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PREDICTING CORPORATE FINANCIAL CRISIS USING SOM-BASED NEUROFUZZY MODEL

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ABSTRACT: Being aware of the risk in advance necessitates intricate processes but is feasible. Although previous stud ies have demonstrated high accuracy, their performance still leaves room for improvement. A self-organizing feature map (SOM) based neurofuzzy model is developed in this study to provide another alternative for forec asting corporate financial distress. The model is designed to yield high prediction accuracy, as well as reference rules for evaluating corporate financial status. As a database, the study collects all financial reports from listed construction compa nies during the latest decade, resulting in over 1000 effective samples. The proportion of “failed” and “non-failed” companies is approximately 1:2. Each financial report is comprised of 25 ratios which are set as the input variable s. The proposed model integrates the concepts of pattern classification, fuzzy modeling and SOM-based optimization to predict corporate financial distress. The results exhibit a high accuracy rate at 85.1%. This model o utperforms previous tools. A total of 97 rules are extracted from the proposed model which can be also used as reference for construction practitioners. Users may easily identify their corporate financial status by using these rules.

Keywords: SOM optimization; Fuzzy; ANN; financial distress; financial crisis; construction companies; prediction

1. INTRODUCTION

Financial distress often leads to the bankruptcy or demise of a company. The recent series of financial storms have made companies increasingly cautions of this danger. Prediction of financial distress, thus, is of significance for financial institutions, creditors and investors. Since the 1960s, scholars have been interested in adopting financial ratios in an attempt to forecast corporate financial distress. The work of Beaver (1966) demonstrates that corporate failure can be observed and predicted using dichotomous classification of the selected financial ratios. That study concludes that the best predictor of bankruptcy is the cash flow to debt ratio. Since then various financial ratios have been used in a variety of studies to predict the likelihood of financial distress. The selections of financial ratios for prediction of bankruptcy or financial distress vary depending on the type of business, scope of the research, input variables, the definition of financial distress itself, and the methodology [1].

Companies in the construction trade tend to face a high degree of uncertainty. Such uncertainty may come from technical or managerial difficulties, disputes, safety issues, surges in cash outflow, or even manipulation of financial leverage. The uncertainty enhances the likelihood of financial distress which can be revealed in financial statements [2]. In addition, the financial status and capital structure of companies in the construction industry are relatively different from those in other industries [3]. Since the 1970s, there have been several examples proving the feasibility of predicting corporate bankruptcy in other industries [4][5][6]. It is found that traditional prediction models, based on the assumption of a linear relationship among input variables, do not perform well using real-world data [7]. Practitioners have thus started to apply non-linear models in some cases so as to overcome this limitation. Models for construction related studies found in literature include Artificial Neural Networks (ANN), Case Based Reasoning (CBR), Fuzzy Logic Control (FLC), Support Vector Machines (SVM), data mining, and so on. Most are capable of yielding relatively accurate rates, usually greater than 80%, for predicting financial distress in common companies. For example, Chen and Du adopt the neural networks and data mining techniques to build a model for prediction corporate financial distress. They reach a prediction accuracy of 82.14% [8]. However, the parameter settings of these models are usually formulated based on trial-and-error or expertise, which makes them subject to need for modification for databases or demands that are constantly updated. Additionally, firms in the construction industry have specific features different from those in other industries. Financial analysis and prediction for companies in the construction industry is a fairly recent development. Methods have not been adopted until the studies in the 1990s. Scholars have pointed out that these unique characteristics mean that methods developed for the manufacturing industry, for example, may not be appropriate for companies in the construction industry [3]. In one recent study, an accurate prediction rate for construction related companies reaches 78.9% [9].

