Intelligent Financial Warning Model Using Fuzzy Neural Network and Case-Based Reasoning

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Abstract - Creating an applicable and precise financial early warning model is highly desirable for decision makers and regulators in the financial industry. Although Business Failure Prediction (BFP) especially banks has been extensively a researched area since late 1960s, the next critical step which is the decision making support scheme has been ignored. This paper presents a novel model for financial warning which combines a fuzzy inference system with the learning ability of neural network as a Fuzzy Neural Network (FNN) to predict organizational financial status and also applies reasoning capability of Fuzzy Case-Based Reasoning (FCBR) to support decision makers measuring appropriate solutions. The proposed financial warning model generates an adaptive fuzzy rule base to predict financial status of target case and then if it is predicted to fail, the FCBR is used to find similar survived cases. Finally according similar cases and a fuzzy rule base, the model provides financial decisions to change particular features as company goals in upcoming year to avoid future financial distress.

Keywords: Financial early warning system, Fuzzy neural network, Fuzzy case-based reasoning, Business failure prediction.

I. INTRODUCTION

Business failure prediction (BFP), which has long been studied extensively in the finance as well as information technology, as a financial early warning model is a particular data analysis model which should answer some fundamental questions such as: What are the significant features that can describe companies in distress and health? How the significance of these features can be evaluated and considered in prediction? What are the types and possible values of each feature? What are probable problems in data sets which need to be solved beforehand? How much predictive accuracy is essential and how it can be reached? And more importantly what kind of prediction is of interest and practical?

To answer feature selection question, there are many researches which have introduced different failure prediction models examined different sets of features in their models. Among them, the financial ratios compiled from financial statements were considered to have better measures of a corporate current performance than the individual items on the financial statement and were widely accepted because it could make the message of the financial statement more attractive. Regarding other aforementioned questions, gaining appropriate prediction accuracy has been the most important achievement in this field and there are various statistical and artificial intelligence techniques which are used to establish an accurate failure prediction. Among them, Artificial Neural Network (ANN) has become one of the most popular techniques for the prediction of corporate bankruptcy due to its high prediction accuracy. ANN, however, has not been applied widely in financial companies because it is generally difficult to build models. The difficulty stems from many parameters to be set by heuristics. Furthermore it is usually difficult to explain why it produces a specific result, i.e. poor explanation ability. So, there has been a need for other artificial intelligence techniques which have good explanation ability as well as high prediction performance. FNN and FCBR may be an alternative to relieve the above limitations of ANN because they have explanation ability along with reasonable accuracy. Utilizing this kind of techniques in failure prediction seems to be a new and interesting research direction in this field because failure prediction is not just a classical classification and as a practical system it should provide more information to support and guide decision makers.

In current BFP researches, including BFP models using FNN and FCBR, the predictive accuracy is the main focus. There are lack of research in the prediction-based decision making process to prevent probable bankruptcy. The proposed model, which takes all mentioned questions into account in a systematic approach, tries to go through the next step after prediction.

This study outlines the development of a financial early warning model employing FNN along with FCBR. It first uses a feature selection technique to find most significant features and then introduces a preprocessing method to prepare initial database which obviously improves the prediction accuracy. Afterward, it proposes a FNN to predict financial status of target case. It is also applied to cluster the cases according its fuzzy rule base in each
group, i.e. survived and failure, to reduce the space and complexity of problem domain for the next phase. Then, a fuzzy similarity method is employed to form a similarity relationship between rules of one group to other group. According to this relationship, any cluster in one group can be related to a cluster which is the most similar cluster in another group. After that, the fuzzy optimization method is applied to obtain an optimal feature weight vector in each pair related clusters. Finally, FCBR is employed in case retrieval to find similar cases of survived group for target case which is predicted as failure. The proposed model utilizes the retrieved cases’ weighted features, fuzzy rule base and expert knowledge to provide end user suggestions to prevent probable failure.

The rest of the paper is organized as follows: Section 2 briefly reviews prior studies. Section 3 explains the approach of creating the BFP model. The model is presented in Section 4 and the conclusion and further study is provided in Section 5.

