity(L)	6.916	32.179	0.001*	2.824	2
Factor 4 growth(S)	-0.424	0.773	0.389	-0.116	-
Factor 5 Earning ability(E) Managerial capability(M)	2.115	9.742	0.002*	0.973	5
Factor 6 Sensitiveness to market risks (S)	5.672	19.373	0.001*	1.727	3
Log-Likelihood	93.221				

Source: This study.

Note: The mark * denotes significance at the 5% level.

The RMS of samples created by the model is set to stop when it goes under 5%, and the initial value of momentum term is 0.4. The decreased range of each time is 0.95, and the lower limit is 0.1. The total fault tolerance is 4.854% when the training cycle reaches 5000 times. The RMS of the training process is 0.0894 as shown in Figure 3.

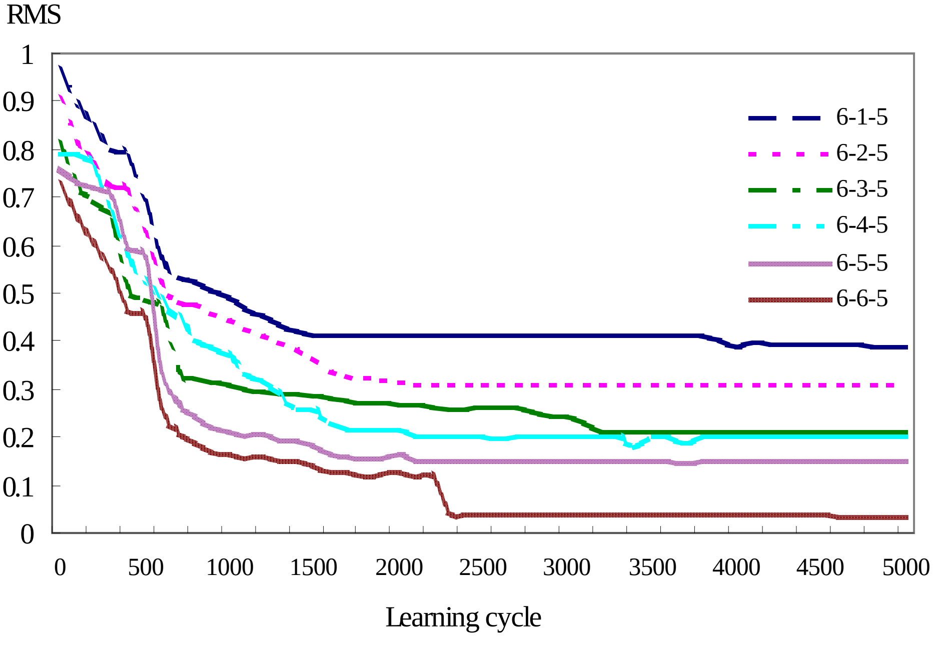

Figure 2. the Factor-BPN relationship between RMS and learning cycle under different number of process elements in hidden layers

Source: This study.

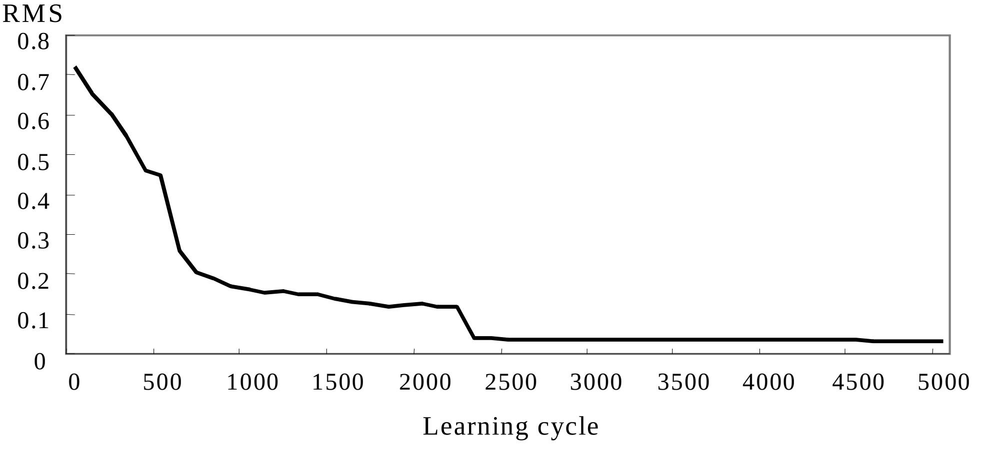

Figure 3. Factor-BPN relationship between RMS and the learning cycle

Source: This study.

