Information Sciences 375 (2017) 296–313

Contents lists available at ScienceDirect

Information Sciences

journal homepage: www.elsevier.com/locate/ins

Financial modeling and improvement planning for the life insurance industry by using a rough knowledge based hybrid MCDM model

Kao-Yi Shen [a], Shu-Kung Hu [b], Gwo-Hshiung Tzeng [c,*]

[a] Department of Banking & Finance, Chinese Culture University (SCE), Taipei 10659, Taiwan
[b] Department of Business and Entrepreneurial Management, Kainan University, Taoyuan 33857, Taiwan
[c] Graduate Institute of Urban Planning, National Taipei University, New Taipei City 23741, Taiwan

ARTICLE INFO

Article history:
Received 16 June 2016
Revised 5 September 2016
Accepted 25 September 2016
Available online 28 September 2016

Keywords:
Multiple criteria decision-making (MCDM)
DEMATEL-based analytic network process (DANP)
Rough set theory (RST)
Fuzzy integral
Financial performance (FP)
Multi-attribute utility theory (MAUT)

ABSTRACT

Financial modeling for the life insurance industry involves two main difficulties: (1) Selecting the minimal and critical variables for modeling while considering the impreciseness and interrelationships among the numerous attributes and (2) measuring plausible synergy effects among variables and dimensions that might cause undesirable biases for an evaluation model. To overcome these difficulties, this paper proposes a two-stage hybrid approach: Rough financial knowledge is retrieved first, and then the obtained core attributes are measured and synthesized using fuzzy-integral-based decision methods. The main innovation of this study is the use of rough knowledge retrieval procedures and fuzzy measures for exploring the synergy effects on financial performance. This approach is expected to support insurers to systematically improve their financial performance. A group of life insurance companies in Taiwan was analyzed, and the findings support the existence of interrelated synergy effects among the core criteria. In addition, five companies were examined to illustrate financial performance improvement planning with this approach. This study bridges the gap between advanced soft computing techniques and pragmatic financial modeling in a dynamic business environment.

1. Introduction

The financial industry is critical to the stability of a nation's economy. Therefore, since the global financial crisis of 2008, increasing interest has been shown in examining the financial performance (FP) of the financial industry, especially for the benefit of stakeholders (e.g., investors, management, and governments). Two mainstream research topics are related to the FP of financial institutions (mainly banks and insurance companies), namely bankruptcy and financial failure prediction [29], and FP evaluation for credit scoring and investment purposes [43]. The present study focused on the evaluation of the FP of life insurance companies. The methodologies adopted in previous research [12] for assessing the FP of financial institutions can be categorized as follows: (1) methodologies based on statistical models, (2) methodologies based on machine learning and soft-computing techniques, and (3) methodologies involving multiple criteria decision-making (MCDM) methods [61]. In

* Corresponding author.
E-mail addresses: kyshen@sce.pccu.edu.tw, atrategy@gmail.com (K.-Y. Shen), syokou@mail.knu.edu.tw (S.-K. Hu), ghtzeng@gm.ntpu.edu.tw, ghtzeng@mail.ntpu.edu.tw (G.-H. Tzeng).

http://dx.doi.org/10.1016/j.ins.2016.09.055

addition, because of the dynamics and complexity of business environments, hybrid approaches (i.e., the integration of more than two methodologies) are increasing rapidly. For example, under the framework of SMAA TRI [54], Angilella and Mazzù [3] proposed the ELECTRE TRI [63] for building a judgmental rating model to support the financing decisions for small and medium-sized enterprises (SMEs). In their model, qualitative judgments and quantitative financial data were considered and integrated for rating SMEs.

Conventional social science studies have mainly been based on statistical methods for identifying the relationships between selected financial variables and the subsequent FP of financial companies. Methods such as discriminant analysis, factor analysis, principal component analysis (PCA), and logit regression have been widely adopted in previous research. Following the work of Altman [1], discriminant analysis has been widely used for analyzing the financial failure of companies [28]. Subsequently, the logit-regression-based synthesized score approach (Z-score) presented in the influential papers [1,2] became prominent; for example, West [60] used logit regression along with factor analysis to measure the FP of banks. Other statistical methods, such as probit analysis and PCA, have been applied or combined for predicting the FP of banks [8]. Kumar and Ravi [28] presented a systematic review of this research area. However, regarding the statistical approach, the following three aspects are questionable: (1) The assumption of independence among the variables, (2) certain probabilistic assumptions, and (3) the additive-type aggregation in the synthesized score approach. In a complex financial environment, interrelationships among variables often exist; however, owing to the limitations of statistical methods, certain interrelated or nonadditive-type influences cannot be measured or modeled accurately.

Machine learning techniques (e.g., artificial neural networks (ANNs), genetic algorithms (GAs), decision trees (DTs), and support vector machines (SVMs)) are useful for determining nonlinear relationships among data sets. Most machine learning techniques do not require the probabilistic distribution of data to be assumed; therefore, they are more practical for real business applications. A recent survey of machine learning methods used for predicting financial crises [30] suggested that bankruptcy prediction and credit scoring could be regarded as classification problems in machine learning. The survey categorized the adopted techniques as single or hybrid classifiers. Of the various classifiers, the ANN-related techniques (e.g., back-propagation, self-organizing map, and competitive learning neural networks) are probably the most dominant for financial prediction problems. For example, a previous study [7] compared the financial distress prediction results of ANN techniques with statistical methods for life insurance companies. The back-propagation ANN technique was found to outperform traditional statistical methods. ANN techniques mimic the learning mechanism of the brain, and the learned results are stored in the connections between neurons; the learning process and learned results are often criticized as a “black box,” implying that understanding the outcomes is difficult [13]. Some single classifiers, such as SVM [59] and GA [37], have a similar drawback. Hybrid classifiers often involve the integration of two or more techniques (e.g., GA+ANN+ ARIMA [58] and DT+ANN+SVM [24]). One of the techniques is used for performing the initial classification, and the others are used for the tuning parameters of the hybrid models [23]. Generally, machine-learning-based studies have focused on increasing the accuracy of classification or prediction.

Soft computing techniques (mainly the fuzzy set [64] and rough set [39] theories, which are discussed here) are based on solid mathematical foundations, and are used for modeling the impreciseness or uncertainty in a system. They have been widely applied in engineering [66] and social economics [56,66]. One of the key advantages of soft computing techniques is their logical reasoning capability, which can help obtain meaningful knowledge (i.e., logic or rules) for solving a problem. These techniques are often integrated with machine learning techniques for solving the FP evaluation problem. For example, ANN techniques and fuzzy inference were integrated to address the credit scoring problem [33] and the adaptive-network-based fuzzy inference system was integrated with the dominance-based rough set approach (DRSA) for evaluating the FP of banks [45]. As suggested by the aforementioned survey [30], soft-computing-integrated classification techniques appear to be the most promising direction for future research on FP prediction.

The third category of methodology used for assessing the FP or operational efficiency of financial institutions comprises MCDM methods. Recently, Fethi and Pasiouras [13] and Zopounidis et al. [67] presented updated reviews on this approach. The fuzzy set theory is commonly incorporated in MCDM methods for FP evaluation problems [34,44] to mimic the imprecise judgments and reasoning of decision-makers (DMs). The MCDM approach considers multiple criteria (the terms “attributes” and “criteria” are used interchangeably in this paper) simultaneously to make ranking or selection decisions, and is based on utility theory, as developed in economics [65]. Other methods that involve the construction of decision models on the basis of pairwise comparisons between criteria are also used; of these methods, analytic hierarchy process (AHP) extended methods have attracted the most attention. The original AHP [41] is based on the assumption of the independence of criteria. The generalized analytic network process (ANP) [42] allows internetwork relationships in its model. The generalized ANP has been adopted for evaluating the performance of wealth management banks [62] and commercial banks [46]. The MCDM approach is based on the experience and knowledge of DMs and experts, and is therefore appropriate for in-depth investigations of relationships between the predefined criteria (attributes) of a complex problem, or system [65].