II. LITRATURE REVIEW

Since the advent of various financial crises in the 1990s and 2000s, particularly the recent recession in mid-2008, there have been extensive investments in the construction of accurate computational systems to predict the financial status of corporation. From 1980–1996 three-quarters of IMF countries experienced bank failures which were not restricted to particular geographic regions, levels of development or banking system structures [1]. These bank failures, along with many enterprise bankruptcies, are given as clear evidence of serious financial distress in previous researches. To tackle these problems, various types of analysis models and systems to forecast the financial situation of an organization have been developed. Although it has been proved that these models are useful to managers and regulators with authority to prevent the occurrence of crises and failures [2, 3], some drawbacks make them inapplicable as inevitable and vital system for business. Bankruptcy prediction as a financial early warning system is different from classical pattern recognition problems, such as face and voice recognition. Its objective is not just to provide a classification of a company’s financial state. The stakeholders including managers, policy makers, regulators and customers need more information on how the classification was reached and what are the reasons behind the prediction and what should be done to avoid probable bankruptcy. This information can be provided by an appropriate model for financial warning system. Most of existing approaches using statistical methods have different deficiencies [3] [4]. On the other side, the growing development and application of computational intelligence techniques have led researchers to employ new methods in financial warning systems such as Support Vector Machine [5, 6], Genetic Algorithm [7], Rough Sets [8], Artificial Neural Network [9, 10] and Fuzzy systems [11]. Ravi Kumar and Ravi [12] provide a detailed review of these models and methods in the domain of bankruptcy prediction and demonstrate their better performance in different aspects like accuracy. But there is still a remarkable shortage in supportive knowledge faced of the aforementioned models. They just try to classify and predict the companies’ financial status without providing knowledge to assist decision makers to determine the corporation goals according this prediction.

A. Fuzzy Neural Network

The idea of integrating computational intelligence techniques to reach a desirable result has been introduced in recent years and has led to the appearance of hybrid models. These models may embed different techniques in an integrated model, or may use different techniques separately, considering a unique weight for each one to produce prediction. The result of these models in research has shown that they outperform other computational intelligence techniques [2]. Fuzzy Neural Network (FNN), which is a hybrid embedded model, uses ANN and Fuzzy Systems to create a robust hybrid classifier and forecaster tool in different fields. In some recent researches, different kinds of FNNs are used to classify and predict financial status [4, 9, 13, 14]. The main advantages of FNN are their consistent FRB gained from fuzzy systems along with their learning ability and accuracy obtained from ANN, to prevent probable future crises. These models not only predict the financial situation of a corporate business relatively accurately, but also provide a knowledge base which may be used to categorize the problem and make decisions to prevent such circumstances before they spiral out of control. All types of FNN can be generally categorized to two groups: (1) FNNs with self-tuning ability which requires an initial rule base to be specified before training [15, 16]. (2) FNNs which have the capability to automatically create fuzzy rules from numerical training data [17, 18]. The main advantage of the latter category is that it can actually extract knowledge from implicit patterns in numerical data by automatically generating an FRB. Moreover, it does not need to have prior knowledge, such as the number of clusters (fuzzy sets) for each variable and characteristics of these clusters. Our proposal attempts to develop the second group of FNNs.

B. Fuzzy Case-Based Reasoning

Case-Based Reasoning (CBR) is widely used to predict the financial status [8, 19] recent years. CBR is not only a non-linear, non-parametric and an incremental learning method but also can process data explicitly to explain analytic results and make valuable and useful knowledge that can aid the recovery of a company that was predicted to fail. Likewise, large volumes of historical cases can be efficiently stored and managed by database techniques in CBR [20]. In spite of these merits, CBR has hardly attracted researchers’ interest due to its
low prediction accuracy in comparing with ANN. There have been many studies to enhance the performance of CBR. Most of them have introduced different methods for determining optimal feature weight vector and selecting proper similarity function and appropriate number of similar instances for the target case which have significant influence on accuracy.

Most existing researches use crisp set for feature representation and traditional distance function on matching features, which are time consuming and impractical. Applying fuzzy systems and linguistic terms in CBR is another direction of research in this study. There are some studies which use linguistic terms defined as fuzzy sets for features’ value in case representation and an algorithm for analogical reasoning based on fuzzy theoretic similarity measures [21, 22]. These investigations have pointed out that Fuzzy CBR not only well performs cross-industrial comparison, but also provides more friendly suggested solutions, wherein the fuzzy membership degrees in the solutions can be interpretable. Also, it has been proved that the rate of accuracy can be enhanced much higher when fuzzy set theory was deployed in CBR.

