

**APPLICATION OF NEURAL NETWORK ON EARLY WARNING SYSTEM BY RATING FOR THE CREDIT DEPARTMENT OF FISHERMEN ASSOCIATION IN TAIWAN**

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**ABSTRACT**

Series of financial crises arose in Taiwan since 1997 Asia financial crises, and it starts happened to the community financial institutions since then. In general, damages and impacts to the community and industry are always far more serious than that caused economy by the bankruptcy of a company. Thus, a more accurate financial warning system for governing community financial institutions is more needed than ever. However, past researches of financial distress prediction, which applied the traditional statistical techniques is very limited, and there have been more artificial neural network (ANN) suggested to this field recently. According to these ANN researches, financial distress predictions models build by artificial neural network are more feasible than traditional statistical methods. This paper, theoretically and empirically, applied the back-propagation network (BPN) to build the financial distress prediction models, and empirical results show function of BPN on crisis management mechanism toward the community financial institution in Taiwan is quite well. In addition, the predictability comparison provides the highest accuracy for Primitive BPN (81.10%) in the surveillance system, followed by Factory BPN (77.85%) and Ordered Logit (75.90%).

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

**Introduction**

Owing to financial liberalization, the cooperative bank of credit department, credit department of farmers and fishermen association have been on the downgrade for the past few years in Taiwan<sup>1</sup>. Competition among the financial institutions are intensive, and the crisis of operating emerged from defective financial frame, especially the credit departments, such as cooperative association of credit, credit department of farmer and fishermen have been seriously concerned. In fact, the management and operation regarding financial institutions with an omen of crisis I order to detect and take the effect measure at an early date is needed.

Beaver (1966) started with using financial ratios to predict financial failure and many followed (Altman, 1968). Although the traditional financial distress prediction models in the past have not been entirely satisfactory, there has been strong and continued interested in the field of financial early warning system because accurate instruments would benefit many interested parties. Since 1994, many examined the viability of an alternative methodology for 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 (Alataris et al., 2000; Randall and Dorsey, 2000; Siermala and Vihinen, 2002; Bongini et al., 2002; Verikas and Bacauskiene, 2002; Waszczyszyn and Bartczak, 2001; Alessandri, 2003; Chen et al. 2003; Chen and Leung, 2004). In this study, the ANN-based model, such as Backpropagation Network are compared with the Ordered Logit Model. The objective of this study are: 1) Construct an early warning system for credit department of fishermen association in Taiwan to detect the potential financial problem; 2) Establish an early warning system according to scoring credit department of

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<sup>1</sup> the default loan rates (%) since 1997/12 to 2002/12 are 8.53, 10.57, 13.7, 15.68, 16.39 15.37 respectively; which compare to foreign banks in Taiwan at the same periods: 1.07, 1.64, 3.20, 3.22, 3.53, 2.33 respectively are in seriously financial crisis.

fishermen association, which CAMELS guidance indicators are used to quantitative data analysis; 3) Improve the operation of financial institutions based on information provide from early warning system.

### Material and Methodology

#### Ordered Logit Model

In order to solve the limits on regression analysis while discrete independent variables exist, Ordered Logit Model forms by cumulative distribution function with standard logistic distribution is used, which lead the value between zeros to one (Foka and Franses, 2002). The Logit model can be express as follows:

$$Y = \beta_0 + \sum_{j=1}^k \beta_j X_{ij} + e_i, i=1, 2 \dots n \quad (1)$$

where  $X_{ij}$  is explanatory variables,  $\beta_j$  is parameter,  $e_j$  is error term with zero expect value. To show how the model specified in above equation can be estimated, we first take both sides of the equation by except value

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

where  $X_i = (1, X_{i1}, X_{i2}, \dots X_{ik})$

$$\beta = (\beta_0, \beta_1, \dots \beta_k)$$

$E(Y_i)$  value between zero to one, and Logistic distribution is used to transfer  $X_i$  enable  $\beta$  between 0 to 1, then

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

and then transfers to:

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

Let  $P_i = F(E(Y_i))$ , then  $P_i$  can be derived as:

$$P_i = \frac{\exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_k X_{ik})}{1 + \exp(\beta_0 + \beta_1 X_{i1} + \dots + \beta_k X_{ik})} \quad (4)$$

Thus, the Ordered Logit model can be established through Maximum Likelihood Estimation, and explanatory variables are substituted into sample regression model 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  $\lambda(\beta) > X^2$  indicates the significant of the model. Finally, the effective level is measured with standard estimate modulus, and the bigger modulus means strong effective level.