The objective of this study is to develop a hybrid model, combining three algorithms of Self-organizing feature map optimization (SOMO), Fuzzy logic control (FLC), and hyper-rectangular composite Neural Networks (named SFNN) to predict financial distress and to improve accuracy rate for construction companies. Considering data accessibility, the scope is limited to published financial reports for 42 construction companies listed on the Taiwan stock exchange over the last decade. The following 25 published financial ratios are included: profit margin, return on assets, after-tax rate of return, operating profit to paid-in capital ratio, pre-tax net profit to paid-in capital ratio, earnings per share, operating margin, operating profit, growth rate, after-tax net profit growth rate, revenue growth rate, growth rate of total assets, growth in the total return on assets, equity ratio, debt to assets ratio, long-term funds to fixed assets ratio, dependence on borrowing, inventory turnover ratio, receivable turnover ratio, total assets turnover ratio, fixed assets turnover ratio, net worth turnover ratio, current ratio, acid-test ratio, times interest earned ratio. There are numerous reasons identified by the Taiwan Stock Exchange (2010) which can cause corporate financial distress. Five of these which describe corporate financial status, bankruptcy, bouncing, bailout, reorganization, and delisting, are usually considered as indicating a high likelihood of financial distress. We combine the definitions by Steyn-Bruwer and Hamman (2006), to define two types of corporate status, “non-failed” and “failed”, where “failed” indicates any construction company which has positive status for all five of these and “non-failed” have none of them.

2. LITERATURE REVIEW

Scholars and practitioners have reached a similar consensus on corporate financial distress or failure. The most common indicator of corporate financial distress is filing for bankruptcy [10]. However, the definition of corporate financial distress varies. There is no clear line between “failed and “non-failed” firms [11]. Kuruppu et al. (2003) point out, for example, that countries using the creditor orientated concept usually regard liquidation as indicative of insolvency. Muller et al. (2009) suggest that liquidation, mergers, absorption, and delisting can be considered as indicators of corporate financial distress. In fact, the multiple definitions makes prediction of corporate financial distress difficult, with the resulting that, in most studies, corporate financial performance is still dichotomized as “failed” or “non-failed”. For the purpose of this study, a company in categorized as “failed” if it has the features of bankruptcy, delisting, bouncing, bailouts or major organizational restructuring that causes its existing business to be discontinued [12].

Most methods used for predicting financial failure fall into three categories: statistical models, artificial intelligent expert systems (AIES), and theoretical models. Aziz and Humayon point out that most prediction accuracies exceed 80%. Some AIESs perform relatively better in terms of prediction accuracy [13]. One study compares probit, logit and ANN models using financial data for Taiwan public industrial firms for 1998–2005. Its outcomes show that higher prediction accuracy is generally achieved with the ANN models [14]. A genetic based SVM model demonstrates its applicability for predicting financial failure and outperforming the Logit, Probit, BP-ANN and Fix-SVM models. It achieves an accuracy rate of 76% for companies in the Taiwan market [15].

Companies in the construction industry often have to deal with projects that are larger in size (monetary aspect) than their total corporate assets. Project-level performance dominates most corporate operations in the industry [16][17][18][19][20][21][22]. In other words financial performance may be different that in other industries [23][24]. These companies are significantly dependent on how smoothly their construction projects go and how profitable they are. They may have to file for bankruptcy simply due to the failure in one construction project even though their corporate performance does not reveal this danger [25][26]. This increases the difficulty of predicting financial distress. Even so, studies have demonstrated the feasibility of such prediction based on financial variables or ratios [27][28]. Studies surveying and analyzing companies in two Asian construction markets conclude that certain accuracy can be achieved using financial ratios [28][9].

3. DATA COLLECTION AND ANALYSIS

It is suggested that 1067 datasets need to be collected to reach the 95% confidence level for data sampling and 3% limit of error in a 50-50 proportion [29]. Given accessibility to data, this study uses the financial reports from all 52 construction companies listed on the Taiwan stock exchange during recent years (1998-2008). Among these companies, the primary business of 10 out of 52 carry is other than construction related activities. A total of 1848 quarterly financial reports published by the remaining 42 companies during these 11 years are collected and investigated. Entries in the financial reports are examined. 233 datasets are deemed inadequate due to incomplete or doubtful entries, leaving 1615 effective datasets for data analysis. Each financial report contains 25 ratios for profit margin, return on assets, after-tax rate of return, operating profit to paid-in capital ratio, pre-tax net profit to paid-in capital ratio, earnings per share, operating margin, operating profit, growth rate, after-tax net profit growth rate, revenue growth rate, growth rate of total assets, growth in the total returns on assets, equity ratio, debt to assets ratio, long-term funds to fixed assets ratio, dependence on borrowing, inventory turnover ratio, receivable turnover ratio, total assets turnover ratio, fixed assets turnover ratio, net worth turnover ratio, current ratio, acid-test ratio, and times interest earned ratio. Most of these 25 ratios are commonly employed by bankers as key attributes, with the aspects of profitability, solvency, and liquidity, to conduct financial analyses for construction companies [24].

