COMPARISON OF WAVELET NETWORK AND LOGISTIC REGRESSION IN PREDICTING ENTERPRISE FINANCIAL DISTRESS

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ABSTRACT

Enterprise financial distress or failure includes bankruptcy prediction, financial distress, corporate performance prediction and credit risk estimation. The aim of this paper is that using wavelet networks in non-linear combination prediction to solve ARMA (Auto-Regressive and Moving Average) model problem. ARMA model need estimate the value of all parameters in the model, it has a large amount of computation. Under this aim, the paper provides an extensive review of Wavelet networks and Logistic regression. It discussed the Wavelet neural network structure, Wavelet network model training algorithm, Accuracy rate and error rate (accuracy of classification, Type I error, and Type II error). The main research opportunity exist a proposed of business failure prediction model (wavelet network model and logistic regression model). The empirical research which is comparison of Wavelet Network and Logistic Regression on training and forecasting sample, the result shows that this wavelet network model is high accurate and the overall prediction accuracy, Type Ⅰerror and Type Ⅱ error, wavelet networks model is better than logistic regression model.

KEYWORDS

Wavelet Networks; Logistic Regression; Business Failure Prediction; Type I error; Type Ⅱ error.

1. INTRODUCTION

Business Failure Prediction (BFP) can help to avoid investing in business likely to fail. Bankruptcy prediction model enhance the decision support tool and improve decision making [33]. It uses statistical analysis and data mining technique. Statistical business failure prediction models attempt to predict the business' failure or success. The Multiple discriminant analysis (MDA) has been the most popular approaches [6, 13]. There have a large number of alternative techniques available in this MAD model [2, 9, 22, 33]. The data mining techniques include decision tree, support vector machine (SVM) [10], neural networks (NNs) [11], fuzzy system, rough set theory and genetic algorithm (GA) [33]. Various researches have demonstrated the artificial intelligence (AI) techniques serve as a useful tool bankruptcy prediction such as artificial neural networks (ANNs) [30].

The following method or model using for prediction in time series are Box-Jenkins method [28], Grey forecasting model [11], artificial neural networks model [1, 4, 16], Logistic Regression [25, 30], ARMA Model [21]. In Box-Jenkins method, it is difficult to determine the model features; it is also difficult to identify no-steady state. It is not need to calculate the statistical characters in grey forecasting model or neural network model. But, grey forecasting model is suitable for solve exponential growth practical problems. The network modelling approach in artificial neural

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networks model is difficult to determine the network structure by using scientific application. In training and learning state, BP model calculate the optimal weight. This model trapped in a local minimum which will affect the reliability and accuracy of the model. ARMA Model provides one of the basic tools in time series modelling. This method is valid in pure AR model and pure MA model. But, it is difficult for identification in mixed ARMA model. Therefore, using wavelet network clustering capabilities, the input time series sample autocorrelation function (SACF) value and partial autocorrelation function (SPACF) value, the output is the identification of ARMA model. Many researchers [20, 29, 36] discussed the ability of nonlinear approximation of wavelets and neural network models. Some researches [31, 32, 34] studied fuzzy wavelet neural network models for prediction and identification of dynamical systems.

The main contribution of this paper is to propose a financial distress prediction method based on Wavelet Network model and logistic regression model. The financial and non-financial ratios were used to enhance the accuracy of the financial distress prediction model. The dimension of the inputs was reduced using a principal component analysis (PCA) method, and then Wavelet Network model were used to predict the financial distress.

2. LOGISTIC REGRESSION MODEL AND WAVELET NETWORK MODEL

2.1. Logistic regression model

Defines the probability $\pi(x)$ and 1- $\pi(x)$, these probabilities are written in the following form:

$$\pi(x) = P(Y = 1 | X_1, X_2, ..., X_n)$$
$$1 - \pi(x) = P(Y = 0 | X_1, X_2, ..., X_n) \tag{1}$$

This model of the $\ln \frac{\pi(x)}{1-\pi(x)}$ is:

$$\ln \frac{P(Y = 1 | X_1, X_2, ..., X_n)}{1 - P(Y = 1 | X_1, X_2, ..., X_n)} = \ln \frac{\pi(x)}{1-\pi(x)} = \beta_0 + \sum_{j=1}^{n} \beta_j X_j \tag{2}$$

Using the inverse of the Logit transformation of (2), it obtains at the following:

$$P(Y = 1 | X_1, X_2, ..., X_n) = \frac{e^{\beta_0 + \sum_{j=1}^{n} \beta_j X_j}}{1 + e^{\beta_0 + \sum_{j=1}^{n} \beta_j X_j}} = \frac{1}{1 + e^{-(\beta_0 + \sum_{j=1}^{n} \beta_j X_j)}} \tag{3}$$

(3) is a logistic regression model, the conditional mean is between 0 and 1.