FP modeling for financial institutions involves difficulties related to (1) the selection of the minimal and critical variables, (2) the clarification of cause–effect relationships among variables, and (3) the measurement of plausible synergy effects among the criteria and dimensions. The complexity of imprecise and conjoint relationships among dimensions and criteria cannot be measured or modeled accurately using statistical models, a single soft computing technique, or an MCDM method. Therefore, a novel hybrid approach is proposed in this paper. In addition, although a considerable number of studies have adopted various methods and techniques to increase the classification accuracy of FP evaluation, or devise a system of logic or rules for the problem, limited research has been undertaken to diagnose the FP of financial companies for improvement planning. Only a few recent studies [46,48,49] have pursued this direction. Moreover, the present study attempts to obtain more constructive implications regarding improvement planning for addressing the FP modeling problem.

To overcome the aforementioned difficulties, this study proposes a two-stage approach. In the first stage, the learning capability of a soft computing technique is used to retrieve rough knowledge. In the second stage, the core attributes are synthesized using a nonadditive-type fuzzy aggregator to construct a hybrid MCDM model. The expected contributions of the proposed approach are as follows: (1) Retrieving core attributes and rough financial knowledge (decision rules) for enabling in-depth analyses, (2) refining the rough knowledge by identifying cause–effect influences among the core attributes, (3) measuring the synergy effects among dimensions and criteria for performing accurate FP evaluations, and (4) facilitating systematic improvement planning for insurance companies.

The innovations of this study can be outlined in two parts, namely modeling and business applications. Regarding modeling, a novel mechanism is devised for retrieving rough knowledge from historical data, and a nonadditive approach is applied to measure the plausible synergy effects among variables. In literature, the classical financial optimization model (i.e., mean-variance theory [35]) has strengths regarding obtaining optimal results under the expected returns and risk. Mean-variance theory has been applied in many fields (e.g., in supply chain risk analysis [10]); however, it is based on the presumed statistical distributions of data, which have the limitations of the aforementioned statistical approach (e.g., the independence of variables). This study differs from the classical financial optimization model in emphasizing exploring the imprecise patterns and knowledge provided by historical data, which requires fewer assumptions for financial modeling. In the era of "big data," developing ways of leveraging the strengths of machine learning and soft computing techniques to realize accurate modeling is a challenging and yet valuable research topic.

For business applications, new tools for facilitating systematic FP improvement are proposed, namely internetwork relationship maps (INRMs) and directional flow graphs (DFGs). Thus, this study is expected to provide an enhanced understanding of how multidisciplinary methodologies can be integrated to obtain implicit and critical knowledge regarding FP modeling, thereby bridging the gap between academia and practice. Empirical cases of registered life insurance companies in Taiwan were analyzed to illustrate the proposed approach.

The remainder of this paper is organized as follows: Section 2 introduces the background and discusses the development of existing methodologies. Section 3 elucidates the proposed hybrid approach. In Section 4, a group of registered life insurance companies in Taiwan are analyzed as empirical cases. The results and implications of the current study are discussed in Section 5. Finally, Section 6 concludes the study and presents suggestions for future research.

2. Preliminary

This section briefly introduces the background of the present study and discusses the development of methods used for FP prediction and the evaluation problem. The purposes of adopting each method and technique in the proposed approach are also explained and discussed.

2.1. Rough set theory and dominance-based rough set approach

Proposed by Pawlak [39], the rough set theory (RST) has become a widely applied soft computing technique for rule induction and attribute reduction in various applications, such as medical diagnosis [11,55], marketing [31], FP prediction [45], technical analysis (TA) for investment [47], and business analytics [49]. The RST is acknowledged to be suitable for inducting vague or imprecise patterns and knowledge by analyzing the indiscernibility of the attributes of an information system; it has the advantage of being capable of machine learning by processing nonlinear data. Furthermore, it can be used for knowledge retrieval.

However, the classical RST ignores the fact that the attributes of an information system often have ordinal (or preferential) characteristics in certain applications. For example, when predicting the financial insecurity of banks, a low debt ratio is often preferred for classifying a bank as being secure. Therefore, the RST research group proposed a DRSA for decision-making [18,19], in which dominance relationships among the condition and decision attributes are considered for making classifications. This approach is more suitable for solving MCDM problems [14,67]. In the present study, the use of the DRSA was proposed for learning from historical data and for inducting rough knowledge—namely, the core attributes (see Section 3.1) and decision rules—and thereby establishing an initial framework for constructing a hybrid decision model.

2.2. DEMATEL technique and DEMATEL-based ANP method

The Battelle Memorial Institute at Geneva [15] proposed the DEMATEL technique for analyzing and resolving complex social problems. The DEMATEL technique is capable of dividing interrelated criteria and dimensions into cause and effect groups [48]. Furthermore, it can be used for developing a graphical illustration (i.e., an INRM) [40], which may be helpful to life insurance companies for planning systematic improvements. Because the DEMATEL technique can decompose the cause–effect interrelationships in a complex problem, it has been successfully applied to the analysis of various problems, such as portfolio selection [20], supplier selection in a green supply chain [21], and the selection of glamour stocks [50].

In addition, the DEMATEL-based concept can be used to modify the equal-weight assumption for the supermatrix in the original ANP method [16]. The ANP method modified by the DEMATEL is called the DEMATEL-based ANP (DANP) method

[38]. The DANP method is based on an extension of the concepts underlying the AHP and ANP methods [57]. A recent review [34] observed that over the past two decades, apart from hybrid fuzzy MCDM models, extensions of the AHP or ANP methods have been the most widely used. In this study, the DANP method was used for obtaining raw influential weights for use as the initial weights in the calculation of the fuzzy measure parameters (see Sections 3.2 and 3.3).

2.3. Fuzzy integral for nonadditive-type performance aggregation

A considerable number of MCDM methods are based on utility theory, especially the classical multi-attribute utility theory (MAUT) [26]. A fundamental operation (aggregation) is required for obtaining the final evaluation result. However, the widely used additive-type aggregators (e.g., simple average weighting (SAW) and ordered weighted averaging operators [62]) cannot measure interactions between criteria [17]. Therefore, the fuzzy integral technique [52] was used to measure and aggregate the interrelated influences among criteria and dimensions in this study. The fuzzy integral technique has been used in various applications [22,27,32]. Nevertheless, few studies have been performed on the use of the nonadditive-type aggregators for solving the FP evaluation problem [9]. Therefore, the present study attempts to combine the concepts of fuzzy measure [36] and DANP influential weights [40,50] to construct a hybrid fuzzy-integral-based decision model. The objective is to measure (and comprehend) the plausible complex and interrelated influences among the criteria and dimensions. The main goal is to construct a model that could be used not only to make ranking (or selection) decisions but also for planning to improve the FP of life insurance companies toward the aspiration levels.

3. Rough-knowledge-based hybrid approach

In this section, the framework and procedure of the proposed approach are introduced. The approach is divided into two parts: (1) DRSA for investigating imprecise patterns and granules of knowledge by obtaining core attributes and decision rules, and (2) a DRSA-core-attribute-based hybrid decision model for evaluating the nonadditive performance effects among the attributes (criteria).

3.1. DRSA for retrieving rough knowledge

In the first stage, a DRSA classifier is adopted to identify the critical factors (i.e., core attributes) and decision rules (along with granules of knowledge) from complex data. Unlike other machine-learning-based studies that have mainly focused on increasing the prediction accuracy, for the construction of the decision model the present study attempted to leverage the capability of the DRSA for capturing imprecise and implicit patterns and knowledge by preserving the roughness of the processed granules.