#### BPN

Using the ANN to the early warning system is a breakthrough to solve the nonlinear model, which is superfluous when used in the traditional hypothesis. One of the more popular activation functions for ANN is the Backpropagation Network, which is capable of handling large learning problems. A group of BPN is connecting by many artificial neurons, and several layers are included in the BPN and some processing elements in each layer. A completed BPN framework can be classified into three layers: input layer, output layer and hidden layer as shown in Figure1.

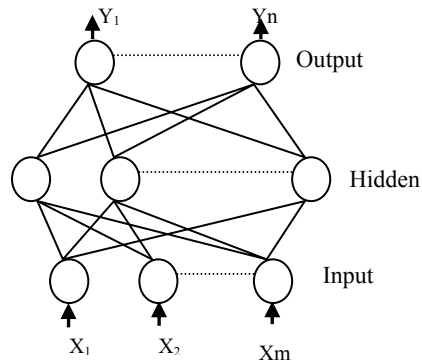


Figure1. Completed framework of BPN

The input layer processing elements deal with the external information and number of elements difference from the issues, and then the linear transfer function is applied. The interactive effect and capability of internal structure is showed in hidden layer, where input variables through input layer are weighted and transferred and then compared with the expect output value. The weights can be adjusted according to delta till the difference between estimate and expect value converge to minimize. Normally, more processing elements in hidden layer will slower the convergence and smaller in delta, but too many processing elements increase the training time only, and no help in reducing delta. In general, the suggested numbers of processing elements is between the means from numbers of input and output layer (Yeh, 2003). Processing elements of output layer express the output variable of network and the numbers of elements also differ from the issues. Nonlinear transfer function applied and the gradient steepest method is used for learning rule in BPN that can minimize the energy function.

### Model Specification

The principle of variables selection and model set up are established for early warning system in this section. Applying financial data collected from Taiwan provincial fishermen's association in 1997 to 2002, and stand on the index of Capital adequacy (C), Asset quality (A), Management (M), Earnings (E), Liquidity (L) and Sensitivity to market risks (S) (CAMELS), the financial factors stand for every financial rates are extracted by Kslomogorov-Smirnov test (K-S test) and factor analysis, and twenty-five financial rate significant variables are selected (see Table-1). The financial ratios and the rating mechanism of the Central Deposit Insurance Corp. on financial institutes are then been treated as the input variables to establish the crisis-warning models: the Ordered Logit Model, the factor analysis BPN and the primitive BPN. The credit departments of fishermen associations in respective regions are rated into A, B, C, D and E rates. The results of the credit rating are 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 predicting capacities of various models are tested by predicting samples and to compare their characteristics.

### Ordered Logit

Ordered Logit Model employed the ratings resulted from cluster analysis and by means of factor analysis induced variable index into a few independent common factor 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 acquire the rated credit departments of fishermen's probability of falling into each rating, which determined the annual credit rating of credit departments.

