DRSA-Based Neuro-Fuzzy Inference Systems for the Financial Performance Prediction of Commercial Banks

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Abstract

This study proposes an integrated inference system to predict the financial performance of banks. The model comprises of two stages. At the first stage, the dominance-based rough set approach (DRSA) method is applied to reduce the complexity of the attributes involved, and the obtained decision rules are further refined by the neuro-fuzzy inference technique to indicate the fuzzy intervals for each attribute. The proposed model not only shows how to explore the implicit patterns regarding the bank's performance change, but also refines the knowledge by tuning the parameters of membership functions for each attribute. At the second stage, the directional influences among the core attributes are further explored. To examine the proposed model, a group of real commercial banks in Taiwan is analyzed to construct the model, and five sample banks are tested to validate its effectiveness. The result provides understandable insights regarding the performance prediction problem of banks.

Keywords: Rough set approach (RSA), dominance-based rough set approach (DRSA), fuzzy inference system (FIS), financial performance (FP), artificial neural network (ANN).

1. Introduction

The financial performance (FP) is crucial to the survivorship of a bank, which is monitored by various stakeholders: potential investors, depositors, creditors, management teams of banks, and the central bank of a nation. In addition, there are practical needs to predict and explore the changes of banks' performances. The improvements of FP can be provided to support investment decisions, and the deteriorations can be regarded as warning signs to prevent financial crises. Owing to its importance, numerous studies have been conducted to examine/predict the performance changes of banks [1-3]. Recent studies also extend the analysis of performance to branch-level [4]. While most researchers seem to agree that the FP may be predicted by analyzing historical data (key financial ratios and operational indicators) [5], the selected indicators/criteria and the ways of modeling are divided. Conventional studies mainly apply statistical analyses for modeling the performance changes; this approach often takes the form of regression model, the discriminant analysis [6], and the factor analysis were used to construct the relationship among the criteria and future performance changes. Nevertheless, the statistical approach has obvious limitations in modeling the problem, such as the assumptions of no interrelationship among the considered variables and the linear relationship of the assumed model [7]. Other researchers from the computational intelligence and the multiple-criteria decision making (MCDM) fields, however, leverage the strength of various computational techniques and domain expert's knowledge [8] to explore the FP prediction problem. Considering the needs of easy-to-understand decision rules and less unrealistic assumptions from the real business world [9], this study takes the computational intelligence approach with the enhanced MCDM analysis to solve the FP prediction problem.

The computational intelligence approach has gained interests from researchers recently due to its capability in modeling non-linear data sets and computational efficiency in finding the optimal solution. Among the various methods and techniques, the data envelopment analysis (DEA) might be the most prevailing one for gauging the performance changes of banks [1, 4]. The DEA method does not need to assume the probability distribution of variables, but the researchers have to select the input and output variables subjectively [10]. The other mainstream techniques include the artificial neural network (ANN), decision trees, and certain soft computing techniques [11]: the fuzzy logic, the grey theory [12], and the rough set approach (RSA) [13-15]. The aforementioned techniques have their own strengths and limitations in modeling complex data set. For example, the

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ANN has strength in minimizing the target errors of the trained model, but it is difficult to retrieve understandable rules from its trained weights and structure [16]; the RSA is capable of inducting easy-to-understand rules [17], but the subjectively discretized interval for each attribute might cause inferior classification results. Therefore, the mentioned techniques still need further improvements to overcome their limitations.

Besides, one problem with applying computational techniques for the FP prediction problem is that most studies were conducted with complicated techniques and advanced algorithms, making it difficult to be understood and applied by management teams or potential investors. Moreover, few studies so far have attempted to integrate various techniques to reduce decision maker's obstacles in adopting the obtained outcomes. The aim of this study, therefore, is to propose an effective computational model that may gain applicable knowledge for supporting decision makers in business practice. To provide understandable rules for decision makers, the DRSA method is applied to reduce the number of variables without losing the model's discriminant capability. However, the original decision rules of the DRSA model may only provide vague concept regarding the bank's performance on each criteria, such as "low," "mediocre" and "high;" decision makers need more clear guidance to categorize the bank's performance while adopting the decision rules. In other words, the granule of knowledge from DRSA model could be adjusted by the neuro-fuzzy technique to increase its classification accuracy. Therefore, the neuro-fuzzy technique is incorporated to refine the DRSA decision rules.

Although the integration of RSA and ANN techniques has been tried before, those studies [16, 18, 19] mainly focused on using the RSA technique to reduce the redundant variables at first, and the ANN technique was then used to increase the accuracy of classification results. Unlike the previous research, the emphasis of this study is to obtain the refined rules for supporting decision makers in judging a bank's performance on each criterion. Furthermore, to enrich the findings, the Decision Making Trial and Evaluation Laboratory (DEMATEL) analysis is conducted for the core attributes to explore the directional influences among the criteria. The acquired findings may thus support decision makers to gain the whole picture regarding the addressed problem.

This paper is organized as follows. Section 2 reviews the DRSA and neuro-fuzzy techniques used in this study. In Section 3, the proposed DRSA-based neuro-fuzzy inference system and the DEMATEL technique are described. Section 4 demonstrates the model by examining a group of real commercial banks in Taiwan. The experiment results are presented and analyzed in Section 5. And concluding remarks are provided in Section 6.

2. Preliminary

The proposed model comprises of DRSA method, neuro-fuzzy inference system and DEMATEL technique. A brief introduction regarding the involved methods and techniques is provided in this section. In addition, the strengths and weaknesses of the involved techniques are also discussed.

A. *RSA and extended DRSA methods*

Proposed by Pawlak [20], the RSA aims to discern complex data sets with uncertainty and ambiguity. The classical RSA has been applied in various fields with positive outcomes, and the application for the bankruptcy prediction problem was also included. However, the classical RSA ignored the preferential characteristic of attributes, and the dominance property of attributes is common in most of the business analyses. For example, in the context of evaluating the solvency of a company, higher liquidity is normally preferred. To improve the limitation of the RSA, Greco et al. [21] proposed the DRSA method to consider the dominance property of attributes. The DRSA method can generate a group of decision rules to classify objects. More detail discussions could be found in the previous studies [21, 22].