2.2. Maximum Likelihood Estimate (MLE)

The maximum likelihood is the method of parameter estimation in logistic regression model. For a set of observations in the data (x_i, y_i), the following equation results for the contribution to the likelihood function for the observation (x_i, y_i) is $\alpha(x_i)$:

$$\alpha(x_i) = \pi(x_i)^{y_i} [1 - \pi(x_i)^{1-y_i}] \tag{4}$$

The observations are assumed to be independent of each other so it can multiply their likelihood contributions to obtain the complete likelihood function $l(\beta)$. The result is given in (5). Where β is the collection of parameters ($\beta_0, \beta_1, ..., \beta_n$) and $l(\beta)$ is the likelihood function of β.

$$l(\beta) = \prod_{i=1}^{n} \alpha(x_i) \quad (5)$$

$L(B)$ is denoted the log likelihood expression.

$$L(\beta) = \ln[l(\beta)] = \sum_{i=1}^{n} (y_i \ln[\pi(x_i)] + (1-y_i)\ln[1-\pi(x_i)]) \quad (6)$$

It employs the techniques of calculus to determine the value of β based on maximum of $L(\beta)$. It takes the derivate of $L(\beta)$ with respect to $\beta_0, \beta_1, ..., \beta_n$ and setting the resulting derivatives equal to zero. These equations are called likelihood estimations, and there is n +1 equation.

2.3. Hypothesis testing

The hypothesis testing that a coefficient on an independent variable is significantly different from zero use Wald statistic. The Wald statistic for the β coefficient is:

$$\chi^2 = \text{Wald} = [\beta / \sigma_\beta]^2 \quad (7)$$

This is distributed chi-square with 1 degree of freedom.

2.4. Wavelet network model t

Wavelet analysis is a new technique designed for multi scale analysis in the time series modelling. Wavelet analysis utilizes the wavelet basis function to approximate and extract the features of interests from the original data. If the function $\varphi(t)$ satisfies the following condition is called wavelet basis function.

$$\int_0^{\infty} \frac{|\varphi(w)|}{w} dw < \infty \quad (8)$$

Where $\varphi(w)$ is the Fourier transform of $\varphi(t)$ in the frequency domain. Variable t can actually have other unit [12].

The wavelet basis function $\varphi_{a,b}(t) = \frac{1}{\sqrt{a}} \varphi(\frac{t-b}{a})$ (9)

Where 'a' refers the scale (dilated) coefficient, 'b' refers the translation coefficient.

Wavelet networks employ activation function that are dilated and translated coefficient of a single function $\varphi : R^d \rightarrow R$, where d is the input dimension [36]. This function called the 'mother wavelet' is localized both in the space and frequency domains [7]. In order to increase convergence speed, the wavelet neural network shows surprising effectiveness in solving the conventional problem of poor convergence or even divergence encountered in other kind of neural network [38].

Wavelet network model is feed forward network model; the wavelet basis function is neuronal activation function. The basic strategy is changing the shape and scale wavelet basis, adjusting the network weights and threshold value to take the error function minimization. Figure 1 is Wavelet neural network structure.

Three layers of the wavelet neural network are input layer, hidden layer and output layer. Each layer is fully connected to the nodes in the next layer.

$\{x_i\}$: The Input value of the sample, $i = 1, 2,.., M$.