The DRSA [18,19] organizes alternatives in a 4-tuple information system (IS); in other words, $IS=(U, A, V, f)$, where U is a finite state of the universe, $A=\{a_1, a_2, ..., a_m\}$ is a finite set of m attributes (criteria), V_a is the value domain of attribute a, and f is a total function defined as f: $U\times A\rightarrow V$ ($f(x, a) \in V_a$ for each $x \in U$ and $a \in A$). In the DRSA, A typically comprises multiple condition attributes (A^C) and a decision attribute. Each attribute can be divided into several states, and the decision attribute is often categorized into ordered classes, such as $Cl=\{Cl_t, t=1, ..., v\}$. Although the DRSA can be used to process all the raw figures directly, to preserve the roughness of the granules (in each attribute) for the construction of the decision model, each condition attribute was divided into certain states in the present study, thereby approximating how experts comprehend these concepts in complex business environments.

Subsequently, $\succeq_a$ is defined as a weak preference relation on U with respect to criterion a ($a \in A$). Then, for objects x, $y \in U$, if $x\succeq_a y$, it denotes that "x is at least as good as y in terms of attribute a." For a set of preference-ordered decision classes (DCs), the upward and downward unions of DCs can be defined as $Cl_s^{\geq} = \bigcup_{r\geq s} Cl_r$ and $Cl_s^{\leq} = \bigcup_{r\leq s} Cl_r$; for brevity, only the upward union is used for the explanation. The upward and downward unions of DCs may therefore describe the dominance relation for any partial set of condition attributes $P \subseteq A^C$. Furthermore, xD_Py denotes that x P-dominates y for all the subsets of attributes in P. The P-dominating and P-dominated sets are defined in (1) and (2).

$$D_P^+(x) = \{y \in U : yD_Px\} \tag{1}$$

$$D_P^-(x) = \{y \in U : xD_Py\} \tag{2}$$

Consequently, $D_P^+(x)$ and $D_P^-(x)$ can be used to define the P-lower and P-upper approximations as (3) and (4). The boundary regions, defined by (5), preserve the uncertain granules of knowledge in reasoning; in other words, the impreciseness in each pair of concepts (e.g., high *debt*) can be retained to capture the imprecise patterns or relationships in a complex system.

$$\underline{P}(Cl_r^{\geq}) = \left\{x \in U : D_P^+(x) \subseteq Cl_r^{\geq}\right\} \tag{3}$$

$$\bar{P}(Cl_r^{\geq}) = \left\{x \in U : D_P^-(x) \cap Cl_r^{\geq} \neq \emptyset\right\} \tag{4}$$

$$Bn_P(Cl_r^{\geq}) = \bar{P}(Cl_r^{\geq}) - \underline{P}(Cl_r^{\geq}) \tag{5}$$

To measure the quality of approximation for every $P \subseteq A^C$, $\alpha_P(Cl)$ is defined as follows for preference-ordered DCs related to P; $|\bullet|$ denotes the cardinality of a set in (6).

$$\alpha_p(Cl) = \left| U - \left(\bigcup_{r \in \{2,\ldots,m\}} Bn_p(Cl_r^{\geq}) \right) \right| \Big/ |U| \tag{6}$$

Dominance-based rough approximations of the upward and downward unions of DCs can be used to obtain a set of decision rules in the form of "if *antecedents*, then *consequence*." In addition, each minimal subset P of A^C (i.e., $P \subseteq A^C$) that satisfies $\alpha_P(Cl) = \alpha_{A^C}(Cl)$ is called a REDUCT; the intersection of all REDUCTs is the core set, which comprises the minimal attributes that may maintain the same level of approximation quality for a DRSA *IS*. In other words, the core attributes obtained by the DRSA represent the criteria that are indispensable for acquiring rough knowledge in a complex system, and they are the inputs for the second stage, in which a hybrid decision model is constructed.

Step 1: Discretize the condition and decision attributes. The discretized intervals should approximate how domain experts comprehend the concepts of the addressed problem.

Step 2: Divide data into a training set and a testing set. Implement the DRSA classifier using the training set until an acceptable level of learning result is obtained. The testing set is then used to validate the learning result.

Step 3: Identify the core attributes and decision rules. Once an acceptable DRSA model is obtained, the corresponding core attributes and decision rules are adopted for constructing the hybrid decision model.

3.2. DEMATEL technique and DANP method

The DEMATEL technique [15] identifies the cause–effect influence relations among the core dimensions or attributes, and determines the influential weights of the DANP (DANP weights), which are used as the initial weights for the subsequent fuzzy measures.

Step 4: Collect experts' opinions (using questionnaires) for constructing the initial direct influence relation matrix $\mathbf{R} = [r_{ij}]_{n\times n}$, where r_{ij} denotes the influence of attribute i on another attribute j as perceived by experts. Averaged opinions are used to form the initial average influence matrix $\mathbf{A}$. All the attributes adopted in the questionnaire are sourced from the core attribute set of the first stage.

$$\mathbf{A} = \begin{bmatrix} a_{11} & \cdots & a_{1j} & \cdots & a_{1n} \\ \vdots & & \vdots & & \vdots \\ a_{i1} & \cdots & a_{ij} & \cdots & a_{in} \\ \vdots & & \vdots & & \vdots \\ a_{n1} & & a_{nj} & & a_{nn} \end{bmatrix} \tag{7}$$

In (7), n equals the number of total attributes in the core set from DRSA ($1 \leq i \leq n$ and $1 \leq j \leq n$).

Step 5: Normalize $\mathbf{A}$ to obtain the direct influence relation matrix $\mathbf{D}$. The matrix $\mathbf{D} = [d_{ij}]_{n\times n}$ can be derived using (8) and (9), and μ is a constant used for normalizing $\mathbf{A}$.

$$\mathbf{D} = \mu \mathbf{A} \tag{8}$$

$$\mu = \min\left\{ \frac{1}{\max_i \sum_{j=1}^{n} a_{ij}}, \frac{1}{\max_j \sum_{i=1}^{n} a_{ij}} \right\},\ i, j \in \{1, \cdots, n\} \tag{9}$$

Step 6: Obtain the total influence relation matrix $\mathbf{T}$. The indirect effects of the model diminish with an increase in the power of $\mathbf{D}$. $\mathbf{T}$ can be expressed as (10) [15].

$$\begin{aligned} &\mathbf{T} = \mathbf{D} + \mathbf{D}^2 + \ldots + \mathbf{D}^w = \mathbf{D}(\mathbf{I} - \mathbf{D}^w)(\mathbf{I} - \mathbf{D})^{-1}, \text{ and} \\ &\mathbf{T} = \left[t_{ij}\right]_{n\times n} = \mathbf{D}(\mathbf{I} - \mathbf{D})^{-1} \text{ While } \lim_{w\to\infty} \mathbf{D}^w = [0]_{n\times n} \end{aligned} \tag{10}$$

Step 7: Analyze the sum of each column and each row in $\mathbf{T}$ to obtain the cause–effect influence relations among the core attributes.

The sum of each row and each column in $\mathbf{T}$ can be denoted by r_i^C ($r_i^C = \sum_{j=1}^{n} t_{ij}$ for $i \in 1, \ldots, n$) and s_j^C ($s_j^C = \sum_{i=1}^{n} t_{ij}$ for $j \in 1, \ldots, n$). Moreover, the difference $r_i^C - s_i^C$ (for $i = 1,\ldots,n$) can be used to divide the criteria (attributes) into two groups, namely the cause and effect groups. If $r_i^c - s_i^c > 0$, then the ith criterion belongs to the cause group; otherwise, it belongs to the effect group. Similarly, the cause–effect influence relations among the dimensions could be determined by $r_i^D - s_i^D$.