B. *Neuro-fuzzy inference system*

The neuro-fuzzy inference technique is a combination of the ANN and the fuzzy inference system (FIS). On the one hand, the ANN is capable in learning complex data set with non-linearity; however, the obtained result from ANN cannot help to explain the causal relationship among the considered variables and the target output. On the other hand, the FIS can offer interpretability for imprecise reasoning. The combination of the two complementary techniques can model the fuzzy reasoning with higher accuracy and understandable if-then rules. The neuro-fuzzy inference system often starts from a set of if-then rules, and the ANN technique is used to tune the membership functions (MFs) for gaining higher performance index or minimizing the modeling errors. The applications of the neuro-fuzzy inference system have been applied in various fields, and certain studies have adopted it for detecting business failure [18] and evaluating banks' loan. Previous studies mainly focused on finding effective rules to identify problematic business or risky loan [19], and relative less attention has been put on analyzing the FP of banks. In other words, a financial analysis based neuro-fuzzy inference system is still underexplored.

3. DRSA-Based Neuro-Fuzzy Inference System

In this section, the involved techniques and how they are integrated are introduced. The FP prediction of banks comprises of multiple aspects (25 requested key ratios in the central bank's report); thus, it begins with using the DRSA to reduce the dimensionalities and inducting decision rules. In the next, the neuro-fuzzy technique is applied to obtain the refined decision rules with fuzzy intervals for each attribute. Finally, the core attributes may be further analyzed by the DEMATEL technique.

A. DRSA method

The DRSA method begins with an information table, and instances (objects) are often placed in rows while attributes (variables/criteria) are located in columns. An attribute often has preference-ordered characteristic if it represents a criterion. The data table is in the form of a 4-tuple information system $IS=(U,Q,V,f)$, where U is a finite set of universe, $Q=\{q_1,q_2,\ldots,q_m\}$ is a finite set of *m* attributes, V_q is the value domain of attribute *q*, $V=\bigcup_{q\in Q}V_q$ and $f:U\times Q\rightarrow V$ is a total function where $f(x,q)\in V_q$ for each $q\in Q$ and $x\in U$. The set Q is often divided into condition set C and decision set D.

The relational operator $\succeq_q$ can be defined as a complete outranking relation on U with respect to a criterion $q\in Q$, in which $x\succeq_q y$ denotes "x is at least as good as y regarding criterion q". The aforementioned complete outranking relation $\succeq_q$ means that x and y are always comparable with respect to criterion q. Decision classes of U can be described as $Cl=\{Cl_t, t=1,\ldots,n\}$, in which $t\in T$, and for each $x\in U$ belongs to only one class $Cl_t\in Cl$. The DRSA method assumes that classes are preference ordered; therefore, the upward union and downward union of classes of U can be defined as: $Cl_t^{\leq}=\bigcup_{s\leq t}Cl_s$ and $Cl_t^{\geq}=\bigcup_{s\geq t}Cl_s$.

The downward and upward union of classes thus help to define the dominance relation D_P for $P\subseteq C$, where C belongs to the conditional set. If an instance is described as x *P*-dominates y with respect to P, then it means $x\succeq_q y$ for all $q\in P$, denoted by xD_Py. The *P*-dominating set and *P*-dominated set are $D_P^+(x)=\{y\in U: yD_Px\}$ and $D_P^-(x)=\{y\in U: xD_Py\}$.

The $D_P^+(x)$ and $D_P^-(x)$ represent a collection of upward and download unions of decision classes, and the *P*-lower and *P*-upper approximation of an upward union $Cl_t^{\geq}$ with respect to $P\subseteq C$ may be defined by $\underline{P}(Cl_t^{\geq})$ and $\overline{P}(Cl_t^{\geq})$ as (1) and (2) :

$$\underline{P}(Cl_t^{\geq})=\{x\in U: D_P^+(x)\subseteq Cl_t^{\geq}\} \tag{1}$$

$$\overline{P}(Cl_t^{\geq})=\bigcup_{x\in Cl^{\geq}}D_P^+(x)=\{x\in U: D_P^-(x)\cap Cl_t^{\geq}\neq\varnothing\} \tag{2}$$

The *P*-lower approximation $\underline{P}(Cl_t^{\geq})$ comprises of all objects x from U whereas all objects y have at least the same evaluation with regard to all criteria P belong to class $Cl_t^{\geq}$ or better. The *P*-upper approximation of an upward union $Cl_t^{\geq}$ with respect to $P\subseteq C$ is the set of all the objects that might belong to $Cl_t^{\geq}$. Also, the *P*-lower approximation and *P*-upper approximation of $Cl_t^{\leq}$ with respect to $P\subseteq C$ can be defined as (3) and (4):

$$\underline{P}(Cl_t^{\leq})=\{x\in U: D_P^-(x)\subseteq Cl_t^{\leq}\} \tag{3}$$

$$\overline{P}(Cl_t^{\leq})=\bigcup_{x\in Cl^{\leq}}D_P^-(x)=\{x\in U: D_P^+(x)\cap Cl_t^{\leq}\neq\varnothing\} \tag{4}$$

Thus, the *P*-boundary of $Cl_t^{\geq}$ and $Cl_t^{\leq}$ are defined as below to describe the doubtful region:

$$Bn_P(Cl_t^{\leq})=\overline{P}(Cl_t^{\leq})-\underline{P}(Cl_t^{\leq}) \tag{5}$$

$$Bn_P(Cl_t^{\geq})=\overline{P}(Cl_t^{\geq})-\underline{P}(Cl_t^{\geq}) \tag{6}$$

And the classification Cl can be further defined by the ratio $\gamma_P(Cl)$ for the criteria $P\subseteq C$ as (7).

$$\gamma_P(Cl)=\left|U-\left(\bigcup_{t\in\{2,\ldots,n\}}Bn_P(Cl_t^{\leq})\right)\right|\Big/|U| \tag{7}$$

In equation (7), $|\bullet|$ denotes the cardinality of a set. The $\gamma_P(Cl)$ represents all of the correctly classified objects with respect to $P\subseteq C$. With the dominance-based rough approximation of upward and downward unions of decision classes, decision rules may be described in the form as: "if *antecedent,* then *consequence.*" For example, given a decision rule $r\equiv$ "if $f_{i_1}(x)\geq r_{i_1}$ &…& $f_{ip}(x)\geq r_{ip}$, then $x\in Cl_t^{\geq}$," then the $y\in U$ supports r if $f_{i_1}(y)\geq r_{i_1}$ &…& $f_{ip}(y)\geq r_{ip}$. The total number of y in the IS is denoted as the SUPPORTs of the decision rule r, which implies the relative strength of a decision rule.

