

Application of Optimized Combination Method to Financial Risk Forecasting for Listed Companies

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Abstract—In a market economy, the competition among enterprises is becoming fiercer. Examples of declaring bankruptcy have become common. Financial risk is predictable, so it is of great practical significance for listed enterprises and the stakeholders to establish an effective financial risk forecasting model. The paper establishes a combination forecast model optimized with ant colony algorithm, to overcome the limitations of single model forecast, based on listed enterprises situation and characters and knowledge of economy management and accounting. It solves the problem of determining weight, and screens out better single forecast model. In this way, forecast content are more comprehensive.

Keywords- financial risk; forecasting; combination forecast model; ant colony algorithm

I. BACKGROUND

As global economy is becoming more and more unified, enterprises, especially listed ones are facing more and more risks. Complete and effective financial risk forecast model can help enterprises to decrease running risk. It is meaningful both theoretically and practically.

It is agreed that a financial risk forecasting system is effective to prevent and control enterprise financial risk. Quite a lot of work has been done on financial risk forecast. Abroad learners try multi-domain methods to study risk forecast [1-6].

Domestic learners establish financial risk forecasting system taking ST (special treatment for abnormal situation including finance and others) companies in domestic stock market as studying objects, adopting single variable analysis, Multiple Linear Regression Discriminant Model and multi-element logical aggressive model [7-13].

But the current research has the following problems:

- A serial of mathematical statistics is taken before model establishing, but this affects the effectiveness.
- Index selection and weight determination are affected by individual bias.
- Existing forecast models aim at kinds of business. They are not specialized.
- Most existing financial risk forecasting uses only one forecasting method. But the model is not very effective, because single forecasting method cannot cover all economical characters.

So, the paper presents optimized combination forecast model, and weight is determined with ant colony algorithm to avoid individual bias.

II. PREPARE FOR FINANCIAL RISK FORECAST MODEL

A. Financial Risk Forecast Case

In forecast system, both financial normal and abnormal enterprises are samples. The sample set is $U = \{u_i\}$, $i = 1, 2, \dots, n$. Every sample takes a serial of qualitative and quantitative indexes as characters:

1. Qualitative factor. Its characters are $R = \{r_j\}$, $j = 1, 2, \dots, m$, representing enterprise name, economic type, trade.
2. Quantitative factor. Its characters are $Q = \{q_j\}$, $j = 1, 2, \dots, m'$, representing financial index characters.
3. Forecast result. Its characters are $D = \{d\}$. Enterprises are divided into b kinds, and then forecast result character d has b possible values.

B. Sample Selection and Determination

The paper studies financial risk probability for listed enterprises, focusing on their main financial indexes. Data source reference comes from CCER Finance Database, China Finance Private Network Data and China InfoBank. Data covers enterprise internal data and public data. It is real and complete, accurate and sufficient for next screening step.

We select finance data of 50 ST companies and 50 non-ST companies from 2008 to 2010. And the 100 companies are divided into training and testing group. 70 companies are taken as training samples to establish enterprise risk forecasting model. And the other 30 companies are taken as testing samples to evaluate the model's forecasting ability.

C. Finance Warning Index Selection

Finance risk will be reflected directly or indirectly by financial indexes, so finance data before finance risk is picked up. Financial index selection should consider mainly about

repayment capability, profitability, growth capacity, operational capacity, and also the previous research result. Financial indexes are listed in Table 1.

TABLE I. FINANCIAL INDEXES TABLE TYPE STYLES

Index type	Symbol	Index name
Repayment capability	X1	current ratio
	X2	quick ratio
	X3	asset ratio
	X4	Current liability
	X5	Inventory turnover ratio
Profitability	X6	net profit rate
	X7	net assets income rate
	X8	return on assets
	X9	basic earnings per share
Growth capacity	X10	growth rate of net assets
	X11	total asset growth rate
	X12	operating income growth rate
	X13	operating profit growth rate
	X14	profits growth after tax
Operational capacity	X15	accounts receivable turnover
	X16	asset turnover ratio
	X17	velocity of liquid assets
	X18	fixed assets turnover

D. Preprocessing original data with Principal Component Analysis

Before preprocessing, the author takes *KMO* inspection and Bartlett Ball degrees inspection, therein *MKO*=0.897 and concomitant probability as 0.0000, both of which are suitable for principle component analysis.