The $\mathbf{T}$ defined in (10) can be denoted as $\mathbf{T}_C$ by assuming that there were k dimensions and n criteria in $\mathbf{T}$. Then, by using the notations from the index matrices [4] (K, L be fixed sets of indices), the submatrices in $\mathbf{T}_C$ can be indicated by (11), and the submatrix $\mathbf{T}_C^{k_i, l_j}$ is assumed to indicate the k_ith (i.e., D_i with p sub-criteria) and the l_jth (i.e., D_j with q sub-criteria) dimensions, where $1 \le p, q \le n$. The submatrix $\mathbf{T}_C^{k_i,l_j}$ can be further defined in (12). The normalization of $\mathbf{T}_C^{k_i,l_j}$ is conducted by $N(\mathbf{T}_C^{k_i,l_j}) = (1/\sum_{\beta=1}^{p}\sum_{\alpha=1}^{q} t_{i_\alpha,j_\beta}^{ij}) \times \mathbf{T}_C^{k_i,l_j}$. Thus, the normalized $\mathbf{T}_C$ can be defined as $\mathbf{T}_C^N$ in (13).

$$\left[K, L, \left\{\mathbf{T}_C^{k_i,l_j}\right\}\right] \equiv \begin{array}{c|ccccc} & l_1 & \cdots & l_j & \cdots & l_k \\ \hline k_1 & \mathbf{T}_C^{k_1,l_1} & \cdots & \mathbf{T}_C^{k_1,l_j} & \cdots & \mathbf{T}_C^{k_1,l_k} \\ \vdots & \vdots & & \vdots & & \vdots \\ k_i & \mathbf{T}_C^{k_i,l_1} & \cdots & \mathbf{T}_C^{k_i,l_j} & \cdots & \mathbf{T}_C^{k_i,l_k} \\ \vdots & \vdots & & \vdots & & \vdots \\ k_k & \mathbf{T}_C^{k_k,l_1} & \cdots & \mathbf{T}_C^{k_k,l_j} & \cdots & \mathbf{T}_C^{k_k,l_k} \end{array} \tag{11}$$

$$\mathbf{T}_C^{k_i,l_j} = \begin{bmatrix} t_{i_1,j_1}^{ij} & \cdots & t_{i_1,j_\beta}^{ij} & \cdots & t_{i_1,j_p}^{ij} \\ \vdots & & \vdots & & \vdots \\ t_{i_\alpha,j_1}^{ij} & \cdots & t_{i_\alpha,j_\beta}^{ij} & \cdots & t_{i_\alpha,j_p}^{ij} \\ \vdots & & \vdots & & \vdots \\ t_{i_q,j_1}^{ij} & \cdots & t_{i_q,j_\beta}^{ij} & \cdots & t_{i_q,j_p}^{ij} \end{bmatrix}, \text{ Where } 1 \le \alpha \le q \text{ and } 1 \le \beta \le p \tag{12}$$

$$\mathbf{T}_C^N = \begin{bmatrix} N\left(\mathbf{T}_C^{k_1,l_1}\right) & \cdots & N\left(\mathbf{T}_C^{k_1,l_j}\right) & \cdots & N\left(\mathbf{T}_C^{k_1,l_k}\right) \\ \vdots & & \vdots & & \vdots \\ N\left(\mathbf{T}_C^{k_i,l_1}\right) & \cdots & N\left(\mathbf{T}_C^{k_i,l_j}\right) & \cdots & N\left(\mathbf{T}_C^{k_i,l_k}\right) \\ \vdots & & \vdots & & \vdots \\ N\left(\mathbf{T}_C^{k_k,l_1}\right) & \cdots & N\left(\mathbf{T}_C^{k_k,l_j}\right) & \cdots & N\left(\mathbf{T}_C^{k_k,l_k}\right) \end{bmatrix} \tag{13}$$

Step 8: Transpose $\mathbf{T}_C^N$ to be the unweighted supermatrix $\mathbf{W}$ in the DANP model (i.e., $\mathbf{W} = (\mathbf{T}_C^N)'$). In addition, matrix $\mathbf{T}_D$ is normalized to become $\mathbf{T}_D^N$ as in (14) and (15), and $d_i = \sum_{j=1}^{k} t_{D_{ij}}^{ij}$, $i = 1, 2, ..., k$ in (15).

$$\mathbf{T}_D = \begin{bmatrix} t_D^{11} & \cdots & t_D^{1j} & \cdots & t_D^{1k} \\ \vdots & & \vdots & & \vdots \\ t_D^{i1} & \cdots & t_D^{ij} & \cdots & t_D^{ik} \\ \vdots & & \vdots & & \vdots \\ t_D^{k1} & \cdots & t_D^{kj} & \cdots & t_D^{kk} \end{bmatrix} \tag{14}$$

$$\mathbf{T}_D^N = \begin{bmatrix} t_D^{11}/d_1 & \cdots & t_D^{1j}/d_1 & \cdots & t_D^{1k}/d_1 \\ \vdots & & \vdots & & \vdots \\ t_D^{i1}/d_i & \cdots & t_D^{ij}/d_i & \cdots & t_D^{ik}/d_i \\ \vdots & & \vdots & & \vdots \\ t_D^{k1}/d_k & \cdots & t_D^{kj}/d_k & \cdots & t_D^{kk}/d_k \end{bmatrix} = \begin{bmatrix} t_D^{N11} & \cdots & t_D^{N1j} & \cdots & t_D^{N1k} \\ \vdots & & \vdots & & \vdots \\ t_D^{Ni1} & \cdots & t_D^{Nij} & \cdots & t_D^{Nik} \\ \vdots & & \vdots & & \vdots \\ t_D^{Nk1} & \cdots & t_D^{Nkj} & \cdots & t_D^{Nkk} \end{bmatrix} \tag{15}$$

Step 9: Obtain the weighted (DEMATEL-adjusted) supermatrix $\mathbf{W}^N = \mathbf{T}_D^N\mathbf{W}$ [38].

The raw influential weight w_i^C of each criterion (i=1, 2, ..., n) can then be obtained as $\lim_{z\to\infty}(\mathbf{W}^N)^z$ until stable; that is, the raw influential weights of the criteria are $\boldsymbol{w}^C = (w_1^C, ..., w_i^C, ..., w_n^C)$.

3.3. Synthesized fuzzy integral using DANP influential weights and fuzzy measure

DMs and researchers planning to evaluate the performance of alternatives on the basis of $\boldsymbol{w}^C$ (using the DANP), cannot overlook the plausible intercriteria or interdimension effects (also termed synergy effects). Consequently, additive-type aggregators (e.g., SAW) might not be suitable for measuring the aforementioned synergy effects; therefore, the use of a nonadditive-type fuzzy integral aggregator [52] is proposed in this study.

Step 10: Calculate the λ-measure function [25]. Let g be a λ-measure function that is defined on a power set $P(C)$ for the finite set (i.e., the core attribute set inducted using the DRSA). Then, g should satisfy the following properties [52]:

$$g : P(C) \to [0, 1],\ \ g(\emptyset) = 0,\ \text{ and } g(C) = 1 \tag{16}$$

$$\forall c_A, c_B \in P(C),\ \ c_A \cap c_B = \emptyset \tag{17}$$

$$g_\lambda(c_A \cup c_B) = g_\lambda(c_A) + g_\lambda(c_B) + \lambda g_\lambda(c_A) g_\lambda(c_B),\ \text{ for } -1 < \lambda < \infty. \tag{18}$$

In (18), λ indicates the aforementioned nonadditive (synergy) effect; for $\lambda < 0$, $\lambda = 0$, and $\lambda > 0$, it denotes the substitutive, additive, and multiplicative effect, respectively. Next, g_i fuzzy density function is defined as (19).

$$\begin{aligned} g_\lambda(\{c_1, c_2, ..., c_n\}) &= \sum_{i=1}^{n} g_i + \lambda \sum_{i_1=1}^{n-1} \sum_{i_2=i_1+1}^{n} g_{i_1} g_{i_2} + \cdots + \lambda^{n-1} g_1 g_2 \cdots g_n \\ &= \frac{1}{\lambda}\left(\prod_{i=1}^{n} (1 + \lambda g_i) - 1 \right) = 1,\ for -1 \le \lambda < \infty \end{aligned} \tag{19}$$

Step 11: Calculate the fuzzy measure based on the concept of MAUT [26]. The aggregated utility regarding C can be indicated as (20).