Therefore, to construct the DRSA-based model in the first stage, the needed steps are as below:

Step 1: Discretize the conditional attributes and the decision attribute. The discretization process helps to identify the target 4-tuple information system for analysis.

Step 2: Make induction from the data set (from the *IS*). The DRSA induction logics are to be implemented. The obtained decision rules and core attributes are to be refined in the next stage.

B. Neuro-fuzzy inference system

At the second stage, to increase the accuracy, the neuro-fuzzy inference technique is adopted by modifying the MFs for each attribute (in each rule) with the corresponding outputs. The training process adjusts the parameters to match the given inputs (attributes in each rule) and output data.

This study adopts the neuro-fuzzy inference system, proposed by Jang [23] to conduct the learning processes. The fuzzy if-then rules are the Takagi and Sugeno's type. To explain the FIS training process in a simple way, assume that there are only two attributes (a_1 and a_2) and an output function f. Given two rules as below:

R1: If a_1 is L and a_2 is L, then $f_1 = p_1a_1 + q_1a_2 + r_1$

R2: If a_1 is H and a_2 is H, then $f_2 = p_2a_1 + q_2a_2 + r_2$

where p_1, p_2, q_1, q_2, r_1, and r_2 denote the parameters of the output functions f_1 and f_2.

There are five layers in the architecture of FIS, and the five layers can be defined and explained as below:

Layer 1: Every node *i* in this layer denotes the membership function of A_i, where A_i is the linguistic classes (such as Low and High). If the input are a_1 and a_2, then the MFs can be described as $\mu_{A_i}(a_1)$ and $\mu_{B_i}(a_2)$.

Layer 2: The nodes in this layer multiple the input signals and send the product out as (8):

$$w_i = \mu_{A_i}(a_1) \times \mu_{B_i}(a_2) \tag{8}$$

In (8), *i*=1 and 2, and the output of each node represent the firing strength of a rule.

Layer 3: In this layer, the *i*th rule's relative firing strengh to the sum of total rules is described as $\overline{w_i}$, and $\overline{w_i} = w_i/(w_1 + w_2)$, where *i*=1, 2.

Layer 4: The output of the node *i* in this layer can be denoted as $\overline{w_i} f_i$, where *i*=1, 2.

Layer 5: The output of this layer is the overall output, which can be described as (9):

$$\sum_i \overline{w_i} f_i = \sum_i w_i f_i \Big/ \sum_i w_i, \text{ where } i=1,\ 2. \tag{9}$$

Briefly speaking, the learning process follows the classical ANN algorithm (back-propagation), and the goal is to minimize the sum of squared errors (from the differences between the target output and actual output) to adjust the parameters for $\mu_{A_i}(a_1)$ and $\mu_{B_i}(a_2)$. Therefore, the steps involved in the second stage are summarized as below:

Step 3: Select instances for the training of fuzzy if-then rules. From the Step 2, the decision rules with strong supports can be found, and the instances that support the rule and the instances against the rule can be combined as a training set.

Step 4: Set the number and type of MFs for each attribute to proceed the learning. The number of MFs for each attribute should be the same as the discretization result in the DRSA model. For example, if there are only two discretized classes of attribute a_1 (i.e. "L" and "H"), then the number of MFs for a_1 in the neuro-fuzzy inference system should be two. Despite the variety of MFs, this study chooses the triangular MF for the attributes involved due to its popularity in financial applications.

Step 5: Train the neuro-fuzzy inference system until the sum of squared errors to be stable and minimized. Then, the trained FIS can be examined by the original data or additional data to validate the system.

Step 6: Retrieve the parameters for the MFs of each attributes.

The steps 1-2 can find the strong decision rules with reduced dimensionality; in addition, the steps 3-6 further refined the rules by adjusting the parameters for all of the MFs of attributes in each rule.

C. DEMATEL technique

The DEMATEL technique was proposed to solve complex social problems [24], which has been applied in various decision making problems, such as the science park evaluation [25], the analysis of e-learning [26], and the assessment of stocks [8]. The DEMATEL technique is applied to explore the total and net influential weights of core criteria. The following steps are as below:

Step 7: Collect domain experts' opinions for the initial average matrix $\boldsymbol{A}$. Opinions can be collected through questionnaire, where experts are asked the direct influence that they feel criterion *i* will have on the other criterion *j*, indicated as a_{ij}. The expected scale ranges from 0 (no influence) to 4 (very high influence), and the average of the expert's opinions is used in $\boldsymbol{A}$.

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & \cdots & a_{nj} & \cdots & a_{nm} \end{bmatrix}, \tag{10}$$

where *n* is the number of the considered criteria.

Step 8: Normalize A to get the direct influence matrix D, which can be obtained by finding the constant number *k*.

$$\boldsymbol{D} = k\boldsymbol{A} \tag{11}$$

$$k = \min\left\{ \frac{1}{\max_i \sum_{j=1}^n a_{ij}}, \frac{1}{\max_j \sum_{i=1}^n a_{ij}} \right\} \tag{12}$$

where $i, j \in \{1, \cdots, n\}$.