$\{y_p\}$: The output value of the sample p.

w_k : The weight of linking hidden layer with output layer, $k = 1, 2,.., K$

The output value of the sample p in network:

$$y_p = \sigma[\sum_{k=1}^{K} w_k \sum_{i=1}^{M} x_i \varphi(\frac{i-b_k}{a_k})] : \sigma(t) = 1/(1+\exp(-t)) \qquad (10)$$

$$y = \begin{cases} 1 & \sigma(t) > 0.5 \\ 0 & \sigma(t) < 0.5 \end{cases}$$

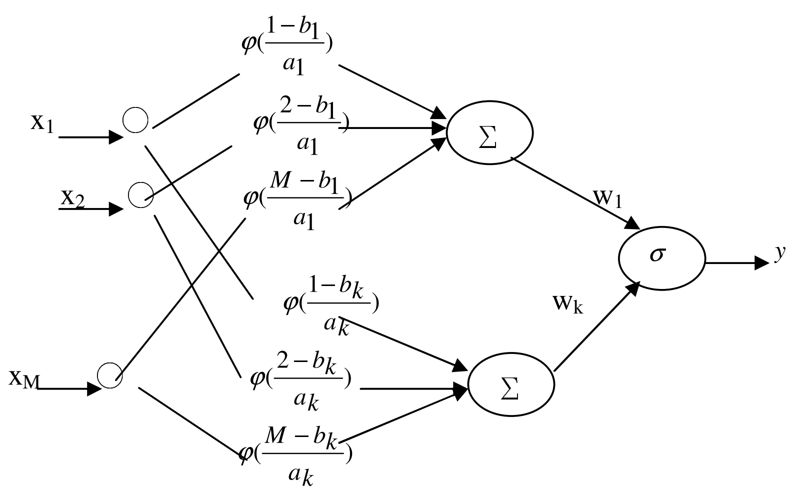

Figure 1: Wavelet neural network structure

The minimum mean error function:

$$E = \frac{1}{2} \sum_{p=1}^{P} \{d_p - y_p)^2 \qquad (11)$$

Where

d_p : The output of expected classification of the sample p, d_p := 1 or 0

M: The number of input layer.
K: The number of hidden layer
P: The number of sample

2.5. Wavelet network model training algorithm

The training algorithm for a wavelet neural network is as follows [35].

(1) Select the no of hidden nodes required. Initialize parameters $a_k, b_k, and\ w_k$ with random number in $[-1, 1]$. Give objective mean error $E_{\max}$. The Mother wavelet is has the following form

$$\varphi(t) = \cos(1.75t)\exp(-t^2/2) \qquad (12)$$

$$\frac{d\varphi}{dt} = -[t\cos(1.75t) + 1.75\sin(1.75t)]\exp(-t^2/2]$$

When taken as Gaussian wavelet it become

$$\varphi(t) = \exp(-t^2/2) \tag{13}$$

(2) Input training sample $\{x_i\}$ and the objective output $\{d_p\}$. Calculate the output $\{y_p\}$ and he minimum mean error function E.

(3) Adjust $a_k, b_k, and\ w_k$ for reducing the error of production. Use the conjugate gradient descend algorithm is employed:

$$\begin{aligned}
w_k(t+1) &= w_k(t) + \eta\frac{\partial E}{\partial w_k} + \alpha\Delta w_k(t) \\
a_k(t+1) &= a_k(t) + \eta\frac{\partial E}{\partial a_k} + \alpha\Delta a_k(t) \\
b_k(t+1) &= b_k(t) + \eta\frac{\partial E}{\partial b_k} + \alpha\Delta b_k(t) \\
t' &= \frac{i - b_k}{a_k}
\end{aligned} \tag{14}$$

Where

$$\begin{aligned}
\frac{\partial E}{\partial w_k} &= -\sum_{p=1}^{P}\sum_{i=1}^{M}(d_p - y_p)\sigma'(t')x_i\varphi(t') \\
\frac{\partial E}{\partial a_k} &= -\sum_{p=1}^{P}\sum_{i=1}^{M}(d_p - y_p)w_k x_i \frac{\partial}{\partial a_k}\varphi(t')\frac{\partial}{\partial a_k}\sigma(t') \\
\frac{\partial E}{\partial b_k} &= -\sum_{p=1}^{P}\sum_{k=1}^{M}(d_k^p - y_k^p)w_k \frac{\partial}{\partial b_k}\varphi(t')\frac{\partial}{\partial b_k}\sigma(t')
\end{aligned} \tag{15}$$

Where η and α are the learning and the momentum rates respectively.

(4) Return to step (2) the process is continued until E satisfies the give error criteria, and the whole training of wavelet neural network is completed.