Of all effective datasets, the largest portion is made up of 1050 “non-failed” financial datasets, 65.02% of the total. In other words, approximately one-third of construction companies have experienced or are experienced financial distress in the last decade, a period that includes two major Asian financial storms. It seems that construction companies experiencing financial distress perform relatively weakly in comparison to “non-failed” ones as can be observed in Table 1. For example, construction companies with financial distress have on average a -39.6% rate of return, while “non-failed” ones at least reach an average positive rate of return of 1.3%. “Failed” firms have a high possibility of failing to repay their debt because their times interest earned ratio is -21.8 on average. However, there is not much difference in most ratios revealed between these two types of firms. Comparison of the values in the average column of Table 1 shows that most of their corresponding standard deviations are significant. For example, the average operating profit for both types of firms is negative with significantly larger standard deviations. Even though ratios for features such as return on assets, earnings per share and growth rate seem better for “non-failed” firms, according to their corresponding standard deviations, the actual corporate performance still shows high divergence.

Table 1. Basic comparison using 25 ratios

	“Failed” construction firms		“Non-failed” construction firms	
	Average	St. Dev.	Average	St. Dev.
Profit margin	-370.5	1856.1	-46.3	1376.6
Return on assets	-2.0	6.2	0.5	3.4
After-tax rate of return	-39.6	158.1	1.3	7.2
Operating profit to paid-in capital ratio	-1.1	6.4	3.3	7.8
Pre-tax net profit to paid-in capital ratio	-5.2	16.2	2.9	9.1
Earnings per share	-0.5	1.7	0.3	0.9
Operating margin	-0.6	70.5	17.7	28.3
Operating profit	-142.6	662.3	-79.6	1247.2
Growth rate	0.1	274.8	11.6	37.4
After-tax net profit growth rate	-342.4	3200.4	112.8	2177.8
Revenue growth rate	338.0	2807.7	609.1	10439.9
Growth rate of total assets	-2.0	44.8	13.5	40.7
Growth in the total return on assets	0.5	10.2	0.3	4.2
Equity ratio	27.4	40.1	50.0	17.7
Debt to assets ratio	72.6	40.1	50.0	17.7
Long-term funds to fixed assets ratio	10764.3	62808.3	4943.4	20226.0
Dependence on borrowing	368.9	1186.6	91.7	65.5
Inventory turnover ratio	0.2	1.3	0.4	3.0
Receivable turnover ratio	7.8	50.4	28.2	271.1
Total assets turnover ratio	0.0	0.1	0.1	0.1
Fixed assets turnover ratio	19.0	215.3	9.9	63.1
Net worth turnover ratio	0.3	1.5	0.2	0.2
Current ratio,	144.9	125.1	336.8	1092.6
Acid-test ratio	18.4	61.2	90.0	454.0
Times interest earned ratio	-21.8	1073.9	887.6	7928.0