Step 9: Find the total influence matrix $\boldsymbol{T}$, which is calculate by using (13):

$$\boldsymbol{T} = \boldsymbol{D} + \boldsymbol{D}^2 + ... + \boldsymbol{D}^w = \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D}^w)(\boldsymbol{I} - \boldsymbol{D})^{-1} \quad (13)$$

$$\boldsymbol{T} = \boldsymbol{D}(\boldsymbol{I} - \boldsymbol{D})^{-1}, \text{ when } \lim_{w\to\infty} \boldsymbol{D}^w = [0]_{n\times n} \quad (14)$$

The total influence matrix $\boldsymbol{T}$ is as (15):

$$\boldsymbol{T} = \begin{array}{cc} & \begin{array}{ccccc} \boldsymbol{D}_1 & & \boldsymbol{D}_j & & \boldsymbol{D}_n \\ c_{11}...c_{1m_1} & \cdots & c_{j1}...c_{jm_j} & \cdots & c_{n1}...c_{nm_n} \end{array} \\ \begin{array}{cc} \boldsymbol{D}_1 & \begin{array}{c} c_{11} \\ c_{12} \\ \vdots \\ c_{1m_1} \end{array} \\ \vdots & \vdots \\ \boldsymbol{D}_i & \begin{array}{c} c_{i1} \\ c_{i2} \\ \vdots \\ c_{im_i} \end{array} \\ \vdots & \vdots \\ \boldsymbol{D}_n & \begin{array}{c} c_{n1} \\ c_{n2} \\ \vdots \\ c_{nm_n} \end{array} \end{array} & \begin{bmatrix} \boldsymbol{W}_{11} & \cdots & \boldsymbol{W}_{1j} & \cdots & \boldsymbol{W}_{1n} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{W}_{i1} & \cdots & \boldsymbol{W}_{ij} & \cdots & \boldsymbol{W}_{in} \\ \vdots & & \vdots & & \vdots \\ \boldsymbol{W}_{n1} & \cdots & \boldsymbol{W}_{nj} & \cdots & \boldsymbol{W}_{nn} \end{bmatrix} \end{array} \quad (15)$$

In Eq. (15), D_i denotes the ith dimension. Take the c_{1m_1} in the cluster W_{11} for example, it denotes the m_jth criterion of dimension D_1. The average of all the elements in each cluster is described as d_{ij} for the element on the ith row and jth column in $\boldsymbol{T}^{\boldsymbol{D}}$:

$$\boldsymbol{T}^{\boldsymbol{D}} = \begin{bmatrix} d_{11} & \cdots & d_{1j} & \cdots & d_{1n} \\ \vdots & & \vdots & & \vdots \\ d_{i1} & \cdots & d_{ij} & \cdots & d_{in} \\ \vdots & & \vdots & & \vdots \\ d_{n1} & \cdots & d_{nj} & \cdots & d_{nn} \end{bmatrix} \quad (16)$$

Step 10: Decompose $\boldsymbol{T}$ to calculate the directional influences of criteria. The sum of rows and the sum of columns of the total-influence matrix $\boldsymbol{T}$ are expressed as vectors $\boldsymbol{r}$ and $\boldsymbol{d}$, where the ith elements of vectors $\boldsymbol{r}$ and $\boldsymbol{d}$ can be denoted as r_i and d_i. If $r_i - d_i$ is positive, then the ith criterion belong to the cause group; otherwise, the effect group. Similarly, the sum of rows and the sum of columns of $\boldsymbol{T}^{\boldsymbol{D}}$ are expressed as vectors $\boldsymbol{R}$ and $\boldsymbol{D}$, where the ith elements of vectors $\boldsymbol{R}$ and $\boldsymbol{D}$ can be denoted as R_i and D_i. If $R_i - D_i$ is positive, then the ith dimension belong to the cause group; otherwise, the effect group.

4. Empirical Case

To illustrate the steps involved, a group of real commercial banks in Taiwan was analyzed as an empirical case. The ROA (return on assets) ratio was chosen to indicate the FP of a bank, and the financial data of banks were matched with their ROA changes in the subsequent year to induct the decision rules. The conceptual flow of this study is illustrated as Figure 1.

A. Data

The central bank of Taiwan requests all of the domestic banks to report their quarterly financial results and performance indicators in six dimensions: (1) Capital Sufficiency; (2) Asset Quality; (3) Earnings and Profitability; (4) Liquidity; (5) Interest Rate Sensitivity; (6) Growth; in addition, there are 25 attributes (criteria) extended from the six dimensions, and the central bank of Taiwan releases this reports on its website regularly [27]. The brief definitions of the 25 attributes are in Table 1, and this study adopted the released reports from the central bank of Taiwan. The required 25 indicators are officially monitored by the central bank; therefore, the current study includes all of those indicators for the empirical case.

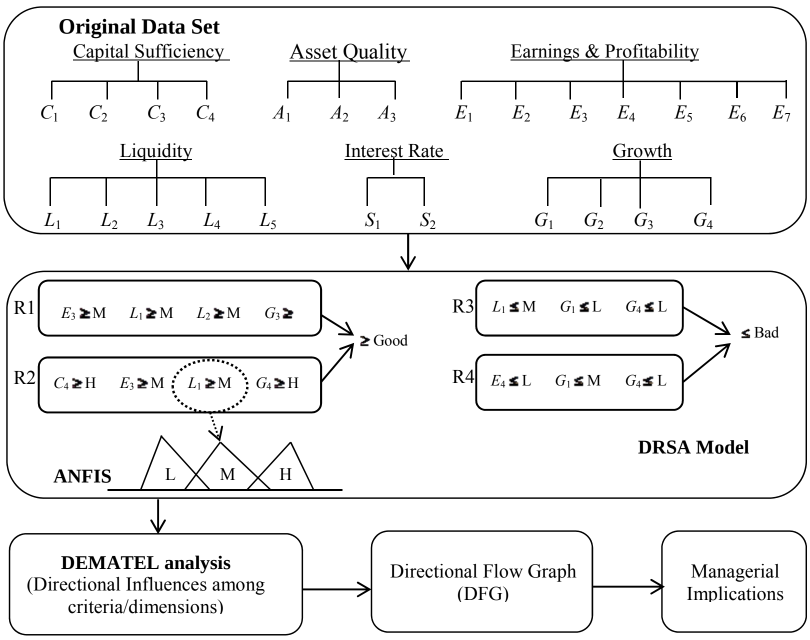

Figure 1. Conceptual flow of this empirical case.