### Factor-BPN

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

Table.1. Selection of financial risk index variables

CAMELS	Financial risk index variables	operation performance
Capital adaptability	X <sub>1</sub> self-owned capital ratio	+
	X <sub>2</sub> self-owned venture capital ratio	+
	X <sub>3</sub> dunning and loan ratio	-
Assets quality	X <sub>4</sub> bad debt allowance and loan ratio	-
	X <sub>5</sub> bad debt and total assets ratio	-
	X <sub>6</sub> revenue and capital ratio	+
Management performance	X <sub>7</sub> operating expenses and assets ratio	-
	X <sub>8</sub> operating expenses and revenue ratio	-
	X <sub>9</sub> interest exchange and savings ratio	-
	X <sub>10</sub> interest exchange and interest return	-
	X <sub>11</sub> rate of return on assets	+
Earnings	X <sub>12</sub> rate of return on net value	+
	X <sub>13</sub> profit margin	+
	X <sub>14</sub> interest return and loan ratio	+
Liquidity	X <sub>15</sub> liquidity ratio	+
	X <sub>16</sub> liquidity preparation ratio	+
	X <sub>17</sub> loans and deposits ratio	-
	X <sub>18</sub> interest sensitiveness	*
	X <sub>19</sub> interest sensitiveness gap	+
Sensitiveness to market risks	X <sub>20</sub> deposit interest rate discrepancy	-
	X <sub>21</sub> ratio of assets and risks	-
	X <sub>22</sub> asset growth rate	+
	X <sub>23</sub> deposit growth rate	+
	X <sub>24</sub> loan growth rate	+
	X <sub>25</sub> pre-tax net profit growth rate	+

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

### Primitive-BPN

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

In general, the optimal framework of artificial neural network can be tested and learnt 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 employed Delta Rule and the transfer function is Sigmoid Function. When the model is done, all sample data are input in the model to acquire various credit departments of fishermen’s probability of credit ratings.

**Empirical Results**

**Ordered Logit**

Table-2 lists the relevant results of Ordered Logit Model, and its Log-Likelihood is significant (p=0.001), which shows that the model fits well. Except Factor 4, the other five factors, under the 5% significant level, demonstrate the statistical significance. According to table-1, the importance of significant variable factors resulted from the Ordered Logit Model can be ordered as followings: 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).

Table-2 Evaluated results of 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)	8.898	44.775	0.001*	3.179	1
Assets quality(A)					
Factor 2					
Liquidity (L)					
Managerial capability(M)	4.224	18.488	0.001*	1.085	4
Sensitiveness to market risks(S)					
Factor 3					
Assets quality(A)					
adaptability(C)	6.916	32.179	0.001*	2.824	2
Liquidity(L)					
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				

Note: \* means significant factor<math>\alpha=0.05</math>.

**Factor-BPN**

The model induces variable indexes by means of factor analysis to inter-independent common factors and ranked ratings according to various groups’ financial attributes, which is used to execute 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 number reach seven, the RMS is high

and the convergent speed 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.

The RMS of samples created by the model is set to stop when it goes under 5%, and initial value of momentum term is 0.4. The decrease range of each time is 0.95, and 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 and shown in Figure 3.

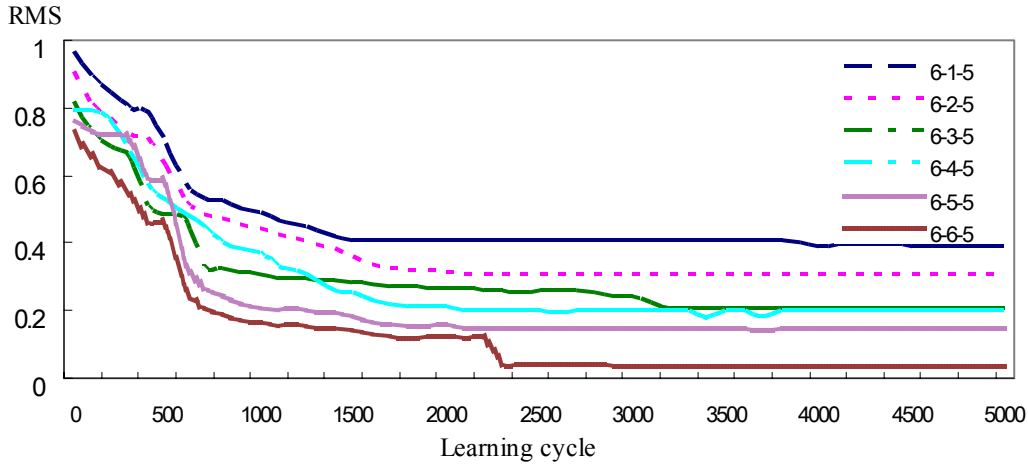


Figure.2. Factor-BPN relationship between RMS and learning cycle under different number of process elements in hidden layer