2.6. Accuracy rate and error rate

Since Type I error only creates a lost opportunity cost from not dealing with a successful business, for example, missed potential investment gains [17], therefore Type I error is more important than Type II error. The objectives of predictive of accuracy should be to reduced Type I error while keep Type II error. Table 1 denotes as robustness of model. The measure used for calculating the accuracy of classifying distressed companies and no-distressed companies have:

Type I error = $\frac{B}{A+B}$

Type II error = $\frac{C}{C+D}$

E = $A/(A+B)$

F = $D/(C+D)$

G = $(A+D)/(A+B+C+D)$

Where

Type I error: refer to the situation when actual failure company is classified as non failures company

Type II error: refer to the situation when actual non failure company is classified as Failures Company.

C: the number of Type I error that is the number of distressed companies in the sample based on actual observation that was misclassified as a non-distressed company.

B: the number of Type II error that is the number of non-distressed companies in the sample based on actual observation that was misclassified as a distressed company.

A: the number of non-distressed accurately classified by the models

D: the number of distressed accurately classified by the models

E: The accuracy of classification of non-distressed company

F: The accuracy of classification of distressed company

G: The oval accuracy of classification

Table 1: Robustness of model

No-distressed Observed value	Non-distressed company	Distressed company	Accuracy of Classification
Non-distressed company	A	B	E
Distressed company	C	D	F
Overall accuracy of classification			G

3. EMPRICAL RESEARCH

We random select in the stock market listed company's traditional manufacturing in Taiwan to analysis the wavelet network model prediction. The steps of business failure prediction model (Wavelet network model and logistic regression model) are:

Step 1: Financial ratio of dataset
Step 2: Identification of independent variables
Step 3: Reduced the number of financial ratio
  (a) Kolmogorov-Smirnov test (K-S test)
  (b) Wilcoxon test
  (c) Principal component analysis
Step 4: Building the wavelet networks model
  (a) Wavelet networks model
  (b) Training for a wavelet neural network
  (c) Robustness of model in prediction accuracy
Step5: Building Logistic regression model
  (a) Logistic regression model
  (b) Training for Logistic regression
  (c) Robustness of model in prediction accuracy
Step 6: Comparison of Wavelet Network and Logistic Regression

3.1. Financial Ratio of Dataset

A dataset of covariates used in this study includes a combination of financial ratios and market variables [15]. Some researches such as [3, 8, 9, 23~24, 26~27, 39] have been widely used financial ratios in explaining the possibility of business financial distress. Gibson [14] suggests five factors (Profitability, Liquidity, Leverage, Efficiency, and Valuation ratio) for evaluation enterprise financial failure. Table 3 is the 15 rations selected in this study.

Table 3: The 15 rations selected in this study

	Category	Covariate	Code	Definition
x_1	Profitability	EBIT margin	EBT	EBIT/operating revenue
x_2		Return on Equity	ROE	Net income/ Total equity
x_3		Return on Assets	ROA	Net income/ Total assets
x_4	Liquidity	Current ratio	CUR	Current assets/ current liabilities
x_5		Quick ration	QUK	Quick assets/ current liabilities
x_6	Leverage	Debt ratio	DET	Total liabilities/ Total assets
x_7		Debt to Equity ratio	DER	Total liabilities/ Total equity
x_8	Efficiency	Fixed Asset turnover	FAT	Revenue/Asset
x_9		Capital turnover	CAT	Operating revenue/ operating invest capital
x_{10}	Valuation ratio	Price to Sales ratio	PSR	Stock price per share/ Sales per share
x_{11}		Price earnings ratio	PER	Stock price per share/Earnings per share
x_{12}		Price to book value	PBV	Stock price per share/Equity per share
x_{13}	Growth ability	Operating Profit grew	OPG	Operating Profit grew rate
x_{14}		Net profit grow rate	NPG	Net profit grow rate
x_{15}		Inventory turning rate	ITR	Sale/ Inventory

3.2. Data collection and Sample

This paper random select sample listed companies from 2006 to 2009 for estimating sample.

3.3. Reduced the number of financial ratio

There are three ways to reduce the large number of financial indicators (1) Financial indicators normal distribution test (Kolmogorov-Smirnov test (K-S test)) (2) Paired samples' significant test in financial indicators (Wilcoxon test) (3) Principal component analysis (PCA). PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The number of principal components is less than or equal to the number of original variables.