Besides, owing to the financial crisis in 2008 and 2009, the performance patterns should be different compared with previous periods. Therefore, the 34 commercial banks' data were collected from 2008 to 2012 in this study. To validate the proposed model, the data from 2008 to 2011 were used to obtain the decision rules, and the remaining data were examined to test the model.

B. DRSA model with decision rules

In this study, the FP prediction problem was modeled by matching a bank's financial variables (the 25 conditional attributes) with its performance change in the subsequent year (decision class), which may be regarded as a one-period lagged model. Before applying the DRSA method, the decision attribute and the 25 attributes need to be discretized at first. As the change of ROA was chosen to indicate the improvement/deterioration of FP, this study ranked the change of ROA for banks in each year; then, we categorized the top performing 1/3 banks (the current ROA must also be positive) as the "Good" decision class and the bottom 1/3 banks as the "Bad" decision class. And the other banks ranked in the middle were not included in the DRSA model. As for the 25 conditional attributes, all of them were ranked from high to low in each year, and the top 1/3, the middle 1/3 and the bottom 1/3 were categorized as "H", "M" and "L" to represent "High", "Mediocre" and "Low" respectively. The DRSA modeling was conducted by using the jMAF software [22], developed by the Laboratory of Intelligent Support System from the Poznan University of Technology. After applying the DRSA technique, the obtained strong decision rules (with more than six supports) are summarized in Table 2. Also, the summary of the selected attributes is shown in Table 3 to indicate the original data ranges (data for constructing the model) of the attributes involved in the strong decision rules.

C. Combined computational intelligence model

The aforementioned discretization was done intuitively at first. Both financial attributes and decision classes were discretized by the 3-level ranking method (i.e. rank the top 1/3, middle 1/3 and bottom 1/3 banks as "H", "M" and "L" for each attribute; also, rank the top 1/3 Δ ROA banks as "Good" and the bottom 1/3 ΔROA banks as "Bad" decision classes in subsequent year) in the first stage. After obtaining the decision rules from the DRSA model (such as R1: **If** [$E_3 \geq$M and $L_1 \geq$M and $L_2 \geq$M and $G_3 \geq$H] **then** [$\geq$Good]), the raw financial figures of each criterion (such as E_3=2%) were used as inputs, and the Good or Bad decision class was replaced by "1" or "3" as target output for the training of neuro-fuzzy inference system. To minimize the modeling errors for discretization, a neuro-fuzzy technique was

Table 1. Description of variables used in this study.

Dimension		Description	Definition
Capital Sufficiency	C_1	Regulatory Capital to Risk-Weighted Assets	Regulatory capital/Risk-weighted assets
	C_2	Tier 1 Capital to Risk-Weighted Assets	Tier 1 capital/ Risk-weighted assets
	C_3	Debt-Equity Ratio	Debt/Net worth
	C_4	Net Worth to Total Assets	Net worth/Total assets
Asset Quality	A_1	Non-Performing Loan (NPL) Ratio	Non-performing loan/Loan and discount
	A_2	Loan Loss Reserve to NPL	Loan loss reserves/NPLs
	A_3	Possible Loss of Classified Assets to Reserve	Possible loss of classified assets/Reserves
Earnings and Profitability	E_1	Net Income Before Tax to Equity	NIBT/Average equity
	E_2	NIBT with Loan Loss Provision to Equity	NIBT with loan loss provision/Equity
	E_3	NIBT to Asset	NIBT/Average asset
	E_4	NIBT and Loan Loss Provision to Average Assets	(NIBT + loan loss provision) / Average asset
	E_5	Net Interest Revenues to NIBT	Net interest revenues / NIBT
	E_6	NIBT to Total Net Revenues	NIBT / Total net revenues
	E_7	NIBT per Employee	NIBT / Employees
Liquidity	L_1	Liquidity ratio	Liquidity ratio
	L_2	Loans to Deposits	Loans / Deposits
	L_3	Time deposits to Deposits	Time deposits / Deposits
	L_4	NCDs to Time Deposits	NCDs / Time deposits
	L_5	180 day's Accumulated Gap of Assets and Liabilities to Equity	Accumulated gap of assets and liabilities(180 days) / Equity
Interest Rate Sensitivity	S_1	Interest rate sensitivity assets to Interest rate sensitivity liabilities	Interest rate sensitivity assets /Interest rate sensitivity liabilities
	S_2	Interest Rate Sensitivity Gap to Equity	Interest rate sensitivity gap/Equity
Growth	G_1	Deposit growth rate	Deposit growth rate
	G_2	Loan growth rate	Loan growth rate
	G_3	Investment growth rate	Investment growth rate
	G_4	Guarantee growth rate	Guarantee growth rate

incorporated at this stage. The instances that supported each strong decision rule were collected and trained—for gaining the refined ranges for discretization—with the same number of instances that belong to the opposite decision class. Take the training of the rule R1 for example, the input variables are [E_3, L_1, L_2, G_3], and the output variable is decision class. The four decision rules were all trained in this approach.

Table 2. Decision Rules with more than six supports.

Rule		If (conditional attributes) **then** (decision class)	Support
R1	**If**	($E_3 \geq$ M and $L_1 \geq$ M and $L_2 \geq$ M and $G_3 \geq$ H) **then** ($\geq$ Good)	8
R2	**If**	($C_4 \geq$ H and $E_3 \geq$ M and $L_1 \geq$ M and $G_4 \geq$ H) **then** ($\geq$ Good)	7
R3	**If**	($L_1 \leq$ M and $G_1 \leq$ L and $G_4 \leq$ L) **then** ($\leq$ Bad)	7
R4	**If**	($E_4 \leq$ L and $G_1 \leq$ M and $G_4 \leq$ L) **then** ($\leq$ Bad)	8

Table 3. Summary of the attributes used in decision rules.

