INTERNAL CONTROL AND FRAUDULENT LITIGATION PREDICTON: APPLICATION OF NEURO FUZZY SYSTEM

Hsueh–Ju Chen*, Shaio Yan Huang**, Chin–Shien Lin***

Abstract

Since a leading conceptual model for the detection of management fraud was initially presented in Loebecke and Willingham (1988), different methods including cascaded logit models, fuzzy systems, neural networks (NNs) model have been applied to promote detection ability of fraud. However, those methods have their inherent limits. Therefore, this study tries to construct a hybrid approach combining the functionality of fuzzy logic and the learning ability of neural network to establish a prior alarm system for fraud lausuits which result from the defective internal controls. The results show that neuro fuzzy with a more accurate prediction not only turns out to be a support system for auditors' daily practice, it also proposes an assumption foundation for future research through its comprehensive explanation about mapping function among variables.

Keywords: Internal Control, Management Fraud, Neuro Fuzzy System

** Associate Professor, Department of Accounting, National Chung Hsing University*
*** Department of Accounting and Infotmation Technology, National Chung Cheng University, No. 168 University Rd., Min-Hsiung, Chia-Yi, Taiwan, 621, Tel: 886-921740591, E-Mail: elsewheret@yahoo.com.tw*
****Professor, Department of Business and Administration, National Chung Hsing University*

1. Introduction

With several witnesses such as Enron's bankruptcy in USA, Boda's collapse in Taiwan and Guangxia's accounting scandal in China, fraud problem has never been a single issue but has been spreading out to be a global focus. Suddenly, the "watch dog" was criticized to be behaved more like a lap dog (Briloff, 2001, p. 131) and attention to auditors' responsibility is greatly being drawn. SAS No. 82 emphasizes auditor's responsibility and practically provides auditors with "how to" guidance on fraud detection whereas SAS No. 99 steps further into a brainstorming session that requires auditors to interact with audit team members to discuss fraud and to document the discussion. Also, a number of comparative studies have tended to be largely descriptive documentations of fraud risk factors (Romney et al., 1980; Loebbecke et al., 1989) and even further attempted to investigate the relative importance of "red flags" or "red-flag cues" (Bell & Carcello, 2000; Apostolou, et al., 2001), as well as audit decision support system implementation (Galderon and Cheh, 2002). Unfortunately, despite their efforts devoted, one thing that holds true is that financial sandals incur repeatedly.

As regarded, the general public starts to query about the performance of the companies' internal control and turns to the external supervision mechanism for eradication of business financial fraud. In a matter of fact the internal and external regulations have their intended purposes. Internal control is conducted to ensure a company's a stable financial status, proper operation and compliance with applicable laws. With regards to external regulations, it is typically realized by a company which assigns reputable celebrities outside the company to serve as independent directors or supervisors, in hope that they can oversee the company's operation from an independent, impartial position. Unfortunately these "outsiders" are not familiar with the company as "insiders"; thus the external regulation does not always work. Although external regulation may strengthen a company's internal control performance, internal control is the key system that may eliminate financial fraud.

Furthermore, regarding studies on early warning models of management fraud, Loebbecke, et al. (1989) first proposed the conceptual model. After that, there were many studies launched based on their study structure. Bell, et al. (1993) used the cascaded logit model and other statistic approaches to test this model. Hansen et al. (1996) employed the generalized qualitative response model, and Bell and Carcello (2000) utilized the logistic regression for the same test. Besides, artificial intelligence tools, including expert systems, fuzzy logic modules and ANN, were also introduced. Based on the structure delivered by Loebbecke, et al. (1989) and risk factors proposed by Bell, et al. (1993), Ashutosh and Tallura (1998) used fuzzy logic to evaluate management fraud risk. Feroz et al. (2000), on ground of the "red signal" set forth in SAS No. 53, used ANN to detect companies that the Securities and Exchange Commission (SEC) may deem unreliable. Davis et al. (1997) integrated expert systems and ANN into a hybrid model to assess internal control risk. They at first used an expert system to indicate the relation between internal control rules. After prior processing by the expert system, data are sent to the ANN system to build a more complicated relation between variables. The testing dataset of model achieved an accuracy rate as high as 78%. In spite of the experimental data used in that study failing to completely reflect the complexity during actual auditing procedures, the study approach identified the possibility of the combination between an expert system and ANN.

Basically, expert systems, fuzzy logic and artificial neural networks (ANN) provide great helps for managers in making decisions. An expert system enable rules of thumb to be incorporated; fuzzy logic describes practical problems by the more human like reasoning method and also allows existing inaccuracy and uncertainty in the dataset; and ANN has an ability of learning from the observed data. However, the difficulty to obtain the correct knowledge base by expert system and fuzzy logic as well as the impossibility to explain the causal relationship among the variables by ANN have constrained the application of each method in business management An improvement is expected to be evident if there is ability that can explain the causal relationship among the variables and also can learn from the data set. Currently, the tool that can offer such characteristics is a learning-based fuzzy expert system -- neural fuzzy.

Therefore, this study aims to propose a hybrid, neuro fuzzy, to construct a fraudulent litigation early warning system, which combines the functionality of the fuzzy logic and learning ability of neural network with Taiwan data. In addition to increasing the prediction accuracy and fraudulent litigation detecting power, the research is hoping to provide the detailed instructions to avoid the fraudulent litigation through the knowledge base obtained from the learning process, which can possibly provide a new perspective for the financial diagnosis. Accordingly, the major contributions of the study are threefold: (1) to be a cross-border research, which is academically different from previous studies that much limit in USA; (2) to observe the characteristics of existing internal controls of public corporations for establishing a sound corporate governance; (3) to launch an early-warning model that is applicable to other auditing issues such as preliminary information risk assessment, errors and fraud, going-concern audit opinion, financial distress prediction, and bankruptcy prediction, etc.

The remainder of the paper is organized as follows. In section two, prior researches on category techniques used in fraud prediction are reviewed. The third section outlines the construction of the machine learning fuzzy expert system. The fourth section describes sample data and methodology and the fifth section analyzes the results obtained. The paper concludes with some final reflections on the results and their notion to auditors' internal control system assessments as well as limitations of this study and research directions for coming future.