$$u(c_1, c_2, \ldots, c_n) = \sum_{i=1}^{n} w_i u(c_i) + \lambda \sum_{i=1, j>1}^{n} w_i w_j u(c_i) u\left(c_j\right) + \cdots + \lambda^{n-1} w_1 w_2 \cdots w_n u(c_1) u(c_2) \cdots u(c_n) \tag{20}$$

where $u(c_1^0, c_2^0, ..., c_n^0) = 0$ and $u(c_1^*, c_2^*, ..., c_n^*) = 1$; $u(c_i)$ is a conditional utility function of c_i, and $u(c_i^0) = 0$, $u(c_i^*) = 1$, for $i = 1$, 2, ..., n; $w_i = u(c_i^*, c_{\neg i}^0)$; λ is a solution of $1 + \lambda = \prod_{i=1}^{n} (1 + \lambda w_i)$. Thus, (19) can be redefined as (21) based on the concept of MAUT.

$$\begin{aligned} g_\lambda^{(n)}(\{c_1, c_2, \ldots, c_n\}) &= \sum_{i=1}^{n} g_\lambda^{(1)}(\{c_1\}) + \lambda \sum_{i=1, j>1}^{n} g_\lambda^{(2)}(\{c_i\}) g_\lambda\left(\left\{c_j\right\}\right) \\ &\quad + \cdots + \lambda^{n-1} g_\lambda^{(n)}(\{c_1\}) g_\lambda(\{c_2\}) \cdots g_\lambda(\{c_n\}) \end{aligned} \tag{21}$$

where $g_\lambda^{(n)}(\{c_1^*, c_2^*, ..., c_n^*\}) = g_\lambda^{(n)}(\{c_1, c_2, ..., c_n\}) = 1$; also, $g_\lambda^{(1)}(\{c_i^*\}) = 1$ and $g_\lambda^{(1)}(\{c_i^0\}) = 0$ (for $i = 1$, 2, ..., n). In addition, $w_i = u(c_i^*, c_{\neg i}^0) = g_\lambda^{(1)}(\{c_i\})$and $1 + \lambda = \prod_{i=1}^{n} (1 + \lambda g_\lambda^{(1)}(\{c_i\}))$.

Step 12: Incorporate the influential weights $\boldsymbol{w}^C = (w_1^C, ..., w_i^C, ..., w_n^C)$ obtained using the DANP as the initial weights for fuzzy measures.

$$g_\lambda(\{c_1\}), ..., g_\lambda(\{c_i\}), ..., g_\lambda(\{c_n\}) = \gamma(w_1^C, ..., w_i^C, ..., w_n^C) = (\gamma w_1^C, ..., \gamma w_i^C, ..., \gamma w_n^C) \tag{22}$$

In (22), γ is the adjustment coefficient; w_i^C is the DANP influential weight of the ith criterion.

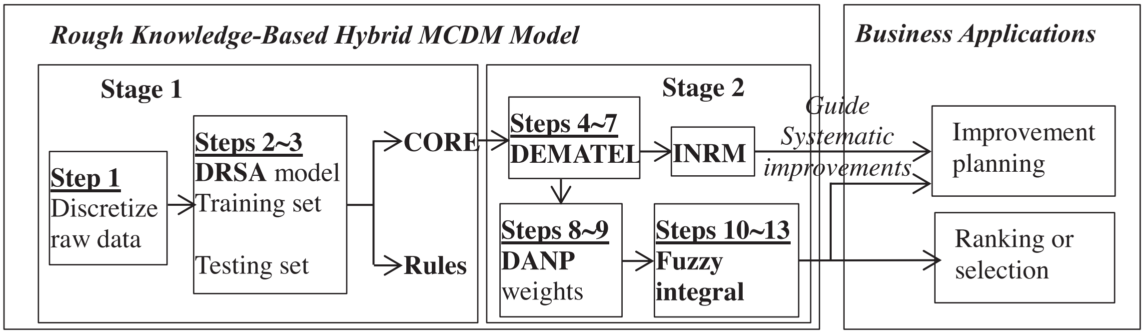
Step 13: Aggregate the final performance score based on the fuzzy integral.

Let h be a measurable set function for performance, defined on the fuzzy measurable space. Assume that $h(p_1) \ge h(p_2) \ge ... \ge h(p_n)$, then the fuzzy integral (also termed the Choquet integral, e.g., $(c)\int hdg$) of the fuzzy measure $g_\lambda(\cdot)$ with respect to $h(\cdot)$ can be defined as (23), according to the previous work [32]:

$$\begin{aligned} (c)\int hdg &= h(p_n) g(H_n) + [h(p_{n-1}) - h(p_n)] g(H_{n-1}) + \cdots + [h(p_1) - h(p_2)] g(H_1) \\ &\text{where } H_1 = \{c_{p_1}\},\ H_2 = \{c_{p_1}, c_{p_2}\}, \ldots, H_n = \{c_{p_1}, c_{p_2}, \ldots, c_{p_n}\} = C. \end{aligned} \tag{23}$$

The research flow corresponding to the aforementioned steps is shown in a simplified form in Fig. 1. It consists of two main parts: the hybrid model and business applications. The details of how each technique is integrated are presented in Fig. 2.

Aside from applying the proposed approach to the FP modeling of companies or institutions, this hybrid approach can be further generalized for solving other decision problems, such as the evaluation or selection of various new suppliers, products, and projects. The generalized model comprises two stages. The first stage adopts the rough machine learning mechanism to induct the minimal and indispensable CORE attributes regarding the evaluation of alternatives, as shown in



Main functions/purposes of the involved methods

Methods	**DRSA**	**DEMATEL**	**DANP**	**Fuzzy integral**
Functions (Purposes)	1. Retrieve **CORE** attributes 2. Obtain rough knowledge	1. Adjust dimensional weights in **DANP** 2. Obtain internetwork relationship map (**INRM**) for guiding systematic improvements	1. Adjust parameters in fuzzy measures for forming **fuzzy integral** performance evaluation	1. Measure plausible synergy effects among criteria 2. Obtain the final performance scores for ranking or selection 3. Identify priority gaps for improving towards the aspiration levels
Foundations	Soft computing and applied mathematics	MCDM	MCDM	Soft computing, applied mathematics, and economics

Fig. 1. Research flows with main functions of the incorporated methods.

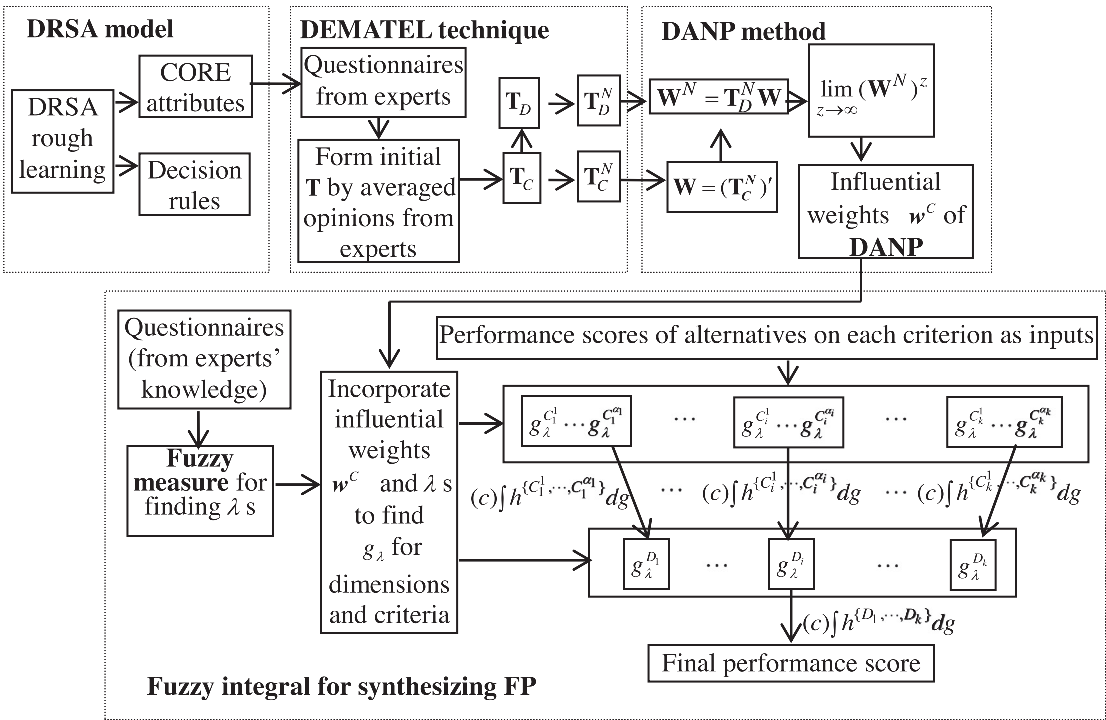


Fig. 2. Integration of techniques and methods in the proposed approach.