	Attributes (unit: %)							
	C_4	E_3	E_4	L_1	L_2	G_1	G_3	G_4
Max	48.87	1.71	2.94	121.35	242.62	58.96	321.70	4481.25
Min	2.31	-6.89	-3.84	12.10	20.16	-15.79	-56.51	-60.84
AVG	6.95	-0.01	0.54	27.60	76.09	7.83	41.40	86.20
SD	5.50	1.32	0.82	15.27	24.17	11.86	88.79	543.04

To be in line with the three-level discretization conducted in the initial DRSA modeling, each criterion was assigned three fuzzy intervals to represent "H", "M", and "L" respectively, and the commonly applied triangular membership function was adopted for all of the attributes involved in each rule. As there were four decision rules with more than six supports (Table 2), the trained results (the fuzzy inference system with defined "low", "middle", "high" intervals for each criterion) for each decision rules are shown in Table 4, and the classification rate for each subset of decision rules (four subsets of training data) all reached 100% correctness by using the same data set.

Although the refined rules (Table 4) have provided easy-to-understand guidance regarding the FP prediction of banks, the DEMATEL analysis may further enrich the findings by exploring the directional influences among the core criteria; therefore, a more comprehensive view could be obtained to support the management teams in making business decisions. The initial average matrix $\boldsymbol{A}$ was calculated by averaging the eight domain expert's opinions, and the result is shown in Table 5.

Following Step 9 and Step 10 in Section 3, the total influence matrix of the eight criteria $\boldsymbol{T}$ (Table 6) and the total influence matrix of dimensions $\boldsymbol{T}^D$ (Table 7) were obtained.

Table 5. Initial average matrix $\boldsymbol{A}$.

	C_4	E_3	E_4	L_1	L_2	G_1	G_3	G_4
C_4	0.00	2.25	2.38	3.63	2.13	2.38	3.63	1.75
E_3	3.13	0.00	3.71	3.25	2.88	3.63	3.88	3.13
E_4	3.13	3.75	0.00	3.14	3.25	3.50	2.75	3.63
L_1	2.13	2.25	1.75	0.00	3.57	1.88	2.13	2.13
L_2	2.88	2.63	2.88	2.63	0.00	3.71	2.13	2.13
G_1	2.75	3.63	3.50	3.25	3.63	0.00	2.71	2.13
G_3	2.25	2.50	2.25	2.13	1.50	1.25	0.00	2.14
G_4	1.38	1.38	1.25	1.25	1.38	2.25	1.63	0.00

Table 6. Total influence matrix $\boldsymbol{T}$.

	C_4	E_3	E_4	L_1	L_2	G_1	G_3	G_4	r_i
C_4	0.32	0.42	0.42	0.49	0.42	0.43	0.48	0.38	3.36
E_3	0.53	0.43	0.55	0.57	0.54	0.57	0.58	0.52	4.30
E_4	0.53	0.56	0.41	0.56	0.55	0.56	0.54	0.53	4.24
L_1	0.37	0.39	0.36	0.31	0.43	0.38	0.39	0.36	2.99
L_2	0.46	0.46	0.46	0.48	0.37	0.50	0.45	0.42	3.61
G_1	0.50	0.54	0.53	0.55	0.54	0.41	0.52	0.46	4.06
G_3	0.35	0.36	0.35	0.36	0.33	0.32	0.28	0.33	2.68
G_4	0.25	0.26	0.25	0.27	0.26	0.29	0.28	0.19	2.06
d_i	3.31	3.44	3.33	3.59	3.44	3.46	3.51	3.20	

Table 4. The five sample banks and the refined decision rules with fuzzy intervals.

	Conditional Attributes				Decision Class	ΔROA in 2012 (%)
Decision Rule 1	$E_3 \geq$ M L:[-9.00,-5.53,-2.06][1] M:[-5.53,-2.06,0.39] H:[-1.99,1.43,4.88]	$L_1 \geq$ M L:[0.61,14.73,28.86] M:[14.72,28.85,42.89] H:[28.84,42.95,57.05]	$L_2 \geq$ M L:[60.69,70.30,80.00] M:[70.37,79.94,89.71] H:[79.92,89.69,99.41]	$G_3 \geq$ H L:[-121.60,-56.50,8.57] M:[-56.51,8.58,73.68] H:[8.58,73.68,138.80]	Good	
Bank *A*	E_3 =0.70	L_1=31.33	L_2=80.82	G_3=41.59	Good	209
Bank *B*	E_3 =0.81	L_1=28.15	L_2=76.24	G_3=21.98	Good	35
Decision Rule 2	$C_4 \geq$ H L:[-2.76,4.80,12.38] M:[4.83,12.37,19.97] H:[12.40,19.97,27.55]	$E_3 \geq$ M L:[-0.56,0.09,0.63] M:[0.13,0.75,1.28] H:[0.46,1.21,1.86]	$L_1 \geq$ M L:[-36.36,16.21,68.78] M:[16.21,68.78,121.30] H:[68.78,121.30,173.90]	$G_4 \geq$ M L:[-122.10,-45.73,30.64] M:[-45.73,30.65,107.00] H:[30.64,107.00,183.40]	Good	
Bank *C*	C_4=42.5	E_3=1.29	L_1=25.02	G_4=22.23	Good	13
Decision Rule 3	$L_1 \leq$ M L:[-11.81,13.35,35.95] M:[12.65,41.61,61.55] H:[37.01,53.86,86.03]	$G_1 \leq$ L L:[-46.40,-15.49,13.54] M:[-15.79,15.93,45.53] H:[5.98,44.56,76.04]	$G_4 \leq$ L L:[-95.49,-51.85,-8.62] M:[-51.97,-9.02,34.31] H:[-11.27,34.02,77.87]		Bad	
Bank *D*	L_1=15.41	G_1=-9.06	G_4=-10.10		N.A.	0
Bank *E*	L_1=20.07	G_1=3.39	G_4=-27.88		Bad	-185

[1]The unit of the numbers within the bracket is in %.

By the calculations of $r_i + d_i$ and $r_i - d_i$, the eight criteria could be divided into cause group (if $r_i - d_i$>0) and effect group (if $r_i - d_i$<0), and the relative importance could be indicated by $r_i + d_i$. The four dimensions were also divided into cause group and effect group by examining $R_i - D_i$.

Table 7. Total influence matrix of dimensions $\boldsymbol{T}^D$.