The paper selects 18 financial indexes as forecasting variables. Too many indexes will cause too much redundant data, complicated calculation, slow convergence and irregular calculation. Besides, some of the financial indexes have little effectiveness; some are relative. So the paper uses Principal Component Analysis to get 6 principle components, Y_1, Y_2, L, Y_6 , by calculating related coefficient matrix. It is shown in Table 2.

III. DESIGN AND IMPLEMENTATION OF SINGLE FORECAST MODEL

A. Logistic Regression Model

Logistic regression model makes probabilistic predictions for problems that are influenced by kinds of factors. In the paper, the prediction objects are divided into two kinds, ST ones and non-ST ones. So, Logistic regression model can be used for the case. For company i ($i=1,2,L,n$), if its logistic regression value p_i is close to 0 (or $p_i \approx 0$), it is judged as financial distressed; if its logistic regression value p_i is close to 1 (or $p_i \approx 1$), it is judged as financial normal. And the farther is p_i from 0, the smaller crisis possibility is; and vice versa.

TABLE II. TABLE OF COMPONENT MATRIX

Index	Component					
	Y1	Y2	Y3	Y4	Y5	Y6
X1	.962	.019	-.055	-.042	.005	.095
X2	.958	.150	-.038	-.022	.028	.089
X3	.354	-.265	.943	-.025	.020	.086
X4	.553	-.268	-.045	-.028	.923	.076
X5	.866	.139	.120	-.089	.042	.021
X6	.024	.843	.724	.188	.216	-.254
X7	.123	.865	.154	.124	.057	-.015
X8	.235	.625	.111	.044	-.074	.188
X9	-.023	.597	.039	-.121	.152	.097
X10	.096	.378	.293	-.075	-.235	.434
X11	-.186	.710	-.223	-.304	-.281	.463
X12	.102	.457	-.395	-.143	.384	.279
X13	.012	.251	.665	.071	.247	-.003
X14	.078	.725	.301	-.013	-.114	.304
X15	.786	-.031	.735	.357	.240	.882
X16	.820	-.077	-.320	.224	.275	.387
X17	.938	-.169	-.498	.605	.053	.120
X18	.889	.229	.089	.350	-.685	-.110

The parameters in model are estimated by maximum likelihood estimate method. Suppose there are N samples L_1, L_2, L, L_n , from them n ones are randomly selected, their observation values are y_1, y_2, L, y_n . Suppose that $p_i = P(y_i=1|Y_k)$ is the possibility of result $y_i=1$ with given condition Y_k , and $P(y_i=0|Y_k)=1-p_i$ is the possibility of result $y_i=0$.

Then, the possibility of observation value is

$$P(y_i) = p_i^{y_i} (1-p_i)^{1-y_i} \quad (1)$$

So, n likelihood functions of observation is

$$L = \prod_{i=1}^n p_i^{y_i} (1-p_i)^{1-y_i}$$

$$= \prod_{k=1}^n \left[\frac{\exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right)}{1 + \exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right)} \right]^{y_i} \left[\frac{1}{1 + \exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right)} \right]^{1-y_i}$$

$$= \prod_{k=1}^n \frac{\left[\exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right) \right]^{y_i}}{1 + \exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right)} \quad (2)$$

Logistic regression model likelihood function of Logarithm is

$$\ln L = \sum_{i=1}^n \left\{ y_i \left(\alpha + \sum_{k=1}^m \beta_k x_k \right) - \ln \left[1 + \exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right) \right] \right\} \quad (3)$$

Make partial derivation by β_k on both sides of the equation.

$$\frac{\partial \ln L}{\partial \beta_k} = \sum_{i=1}^N \left[y_i x_k - \frac{x_k \exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right)}{1 + \exp\left(\alpha + \sum_{k=1}^m \beta_k x_k\right)} \right] \quad (4)$$

Solve equations $\frac{\partial \ln L}{\partial \beta_k} = 0$ with iterative method, and get the estimation of β_k .