(24). The second stage uses an additive or nonadditive aggregator to synthesize the weighted performance scores for ranking or selection. The additive and nonadditive performance aggregations are indicated in (25.1) and (25.2) respectively.

$$A \overset{R.M.}{\mapsto} A_n^C \tag{24}$$

$$\max F_j \tag{25}$$

$$\text{while } \bigoplus_{i=1}^{n} w_i \times P_{ij} = F_j, \text{ for } i = 1, \ldots, n \tag{25.1}$$

$$\text{While } \oint \left(w_i P_{ij}\right) dg = F_j, \text{ for } i = 1, \ldots, n \tag{25.2}$$

In (24), A denotes the original *IS* set that comprises all the relevant attributes regarding the evaluation of alternatives, A_n^C indicates the CORE set that has n attributes, and $\overset{R.M.}{\mapsto}$ indicates the rough machine learning that transforms A into A_n^C. Assume that there are m alternative in this model, the generalized model aims to select the alternative with the highest F (F_j represents the final performance score of the jth alternative in (25)) in the second stage (for $j = 1,\ldots,m$); w_i denotes the relative importance of the ith criterion in (25.1) and (25.2). $\bigoplus_{i=1}^{n}$ indicates an additive type aggregator, which is not limited to the SAW method. Similarly, $\oint(\cdot)dg$ indicates any nonadditive aggregator (e.g., the Choquet integral in this study) that is capable of measuring the synergy effects among the core criteria. In addition, this model can be extended to support an alternative (e.g., a company or a project) to identify its improvement priority using its weighted performance scores. Therefore, compared with the conventional MCDM or financial models, this hybrid decision model could play a more constructive role in solving practical problems.

4. Empirical cases from the life insurance industry

In view of the importance of the life insurance industry to the stability of the national economy, in 2009 Taiwan made it mandatory for all registered life insurance companies to report their operational and financial performance to the public. To illustrate the application of the proposed nonadditive hybrid approach to FP diagnoses, openly accessible data from the life insurance industry in Taiwan were analyzed.

4.1. Data

The data examined were obtained from two sources: openly accessible historical reports of life insurance companies, and the opinions and knowledge of eight domain experts (for the fuzzy measures). The historical reports were obtained from the Taiwan Insurance Institute [53], and all the available data—from 2009 to 2013—were used for DRSA modeling in the first stage of the proposed approach for acquiring rough financial knowledge. The aforementioned reports contained 17 indicators from five dimensions: *Capital Structure* (D_1), *Payback* (D_2), *Operational Efficiency* (D_3), *Revenue Quality* (D_4), and *Capital Efficiency* (D_5). A one-period lagged model was constructed by matching each company's condition attributes (i.e., the 17 indicators) at time t with its subsequent FP (return on assets (*ROA*) at time $t+1$ was considered as the decision attribute).

At the second stage, the core attributes obtained in the first stage were used to design a questionnaire, and eight domain experts' opinions were collected to calculate the DANP weights and fuzzy measures and construct a nonadditive hybrid decision model. All the experts have worked in the life insurance industry for more than 15 years, and their job positions include manager, unit manager, assistant vice president, deputy director, and sales director; the experts are from three insurance companies. In addition, a former government official who had worked for the Insurance Bureau in Taiwan was also included as an expert.

4.2. DRSA model for exploring core attributes and decision rules

To retrieve understandable decision rules from the historical data, each attribute was divided into three intervals (i.e., granules of knowledge), such as high (H), middle (M), and low (L), or good (GD), mediocre (MD), and bad (BD), before the construction of the DRSA model; this procedure is also termed as discretization. The three intervals were chosen to mimic the intervals defined by experts for easy comprehension of rough concepts. A commonly used three-level discretization method was employed, and the values of the top 1/3, middle 1/3, and bottom 1/3 companies, which were ranked on the basis of their performance for each condition attribute, were defined as "H," "M," and "L," respectively. Furthermore, the top 1/3, middle 1/3, and bottom 1/3 companies in a ranking list based on the decision attribute were discretized as "GD," "MD," and "BD," respectively.

The sample data comprised 117 observations in four time frames. Observations in the recent time frame were used as the testing set, and the other observations comprised the training set. The DRSA model was implemented by jMAF [6].

Table 1
Classification accuracy of various classifiers (UNIT: %).

	DRSA	VC-DRSA (CL=0.95)	VC-DRSA (CL=0.90)	SVM (RBF kernel)
1	65.21	60.87	62.61	56.14
2	69.57	63.48	67.83	62.61
3	66.96	60.00	69.57	60.87
4	60.87	67.83	62.61	56.82
5	64.35	63.48	59.13	59.52
Average	65.39	63.13	64.35	59.19
Testing set	62.96	51.85	59.26	55.55

Table 2
Core attributes obtained using DRSA.

Dimensions	Condition attributes at *t*		Definitions/Descriptions
Capital Structure (D_1)	*Debt*	C_1	Total debt/total assets
	Δ Provision	C_2	Change rate of provision for life insurance reserve
Payback (D_2)	*1st Y_Premium*	C_3	First year premium ratio
	RY_Premium	C_4	Renewable premium ratio
Operational Efficiency (D_3)	*NCost*	C_5	New contract cost/new contract revenue
	Δ Equity	C_6	Change rate of share holders' equity
	Δ NetProfit	C_7	Change rate of net profit
	CapInvest	C_8	Total invested capital/total assets
Earning Quality (D_4)	*Persistency*	C_9	Persistency of the valid contracts in the 25th month
Capital Efficiency (D_5)	*NetProfitC*	C_{10}	Net profitability of capital utilization
	ROI	C_{11}	Return on investment ratio
	OProfit	C_{12}	Operational profits/operational incomes
	RealEstate	C_{13}	Investment and loan on real estate/total assets
	Decision attribute at t+1		
	ROA	D	Return on assets at $t+1$ period

Table 3
Strong decision rules associated with at least good (≥GD) DC.

Premises	Supports
Δ NetProfit (C_7) ≥ H ∧ *Persistency* (C_9) ≥ M ∧ *OProfit* (C_{12}) ≥ H	12
1st Y_Premium (C_3) ≤ M ∧ *Persistency* (C_9) ≥ M ∧ *NetProfitC* (C_{10}) ≥ M ∧ *OProfit* (C_{12}) ≥ H	9

In addition, variable-consistency DRSA (VC-DRSA) and SVM (by DTREG [51]) models were constructed for comparison. The classification accuracy (CA) rate was used to calculate the correctly classified alternatives and measure each model, and a fivefold cross-validation was repeated five times for each classifier on the training set. The average CA of each classifier is summarized in Table 1. The DRSA model achieved an average CA of 65.39%, the highest average CA among the classifiers. In addition, the entire training set was used to construct a trained DRSA model, which achieved 93.91% (i.e., 108/115) accuracy. The model was further examined using the test set, and an acceptable CA was obtained (i.e., 62.96%, in Table 1) for rough knowledge induction.

The trained DRSA model generated a set of 13 core attributes. To maintain the same level of approximation accuracy, the core set attributes should represent the indispensable variables and criteria for the FP diagnosis problem. Therefore, the core attributes were used to devise a questionnaire to collect the opinions and knowledge of the experts for use in the DANP and fuzzy measures. Brief definitions of the core attributes are provided in Table 2 and strong decision rules obtained from the DRSA model are presented in Table 3.