2. Literature Review

The brief introduction of previous key models that apply to management fraud is provided as follows.

2.1 The Loebbecke and Willingham Conceptual Model

In terms of management fraud, Loebbecke and Willingham (1988) employed fraud red flags listed in SAS No.53 and developed a conceptual model:

P(MI)=f(C, M, A)

In which, MI represents the auditor's assessment of probability of a material misstatement due to fraudulent financial reporting, and C, M, and A refers to the client's conditions, management's motivation, and management's attitudes, respectively. If all three components exist simultaneously, it is extremely likely that management fraud exists. The model also suggests that when only one component is present, there is little likelihood of management fraud, meaning that the detection of management fraud requires comprehensive considerations. Loebbecke et al. (1989) used 77 actual fraud cases mentioned by the partners in the survey to validate the Loebbecke and Willingham assessment model, and found that in 86% of the fraud cases at least one factor from each of the three components was present. This strongly suggests that having all three components is a robust indicator for the existence of management fraud. While the results of Loebbecke et al. (1989) suggest validation of the conceptual model developed by Loebbecke and Willingham (1988), they provided no specific conclusion for any occurrence of fraud cases with one or two of the three components established. This model can be regarded as the origin of the contemporary fraud risk assessment model. Follow-up studies (Fanning et al., 1995; Hansen et al.; 1996, Ashutosh and Tallura, 1998; Bell and Carcello, 2000, etc.) all started with this model and used various decision supporting tools to explore the relation between fraud risk factors and such risk for correct detection.

Bell et al. (2000) proposed a logit discriminant function for the Loebbecke and Willingham (1988) conceptual model. By building the model, the authors added 305 non-fraud cases to the 77 fraud cases collected in Loebbecke et al. (1989). The 382 sample companies in total were then split into a training sample of 37 fraud cases and 143 non-fraud cases and a hold-out sample of 40 fraud and 162 non-fraud cases. Their findings show an accuracy rate of 95%

for fraud cases and 84% for non-fraud cases within the tranining sample, and 88%, 78% respectively for fraud cases and non-fraud cases of hold-out sample. The logit model is provided in the following section.

2.2 A cascaded logit approach

The output value of a regression linear probability model may be unreasonably less than 0 or larger than 1. To address the problem, logistic regression is developed. Fundamentally logistic regression is used for a scenario where there are binary variables. Let $P(y_i = 1) = p_i$, where p_i represents the occurrence probability and $1 - p_i$ the non-occurrence probability. Give a natural log for $\frac{P_i}{1-P_i}$ (also known as odds) and conduct a regression analysis to yield the following linear function.

$$\ln[\frac{p_i}{1-p_i}] = \alpha + \beta X_i \ldots \quad \ldots (1)$$

where x_i represents an explanatory variable and α and β the parameters of the model. This conversion makes the probability of all events fall within a range between 0 and 1. There are many explanatory variables, the equation (1) may be written as a linear function as below.

$$\ln[\frac{P_i}{1-P_i}] = \alpha + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \ldots\ldots + \beta_n X_n \quad \ldots\ldots (2)$$

After substitution, the equation (2) can be expressed as the following.

$$P(y_i = 1 \mid x_i) = P_i = \frac{1}{1+e^{-\varepsilon_i}} = \frac{1}{1+e^{-(\alpha+\beta x_i)}}$$

$$= \frac{e^{\alpha+\beta x_i}}{1+e^{\alpha+\beta x_i}} \quad \ldots\ldots \quad (3)$$

The relation between the probability of the occurrence and a natural variable x_i is shown as in Figure 1.

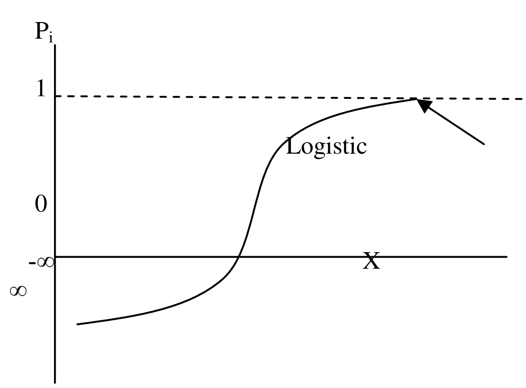


Figure 1. Reaction Curve of Logistic Model

The variable selection method of Cascaded logit tests discriminant ability of variables by the variable types. Namely, it uses a "2×2" contingency table, testing the independence with χ^2, and further building a logit model. In addition to omission of interaction among variables, such relation among variables is not necessarily as described by the logit function, which is also a weakness of this model.

2.3 Expert Systems

An expert system uses the rule "If-Then" to indicate the relation among variables. It not only boasts reduced auditors' inconsistent judgment (Huang J.H., 1989; Sutton et al., 1995) but also provides CPA firms with training materials, expediting newly recruited auditors to learn sufficient auditing procedures, lowering training costs for these firms. Besides, the system also allows proper correction following rapid change of business environment, ensures knowledge accuracy, and retains the accumulated experience and expertise that would be lost due to resignation and retirement of experts (Gray et al., 1991; Lenard et al., 2000). Expert systems are applied in large CPA firms for years; the application scope includes auditing, taxation, management consultation, and computer aided decision support. The literature involves Gray et al., 1991; Sutton et al., 1995; Davis et al., 1997; Eining et al., 1997; Anandarajana and Anandarajanb, 1999; Ragothaman et al., 1999; Lenard et al., 2000, etc.

Apart from the application of expert systems, the building a fraud detection expert system has its weakness -- inconvenient capture of knowledge. It is not easy to present routine work experience in an orderly manner. Furthermore, there is difference inevitably existing among the knowledge provided by experts. The experience of auditors in dealing with fraud is restricted, and there is no virtually recognized fraud expert. The system also requires a staff to monitor the system status from time to time to make sure the system is update in time. Therefore, an effective expert system should be developed and maintained by one or several experts specializing in knowledge management. However, knowledge management experts are scarcely to be found, plus high turnover rate of experienced experts, revealing potential problems of expert systems. Based on the foregoing, we may conclude that building an expert system will take time and money with considerable maintenance cost.