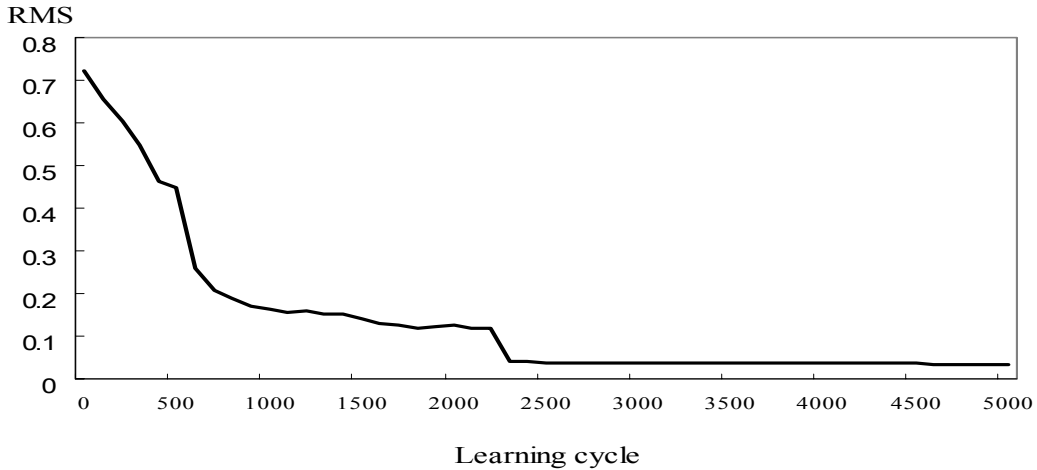


Figure.3. Factor-BPN relationship between RMS and learning cycle

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 five operating levels can be acquired as listed in Table-3. It shows the credit departments of fishermen in high level all featured great emphasis on the assets quality, efficient management, and following operating rules to attach importance on assets adaptability. Observing the first three factors that influenced their operating performance reveals they cover most of the rating index of CAMELS, which indicate a good credit department should integrate the overall operating strategy in its business investment composition. While credit departments on lower level took great risk in their investment composition and accordingly increased 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

Input units	Relative intensity (intensity sequence)				
	ON <sub>A</sub>	ON <sub>B</sub>	ON <sub>C</sub>	ON <sub>D</sub>	ON <sub>E</sub>
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)

**Primitive-BPN**

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

The RMS of samples created by the model is set to stop when it goes under 5%, and initial value of momentum term is 0.4. The decrease range of each time is 0.95 and 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.

The network framework of the primitive-BPN model is 25-15-5, and the network weight can be acquired after 5000 times of BPN learning cycle. The weights of process elements on hidden layer acquired from input variables corresponded with the weights of process elements on hidden layer from output variables. Then, the relative intensity of primitive financial variables corresponding to five operating levels are acquired and shown in Table.4.

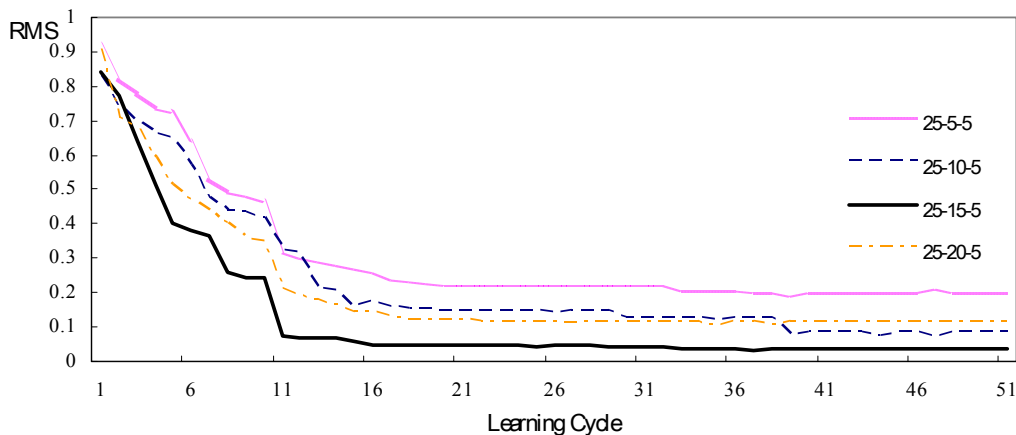


Figure.4. Comparison variety of process element between RMS and Learning cycle for Primitive-BPN