We take Y_1, Y_2, Y_6 selected above as independent variables, logistic regression model as forecast model, and software SPSS18 as calculation and storage tool. There are two kinds of finance, normal and distressed. If financial risk probability p is less than 0.5, the listed company is an ST company, and financial risk will take place in 2 years. If financial risk probability p is bigger than 0.5, the listed company is a non-ST company, and its finance will be normal in 2 years. Table 3 shows that financial data of domestic listed enterprises is reasonable and predictable, and logistic regression model is precise to forecast financial risk.

TABLE III. THE JUDGING RESULTS

Sample class		Forecast result		Sum	Accuracy
		ST company	Normal company		
Training sample	ST company	30	5	35	85.7%
	Normal company	6	29	35	82.9%
Testing sample	ST company	13	2	15	86.7%
	Normal company	2	13	15	86.7%

B. Multiple Linear Regression Discriminant Model

Suppose BP neural network evaluates financial status of forecasting sample companies with a value between 0 and 1, the closer is the output value to 1, the lighter is financial crisis, i.e., normal finance; while, the closer is the output value to 0, the more serious is financial crisis, i.e., the more dangerous is finance.

C. BP Neural Network Forecast Model

Suppose BP neural network evaluates financial status of forecasting sample companies with a value between 0 and 1, the closer is the output value to 1, the lighter is financial crisis, i.e., normal finance; while, the closer is the output value to 0, the more serious is financial crisis, i.e., the more dangerous is finance. In the paper, a 3-layer network model is selected, i.e. hidden layer. BP network is configured as below.

- Determine number of input units

Enterprises' financial status can be judged by financial indexes. The 6 financial indexes after principal component analysis can be input units of BP neural network. So, the number of input units is 6.

- Determine number of output units

Output of training samples are judgment of financial status. The number of output units should be the same with financial status. So, the number of output units is determined as 1.

- Determine hidden units

The number of hidden units is related directly with input and output nodes. Too many or too few hidden units can influence network performance. Too many units lead to long study period and too few cause poor fault tolerance. In the paper, forward network with only on hidden layer is chosen.

Number of hidden units is determined by forum $s \geq k \times \frac{m}{m+n}$ [14], therein, m is number of input units, i.e. 6, n is number of output units, i.e. 1, k is number of learning samples, i.e. 20. So the number of hidden units can be calculated as 17.

D. Training Function

A neural network can simulate any continuous bounded function, if Layer 1 is S Function and Layer 2 is linear function. So, hidden transfer function is determined as S function "tansig", output transfer function is linear function "logsig".

In the paper, rapid and precise training function is obtained by comparison method. Training result of different functions is achieved by using training functions in Mathlab. Levenberg-Marquardt algorithm is chosen. There are 100 samples, therein, 70 ones are training samples, 30 ones are testing samples. And learning factor is $\alpha = \beta = 0.6$, inertial coefficient is $\eta = 1.0$, learning precision is $\varepsilon = 0.001$, maximum iterating steps is 100.

Based on base-pairing rule, discriminant result of training and testing samples is depicted in Table. It shows that accuracy of financial crisis forecasting by BP neural network model is more than 90%. Trained BP neural network model provides a good foundation for dynamic warning.