	D_1	D_2	D_3	D_4	R_i
D_1 (Capital Sufficiency)	0.32	0.42	0.45	0.43	1.63
D_2 (Asset Quality)	0.53	0.49	0.55	0.55	2.12
D_3 (Liquidity)	0.42	0.42	0.40	0.42	1.65
D_4 (Growth)	0.37	0.38	0.39	0.34	1.48
D_i	1.64	1.71	1.79	1.74	

The results for the eight criteria and the four dimensions are shown in Table 8 and Table 9 respectively.

Table 8. Relative influence and cause-effect analysis (criteria).

	r_i	d_i	$r_i + d_i$	$r_i - d_i$
C_4	3.36	3.31	6.68	0.05
E_3	4.30	3.44	7.74	0.86
E_4	4.24	3.33	7.57	0.91
L_1	2.99	3.59	6.59	-0.60
L_2	3.61	3.44	7.05	0.17
G_1	4.06	3.46	7.52	0.59
G_3	2.68	3.51	6.19	-0.84
G_4	2.06	3.20	5.26	-1.14

Table 9. Relative influence and cause-effect analysis (dimensions).

	R_i	D_i	$R_i + D_i$	$R_i - D_i$
D_1 (Capital Sufficiency)	1.63	1.64	3.27	-0.01
D_2 (Asset Quality)	2.12	1.71	3.84	0.41
D_3 (Liquidity)	1.65	1.79	3.44	-0.14
D_4 (Growth)	1.48	1.74	3.22	-0.26

The results of Table 8 and Table 9 are further illustrated as the directional influences among the criteria and dimensions as Figure 2.

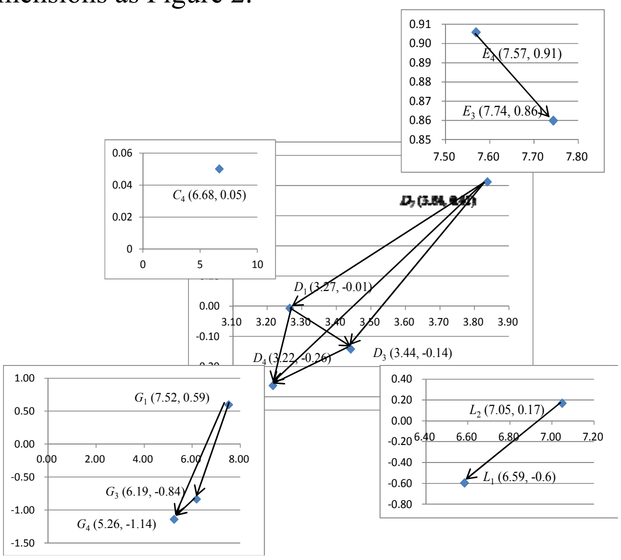

Figure 2. Internetwork relationship map.

5. Results and Discussions

The refined four decision rules were retrieved from a group of commercial banks in Taiwan, and the obtained result can be illustrated as the directional flow graph (DFG) in Figure 3 by referring to the four decision rules and Figure 2. The upper side of Figure 2 (lead to the Good decision class) indicates that E_3 (NIBT to asset) is the driving force for higher liquidity, and higher liquidity may further influence the growth in G_3 (investment growth rate) and G_4 (guarantee growth rate). Or, in other words, the growth in G_3 and G_4 are crucial to future FP improvement; nevertheless, the growth should be supported by superior (i.e., above average) liquidity and earning results. The DFG not only shows the paths to future improvement, but also indicates the symptoms to deterioration. Inferior profitability (E_4) may influence the liquidity ratio (L_1) and the growth dimension; the growth in deposits (G_1) and guarantee (G_4) may cause deteriorated FP in the future. The symptoms of plausible deterioration are important to the authority and management teams to prevent from financial crises, which is also the key reason why the central bank requests the domestic banks to report the 25 indicators in every quarter. The DFG may thus support the management teams to make decisions/plans in various aspects—such as marketing, finance, general operations—to achieve improvement or prevent deterioration in FP.

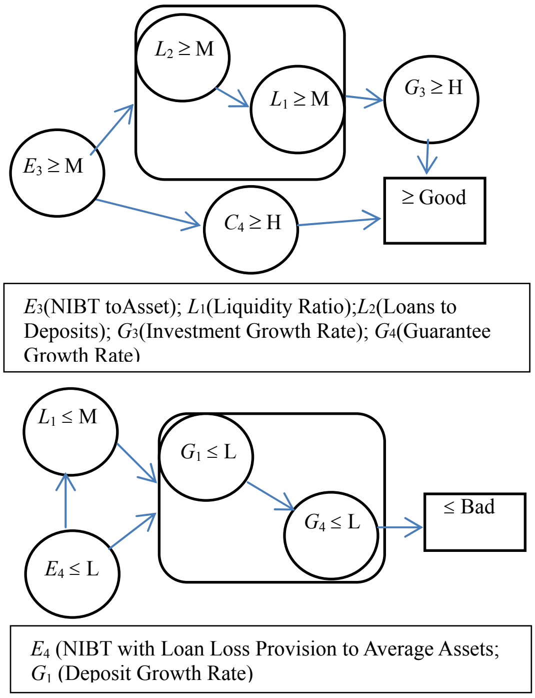

Figure 3. Directional flow graph (DFG).

After refining the four decision rules by the neuro-fuzzy technique, the five banks' financial data in

2011 were examined to compare with their actual performance in 2012. The five sample banks—(*A*) E. Sun bank; (*B*) Standard Chartered bank; (*C*) Cosmo bank; (*D*) Far Eastern bank; (*E*) First bank—were matched with the strong decision rules. The five banks' financial figures and the fuzzy intervals of corresponding attributes are listed in Table 4, and only three decision rules were matched. The justification processes used the five banks' real figures on each criterion in 2011, and transformed the raw figures into discretization results. Take Bank *E* for example, its real figures for L_1, G_1, G_4 equal to 20.07%, 3.39%, and -27.88% in 2011 respectively. Referring to the obtained fuzzy intervals for each criterion in rule R3 (see Table 4), Bank *E*'s criteria L_1, G_1, G_4 were categorized into M, L, and L respectively, which suggests that Bank *E* could be categorized as the "Bad" decision class. Compared with Bank *E*'s actual ΔROA in 2012 (equals to -185%), the result confirmed the correctness of the model's output.