(1) Kolmogorov-Smirnov test (K-S test)

The K-S test has the advantage of making no assumption about the distribution of data. Suppose that an Independent and Identically Distributed (i.i.d.) sample $x_1, x_2, \dots x_n$ with some unknown distribution p and we would like to test the hypothesis that p is equal to a particular (normal) distribution p_0, i.e. decide between the following hypotheses:

$H_0: p = p_0$, $H_1: p \neq p_0$. We know that testing this hypothesis use chi-squared goodness-of-fit test.

(2) Wilcoxon test (Wilcoxon signed-rank test)

The Wilcoxon signed-rank test is a non-parametric statistical hypothesis test used when comparing two related samples, matched samples, or repeated measurements on a single sample to assess whether their population mean ranks differ (i.e. it is a paired difference test). Wilcoxon test used as (1) an alternative to the paired Student's t-test, (2) *t*-test for matched pairs, (3) the *t*-test for dependent samples when the population cannot be assumed to be normally distributed.

(3) Principal component analysis (PCA)

The main purposes of a PCA are (1) the analysis of data to identify patterns (2) finding patterns to reduce the dimensions of the dataset with minimal loss of information. In the table of principal component variance, it select no of components in this data testing, according to the cumulative variance above to 95%.

3.4. Building the wavelet networks model

In wavelet network model, the numbers of neurons of the input and output layers are respectively equal to the number of variables presented simultaneously to the network and to the number of variables that the neural network must estimate. Wavelet network model the number of principal components is equal to the number of input layer neuron. The number of output layer neuron is 1. The output neuron takes the value 0 if the company is healthy (no-financial distress) and 1 if it is bankrupt (financial distress). To determine the number of hidden layer node is by researcher.

After determining the network architecture, its implementation requires two data samples. The first set of data is used for the training, the second for the validation. The neural network is been realized using Matlab software. Model input values of paired samples are the score value of principal components.

3.5 Building Logistic regression model

Logistic regression model input values of paired samples are the score value of principal components. The dependent variable in logistic regression is usually dichotomous, that is, the dependent variable can take the value 1 with a probability of success $p(y_i)$, or the value 0 with probability of failure $1 - p(y_i)$.

The Logistic regression is been realized using Spss21.0 software and the Wald statistic for test the $\hat{\beta}$ coefficient.

The predict probability of occurrence $p(y_i)$ given as:

$$p(y_i) = 1/\{1 + \exp[-(\hat{\beta}_0 + \hat{\beta}_1 x_1 + ... + \hat{\beta}_m x_m)]\}$$

The output $p(y_i) > 0.5$ takes the value 0, the company is healthy (no-financial distress) and $p(y_i) < 0.5$ takes the value 1, and the company is bankrupt.

3.6. Robustness of model in prediction accuracy

It easily calculates the accuracy rate and Error rate. Type I error is $\frac{B}{A+B}$% and Type II error is $\frac{C}{C+D}$% (See Table 1).

4. EMPIRICAL ANALYSIS

4.1. Data collection and Sample

This paper select sample listed companies from 2006 to 2009 for training sample. There select 40 paired samples for analysis. It randomly selected 20 paired sample listed companies from 2009 to 2012 for forecasting sample.

Through the kolmogorov- Siminor test (using SPSS20.0 software), no financial indicator on paired sample is normal distribution. Through wilcoxon test, ten variables are selected as potential predictor variables: EBIT margin (x_1), Return on Equity (x_2), Return on Assets (x_3), Current ratio (x_4), Quick ration (x_5), Fixed Asset turnover (x_8), Price earnings ratio (x_{11}), Price to book value (x_{12}), Operating Profit grew (x_{13}), Net profit grow rate (x_{14}). The paired financial indicators sample wilcoxon test denotes as Table 4.

Table 4: The paired financial indicators sample wilcoxon test

Financial indicator	Statistic Z-value	2-taied test p-value	Result
X_1 (EBIT)	-2.012	0.042	*
X_2 (ROE)	-3.325	0.001	*
X_3 (ROA)	-4. 855	0.000	*
X_4 (CUR)	-4.121	0.000	*
X_5 (QUR)	-1.968	0.045	*
X_6 (DET)	-1.763	0.084	
X_7 (DER)	-0.213	0.812	
X_8 (FAT)	-2.164	0.032	*
X_9 (CAT)	-1.357	0.160	
X_{10} (PSR)	-1. 656	0.085	
X_{11} (PER)	-3.902	0.002	*
X_{12} (PBV)	-1.993	0.047	*
X_{13} (OPG)	-2.133	0.034	*
X_{14} (NPG)	-3.258	0.001	*
X_{15} (ITR)	-1.885	0.068	

* Significant at 5 percent level

4.2. Principal component analyse

PCA is statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables. It uses SPSS 21.0 software on PCA. It gets 8 principal components (z_1, z_2, z_3, z_4, z_5, z_6, z_7, z_8), it contains the original 10 financial indicators 97.82% (see table 5).