The network framework of the Factor-BPN model is 6-6-5. After 5000 times of network training cycle, the relative intensity of six factor input variables corresponding to five operating levels can be obtained as listed in Table 3. This shows that the credit departments for fishermen associations on high levels all feature great emphasis on the assets quality, efficient management, and following operating rules to attach importance on assets adaptability. The first three factors that influence their operating performance reveal that they cover most of the rating index of CAMELS; this indicates that a good credit department should integrate the overall operating strategy in its business investment composition. While credit departments on lower levels on the other hand, take a great risk in their investment composition and accordingly increase the sensitiveness to the market risks, which in turn degrades assets quality with poor earning ability and assets adaptability.

Table 3. Corresponding intensity between input and output variables in the Factor-BPN model

	Relative intensity (intensity sequence)				
Input units	ON_A	ON_B	ON_C	ON_D	ON_E
Factor 1	7.121 (1)	5.699 (2)	2.940 (4)	-13.355 (1)	-2.256 (3)
Factor 2	-1.123 (6)	2.115 (4)	-0.980 (6)	-1.932 (5)	-0.913 (5)
Factor 3	3.549 (3)	-4.136 (3)	-12.765 (1)	-3.549 (4)	-4.689 (2)
Factor 4	2.335 (5)	1.337 (6)	1.686 (5)	0.543 (6)	0.548 (6)
Factor 5	-3.856 (2)	8.655 (1)	-5.446 (3)	-5.682 (3)	2.091 (4)
Factor 6	2.824 (4)	-1.788 (5)	9.493 (2)	-7.612 (2)	-8.654 (1)

Source: This study.

4.3 Primitive-BPN Model

Using primitive financial variables, this model reflects the corresponding relationship between input and output units via ceaseless learning and training of the BPN, in which the influential process elements provided relatively large weight numbers. It is also compared with the factor analysis in the post network model to facilitate understanding of the features of the BPN. The network framework of the primitive BPN is 25-15-5 and has a single hidden layer. In Figure 4, various numbers of process elements in the hidden level are compared to observe the relationship between the RMS and the learning cycle. The RMS and the convergent speed are at their best when there are 15 process elements.

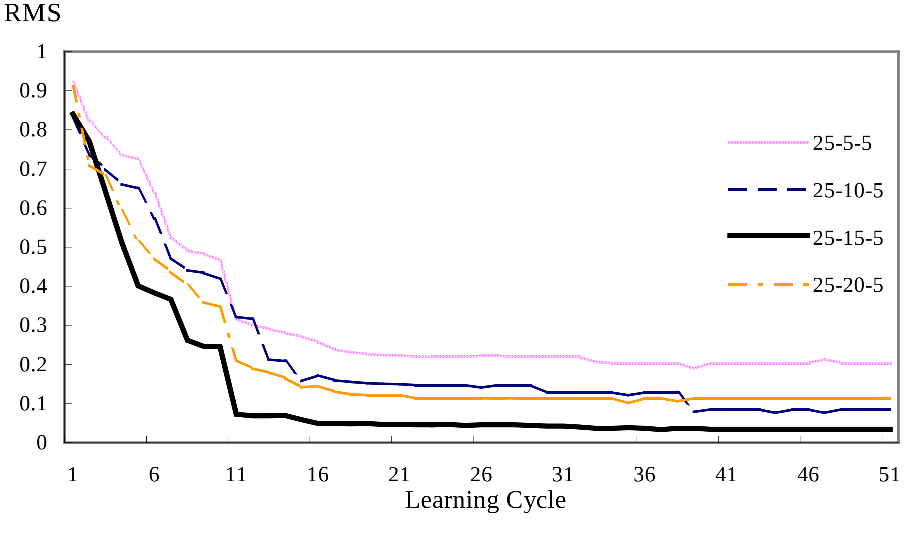

Figure 4. Comparison variety of process element between RMS and the Learning cycle for the Primitive-BPN

Source: This study.

The RMS of samples created by the model is set to stop when it goes under 5%, and the initial value of momentum term is 0.4. The decrease range of each time is 0.95 and the lower limit is 0.1. The total fault tolerance is 3.347% when the training cycle reaches 5000 times.　The RMS of the training process is 0.0722 as shown in Figure 5.