The result shows that Bank *A*, Bank *B* and Bank *C* should be categorized as the "Good" decision class, and their ΔROA in 2012 were 209%, 35% and 13% respectively. The findings of Bank *D* are interesting for further discussion. If we use the original ranking approach (i.e. rank the top 1/3, middle 1/3 and bottom 1/3 banks as "H", "M" and "L" for each attribute) for the discretization of Bank *D* and Bank *E*, they all complied with the decision rule R3; however, the G_4 value of Bank *D* equaled to -10.10%, which was more appropriate to be categorized into the 2nd fuzzy interval (i.e. M: [-51.97,-9.02,34.31], the unit is percentage %) considering the refined decision rule R3 (Table 4). Thus, Bank *D* could not be categorized by the decision rule R3, and only Bank *E* was classified as the "Bad" decision class. The actual ΔROA of Bank *D* and Bank *E* in 2012 were 0% and -185% respectively; after referring the refined decision rules, Bank *D* was avoided from being misclassified as the "Bad" decision class.

To examine the effectiveness of the incorporated neuro-fuzzy technique, the other two discretization methods—equal width and normal distribution-based discretization (i.e., refer $\mu \pm 0.5 \times SD$ to divide each criterion into three categories)—were also conducted to compare with the fine-tuned results. The justifications of the other three discretization methods were all similar; the original financial figures of the five banks in 2011 were transformed into H/M/L according to the used discretization method, and the transformed ratings (i.e. H/M/L) on each criterion were matched with the three decision rules (i.e. R1, R2, and R3) for each bank. If a rule was matched, the corresponding decision class would be listed in the last column of Table 10; otherwise, it would show "N.A." instead. The three benchmarked discretization methods (i.e., original ranking, equal width, and normal distribution-based methods) are compared and summarized in Table 10.

Table 10. Comparison of the three discretization methods.

	Bank	Rule	C_4	E_3	E_4	L_1	L_2	G_1	G_3	G_4	Class
Original three level ranking	*A*	R1	M	H	L	H	H	H	H	M	Good
	B	R1	H	H	M	M	M	L	H	L	Good
	C	R2	H	H	M	M	M	L	H	H	Good
	D	R3	H	L	M	L	H	L	L	L	Bad[1]
	E	R3	L	M	H	L	H	L	H	L	Bad
Equal width	*A*	--	L	M	M	L	M	H	L	M	N.A.
	B	--	L	M	M	L	M	L	L	M	N.A.
	C	--	H	M	M	L	M	L	L	M	N.A.
	D	R3	L	L	M	L	H	L	L	L	Bad[1].
	E	R3	L	L	H	L	H	L	M	L	Bad.
Normal distribution based	*A*	--	M	M	L	M	M	H	M	M	N.A.
	B	--	M	M	M	M	M	L	M	M	N.A.
	C	R2	H	H	M	M	M	L	M	H	Good
	D	R3	M	L	M	L	H	L	M	L	Bad[1]
	E	--	L	M	H	L	H	M	H	L	N.A.

[1]Bank *D*'s performance in 2012 should not be classified as Bad decision class.

To enrich the findings, the obtained DFG (Figure 3.) could be applied to support the banks to improve their future FP. Take the Bank *E* for example, it was underperformed on criteria L_1 (for Rule R1) and on C_4, L_1, G_4 (for Rule R2) to be classified as the "at least Good" decision class. As L_1 (Liquidity ratio) is highlighted by both rules, it may set this criterion as the first priority for improvement; furthermore, since L_1 is influenced by L_2 (Loans to Deposits) and E_3 (NIBT to Assets), Bank *D* should consider this plausible interrelationship while planning for future improvements.

6. Conclusion and Remarks

To conclude, the present study proposes an integrated computational intelligence model, considering decision maker's practical requirements (understandable rules with suggested intervals for each criterion) to explore the implicit patterns for the FP prediction problem. Due to the size and complexity of the attributes involved, there is a practical need to retrieve the critical attributes by the DRSA method. Furthermore, the roughly discretized criteria for the decision rules are refined by the neuro-fuzzy inference technique, which achieves superior classification result compared with the original three-level ranking discretization and the other two benchmark methods (Table 10). To enrich the findings, the DEMATEL analysis supports to generate the directional influences of the core criteria (see Table 8, Table 9 and Figure 1.) and DFG (Figure 2.); therefore, not only the decision rules are discovered, but also the interrelationship among the core criteria is unveiled. Those findings contribute to the requirements of decision makers for making prediction/planning in a real business environment.

The previous studies mainly utilized RSA to reduce the variables for modeling [19], and ANN technique was applied to learn the implicit patterns between the simplified input and output variables. However, the knowledge only resided in the connected weights and structure of the ANN model, which was difficult to comprehend. To overcome this disadvantage, this study proposes the neuro-fuzzy technique to learn the suggested fuzzy intervals for each criterion. Therefore, the novelty of the present study may be concluded: 1) refine the DRSA decision rules by the neuro-fuzzy technique for obtaining a more clear guidance; 2) explore the directional influences of the DRSA decision rules by incorporating DEMATEL analysis to form a DFG, which may provide much more insights for decision makers.

Despite the advantages of the proposed model, it does have some limitations. First, the DRSA-based neuro-fuzzy model only inducts from historical data, and the result might lack theoretical supports. The obtained decision rules only help to identify historical patterns, and the prediction capability depends on the assumption that recent patterns will reoccur in the near future. Second, the training of the neuro-fuzzy model depends on the chosen instances. If an instance holds extreme value in certain attribute, the fuzzy interval on the attribute might be highly influenced. Therefore, the decision makers should understand the limitations before jumping to the conclusions.

The present study is in the experimental stage, and more data has yet to be examined. There is a continuing need for an effective method that can retrieve useful patterns (knowledge) from a complex data set, and the applications in the financial field often have high business value. Further research is suggested to explore the applications in the other markets or financial industries.

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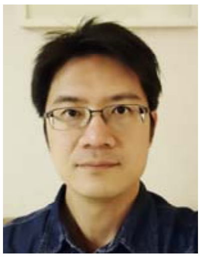

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