Tab 5: The principal component Variance

Principal components	Eigenvalue	Variance (%)	Cumulated Variance (%)
z_1	3.165	31.642	31.642
z_2	1.315	13.043	44.685
z_3	1.088	10.863	55.548
z_4	0.935	9.347	64.895
z_5	0.921	9.225	74.120
z_6	0.834	8.336	82.456
z_7	0.781	7.712	90.168
z_8	0.753	7.652	97.820
Z_9	0.155	1.540	99.760
Z_{10}	0.065	0.640	100.00

The component score express as:

$$z_i = a_{1i}x_1^* + a_{2i}x_2^* + a_{3i}x_3^* + a_{4i}x_4^* + a_{5i}x_5^* + a_{8i}x_8^* + a_{11i}x_{11}^* + a_{12i}x_{12}^* + a_{13i}x_{13}^* + a_{14i}x_{14}^*$$

Where $i = 1, 2, ..., 8,$ $x_1^* = {x_i - \overline{x_i}}/{s_i}$, $\overline{x_i}$: the mean of financial indicator, s_i: the standard deviation of financial indicator. Table 6 is denoted as the component scored matrix.

For example,

$$z_1 = -0.068x_1^* - 0.03x_2^* + 0.538x_3^* + 0.615x_4^* - 0.056x_5^* - 0.042x_8^* - 0.034x_{11}^* - 0.052x_{12}^* - 0.085x_{13}^* - 0.176x_{14}^*$$

Table 6: The component scored matrix.

Principal component	z_1	z_2	z_3	z_4	z_5	z_6	z_7	z_8
x_1^* (EBIT)	-0.068	0.008	0.054	-0.013	0.046	0.017	0.072	0.027
x_2^* (ROE)	-0.03	-0.011	-0.112	-0.042	-0.006	0.003	- 0.003-	-0.041
x_3^* (ROA)	0.538	-0.036	-0.035	-0.058	-0.024	-0.036	-0.012	-0.124
x_4^* (CUR)	0.615	-0.010	-0.042	-0.042	-0.038	-0.035	-0.003	-0.127
x_5^* (QUR)	-0.056	0.040	0.019	0.016	0.011	0. 986	0.006	-0.011
x_8^* (FAT)	-0.042	0.032	0.012	-0.043	0.0031	0.036	0.052	0.053
x_{11}^* (PER)	-0.034	0.056	0.079	0.009	-0.006	0.002	0.912	-0.019
x_{12}^* (PBV)	-0.052	0.031	0.048	-0.007	0.589	0.017	-0.054	-0.078
x_{13}^* (OPG)	-0.085	-0. 042	-0.012	0.831	-0.006	0. 015	0.008	-00.94
x_{14}^* (NPG)	-0.176	0.055	0.024	-0.017	-0.068	-0.011	-0.017	5.015

4.3. Wavelet network model training and forecasting

The wavelet network training and forecasting use Mat lab software. Vector $(z_1, z_1, z_3, z_4, z_5, z_6, z_7, z_8)$ is input of this model. Model input values of paired samples are 40, the input layer neuron is 8. The hidden layer neuron is 6 and the output layer neuron is 1. Set minimum mean error function $E = 0.001$, $\eta = 0.1$, $\alpha = 0.01$. The paired samples are 40 for training test. Predicted results denoted as table 7.

Table 7: Robustness of model (training sample)

No-distressed / Observed value	Non-distressed company	Distressed company	Accuracy of Classification (%)
Non-distressed company	38	2	95
Distressed company	1	39	97.5
Overall accuracy of classification			96.25

Type I error is $\frac{B}{A+B}\% = 5\%$ and Type II error is $= \frac{C}{C+D}\% = 2.5\%$

In order to test the predictive capability of model, paired samples are 20 for forecasting test. Predicted results denoted as table 8.