III. THE APPROACH FOR MODELING FINANCIAL WARNING

The proposed approach for making the model contains three main phases which are explained as follows: 1) Preparation phase including feature selection, preprocessing and fuzzy clustering, 2) Rule generation phase including rule generation, learning and rule similarity and 3) decision support phase including case retrieving, interaction with expert and suggestion. The above components are explained in detail in following sections. Figure 1 represents the approach clearly.

A. Preparation phase

This phase includes three main steps which are feature selection, preprocessing and fuzzy clustering. These steps are essential parts of the establishing the proposed model. This phase is demonstrated by Figure 2.

![Figure 2: Preparation phase](image)

Feature selection: many researches in failure prediction have proved that financial ratios calculated from the absolute values in statements are expected to be useful. Various statistical methods, such as ANOVA and the stepwise method of MDA, and intelligent methods, such as decision trees and genetic algorithms, can be used to choose significant features. These features distinguish companies in distress from those in health. In our model the Genetic Algorithm can be applied for feature selection.

Preprocessing: over recent years, the imbalanced data-sets problem has demanded considerable attention in the field of classification and prediction. This problem occurs when the number of instances of one class is much lower than the instances of other classes. This study focuses on two class imbalanced data-sets problem, where there is only one positive class (failure corporate) with a lower number of examples, and one negative class (survive corporate) with a higher number of examples. During learning from imbalanced data-sets, the classifier will obtain a high predictive accuracy for the majority class, but will predict poorly for the minority class which is equally necessary in prediction [23]. Likewise, the classifier may consider the minority class as noise, which is then ignored. There is some research which shows that the imbalanced data-sets problem has a negative influence on the ability of most classification methods [24, 25]. There are a large number of techniques which have been proposed to deal with imbalance data-sets problem. There is some research demonstrating that among external techniques, oversampling methods, especially SMOTE, significantly improves the prediction accuracy of fuzzy rule base classifiers [26-28]. This approach effectively makes the decision region of minority class more general, and therefore the over-fitting problem is avoided and minority examples spread further into the majority samples [28]. This technique can be employed in our model.

Fuzzy clustering: fuzzy rules are derived from clusters. Performing a cluster analysis is important is the first step towards modeling the problem. There is a novel self organizing clustering technique which outperforms other techniques; Discrete Incremental Clustering (DIC)
method which is introduced in our model is a dynamic clustering technique avoiding drawbacks such as stability-plasticity and inflexibility found in other methods and computing trapezoidal-shaped fuzzy [29].

B. Rule generation phase

This phase contains four main steps. Two of them are rule computing and learning which can be gained through a FNN. In this phase an FNN structure and its rule generation algorithm can be applied to obtain fuzzy rule base for prediction and also clustering. According to the prediction, the fuzzy rules are categorized into two failed and survived category which are used to cluster the case base. Each rule should indicate one cluster. To perform these steps, recent efficient and accurate FNNs [9, 29] which are used to failure prediction, can be employed. These studies have demonstrated that not only the predictive accuracy of FNN is completely competitive to that of neural network but also it supplies the explanatory analysis knowledge which is useful to support decision makers. In rule generation step, the fuzzy clusters and data base which are obtained in prior phase are applied to form the structure of the FNN and run the rule generation algorithm respectively to gain initial fuzzy rule base. In the learning step, a learning algorithm is used to update and modify the initial fuzzy rule base to gain more predictive accuracy. The sample structure of FNN and its rule generation and learning method is demonstrated in Figure 3.

As shown in Figure 3, each rule is nominated by one R node in FNN structure. According to the output of the FNN these rules is categorized into two groups: Failed and Survived. In addition, these rules will be used to cluster the case base in each group.

The third step in this phase is making a one to one relationship between rules of these two categories. This relationship is formed based on the similarity of the rules. A fuzzy similarity method can be used to indicate the relationship. In the Fuzzy rule base, which is provided in this phase, each rule in Fail category is related to one rule in Survive category and vice versa. It should be mentioned that we assume that all features are involved in each rule otherwise for feature which is not involved we can compute the average value of feature’s cases which are satisfied the rule.

As a result of the third step, a trained fuzzy rule base, which will be used to predict the financial status of target case, is provided. Also, this fuzzy rule base along with the data base which has been obtained in previous phase is applied to make a clustered case base in step four. We can generate a clustered case base which is divided into two Survive and Fail categories and each category is clustered to n cluster based n rules. So, each case belongs to one cluster of a category. Also, according the similarity relationship between rules which is defined in prior step, each cluster in one category is related (similar) to one cluster of another category. Finally, we can define two particular features for each case which indicate the cluster in which the case is located and the cluster in another category which is similar to case cluster.