4. DEVELOPING THE SFNN MODEL

The SFNN model integrates the concepts and mecha nisms of the HRCNN [30][31] Fuzzy, and SOMO [32] [8]. The model starts with the development of the HRCN N as shown in Figure 1. To guarantee 100% training, the HRCNN adopts the Supervised Decision-Directed Learning (SDDL) algorithm, and therefore, its o utput and rules can be expressed by

$$Out(x) = f\left(\sum_{j=1}^{J} Out_j(x) - \eta\right) \quad , \qquad (1)$$

$$Out_j(\underline{x}) = f\left(net_j(x)\right), \qquad (2)$$

$$net_j(\underline{x}) = \sum_{i=1}^{p} f\left((M_{ji} - x_i)(x_i - m_{ji})\right) - p \,, \qquad (3)$$

$$f(x) = \begin{cases} 1 & if \quad x \ge 0 \\ 0 & if \quad x < 0 \end{cases} \quad , \qquad (4)$$

where M_{ji} *and* m_{ij} ∈ R are the weights of the j^{th} neur on of the hidden layer, $\underline{x} = (x_1, \ldots, x_p)^T$ stands for trai ning data, p is the dimension of the input variable, η∈ R, and the output is $Out(\underline{x})$: $R^p \rightarrow \{0,1\}$.

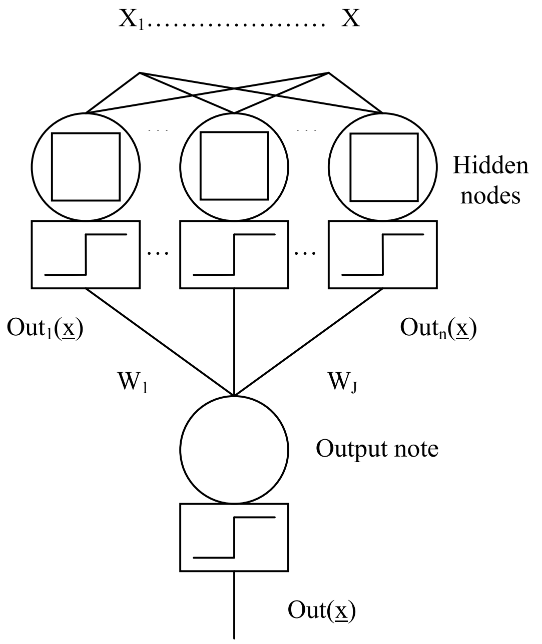

Figure 1.
Hyper rectangular composite neural network (HRCNN)

Next, the rules can be extracted using

$$If\ (\underline{x} \in [m_{11}, M_{11}] \times \cdots \times [m_{1p}, M_{1p}])\quad Then\ Out(\underline{x}) = 1;$$
$$\cdots \qquad (5)$$
$$If\ (\underline{x} \in [m_{J1}, M_{J1}] \times \cdots \times [m_{Jp}, M_{Jp}])\quad Then\ Out(\underline{x}) = 1.$$

Integrating the fuzzy concept, the network mechanis m is restructured as shown in Figure 2. To measure si milarity (or distance) between the inputs and the hyp er-rectangular area, $m_j(\underline{x})$ is employed to replace Equation (4) as follows:

$$m_j(\underline{x}) = \exp\left\{-s_j^2\left[per_j(\underline{x}) - per_j\right]^2\right\} \qquad (6)$$

where $per_j = \sum_{i=1}^{p}\left(M_{ji} - m_{ji}\right);$ (7)

$$per_j(\underline{x}) = \sum_{i=1}^{p}\max\left(M_{ji} - m_{ji}, x_i - m_{ji}, M_{ji} - x_i\right).$$

(8)

Accordingly, the following equation represents the output of the fuzzy based HRCNN:

$$Out(\underline{x}) = \sum_{j=1}^{J} w_j m_j(\underline{x}) + \theta \quad , \qquad (9)$$

where w_j is the weight of the j^{th} neuron of the hidden layer, s_j is the sensitivity, and θ indicates an adjustabl e value.