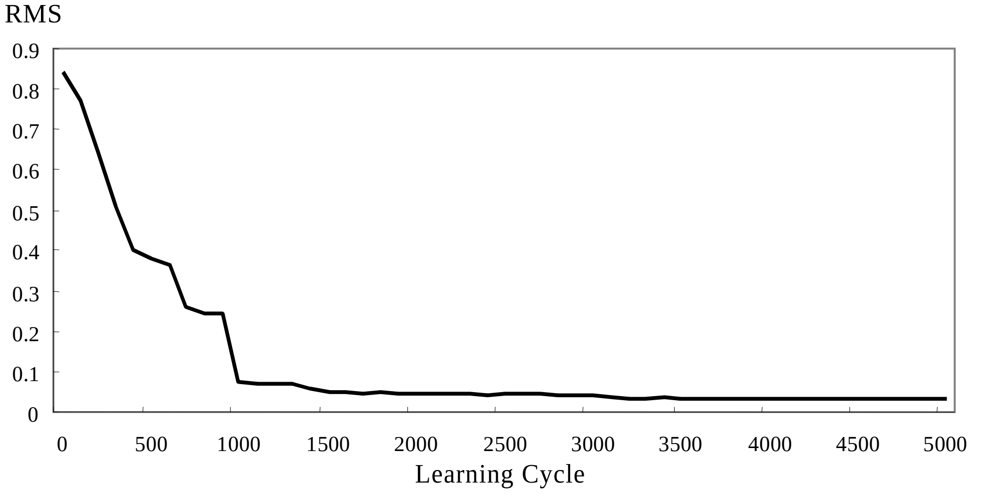

Figure 5.　the Primitive-BPN relationship between RMS and the learning cycle

Source: This Study.

The network framework of the primitive-BPN model is 25-15-5, and the network weight can be obtained after 5000 times of the BPN learning cycle.　The weights of process elements on the hidden layer are obtained from input variables corresponding with the weights of process elements on the hidden layer from output variables.　The relative intensity of primitive financial variables corresponding to five operating levels is shown in Table 4.　It shows that the affecting variables of credit departments of A and B levels are similar to the variation of sequence, which suggest good credit departments not only have strong earning ability, but also follow a comprehensive operating rule which emphasizes assets quality, managerial capability and assets adaptability.　On level C, X_6 and X_8 imply incoherence between managerial capability and the expected operation-affecting directions, which indicates poor managerial capability.　On level D, the major affecting variables include assets quality and sensitiveness to market risks, which imply increasing sensitiveness to market risks would degrade assets quality. Credit departments on level E fail the expected affecting direction and are mostly concentrated on earning ability and liquidity, which imply poor earning ability and poor liquidity.

Table 4. The relative intensity of input variables of the Primitive-BPN

A level		B level		C level		D level		E level	
X_6	21.013	X_{12}	14.498	X_6	-7.008	X_5	-4.557	X_{13}	-2.239
X_{12}	18.620	X_{11}	12.306	X_7	-6.321	X_4	-3.468	X_{12}	-1.137
X_{11}	12.520	X_1	9.255	X_2	-5.247	X_{21}	-3.451	X_6	-1.136
X_5	-7.946	X_6	6.969	X_1	5.826	X_8	-1.353	X_{15}	-0.126
X_1	6.751	X_5	-3.372	X_8	-4.950	X_{18}	1.150	X_2	-0.107
X_2	6.603	X_{13}	-3.298	X_{10}	-4.842	X_3	-1.124	X_1	0.105
X_{15}	6.161	X_{15}	3.077	X_{18}	4.517	X_{14}	1.049	X_5	-0.098
X_{13}	6.078	X_9	3.036	X_{12}	3.857	X_{20}	-1.035	X_{11}	0.097
X_{23}	5.169	X_2	2.582	X_{11}	3.790	X_6	0.880	X_8	-0.082
X_{21}	-3.712	X_{16}	1.854	X_5	-2.722	X_{12}	0.632	X_{25}	0.059
X_{19}	3.558	X_{14}	1.777	X_9	-2.609	X_{13}	-0.606	X_{18}	0.057
X_{18}	2.739	X_7	-1.368	X_3	2.009	X_2	0.466	X_4	-0.044
X_8	-2.448	X_{21}	-1.223	X_{21}	-1.795	X_{16}	0.417	X_{14}	0.039
X_{14}	1.912	X_{25}	0.955	X_{16}	1.402	X_{19}	0.326	X_9	0.030
X_{20}	-1.762	X_{24}	0.880	X_{20}	-1.292	X_{15}	0.300	X_{24}	0.028
X_{16}	1.659	X_{20}	-0.828	X_{14}	1.216	X_{25}	0.282	X_3	0.026
X_{24}	1.624	X_{17}	-0.811	X_{13}	-1.191	X_{17}	-0.277	X_{21}	-0.026
X_{17}	-0.660	X_8	-0.330	X_{25}	0.484	X_1	0.112	X_{19}	0.011
X_{25}	0.577	X_4	-0.288	X_{24}	0.423	X_9	0.098	X_{16}	0.009
X_{22}	0.561	X_{10}	-0.280	X_{17}	-0.411	X_{11}	0.095	X_{10}	-0.009
X_4	-0.541	X_{22}	0.270	X_{23}	0.397	X_{24}	0.092	X_{22}	0.009
X_9	-0.517	X_{18}	0.258	X_{15}	0.379	X_7	-0.088	X_{17}	-0.008
X_3	-0.501	X_{23}	0.250	X_{22}	0.368	X_{23}	0.085	X_{23}	0.008
X_{10}	-0.488	X_3	-0.244	X_4	-0.358	X_{10}	-0.083	X_7	-0.008
X_7	-0.160	X_{19}	0.080	X_{19}	0.118	X_{22}	0.027	X_{20}	-0.003

Source: This study.