2.4 Artificial Neural Network (ANN)

Neural networks have many different topologies for different problem. Among them, back-propagation is the most well-known and commonly used, categorized as one of the supervised learning models. It draws the mapping function between the input and output from the data set provided. Usually the mapping function is too complicated to explain the causal relationship between the variables with ease. The topology shown in Figure 1 reflects three types of layers: input layer, hidden layer, and output later. Every node in the input layer represents an independent variable whereas the node in the output layer represents the dependent variable. The function of the nodes in the hidden layer is to complete the nonlinear transformation calculation.

When the obtained model is employed to forecast, each node in the input layer will send its value to the hidden layer. Each node in the hidden layer will calculate the weighted sum of the input values according to the "after–trained" edge weight, and perform the nonlinear transformation of the sigmoid function to produce an output which is the input of the next hidden layer. Then each node in the second hidden layer and each node in the output layer will repeat the same procedure to produce an output. The final output of the node in the output layer will be the output of the model.

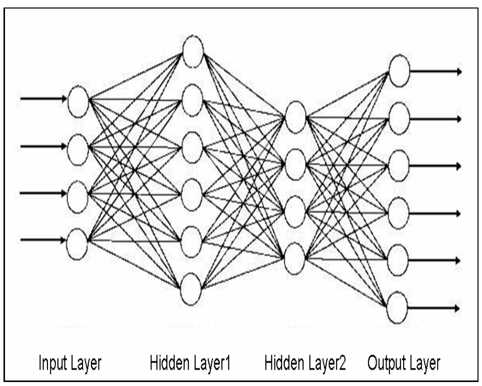


Figure 2. Neural network topology

The purpose of the back-propagation training is to obtain the weight of each edge to minimize the squared error sum between the actual value and the predicted value. First and foremost, each edge is given a random value. Next, the squared error sum between the actual value and the predicted value can be calculated. Then the weight is updated according to the gradient search method until the squared error sum is less than or equal to the threshold value. The eventually obtained model is called one that has been trained, which can then be used to forecast. Hornik (1989) has proven that neural network can approximate any function, given enough numbers of hidden layers and nodes. Nevertheless, neural network still has drawbacks such as the overwhelming problem that the prediction performance is good for in-sample data but bad for out-sample data, and the black box problem that can not explain the causal relationship among variables, which constrains its application to managerial problems.

Combining the findings of the above studies, it appears that conventional methods have serious weaknesses in distributional and linearity assumptions. Conversely, the expert system provides a more detailed relationship among variables through the "IF-THEN" rules; however, its difficulty in obtaining the correct knowledge base makes this approach unsuitable. More sophisticated, neural network is good at capturing the mapping relationship among variables especially the nonlinear one, however it cannot explain the causal relationship among the variables due to its complicated topology. Therefore, our study differs from prior literature by exploring the fudulent litigation problem through a hybrid method which is described below.

3. Implementation of Neural Fuzzy

The basic structure of the neural fuzzy can be divided into two parts: construction and parameter adjustment of a fuzzy logic expert system. A brief introduction of the two major parts is provided below:

3.1 Construction of a fuzzy logic expert system

Principally fuzzy logic refers to dealing with the extent that an object belongs to a fuzzy set; it often uses $\mu_A(x)$ to describe the extent that an object x belongs to Fuzzy Set A. Although the mapping function among variables described by "IF-THEN" rules is still the underpinning of a "fuzzy" expert system, the fuzzy logic system however distinguishes itself from the "traditional" expert systems by using linguistic terms instead of mathematical expressions in describing the linguistic variables. To clarify, we assume that a fuzzy logic system contains only one rule which can be described as equation (1):

"If the management's characteristic is medium, and the industry's characteristic is low, Then the fraudulent litigation risk will be very_low" …………………………………… (1),

where the management's characteristic, industry's characteristic, and fraudulent litigation risk are linguistic variables, and HIGH and LOW are known as linguistic terms. The whole statement, equation (1), is called a fuzzy rule. Several rules constitute a fuzzy logic model. The procedure to construct a fuzzy expert system consists of three steps: fuzzification, construction of knowledge base, and defuzzification.

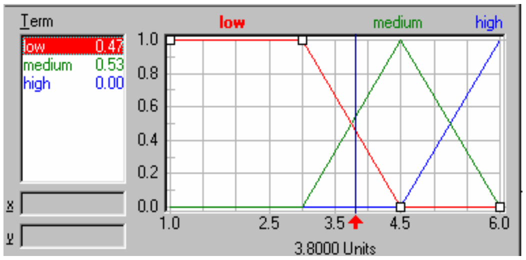
The whole statement constitutes a fuzzy rule. A fuzzy logic expert system is composed of a series of fuzzy rules, with three composition procedures: fuzzification of linguistic variables, building of a knowledge library, and defuzzification of linguistic variables.

3.1.1 Fuzzification

Each variable in the fuzzy rule can be defined by several linguistic terms. Each linguistic term has a corresponding membership function. For example, If the management's characteristic of a company is 3.8 and the management's capability is 3.5, respectively. Then every membership function value for each linguistic term can be found in Figure 3:

Management's characteristic: $\mu_{low}(3.8)= 0.47$, $\mu_{medium}(3.8)= 0.53$, $\mu_{high}(3.8)= 0$

Management's capability: $\mu_{low}(3.5)= 0.55$, $\mu_{medium}(3.5)= 0.45$, $\mu_{high}(3.5)= 0$



a. Management's characteristic

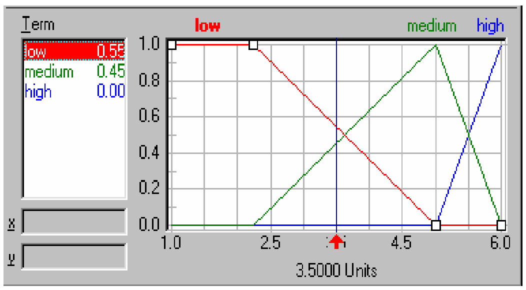


Figure 3. Membership Function of Each Variable

In other words, the extent to which Management's characteristic, 3.8, belongs to fuzzy sets, low, medium, and high are 0.47, 0.53, and 0.0 respectively. Similarly the extent that Management's capability, 3.5, belongs to fuzzy sets, low, medium, and high are 0.55, 0.45, and 0 respectively. Observably, a subject can be allocated to varied fuzzy sets with different membership function values simultaneously, which breaks the binary logic rule and makes the multi-attribute expression possible.