TABLE IV. THE DISCRIMINANT RESULTS

ample class		Forecast result		Sum	Accuracy
		ST company	Normal company		
Training sample	ST company	33	2	35	94.2%
	Normal company	3	32	35	91.4%
Testing sample	ST company	1	14	15	93.3%
	Normal company	2	13	15	93.3%

IV. OPTIMAL COMBINATION FORECAST MODEL DESIGN

Normally, combination forecast is more effective than single forecast. Single forecast may ignore or discard some factors, while combination can make full use of related information. Combination forecast improves accuracy with offsetting effect, by decreasing bias effect and fluctuation effect of forecast error [15]. So, combination forecast can lead to better forecast result of financial risk.

A. Optimal Combination Forecast Model

Suppose there are m ($m \geq 2$) single unbiased prediction methods $y_1(t), y_2(t), \dots, y_m(t)$, forecast value of method i in term t is y_{it} , $i = 1, 2, K, m$, $t = 1, 2, K, T$, then, forecast error of method i in term t is $e_{it} = (y_t - y_{it})$. Suppose combination weight is w_i , $i = 1, 2, K, m$. To guarantee combination forecast unbiased, weighting coefficient should meet Formula 2.

$$w_1 + w_2 + K + w_m = 1 \quad (5)$$

Suppose $\hat{y}_t = w_1 y_{1t} + w_2 y_{2t} + K + w_m y_{mt}$ is combination forecast of y_t .

Suppose e_t is combination forecast error in term t , then

$$e_t = y_t - \hat{y}_t = \sum_{i=1}^m w_i e_{it} \quad (6)$$

Then quadratic sum of combination forecast is Formula 4.

$$W_1 = \sum_{t=1}^N e_t^2 = \sum_{t=1}^N \sum_{i=1}^m \sum_{j=1}^m w_i w_j e_{it} e_{jt} \quad (7)$$

In optimal combination forecasting, objective function is often presented in error, to make error minimum and closer to reality. Weight optimization model is constructed as formula 5.

Therein, X is objective function, to achieve minimum quadratic sum, weight coefficient w_i is the condition. So, optimal combination forecast model can be constructed as Formula 6.

$$\begin{cases} \min X = X(w_i) \\ s.t. \sum_{i=1}^m w_i = 1 \\ w_i \geq 0 \end{cases} \quad (8)$$

$$f(t) = w_1 y_1(t) + w_2 y_2(t) + L + w_z y_z(t) \quad (9)$$

B. Optimal Combination Forecasting Result

To increase the forecast accuracy, we use Ant Colony Algorithm to optimize weight of combination forecast model. And the model is experimented with y_1, y_2, y_3 as input.

Based on the previous financial classification, ST companies are taken as financial distressed. Non-ST companies are taken as financial normal. The forecast result is shown in Table 5. It can be seen that optimal combination model is better than other single forecasting model.

V. COMPARISON FORECAST RESULTS

It can be seen from Table 3 and Table 5 that financial risk forecast accuracy with combination forecasting model is obviously higher than with other single models.

A lot of empirical investigation indicated that Logit model's discrimination ability is stronger than Multiple Linear Regression Discriminant Model; artificial neural network can forecast better than Multiple Linear Regression Discriminant Model. While, comparison between Logit model and artificial neural network model will reach different conclusions under different research conditions. This experiment indicates that artificial neural network model is better for forecasting than Logit model, and combination forecasting model obviously

has more accurate forecasting than other single modes, with average accuracy of 100%. But this is too theoretical to achieve in real application.

TABLE V. THE FORECAST RESULTS

Sample class		Forecast result		Sum	Accuracy
		ST company	Normal company		
Training sample	ST company	35	0	35	100%
	Normal company	0	35	35	100%
Testing sample	ST company	15	0	15	100%
	Normal company	0	15	15	100%

VI. CONCLUSION

To solve the problem of financial risk warning for domestic listed enterprises, the paper presents optimal combination forecasting model to forecast financial risk, to provide effective direction for decision making. The author establishes mathematic model with a lot of financial data from 300 Shenzhen and Shanghai Stock Exchanges. It aims at enterprises' real existing financial problems.

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