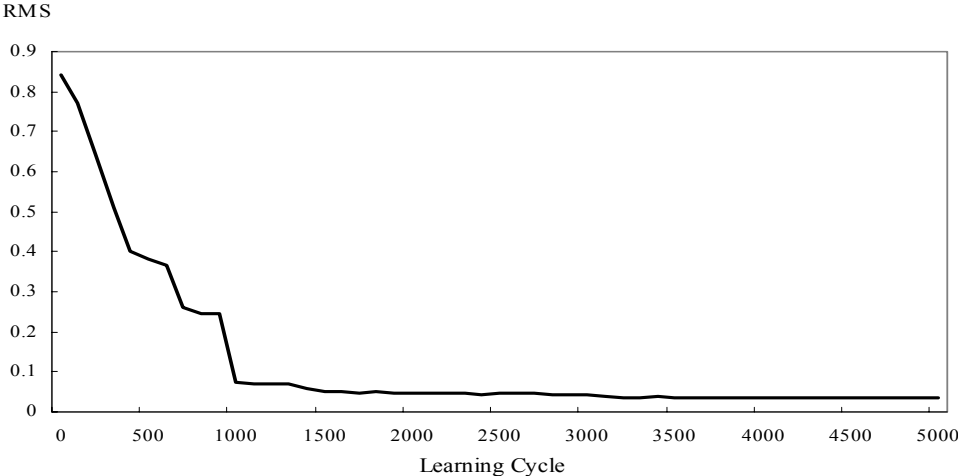


Figure.5. Primitive-BPN relationship between RMS and learning cycle

It shows the affecting variables of credit departments of A and B level are similar in sequence, which suggest good credit departments have strong earning ability and follow a comprehensive operating rule which emphasize assets quality, managerial capability and assets adaptability. On C level,  $X_6$  and  $X_8$  imply incoherence between managerial capability and the expectant operation-affecting directions, which indicated poor managerial capability. On D level, 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 E level failed the expectant 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 Primitive-BPN