3.1.2 Building of a knowledge base

The knowledge base is a function of a series of "IF-THEN" statements. Assume that a neuro model is constructed with three independent variables and three dependent variables. Each independent variable is described with three linguistic terms whereas the dependent variable is with five. Then the complete knowledge base consists of 3*3*3*5=135 Rules. Each rule contains an "IF" and a "THEN" constituent. The former evaluates the extent the objects satisfy the requirements, and the later represents the response of the system. According to the definition of the composite fuzzy set by Thole (1979), the validity of "THEN" depends on the minimum value of the membership function values stated in the "IF" part. Taking the above example for instance, the validity extent of the "THEN" part is 0.53, i.e., min{Management's characteristic, Management's capability}=min{0.53 , 0.55}= 0.53, the validity extent of the system response, the fraudulent litigation risk will be very_low, is 0.53.

3.1.3 Defuzzification

After fuzzification and the inference process, each case would have the corresponding values for each linguistic term which are used to describe the output variable. For example, equation (1) has the validity 0.53 for "fraudulent litigation risk is very_low". Similarly, assume that the validity for a medium level of fraudulent litigation risk is 0.4, and for a low fraudulent litigation risk, 0.2. The process to transform these values into a numeric value is called defuzzification. Usually, the defuzzification process consists of two main steps. The first step is to find the representative value of each term, then combining all the values. The representative value is usually the one with the highest membership function value. The most commonly used method to combine the representative values is to calculate the weighted average of these values. For example, if the representative value for each term is {0.2,0.5,0.7} for low, medium, and high respectively, then the combining value is equal to 0.41*(0.2) + 0.4*0.5 + 0.2*0.7 = 0.422. In other words, the probability of bankruptcy is 0.422. This method is called the gravity method. There are also some other methods for defuzzification, please refer to Tong and Bonissone (1984) and Zimmermann (1987). As for the details about the fuzzy logic, please refer to Klir and Yuan (1995). The application of the fuzzy expert system can be found in Zimmermann and Zysno (1983), Leszczynski, Penczek and Grochulskki (1985), Sugeno, et al (1986), Tahani and Keller (1990), Levy, Mallach, and Duchessi (1991), De Neyer, Gorez and Barreto (1993), Chen and Chiou (1999).

What we have introduced above is called the fuzzy expert system. However, having each rule treated equally important by the system is hardly pragmatic in the real life. One method to rectify such a shortcoming is to assign each rule a weight, namely the degree of support (DOS), representing the relative importance of each rule. The validity of "THEN" fraction hence is a function of the validity of "IF" fraction multiplied by the DOS. Unfavorably, how to decide the DOS value for each rule reflects an imperfection for improvement. The learning ability of neural network among all the possible solutions can be an advanced alternative. Neural network can be used to fine tune the parameters of the fuzzy expert system, which is what we call the neuro fuzzy.

3.2 Learning of Fuzzy Expert Systems

Fundamentally, neuro fuzzy utilizes the functionality of the fuzzy expert system to construct the relationship among the variables, with the characteristics of fuzzy logic to tolerate the uncertainty and inaccuracy of the variables, and utilizing the learning ability of neural network to fine tune the parameters of the fuzzy expert system. There are some different methods to combine these two methods, please refer to Pedrycz and Card (1992), Buckley and Hayashi (1994), Lin and Lee (1996), and Nauck and Kruse (1996) for the details. This research adopts the fuzzy associative memory (FAM) proposed by Kosko (1992). This method has been applied to many areas (Stoeva, 1992; Inform, 1993; and Von Altrock, 1997) due to its learning ability and simplicity in implementation.

Taken in total, the procedures to construct a neuro fuzzy system can be described as follows.

1. To divide the data set into training and testing data set.
2. To construct a complete knowledge base and set all the DOS values equal to 0 as an initial solution.
3. To use the learning ability of neural network to fine tune the DOS value of each rule. If a specific relationship among variables described by a rule does exist in the data set, the DOS value of this rule will be strengthened; otherwise, the DOS value still remains as 0.
4. The training process will be terminated when the mean squared error between predicted value and real value is less than a predetermined threshold value. Afterwards, all the rules with DOS values less than certain threshold values will be deleted (this is what we call cut), and the left rules present the relationship among variables in the data set.
5. If the prediction accuracy is high for the testing data set by using the obtained the knowledge base, then the model is already established; otherwise, repeat step 3 and step 4.

4. Methodology

4.1 Sample selection and study period

The sample of sued cases for the study was selected from the Securities and Futures Institute of Taiwan that ever experienced litigation during the period 1993-2002. The case was only chosen if it had the following features: (1) it was a public-trading company, (2) suspicion to fraud was primary element for suing, (3) litigation risk factors were associated with the deficiency of internal control, and (4) fraudulent action was conducted by the persons who worked for the sued firm. Further, this study followed the "matched-pair sampling" technique by Coats and Fant (1993), selecting non-sued firms from the same time period and industry as the sued firms. Our final sample size includes 74 sued cases and 148 non-sued cases, respectively.

To discover the ability of models on making accurate prediction, the sample set of 222 cases was subdivided into a training sample and a testing sample based on random numbers generated by the computer. The training sample is used to set up model for logit or to calculate network weights, and hence the testing sample is for measuring predictive accuracy of the models. The data of a training sample combined 49 sued and 98 non-sued cases while a testing sample consisted of 25 sued and 50 non-sued cases.