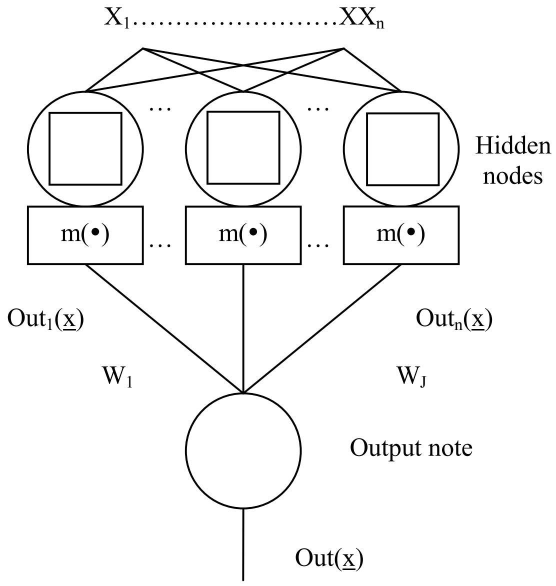

Figure 2 Fuzzy based hyper rectangular composite neural network (FHRCNN)

It is obvious that $m_j(\underline{x})$ is more flexible than the Gaussian function, since it can be adjusted to be either a Gaussian or a Step function. The rule extracting function is similar to that in Equation (5) but is re-written as

$$\text{If}(\ \underline{x}\ \text{is}\ HR_1)\quad \text{Then}\ Out(\underline{x})\ is\ w_1\ ;$$
$$\cdots$$
$$\text{If}(\ \underline{x}\ \text{is}\ HR_j)\quad \text{Then}\ Out(\underline{x})\ is\ w_j\ ; \qquad (10)$$
$$\cdots$$
$$\text{If}(\ \underline{x}\ \text{is}\ HR_J)\quad \text{Then}\ Out(\underline{x})\ is\ w_J\ ,$$

where $HR_j \in [m_{j1},M_{j1}] \times \ldots \times [m_{jp},M_{jp}]$. Output values are obtained using center average defuzzifier.

The last step in the development of the SFNN is to optimize the network parameters (Figure 2) using SOMO. The practicability of SOMO in dealing with optimization problems has been demonstrated [32][33]. Let each parameter set have a corresponding vector in $[l_1,h_1] \times \ldots \times [l_n,h_n]$. After initializing, the winner neuron j^* is obtained as follows:

$$j^* = Arg\max_{1\le j\le M\times N} \varphi_j(\underline{x}(k), \underline{w}_j(k)) = Arg\min_{1\le j\le M\times N} \left\|\underline{x}(k) - \underline{w}_j(k)\right\|,$$

(11)

where $\underline{x}(k)$ represents an input pattern;

$\underline{x}(k) = \left[x_1(k), \ldots, x_n(k)\right]^T$ is the k^{th} input pattern;

$\varphi_j(\cdot,\cdot)$ stands for the activation function of neuron j;

and $\|\cdot\|$ is the Euclidean norm.

We adjust the weights for j* and its neighbors according t o the following equation:

$$\underline{w}_j(k+1) = \underline{w}_j(k) + \lambda_1 \Lambda_{j^*,j}[\underline{w}_{j^*}(k) - \underline{w}_j(k)] + \lambda_2(1 - \Lambda_{j^*,j})\underline{n}$$
$$for\ 1 \le j \le M \times N$$

, (12)

where $\Lambda_{j^*,j} = 1 - \frac{d_{j^*,j}}{\sqrt{M^2+N^2}}$; λ_1 and λ_2 are the learning rates, usually in the ranges of $0 < \lambda_1 \le 0.3$ and $0 < \lambda_2 \le 0.2$; $\underline{n} = (n_1, \cdots, n_n)^T$ is defined as a noise vector for the new weight vector.

Through certain iterations are determined by a pre-specified number, the SOMO algorithm yields the optimal parameter set for the network. Hence, the SFNN is established and is capable of dealing with classification problems.

Once all effective datasets are normalized the input variables are set to these 25 ratios. The1615 datasets are randomly divided 90-10% for the training and testing categories, respectively, Table 2 shows the results obtained using fuzzy based HRCNN and SFNN.

The SFNN achieves a prediction accuracy of 85.1% which outperforms that of the Fuzzy based HRCNN and previous models [8][33]. In addition, the SFNN generates 49 and 48 valuable rules, for determining "failed" and "non-failed" construction companies, respectively. Table 3 shows all the extracted rules that recognize the corresponding patterns.