Table 8: Robustness of model (forecasting sample)

~~No distressed~~ Observed value	Non-distressed company	Distressed company	Accuracy of Classification (%)
Non-distressed company	16	4	80
Distressed company	3	17	85
Overall accuracy of classification			82.25

Type I error is $\frac{B}{A+B}\% = 20\%$ and Type II error is $= \frac{C}{C+D}\% = 15\%$

4.4. Logistics regression model training and forecasting

Model input values of paired samples are 40. Vector $(z_1, z_1, z_3, z_4, z_5, z_6, z_7, z_8)$ is input of this model. The Logistic regression is been realized using Spss21.0 software and the Wald statistic for test the $\hat{\beta}$ coefficient. Since

$$\chi^2 = \text{Wald} = [\beta/\sigma_\beta]^2 = 24.123$$

It has 0.1% significant effective. The logistic regression model is:

$$p(y_i) = 1/\{1+\exp[-0.0448 - 1.286z_1 - 0.654z_2 - 0.295z_3 - 0.879z_4 + 0.308z_5 - 2.55z_6 + 0.985z_7 - 0.675z_8]\}$$

Table 9 is denoted as the results of logistic regression.

Table 9: The results of Logistic regression model

Variable	coefficient	Standard deviation	Wald statistic	Degree freedom	probability
z_1	-1.286	0.413	10.356	1	0.001
z_2	-0.654	0.346	3.378	1	0.056
z_3	--0.295	0.276	1.211	1	0.294
z_4	-0.879	1.421	0.389	1	0.531
z_5	0.308	0.324	0.926	1	0.334
z_6	-2.555	1.692	1.467	1	0.224
z_7	0.985	0.268	0.152	1	0.716
z_8	-0.675	0.311	4.971	1	0.025
constant	-0.448	0.388	1.273	1	0.251

Table 10 and table 11 are robustness of model in training and forecasting samples respectively.

Table 10: Robustness of model (training sample)

~~No distressed~~ Observed value	Non-distressed company	Distressed company	Accuracy of Classification (%)
Non-distressed company	30	10	75
Distressed company	8	32	80
Overall accuracy of classification			77.5

Type I error is $\frac{B}{A+B}\% = 25\%$ and Type II error is = $\frac{C}{C+D}\% = 20\%$

Table 11: Robustness of model (forecasting sample)

~~No distressed~~ Observed value	Non-distressed company	Distressed company	Accuracy of Classification (%)
Non-distressed company	14	6	70
Distressed company	3	17	85
Overall accuracy of classification			77.5

Type I error is $\frac{B}{A+B}\% = 30\%$ and Type II error is = $\frac{C}{C+D}\% = 15\%$

4.5. Comparison of Wavelet Network and Logistic Regression

In comparison of Wavelet Network and Logistic Regression on training and forecasting sample, from the table 7, table 8 and table 10, table 11, no matter how the overall prediction accuracy, Type Ⅰ error and Type Ⅱ error, wavelet networks model is better than logistic regression model.

5. CONCLUSION

This paper select sample listed companies from 2006 to 2009 for training sample. There select 40 paired samples for analysis. It randomly selected 20 paired sample listed companies from 2009 to 2012 for forecasting sample.

Wavelet method and Logistic regression are introduced to suppress the financial distress prediction accuracy degradation due to potential accounting noise. In this paper, it use Kolmogorov-Smirnov test (K-S test), Wilcoxon test, Principal component analysis (PCA) to select potential predictor variables that are informative and closely related to companies' financial condition.

In this paper, it has two experiments to compare the prediction accuracy between Wavelet methods with Logistic regression method. From the results of training and forecasting sample test, the wavelet networks model in this paper on enterprise's financial distress early warning is valid. The result of comparison of Wavelet Network and Logistic Regression denoted as table 12.

Table 12: Comparison of Wavelet Network and Logistic Regression

Model		Training	Forecasting
Wavelet Network model	Type Ⅰ error	0.05	0.2
	Type Ⅱerror	0.025	0.15
	Overall accuracy of classification	0.9625	0.8225
Logistic Regression	Type Ⅰ error	0.25	0.30
	Type Ⅱerror	0.2	0.15
	Overall accuracy of classification	0.775	0.775

In Table 12, the comparison of Wavelet Network and Logistic Regression on training and forecasting sample, no matter how the overall prediction accuracy, Type Ⅰ error and Type Ⅱ error, wavelet networks model is better than logistic regression model.

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