4.2 Variables Selection and Instrument Design

The variables selected by the current study are through the implementation of "content analysis" technique applied to sued cases reading. Two CPAs from Big 4 were invited to select fraudulent risk factors associated with internal control systems of sued firms. Both also compared their selections and then discussed all discrepancies, however, any unsolved discrepancies were left to the third CPA to look at and the final decision would be consequently made. Details of 27 risk factors are shown in Table 1.

For sued firms, acquiring internal control data is a tough or impossible mission as the majority of them no longer exist. Therefore, it is automatically assumed by this study that any internal control factor is found to be violated by sued firms, the magnitude of such a violation is recoded as 2, otherwise, as 5. The reason for choosing 2 and 5 as measure base is to avoid the over-accurate prediction resulted from "extreme-middle- number selection".

For non-sued firms, data were collected from a questionnaire survey by asking internal auditor-subjects to conduct a self-assessment of pre-selected 27 control factors according to the condition of internal control practicing at the time. Participants were elicited using a six-point, Likert-type scale ranging from "strongly disagree" (scored as 1) to "strongly agree" (scored as 6).

4.3 Assessments of Model Performance

4.3.1 Prediction accuracy

One of the most commonly used performance criteria is the accuracy rate. Let ϑ denote the accuracy and be calculated by the following formula.

$$\vartheta = \frac{A + D}{A + B + C + D}$$

where A and D represent the number of companies predicted correctly; B and C represent the number of wrong predictions. All these four categories are summarized in Table 2.

4.3.2 The detecting power

As the proportion of the bankrupt companies in this case is much lower than the healthy ones, the criterion to maximize the total accuracy rate would lead to minimize a Type I error (consider a healthy company as a bankrupt one), hence a Type II error would be naturally raised. However, it is more important to classify a bankrupt firm correctly than to classify a non-bankrupt firm correctly, which means that minimizing a Type II error is outweighed. For example, maximizing the detecting power, the test concludes a bankruptcy for a no bankruptcy data set is less of a problem for investors.

4.3.3. Misclassification Cost

It is believed that the costs for a Type II error is usually much greater than that for a Type I error for investors (Hansen, ed al., 1996). Therefore, we subjectively assume that the costs of a Type II error is at least 100 times that of a Type I error. In addition, a sensitivity analysis was also performed by changing a multiple of 50, 200, 500 and 1000 each in turn to investigate if the cost gap between a Type I error and a Type II error affects model performance. Let k1 denote the misclassification cost of a Type I error and let k2 be the misclassification cost of a Type II error, assuming $k2 = m \times k1$. The total misclassification cost, π , can be expressed in the following formula:

π = (k1B+k2C) = (k1B + m k1C) = k1 (B+mC).

4.3.3. Comparison with CPAs' judgments

Alternatively, to test how well the established models can be applied to practice, 30 CPA-subjects from Big Four who had, on average, about eleven-year auditing experience read realistic cases selected from the testing data set. After reading the case materials, we asked the CPAs to assess the presence or absence of suing for the distributed cases. Interestingly, 27 male CPA-subjects were involved, indicating that males still dominate senior positions in Taiwan.

4.4 Model setup

4.4.1 Logit model

Before setting up the logit model, a factor analysis method is used to re-extract each factor from 27 questions as an input variable and four-category variables are derived. The fraud litigation prediction was therefore tested using the following logit model:

$$P' = \alpha+\beta1MC+\beta2MCA+\beta3OCFS+\beta4SSM$$

Where:

MC	=	Management characteristics
MCA	=	Management capability
OCFS	=	Operating characteristics and financial stability
SSM	=	Susceptibility of assets to misappropriation

5. Empirical Findings and Analysis

5.1 Descriptive statistics

Of the participants, 93 (53%) were females and 81 were males (47%), having an average of 2.5 years of experience. Of the sample, the majority of the shares was held by institutional and individual investors. Twenty-one companies had total sales over NT$101 billion. In addition, From Table 1, it is interesting to note that the strongest factors related to fraud litigation are: management decisions dominated by a single person (F1); management's aggressive attitude toward financial reporting (F2); and complicated related-party transactions (F25). On the other hand, the internal auditors of non-sued firms, overall, possessed a positive perception on their existing internal control systems, except on Factors 1, 18 and 25. Attention must be given that highly risky management characteristics observed from sued firms are also found in non-sued firms, implying that there is always a potential for firms getting troubles regardless of how healthy the firm is at the time as family firms are the dominant organizational forms throughout Taiwan economy. Besides, policies of required vacations for financial personnel were absent with magnitude (F18) and notes receivable were regularly pledged for financing (F27) signify the concern for employees' ethics as well as cash management.

5.2 Test for Normality

Prior to analysis, use Kolmogorov-Smirnov statistic to determine whether variables are distributed normally. The results are shown in Table 3; all variables are significant,

Table 3. Test for Normality

Variables	Kolmogorov-Smirnov Test		
	Statistic	Freedom	Sig.
Management characteristics	.111	222	.000
Management capability	.204	222	.000
Operating characteristics and financial stability	.083	222	.001
Susceptibility of assets to misappropriation	.101	222	.000
Fraudulent litigation probability	.426	222	.000

indicating abnormal distribution of each variable. And, when building a prediction model, we employ LOGIT, instead of discriminant analysis, for a comparison basis.

5.3 Prediction Performance Comparison

5.3.1 Classification accuracies

As stated above, compared to Type I error, Type II error causes greater loss to auditors and investors. Table 4 shows the average of NF and Logit for thirty entries of empirical data under different misclassification cost ratios. In addition to featuring better accurancy rate than Logit, NF is also superior to Logit at misclassification costs. The empirical findings prove that NF, which has learning ability, is more capable of capturing the relation between dataset variables, in comparison with Logit, suggesting that the relation between variables is possibly more complicated than that described by Logit.