A typical rule, for example, determining a "failed" construction company can be explained as

If $-9787.1 \le$ *Profit margin* ≤ 3456.4,
$-65.2 \le$ *Return on asset* ≤ 11.7,
⋮ (13)
$-16987.9 \le$ *Times interest earned ratio* ≤ -16786.3,

Then the company is in financial distress.

Practitioners can utilize the rules to directly predict the financial failure of construction companies. The SFNN model is more convenient than other models since programming codes are not required to run the model again and again to yield the results. In addition, users can adopt only the first five rules to approximately recognize half patterns of corporate financial distress. Anyone who has basic financial knowledge may easily and quickly examine their corporate financial status.

Table 2. Results of SFNN and Fuzzy embedded HRCNN

	SFNN	Fuzzy embedded HRCNN
Rule number for "non-failed" companies	48	53
Rule number for "failed" companies	49	54
Successful training rate	94.6%	94.5%
Successful testing rate	85.1%	80.1%

Table 3. Extracted rules

"Failed" construction companies				"Non-failed" construction companies			
Extracted rule	Numbers of classified pattern	Extracted rule	Numbers of classified pattern	Extracted rule	Numbers of classified pattern	Extracted rule	Numbers of classified pattern
1st	104	26th	5	1st	127	26th	8
2nd	40	27th	5	2nd	121	27th	7
3rd	40	28th	5	3rd	114	28th	7
4th	34	29th	4	4th	94	29th	6
5th	22	30th	4	5th	53	30th	6
6th	11	31st	4	6th	45	31st	5
7th	10	32nd	4	7th	45	32nd	5
8th	10	33rd	4	8th	41	33rd	5
9th	8	34th	4	9th	20	34th	5
10th	8	35th	3	10th	19	35th	5
11th	8	36th	3	11th	17	36th	5
12th	8	37th	3	12th	17	37th	5
13th	8	38th	3	13th	17	38th	4
14th	8	39th	3	14th	16	39th	4
15th	8	40th	3	15th	16	40th	4
16th	7	41st	3	16th	15	41st	4
17th	7	42nd	3	17th	14	42nd	4
18th	7	43rd	3	18th	13	43rd	4
19th	7	44th	3	19th	12	44th	3
20th	7	45th	3	20th	12	45th	3
21st	6	46th	2	21st	11	46th	2
22nd	6	47th	2	22nd	11	47th	2
23rd	6	48th	2	23rd	10	48th	1
24th	6	49th	2	24th	10		
25th	5			25th	9		

5. CONCLUSION

Financial distress is fatal to corporate operations. Being aware of the risk in advance necessitates intricate processes but is feasible. Scholars and practitioners in the construction industry have been trying to develop tools for the prediction of corporate financial distress for years. Previous studies have demonstrated high accuracy but results still leave room for improvement. This is due to the unique characteristics of construction companies. A hybrid model, the SFNN, is developed in this study to provide a better alternative for forecasting corporate financial distress. The model offers improved prediction accuracy, as well as reference rules for evaluating corporate financial status. As a database we collect all financial reports from listed construction companies during the latest decade, resulting in 1615 effective samples. The proportion of "failed" and "non-failed" companies is approximately 1:2. Each financial report is comprised of 25 ratios which are set as the input variables. The SFNN model integrates the concepts of pattern classification, fuzzy modeling and SOM-based optimization to predict corporate financial distress. The results exhibit a high accuracy rate at 85.1%. This model outperforms previous tools. A total of 97 rules are extracted from the proposed model which can be also used as reference for construction practitioners. Users may easily identify their corporate financial status by using these rules.

The SFNN model has both practical and theoretical implications. It can be used to predict corporate financial distress and generate rules, giving users a guideline to examine their corporate financial status. The accuracy can be improved by integrating other advanced algorithms or concepts. Once detailed data are acquirable, input variables may be re-considered. With further integration of other algorithms, the model may be employed with quantified non-financial data. Future studies would involve establishing expert systems to create rules for decision making. Based on thorough feature investigation, the scope can be extended to other industries or markets.

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