4.3. DANP weights for supporting fuzzy measures

The CORE attributes could be used to identify the critical attributes and dimensions for constructing a hybrid FP diagnosis model. This study adopted DMATEL and DANP analyses for two main reasons: (1) for identifying the cause–effect influence relations among the core attributes and dimensions, and (2) for adjusting the dimensional weights in the conventional ANP model for obtaining DANP weights.

For the DEMATEL analysis, experts were asked to provide their opinions regarding the influence of each attribute (criterion) *i* on another attribute *j*; the opinions ranged from 0 (*no influence*) to 4 (*very strong influence*) in the questionnaire (see [46]) for the format of the DEMATEL questionnaire). The average opinions of the eight experts formed the initial average matrix **A** (Table A.1). Next, **A** was transformed into **T** (Table A.3) and the normalized dimensional influence relation matrix

Table 4
Cause–effect influence relations among the core dimensions and criteria.

Dimensions	r_i^D	s_i^D	$r_i^D - s_i^D$	$r_i^D + s_i^D$	Criteria	r_i^C	s_i^C	$r_i^C - s_i^C$	$r_i^C + s_i^C$
D_1	0.62	0.64	−0.02	1.26	C_1	2.02	1.96	0.06	3.98
					C_2	1.37	1.39	−0.02	2.76
D_2	0.79	0.69	0.10	1.48	C_3	2.05	1.70	0.35	3.75
					C_4	2.07	1.88	0.19	3.95
D_3	0.75	0.92	−0.16	1.67	C_5	2.20	2.07	0.13	4.27
					C_6	1.26	2.03	−0.77	3.29
					C_7	2.07	3.03	−0.96	5.10
					C_8	2.54	2.47	0.08	5.01
D_4	0.80	0.76	0.04	1.55	C_9	2.21	2.03	0.18	4.24
D_5	0.87	0.82	0.05	1.69	C_{10}	2.56	2.09	0.46	4.65
					C_{11}	2.72	1.88	0.84	4.60
					C_{12}	2.45	2.89	−0.44	5.34
					C_{13}	1.80	1.90	−0.09	3.70

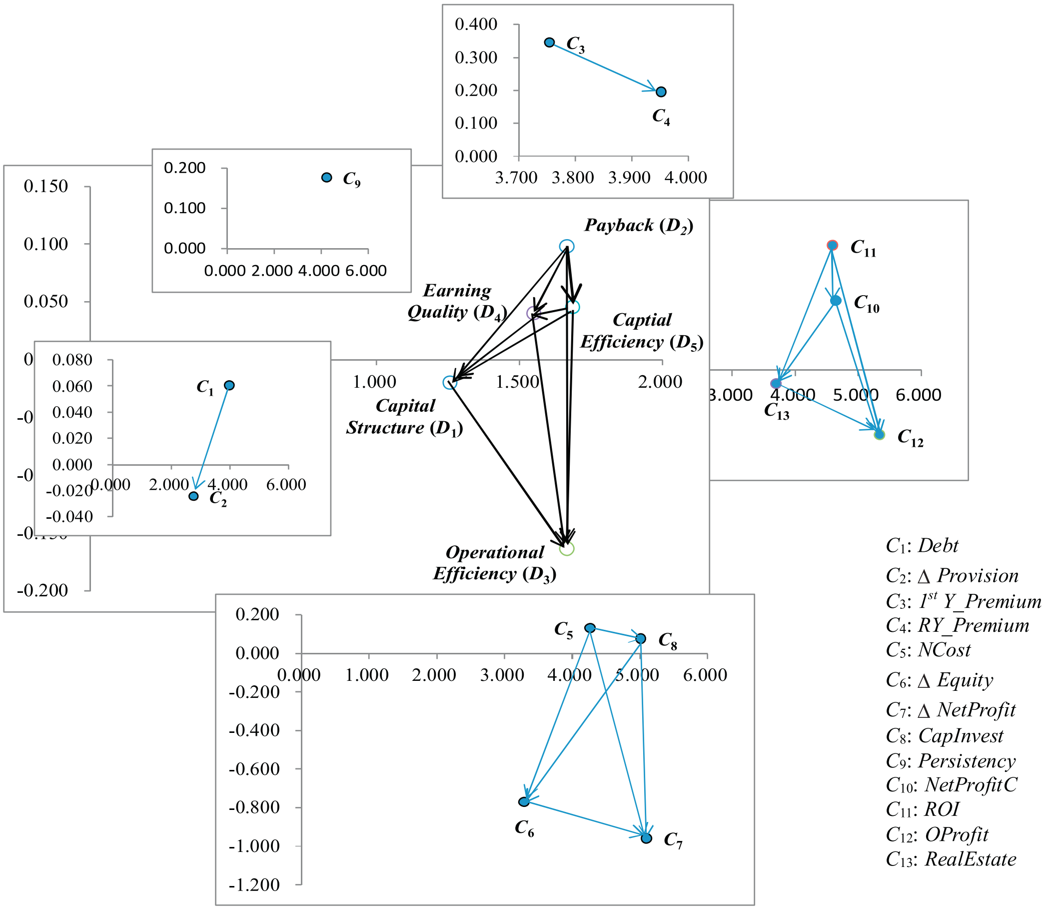


Fig. 3. Internetwork relationship map (INRM).

$\mathbf{T}_D^N$ (Table A.4), respectively. The $r_i^C - s_i^C$ and $r_i^D - s_i^D$ were from matrices $\mathbf{T}$ and $\mathbf{T}_D^N$, which were used to divide the criteria and dimensions into cause and effect groups, as summarized in Table 4. Furthermore, the influence relations are shown as an INRM in Fig. 3.

In addition, based on the INRM (Fig. 3), the directional influences among the dimensions and criteria can be integrated with the strong decision rules (Table 3) to form the DFG (Fig. 4) for gaining implications. DMs can obtain the cause–effect influence relations among the dimensions, criteria, and decision rules to plan for improvements systematically.

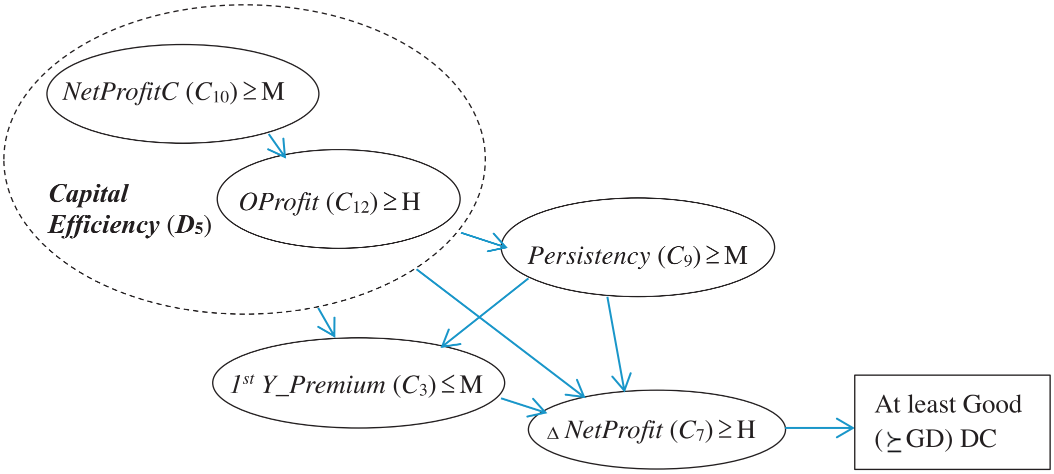


Fig. 4. Directional flow graph (DFG).

Table 5
DANP weights for the evaluation model.