5.4 Results of Each Model

5.4.1 Logistic regression results

The empirical findings of a logistic regression model are listed in Table 5. Apart from insignificant characteristics of the management, the other aspects are significant (α=0.01), implying that the more stable the operation and financial characteristic is, or the more complicated the accounting system is, the lower occurrence probability of fraudulent litigation will be. The result is consistent with expectation. Other than that, "the management characteristics" discords with the expectation, which indicates higher occurrence probability of fraudulent litigation in case of higher knowledge and ability of the management, and implies suspected occupational ethics for the management. Therefore, it is required to reinforce occupational ethic principles in schools or career education. As the "management characteristics" is insignificant, as stated above, the questionnaire shows the aspect of the management in Taiwanese listed companies is likely to have higher risk; thus a model cannot distinguish prosecuted companies from non-fraud ones with these variables, which does not suggest that the aspect is less important.

5.4.2 The neural fuzzy knowledge base

To explore the relation between variables captured by the neural fuzzy knowledge base, we rank the knowledge base by the management characteristic, ability, Operating characteristics and financial stability, and Susceptibility of assets to misappropriation, as shown in Table 6. In Table 6, the management characteristic, ability, Operating characteristics and financial stability in Rule 1 and Rule 2, Rules 3, 4 and 5, Rule 6 and Rule 7 are of the same, although the impact of Susceptibility of assets to misappropriation on fraudulent litigation risk may be negative (e.g. Rule 1 and Rule 2, or Rules 3, 4 and 5) or null (e.g. Rule 6 and Rule 7), indicating non-linear effect of variables on fraudulent litigation risk.

Besides, as can be seen in Table 7, in which the management characteristic, ability, and Susceptibility of assets to misappropriation are of the same in Rule 1 and Rule 2, Rule 3 and Rule 4, and Rule 5 and Rule 6, and the impact of operating characteristics and financial stability on fraudulent litigation risk may be negative (e.g. Rule 1 and Rule 2, Rule 3 and Rule 4) or null (e.g. Rule 5 and Rule 6).

Fundamentally the result of the Logit model suggests significantly negative correlation between the two variables -- the management characteristics and the management ability -- in their effect on the occurrence of fraudulent litigation. But, the neural fuzzy knowledge base proposes a scenario consideration for the effect of these two variables on the fraudulent litigation occurrence and suggests that there's no effect in some scenarios. This proves that, compared to the Logit model, neural fuzzy can provide more detailed relation between variables, as well as more accurate prediction results.

On the other hand, in order to demonstrate the model's effectiveness and efficacy, this study selects randomly selects 30 companies (10 fraud companies and 20 non-fraud companies). By offering all the indicators of the 30 companies, we ask auditors to evaluate the probability that fraud would occur to these companies. Senior auditors in some large Taiwanese CPA firms are the study's target respondents. Among these 30 companies, according to the survey, the auditors merely correctly identify 18 companies (i.e. a success rate of 60%), testifying the essentiality of auditing decision support tools. The conceptual model (from a perspective of internal control) developed by this study, no matter whether it is constructed by using the Logit model or the neural fuzzy model, records an accuracy rate larger than 65%, which suggests that these two models actually provide effective supports during auditing procedures.

6. Conclusion and Suggestion

The assessment of fraud risk is a highly professional job, especially for fraudulent behaviors of senior management. With subsequent occurrence of financial scandals (including e.g. Taiyu, Kuo Yang Construction, Lee and Li Attorneys, Procomp, Infodisc, and Enron, Worldcom, etc. in Taiwan or other countries), some issues like how to assist auditors in detecting and assessing management fraud risk with valid auditing decision support tools underscore the importance of detecting management fraud.

Starting from the perspective of internal control and by referring to red flags listed in Statement of Auditing Standard, ("SAS") No.82 for potential financial fraud cases, the study lists possible fraud risk factors and, through the analysis of practical litigation cases by CPAs, categorizes the major risk factors that lead to lawsuits in Taiwan. Based on these risk factors, a questionnaire is designed and distributed for data collection. This study further uses a neural fuzzy system in combination with the knowledge base of fuzzy logics that describes the relation between variables, as well as non-linear relation captured by the artificial neural network and learning ability, to construct an internal control based early warning system on fraudulent litigation.

Using a sample of 222 cases of which 74 were sued and 148 were non-sued. The study finds that, according to the logistic regression result, three-category risk factors such as management capability, operating characteristics and financial stability, and susceptibility of assets to misappropriation that should be significantly concern to auditors when making a fraudulent litigation judgment. Also, a more interesting finding is that the possibility of suing increased whenever management capability improved. This phenomenon is contrary to the previous study (Apostolou, et al., 2001), indicating that management capability plays an important role in committing frauds since the ethical expectation is disregarded. Calls for attention drawn to an ethical framework, specifically to address complex issues of ethical reasoning, is reserved for future researches in emerging markets where cultural differences exist and corruption is widespread. However, with respect to accuracy rate and misclassification costs, a neural fuzzy system features better performance than the logistic regression model. In addition, either neural fuzzy or logit produces an impressive hit rate from the test sample (81% and 75% classification accuracy) when compares with CPA-subjects' judgments (60% classification accuracy). This finding suggests that the models appear fairly to be effective as a tool for assessing fraudulent litigations. Hence, we may conclude that the early warning model based on the perspective of internal control is able to improve auditing effectiveness.

Other than the above, neuro fuzzy provides a much more detailed relationship among the variables than the traditional statistical method. This "exploratory relationship" as a lens in understanding fraudulent litigation patterns implies that new knowledge could be pursued and continuously updated. Therefore, the application of neuro fuzzy to the management field still has a lot of potential. Some suggestions for further research for this issue are presented. First, due to managing financial statements may be more serious today (Sugata, 2006), reaping the advantage of neuro fuzzy in dealing with qualitative variables could challenge for new research that is to take a more extensive menu of non-financial variable set plus financial ratios into fraud-lawsuit examination. Secondly, the proposed model does not aim to find out the best neuro fuzzy model for curing fraudulent litigation problems; instead, it intends to recommend an alternative to solve the problem. The decisions of the membership function shape, the transfer function, the methods to aggregate, and the methods to defuzzify can all be further explored in the future research. Last but not least, we can hardly make specific assessment of pros and cons of an early warning model for dependent variables from an internal control perspective. This study determines a dependent variable based on whether or not the prosecution case is made, and provides objective advantages by letting the value "1" stand for a prosecuted company for fraud and "0" a non-fraud company. However, the weakness may be attributed to the fact that a non-fraud company does not necessarily represent there's no defect in its internal control. The model would be used to create the relation between variables more precisely if we can find a proper indicator to measure internal control in an objective manner.