Note: Variables are in sequence of absolute values.

This section describes the operation performance frame of credit departments of fishermen associations by CAMELS indicators on the basis of these credit departments' data obtained for the period of 1997 to 2002. The financial early warning system for credit departments of fishermen associations proposed by this study can assist managers to be warned before crisis occurs and to take necessary measures to improve their operating strategy. The Ordered Logit model, factor analysis Back Propagation Network model and Primitive Back Propagation network model are established to compare the accuracy of each sampling classification by each model. The results summarized in Tables 5, 6, and 7 shows that the Primitive-BPN model is the best with a correct prediction of 81.10%. It follows the Factor-BPN model (77.85%) and the Ordered Logit model (75.90%).

Table 5. The chaos matrix of the Ordered Logit model

Target value	Predicted value					
	A	B	C	D	E	Sub total
A	11	1	0	0	0	12
B	0	48	0	0	0	48
C	0	0	24	0	0	24
D	0	0	14	34	0	48
E	0	0	5	0	21	26
Sub total	11	49	43	34	21	158

Source: This study.
Note: Prediction correctness: 75.9%; Type I error: 25.68%.

Table 6. The chaos matrix of the Factor-BPN model

Target value	Predicted value					
	A	B	C	D	E	Sub total
A	10	2	0	0	0	12
B	0	48	0	0	0	48
C	0	0	24	0	0	24
D	0	0	12	36	0	48
E	0	0	5	0	21	26
Sub total	10	50	41	36	21	158

Source: This study.
Note: Prediction correctness: 77.85%; Type I error: 22.97%.

Table 7. The chaos matrix of the Primitive-BPN model

Target value	Predicted value					
	A	B	C	D	E	Sub total
A	10	1	2	0	0	12
B	0	47	1	0	0	48
C	0	0	24	0	0	24
D	0	0	11	38	0	48
E	0	0	4	0	21	26
Sub total	10	47	42	38	21	158

Source: This study.

Note: Prediction correctness: 81.1%; Type I error: 20.27%.

V. Conclusion

This study demonstrates how to construct an early warning system for credit departments for fishermen associations in Taiwan in order to detect potential financial problems and improve the operations of financial institutions based on information provided. The results show on various operating levels, the affecting variables of credit departments for fishermen of A and B levels. These are identical with the variation of sequence, which suggested that good credit departments for fishermen have strong earning ability and follow a comprehensive operating rule which emphasized assets quality, managerial capability and assets adaptability. The major characteristic of credit departments for fishermen on level C is poor managerial capability, which resulted in degrading assets quality. On level D, the major affecting variables included assets quality and sensitiveness to market risks. While in level E, credit departments were mostly concentrated on earning ability and liquidity, and when a business strategy of highly risky assets composition failed to yield, the crisis of failure was imminent. It is important message for financial institutions management while these signs of crisis are detected and needed to be addressed with the effective measures by related government authority at an early date.

The study also shows that the primitive-BPN has a relatively high correct prediction while factor analysis fails to get rid of insignificant variables in the process, and suggest that future researches may take a hereditary evolvement method as the basis for element selection to enhance the accuracy of the input variable selection of ANN. Based on past experience, damages and impacts to the fishing community and industry are always far more serious when financial crises occur within the community's financial institutions. Thus, a more accurate financial warning system for governing these financial institutions is in urgent need. However, the reality of Taiwan is that there is no existing mechanism to detect such distress for majority of community's financial institutions, especially the fishermen credit unions; and guidance to improve such conditions is weak. The ANN suggested in this study can provide a bankruptcy predictor of financial distress among credit unions. It is recommended that decision makers initiate a process to integrate this network into these community's financial institutions.

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台灣漁會信用部金融預警系統之研究－類神經網路模式之應用

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本文探討倒傳遞類神經網路（BPN）應用於基層金融財務危機之預測，本研究比較各預警模式之估計樣本預測能力的實證結果顯示，其正確預測能力依序爲原始財務變數倒傳遞網路模式正確預測率（81.1%）爲最佳模式，其他依序爲因素分析後倒傳遞網路模式（77.85%）及 Ordered Logit 模式（75.9%）。事實上，漁會信用部這類基層金融經營若出現問題，將會引起連鎖損害與信用危機問題，故基層金融營運更需要有效的預警系統，基此，本文建議之類神經網路可提供基層金融單位及早發現問題，並採取相關的預防或管理措施。

關鍵詞：早期預警系統、漁會信用部、類神經網路。

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