A level		B level		C level		D level		E level	
X <sub>6</sub>	21.013	X <sub>12</sub>	14.498	X <sub>6</sub>	-7.008	X <sub>5</sub>	-4.557	X <sub>13</sub>	-2.239
X <sub>12</sub>	18.620	X <sub>11</sub>	12.306	X <sub>7</sub>	-6.321	X <sub>4</sub>	-3.468	X <sub>12</sub>	-1.137
X <sub>11</sub>	12.520	X <sub>1</sub>	9.255	X <sub>2</sub>	-5.247	X <sub>21</sub>	-3.451	X <sub>6</sub>	-1.136
X <sub>5</sub>	-7.946	X <sub>6</sub>	6.969	X <sub>1</sub>	5.826	X <sub>8</sub>	-1.353	X <sub>15</sub>	-0.126
X <sub>1</sub>	6.751	X <sub>5</sub>	-3.372	X <sub>8</sub>	-4.950	X <sub>18</sub>	1.150	X <sub>2</sub>	-0.107
X <sub>2</sub>	6.603	X <sub>13</sub>	-3.298	X <sub>10</sub>	-4.842	X <sub>3</sub>	-1.124	X <sub>1</sub>	0.105
X <sub>15</sub>	6.161	X <sub>15</sub>	3.077	X <sub>18</sub>	4.517	X <sub>14</sub>	1.049	X <sub>5</sub>	-0.098
X <sub>13</sub>	6.078	X <sub>9</sub>	3.036	X <sub>12</sub>	3.857	X <sub>20</sub>	-1.035	X <sub>11</sub>	0.097
X <sub>23</sub>	5.169	X <sub>2</sub>	2.582	X <sub>11</sub>	3.790	X <sub>6</sub>	0.880	X <sub>8</sub>	-0.082
X <sub>21</sub>	-3.712	X <sub>16</sub>	1.854	X <sub>5</sub>	-2.722	X <sub>12</sub>	0.632	X <sub>25</sub>	0.059
X <sub>19</sub>	3.558	X <sub>14</sub>	1.777	X <sub>9</sub>	-2.609	X <sub>13</sub>	-0.606	X <sub>18</sub>	0.057
X <sub>18</sub>	2.739	X <sub>7</sub>	-1.368	X <sub>3</sub>	2.009	X <sub>2</sub>	0.466	X <sub>4</sub>	-0.044
X <sub>8</sub>	-2.448	X <sub>21</sub>	-1.223	X <sub>21</sub>	-1.795	X <sub>16</sub>	0.417	X <sub>14</sub>	0.039
X <sub>14</sub>	1.912	X <sub>25</sub>	0.955	X <sub>16</sub>	1.402	X <sub>19</sub>	0.326	X <sub>9</sub>	0.030
X <sub>20</sub>	-1.762	X <sub>24</sub>	0.880	X <sub>20</sub>	-1.292	X <sub>15</sub>	0.300	X <sub>24</sub>	0.028
X <sub>16</sub>	1.659	X <sub>20</sub>	-0.828	X <sub>14</sub>	1.216	X <sub>25</sub>	0.282	X <sub>3</sub>	0.026
X <sub>24</sub>	1.624	X <sub>17</sub>	-0.811	X <sub>13</sub>	-1.191	X <sub>17</sub>	-0.277	X <sub>21</sub>	-0.026
X <sub>17</sub>	-0.660	X <sub>8</sub>	-0.330	X <sub>25</sub>	0.484	X <sub>1</sub>	0.112	X <sub>19</sub>	0.011
X <sub>25</sub>	0.577	X <sub>4</sub>	-0.288	X <sub>24</sub>	0.423	X <sub>9</sub>	0.098	X <sub>16</sub>	0.009
X <sub>22</sub>	0.561	X <sub>10</sub>	-0.280	X <sub>17</sub>	-0.411	X <sub>11</sub>	0.095	X <sub>10</sub>	-0.009
X <sub>4</sub>	-0.541	X <sub>22</sub>	0.270	X <sub>23</sub>	0.397	X <sub>24</sub>	0.092	X <sub>22</sub>	0.009
X <sub>9</sub>	-0.517	X <sub>18</sub>	0.258	X <sub>15</sub>	0.379	X <sub>7</sub>	-0.088	X <sub>17</sub>	-0.008
X <sub>3</sub>	-0.501	X <sub>23</sub>	0.250	X <sub>22</sub>	0.368	X <sub>23</sub>	0.085	X <sub>23</sub>	0.008
X <sub>10</sub>	-0.488	X <sub>3</sub>	-0.244	X <sub>4</sub>	-0.358	X <sub>10</sub>	-0.083	X <sub>7</sub>	-0.008
X <sub>7</sub>	-0.160	X <sub>19</sub>	0.080	X <sub>19</sub>	0.118	X <sub>22</sub>	0.027	X <sub>20</sub>	-0.003

Note: variables are in sequence of absolute values.

### Conclusions

This study constructs an early warning system for credit department of fishermen association in Taiwan in order to detect the potential financial problem and improve the operation of financial institutions based on information provided. The results show on various operating levels, the affecting variables of credit departments of fishermen of A and B level are identical with the variation of sequence, which suggested that good credit departments of 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 of fishermen on C level is poor managerial capability, which resulted in degrading assets quality. On D level, the major affecting variables included assets quality and sensitiveness to market risks. While E level credit departments are mostly concentrated on earning ability and liquidity, and when a business strategy of highly risky assets composition failed to yield, the crisis of failure is imminent.