In sum, our paper is an effort to develop a neuro fuzzy model as a supportive decision tool. The model reflects the incremental importance of only providing objective information so that the auditors' ability to predict a fraud event won't be eroded (Koh and Killough, 1990).

Reference

1. American Institute of Certified Public Accountant, Statement on Auditing Standards No. 82 "Consideration of Fraud in a Financial Statement Audit", AICPA, 1997.
2. American Institute of Certified Public Accountant, Statement on Auditing Standards No. 99 "Consideration of Fraud in a Financial Statement Audit", AICPA, 2002.
3. Apostolou, B.A., Hassell, J.M., Webber, S.A. and Sumners, G.E., "The Relative Importance of Management Fraud Risk Factors," Behavioral Research in Accounting, 13, pp. 1-24, 2001.
4. Anandarajana, M. and Anandarajanb, A.,"A comparison of machine learning techniques with a qualitative response model for auditor's going concern reporting" Expert Systems with Applications, 16, pp. 385–392, 1999.
5. Ashutosh, D. and Talluru, L. "A rule-based fuzzy reasoning system for assessing the risk of management fraud", International Journal of Intelligent Systems in Accounting, Finance & Management, 9, pp.223-241, 1998.
6. Briloff, A. J. (2001). "Garbage in/garbage Out: A Critique of Fraudulent Financial Reporting: 1987-1997 (The COSO Report) and the SEC Accounting Regulatory Process", Critical Perspectives on Accounting, 12, pp. 125-148.
7. Bell T.B. and Carcello, J.V., "A Decision Aid for Assessing the Likelihood of Fraudulent Financial Reporting," Auditing: A Journal of Practice and Theory, 19, 169-185, 2000.
8. Chen, L.-H., and Chiou, T. -W., "A Fuzzy Credit-Rating Approach for Commercial Loans: a Taiwan Case", International Journal of Management Science, 27, pp.407-419, 1999.
9. Davis, J. T., Massey, A. P., and Lovell, R.E.R., "Supporting a complex audit judgment task□An expert network approach",European Journal of Operational Research , 103, pp. 350-372, 1997.
10. De Neyer, M., Gorez, R., and Barreto, J., "Fuzzy Integral Action in Model Based Control Systems", Second IEEE International Conference on Fuzzy Systems, 1, pp.172-177, 1993.
11. Eining, M.M., Donald R. J., and Loebbecke, J.K., "Reliance on Decision Aids: An Examination of Auditors' Assessment of Management Fraud," Auditing: A Journal of Practice and Theory, 16, pp. 1-19, 1997.
12. Feroz, E. H., Kwon, T. M., Pastena, V. S., and Park, K., "The efficacy of red flags in predicting the SEC's target: An artifical neural networks approach", International journal of intelligent systems in accounting, financial and management, 9, pp145-157, 2000.
13. Fanning, K., Cogger, K.O. "Neural network Detection of management fraud using published financial data", International Journal of Intelligent Systems in

Accounting, Finance & Management, 7, pp. 21-41, 1998.
14. Galderon T.G. and Cheh, J.J., "A Roadmap for Future Neural Networks Research in Auditing and Risk Assessment," International Journal of Accounting Information Systems, pp. 203-36, 2002.
15. Gray, G. L., McKee, T. E., Mock,T. J., "The future impact of expert systems and decision support systems on auditing", Advances in Accounting, 9, pp.249-273, 1991.
16. Hansen J. V., McDonald, J. B., Messier Jr., W. F., and Bell, T. B."A generalized qualitative-response model and the analysis of management fraud", Management Science, 42, pp.1022-1032, 1996.
17. Hornik, K. "Multilayer Feedforward Networks are universal Approximators," Neural Networks, 2, pp. 359-366, 1989.
18. Klir, G. J., and Yuan, B., Fuzzy sets and fuzzy logic: Theory and Applications, Upper Saddle River ,NJ: Prentice Hall , 1995.
19. Kosko, B., Neural networks and fuzzy system: A Dynamical System Approach to Machine Intelligence. Englewood Cliffs, N.J., Prentice Hall, 1992.
20. Koh, H.C., Killough, L. N., "The Use of Multiple Discriminant Analysis in the Assessment of the Going-concern Status of an Audit Client," Journal of Business Finance & Accounting, pp. 179-192, 1990.
21. Lenard Mary Jane, Pervaiz Alam, David Booth. "An analysis of fuzzy clustering and a hybrid model for the auditor's going concern assessment", Decision Sciences, 31, pp. 861-884, 2000.
22. Lin, C. -T., and Lee, C. G., Neural Fuzzy System. A Neuro-Fuzzy Synergism to Intelligent System, N.Y: Prentice Hall, 1996.
23. Levy, J., Mallach, E., and Duchessi, P., "A Fuzzy Logic Evaluation System for Commercial Loan Analysis", International Journal of Management Science, 19, pp.651-669, 1991.
24. Loebbecks, J., Eining, M. & Willingham, J., "Auditors' Experience with Material Irregularities: Frequency, Nature, and Detectability", Auditing: A Journal of Practice and Theory, Fall, pp. 1-28, 1989.
25. Loebbecke, J. and Willingham, J., "Review of SEC accounting and auditing enforcement releases", Working paper, KPMG Peat Marwick, 1988.
26. Ragothaman, S., Carpenter, J., and Butters, T."Using rule induction for knowledge acquision: an expert systems approach to evaluation material errors and irregularities", Expert Systems with Application, 9, pp.483-490, 1995.
27. Romney, M., Albreght, W. & Cherrington, D., "Auditors and the Detection of Fraud", Journal of Accountancy, May, pp. 63-69, 1980.
28. Sutton, S.G.., Young, R., and Mckenzie, P. "An analysis of potential legal liability incurred through audit expert systems", International Journal of Intelligent Systems in Accounting, Finance and Management, 4, pp.191-204, 1995.
29. Stoeva, S. P., "A Weight-Learning Algorithm for Fuzzy Production Systems with Weighting Coefficients," Fuzzy Sets and Systems, 48, pp. 87-97, 1992.
30. Von Altrock. C., Fuzzy Logic and NeuroFuzzy Application in Business and Finance, Upper Saddle River, N.J□Prentice-Hall International, 1997.
31. Zimmermann, H. -J. Fuzzy Sets, Decision Making, and Expert Systems, Boston: Kluver Academic Publisher. ISBN 0-89838-149-5, 1987.