The rule generation phase which is illustrated by Figure 4, performs the financial prediction as well as preparation the fuzzy rule base and clustered fuzzy case base for next phase. Clustering the case base significantly reduces the problem dimension.

C. Decision support phase

This phase of making financial warning model is the most important and novel part of the proposed modeling approach. The objective of this phase is that if the target case is predicted as failure, the practical and accurate knowledge can be supplied to support decision makers to avoid failure. This phase contains three main steps: weight optimization, case retrieval and feature nomination for change.

The first step is finding the optimum or near optimum feature weight vector for cases. A fuzzy genetic algorithm is applied to obtain features’ weight. This algorithm
should be used for each pair related clusters separately. As a result of this step each feature obtains a specific weight which is the same for all cases in two related clusters. The object of the optimization algorithm can be maximizing the similarity measure between the cases in two related clusters belonging to two categories.

In the next step, case retrieval, the K most similar cases of survived category should be found to make suggestions. To do this, an appropriate similarity function should be selected. Choosing the proper function depends on criteria such as feature data type, accuracy and function type including intersection distance, cosine distance, or Euclidean distance. Applications of CBR in BFP mainly use similarity measures derived from the Euclidean metric in the context of \( k \)-nearest neighbor (\( k \)-NN). Because the feature data type is linguistic terms in the proposed model, fuzzy \( k \)-NN is recommended to retrieve \( k \) similar survived cases for the target case which is predicted to fail. Another reason to use fuzzy \( k \)-NN is that it supports the flexibility of case matching with different degrees of membership. Then the degree of similarity of the target case to other cases can then be specified in fuzzy membership rather than just the crisp result.

In the last step of this phase, according to the survived case which is retrieved in previous step and expert knowledge, a number of proper financial features should be selected to change. Finding appropriate weighted features is a fuzzy multi objective decision making (FMODM) problem which includes such objectives as maximizing similarity, minimizing cost and maximizing efficiency. To model and solve this problem, expert knowledge plays a significant role which should be taken into account in an interactive scheme. Likewise, the fuzzy rule base, which is generated in a previous phase and indicates the financial status of the corporation, can be employed in sensitivity analysis to check the possibility and suitability of the solutions. Figure 5 describes this phase.

IV. INTELLIGENT FINANCIAL WARNING MODEL

The modeling approach of the proposed financial warning model has been illustrated in the previous section. After training and testing these three main phases, the proposed model will be ready to use. In this section, the proposed model is described.

We assume that the target case as an enterprise with its numerical financial features is the input of the model. First, according to the fuzzy clusters which are obtained in the preprocessing phase, the fuzzy membership value of features in each linguistic term should be computed. The financial status of the target case is then predicted for one or two years ahead. The fuzzy rule base which has been obtained through a FNN in the rule generation phase is applied to the forecast. In addition, the rule base is able to indicate the cluster to which the target case belongs. On the basis of the prediction result, there are two options: 1) If the target case is predicted as survived the case will be retained in a specified survived cluster in the case base; 2) If the target case is predicted as failure, through the relationship which is formed between clusters in the rule generation phase, \( K \) similar survived case in the corresponding cluster to the target case is retrieved. Finally, by use of the FMODM which is formed through \( K \) retrieved cases, expert knowledge and fuzzy rule base, a prediction-based decision model is constructed. This decision model, which should consider different possible financial strategies at various levels, is applied to make a decision, suggestion or recommendation to prevent the predicted financial failure. The structure of this model is an interesting subject which requires more study. The proposed financial warning model is demonstrated in Figure 6.

![Figure 6: Proposed financial warning model](image)

V. CONCLUSION

Although failure prediction has been widely investigated, the problem has mainly been treated as a classical classification or prediction matter and most
available papers have concentrated on predictive accuracy. This paper presents a novel model which goes beyond prediction and provides a prediction-based decision making component to decide, suggest or recommend solutions for decision makers who have the authority to impede imminent failure. The proposed model applies FNN and FCBR to prepare the basis of this component. Studying the technical aspect of the decision making component and implementing this model using real data to obtain experimental results would be an interesting direction for future work.

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