We attempt to describe the operation performance frame of credit department of fishermen by CAMELS indicators on the basis of the sample data of credit department of fishermen from 1997 to 2002. The financial early warning system for credit department of fishermen proposed by this study can assist managers be warned before the crisis occurs and 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 correctness of each sampling classifications by

each model. The research found 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%). It also showed that primitive-BPN has relatively high correct prediction while factor analysis fails to get rid of insignificant variables in the process, and suggest that future researches may take hereditary evolution method as the basis for element selection to enhance the accuracy of input variable selection of artificial neural network.

Table.5 The chaos matrix of Ordered Logit model

Target value	Predicted value					Sub total
	A	B	C	D	E	
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

Prediction correctness: 75.90%; Type I error: 25.68%

Table.6 The chaos matrix of Factor-BPN model

Target value	Predicted value					Sub total
	A	B	C	D	E	
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

Prediction correctness: 77.85%; Type I error: 22.97%

Table.7 The chaos matrix of Primitive-BPN model

Target value	Predicted value					Sub total
	A	B	C	D	E	
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

Prediction correctness: 81.10%; Type I error: 20.27%

### Reference

- Alataris, K., T. W. Berger and V. Z. Marmarelis, (2000), A novel network for nonlinear modeling of neural systems with arbitrary point-process inputs. *Neural Networks*, 13, pp. 255–266.
- Alessandri, A., (2003), Fault diagnosis for nonlinear systems using a bank of neural estimators, *Computers in Industry*, 52, pp. 271–289.

- Altman, E.I., 1968, Financial Ratio Discriminate Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance*, pp. 589-609.
- Bongini, P. L. Laeven, and G. Majnoni, 2002, How good is the market at assessing bank fragility? A horse race between different indicators, *Journal of Banking & Finance*, 26, pp. 1011–1028.
- Chen, A. S., M. T. Leung and H. Daouk, 2003, Application of neural networks to an emerging financial market: forecasting and trading the Taiwan Stock Index, *Computers & Operations Research*, 30, pp. 901–923.
- Chen, A. S. and M. T. Leung, 2004, Regression neural network for error correction in foreign exchange forecasting and trading, *Computers & Operations Research*, 31, pp. 1049–1068.
- Foka, D. and P. H. Franses, 2002, Ordered logit analysis for selectively sampled data, *Computational Statistics & Data Analysis*, 40, pp. 477 – 497.
- Granger, E., M. A. Rubin, S. Grossberg and P. Lavoie, 2001, A What-and-Where fusion neural network for recognition and tracking of multiple radar emitters. *Neural Networks*, 14, pp. 325-344.
- Jagtiani, J. and C. Lemieux, 2001, Market discipline prior to bank failure, *Journal of Economics and Business*, 53, pp. 313–324.
- Lee, T. S., C. C. Chiu, C. J. Lu and I. F. Chen, 2002, Credit scoring using the hybrid neural discriminate technique, *Expert Systems with Applications*, 23, pp. 245–254.
- Park, S. I., M. J. T. Smith and R. M. Mersereau, 2000, Target Recognition Based on Directional Filter Banks and Higher-Order Neural Networks, *Digital Signal Processing*, 10(4), pp.297-308.
- Perraudin, W. R. M. and B. E. Sorensen, 2000, The demand for risky assets: Sample selection and household portfolios, *Journal of Econometrics*, 97, pp. 117-144.
- Qi, M. and Y. Wu. 2003, Nonlinear prediction of exchange rates with monetary fundamentals, *Journal of Empirical Finance*, 10, pp. 623– 640.
- Randall, S. Sexton and Robert E. Dorsey. 2000, Reliable classification using neural networks: a genetic algorithm and backpropagation comparison, *Decision Support Systems*, 30, pp. 11–22.
- Siermala, M. and M. J. M. Vihinen, 2001, On preprocessing of protein sequences for neural network prediction of polyproline type II secondary structures, *Computers in Biology and Medicine*, 31, pp. 385–398.
- Verikas, A. and M. Bacauskiene, 2002, Feature selection with neural networks, *Pattern Recognition Letters*, 23, pp.1323–1335.
- Waszczyszyn, Z. and M. Bartczak, 2002, Neural prediction of buckling loads of cylindrical shells with geometrical imperfections, *International Journal of Non-Linear Mechanics*, 37, pp. 763–775.