Table 1. Auditor Judgments for Fraud-litigation Risk Factors

Four –Category Variables	Fraud-litigation Risk Factors		Sued Cases		Non-sued Cases	
			No. of Violation	Mean	Mean	SD
Management characteristics	F1	Management decisions dominated by a single person or small group	42	3.16	3.83	1.50
	F2	Management displays an overly aggressive attitude toward financial reporting	38	3.43	4.4	1.19
	F3	Management places undue emphasis on meeting target earnings and stock price	18	4.78	4.17	1.31
	F4	Management is effective at remedying the material mistakes which have already been notified	3	5.8	4.97	0.90
	F7	Management displays significant respect for regulatory bodies	26	4.24	5.24	0.70
	F9	Management's reputation in the business community is good	5	5.66	5.20	0.69
	F10	Management turnover has been low in the last three years	5	5.66	4.73	1.40
	F12	There are appropriate procedures for the review of variances from budgeted performance	3	5.80	4.72	1.08
	F20	Accounting policies for estimations are conservative	14	5.05	5.02	0.86
	F24	The client is highly co-operated with the auditor's requests	18	4.78	4.97	0.84
Management capability	F5	Management possesses the sufficient knowledge and experience in coping with the rapid changes of economic environment	2	5.86	4.94	0.82

Table 1 continued

	F6	Management performs risk assessments regularly	8	5.46	4.68	1.03
Operating characteristics and financial stability	F8	Management personal financing is in well condition	14	5.05	5.24	0.71
	F19	The client's accounting system is simple and trouble-free in operation	1	5.93	4.78	0.81
	F23	There are completed records for the client's important regular transactions	6	5.59	5.26	0.64
	F25	Significant and unusual related-party transactions are present	36	3.57	3.41	1.46
	F26	The client's current ratio has been good in the last three years	14	5.05	4.79	0.84
	F27	The client has no any stocks and notes receivable as collateral	26	4.24	4.24	1.52
Susceptibility of assets to misappropriation	F11	There are effective supervision on key controls	12	5.19	4.95	0.78
	F13	There are effective control activities to ensure all rules and regulations being followed	8	5.46	4.82	0.84
	F14	There are lists for the important seals and effective controls for their uses	12	5.19	5.47	0.60
	F15	There are appropriate procedures to approve all transactions	22	4.51	5.26	0.73
	F16	There are effective physical safeguards over assets	28	4.11	5.25	0.63
	F17	There is appropriate segregation of duties for client employees whose work is related to financial matters	25	4.31	5.30	0.76
	F18	There is appropriate policies of required vacations for client employees whose work is related to financial matters	5	5.66	3.31	1.39
	F21	There are effective controls over accounting information system	9	5.39	5.02	0.84
	F22	Transactions are recorded accurately and timely	9	5.39	5.14	0.78

Table 2. Classification table

Actual / Predicted	Actual	
Predicted	Bankrupt	Healthy
Bankrupt	A	B
Healthy	C	D

Table 4. Comparison of Prediction Performance NF vs. Logit

Model / Prediction performance		**NF**	**Logit**
Total accurancy rate		81%	75%
Misclassification cost	cost(B+100C)	87	525
	cost(B+500C)	287	2525
	cost(B+1000C)	537	5025
	cost(B+5000C)	2537	25025
	cost(B+10000C)	5037	50025

Table 5. Logistic Regression for Determinants of Fraud litigation

Variable	Predicted sign	Estimate	Std. error	Wald X	P-value
Constant	?	9.0932	2.6006	12.2257	0.0005
Management characteristics	?	0.3941	0.4883	0.6513	0.4197
Management capability	-	1.2790	0.4152	9.4884	0.0021

Table 5 continued

Operating characteristics and financial stability	-	-1.3298	0.4209	9.9825	0.0016
Susceptibility of assets to misappropriation	-	-2.4837	0.5019	24.4918	0.0000
Model fit statistics Criterion		Intercept Only	Intercept and Covariates		
ACI SC -2 Log L		189.135 192.126 187.135	148.106 163.058 138.106		
No.		147		Significance	0.000
Chi-square		49.0298		% correctly classified 79%	

Table 6. Knowledge base- Impact of susceptibility of assets to misappropriation on fraudulent litigation risk

	IF					THEN
	Management characteristics	Management capability	Operating characteristics and financial stability	Susceptibility of assets to misappropriation	DoS	Fraudulent litigation risk
1	high	high	medium	high	1.00	Medium
2	high	high	medium	low	1.00	High
3	high	low	medium	low	1.00	High
4	high	low	medium	medium	1.00	Low
5	high	low	medium	high	1.00	very_low
6	high	medium	low	high	1.00	very_high
7	high	medium	low	low	1.00	very_high

Table 7. Knowledge base-Impact of Operating characteristics and financial stability on fraudulent litigation risk

	IF					THEN
	Management characteristics	Management capability	Operating characteristics and financial stability	Susceptibility of assets to misappropriation	DoS	Fraudulent litigation risk
1	High	low	high	high	1.00	very_low
2	High	low	low	high	1.00	high
3	High	low	low	high	1.00	very_high
4	High	low	medium	high	1.00	high
5	High	low	high	low	1.00	very_low
6	High	low	low	low	1.00	very_low