Dimensions	D_1		D_2		D_3				D_4	D_5			
w^D	0.16		0.18		0.23				0.20	0.22			
Criteria	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
w^C	0.09	0.07	0.08	0.10	0.05	0.05	0.07	0.06	0.20	0.05	0.04	0.08	0.05
(Rank)	(3)	(5)	(4)	(2)	(7)	(7)	(5)	(6)	(1)	(7)	(8)	(4)	(7)

The matrix **T** was used to obtain the unweighted supermatrix of the criteria (**W**) (see **Step 8**), and the DANP influential weights from the weighted supermatrix $\mathbf{W}^{\alpha}$ are shown in Table 5. After increasing z in $\lim_{z\to\infty}(\mathbf{W}^{\alpha})^z$ up to a level where the weighted supermatrix became stable, the DANP influential weights for the subsequent fuzzy measures were obtained (Table 5).

4.4. Integrated fuzzy integral evaluation model

In previous studies, most decision models employed additive-type aggregators (e.g., SAW and VIKOR) for aggregating the final performance scores of alternatives on the basis of the assumption that no synergy effect (e.g., $1+1 \neq 2$) existed among the criteria or dimensions. Nevertheless, as indicated by the results of the DEMATEL analysis in Section 4.3, cause–effect influence relations among the criteria or dimensions do exist. Therefore, adopting a nonadditive-type aggregator (i.e., fuzzy integral in this study) to measure or capture the synergy effects among the criteria and dimensions is reasonable (see Table 6).

5. Results and discussions

To examine the proposed approach, the data sets of five life insurance companies were obtained from the testing set. The five companies were Zurich International Insurance, Taiwan Branch (*A*), Fubon Life Insurance (*B*), China Trust Life Insurance (*C*), Prudential Life Insurance, Taiwan Branch (*D*), and First Aviva Insurance (*E*). The entire testing set (27 alternatives) was used to transform the raw data of the five companies into performance scores ranging from 0 (*worst*) to 10 (*best*) for each criterion. A percentile transformation method was used; for example, if a company's persistency ratio was ranked to be in the bottom 10% of the test set, then the performance score for this company on this criterion would be 1. To compare the results obtained from the additive- and nonadditive-type aggregators, both SAW and fuzzy integral methods were used. The results are shown in Tables 7 and 8.

The proposed approach was developed for diagnosing the FP of life insurance companies and for supporting the companies in formulating an improvement plan. Therefore, both the final performance aggregation and improvement priority identification when using SAW (additive-type) and fuzzy integral (nonadditive-type) methods are compared and discussed in this section. The aggregated final performance scores (obtained using the aforementioned two methods) and the ranking results for the five example companies are presented in Table 8.

Table 6
Fuzzy measures for each dimension and whole model.

Whole model with 5 dimensions $\lambda^{w}=1.087$, $\gamma^{w}=0.737$, $g_{\lambda}^{(5)}(\{D_1, D_2, D_3, D_4, D_5\}) = 1$			
$g_{\lambda}^{(1)}(\{D_1\}) = 0.118$	$g_{\lambda}^{(2)}(\{D_1, D_2\}) = 0.268$	$g_{\lambda}^{(3)}(\{D_1, D_2, D_3\}) = 0.487$	$g_{\lambda}^{(4)}(\{D_1, D_2, D_3, D_4\}) = 0.712$
$g_{\lambda}^{(1)}(\{D_2\}) = 0.133$	$g_{\lambda}^{(2)}(\{D_1, D_3\}) = 0.309$	$g_{\lambda}^{(3)}(\{D_1, D_2, D_4\}) = 0.458$	$g_{\lambda}^{(4)}(\{D_1, D_2, D_3, D_5\}) = 0.735$
$g_{\lambda}^{(1)}(\{D_3\}) = 0.170$	$g_{\lambda}^{(2)}(\{D_1, D_4\}) = 0.284$	$g_{\lambda}^{(3)}(\{D_1, D_2, D_5\}) = 0.477$	$g_{\lambda}^{(4)}(\{D_1, D_2, D_4, D_5\}) = 0.701$
$g_{\lambda}^{(1)}(\{D_4\}) = 0.147$	$g_{\lambda}^{(2)}(\{D_1, D_5\}) = 0.301$	$g_{\lambda}^{(3)}\{D_1, D_3, D_4\}) = 0.506$	$g_{\lambda}^{(4)}(\{D_1, D_3, D_4, D_5\}) = 0.758$
$g_{\lambda}^{(1)}(\{D_5\}) = 0.162$	$g_{\lambda}^{(2)}(\{D_2, D_3\}) = 0.327$	$g_{\lambda}^{(3)}(\{D_1, D_3, D_5\}) = 0.408$	$g_{\lambda}^{(4)}(\{D_2, D_3, D_4, D_5\}) = 0.782$
	$g_{\lambda}^{(2)}(\{D_2, D_4\}) = 0.301$	$g_{\lambda}^{(3)}(\{D_1, D_4, D_5\}) = 0.497$	
	$g_{\lambda}^{(2)}(\{D_2, D_5\}) = 0.318$	$g_{\lambda}^{(3)}(\{D_2, D_3, D_4\}) = 0.527$	
	$g_{\lambda}^{(2)}(\{D_3, D_4\}) = 0.344$	$g_{\lambda}^{(3)}(\{D_2, D_3, D_5\}) = 0.547$	
	$g_{\lambda}^{(2)}(\{D_3, D_5\}) = 0.362$	$g_{\lambda}^{(3)}(\{D_2, D_4, D_5\}) = 0.517$	
	$g_{\lambda}^{(2)}(\{D_4, D_5\}) = 0.336$	$g_{\lambda}^{(3)}(\{D_3, D_4, D_5\}) = 0.567$	
Capital structure (D_1) $\lambda^{D_1} = 3.202$, $\gamma^{D_1} = 0.658$, $g_{\lambda}^{(2)}(\{C_1, C_2\}) = 1$			
$g_{\lambda}^{(1)}(\{C_1\}) = 0.370$			
$g_{\lambda}^{(1)}(\{C_2\}) = 0.288$			
Payback (D_2) $\lambda^{D_2} = 3.487$, $\gamma^{D_2} = 0.643$, $g_{\lambda}^{(2)}(\{C_3, C_4\}) = 1$			
$g_{\lambda}^{(1)}(\{C_3\}) = 0.286$			
$g_{\lambda}^{(1)}(\{C_4\}) = 0.357$			
Operational efficiency (D_3) $\lambda^{D_3} = 1.699$, $\gamma^{D_3} = 0.665$, $g_{\lambda}^{(4)}(\{C_5, C_6, C_7, C_8\}) = 1$			
$g_{\lambda}^{(1)}(\{C_5\}) = 0.145$	$g_{\lambda}^{(2)}(\{C_5, C_6\}) = 0.325$	$g_{\lambda}^{(3)}(\{C_5, C_6, C_7\}) = 0.638$	
$g_{\lambda}^{(1)}(\{C_6\}) = 0.145$	$g_{\lambda}^{(2)}(\{C_5, C_7\}) = 0.397$	$g_{\lambda}^{(3)}(\{C_5, C_6, C_8\}) = 0.594$	
$g_{\lambda}^{(1)}(\{C_7\}) = 0.202$	$g_{\lambda}^{(2)}(\{C_5, C_8\}) = 0.361$	$g_{\lambda}^{(3)}(\{C_5, C_7, C_8\}) = 0.687$	
$g_{\lambda}^{(1)}(\{C_8\}) = 0.173$	$g_{\lambda}^{(2)}(\{C_6, C_7\}) = 0.397$	$g_{\lambda}^{(3)}(\{C_6, C_7, C_8\}) = 0.687$	
	$g_{\lambda}^{(2)}(\{C_6, C_8\}) = 0.361$		
	$g_{\lambda}^{(2)}(\{C_7, C_8\}) = 0.435$		
Revenue quality (D_4) (only one criterion in this dimension), $g_{\lambda}^{(1)}(\{C_9\}) = 1$			
Capital efficiency (D_5) $\lambda^{D_5} = 1.191$, $\gamma^{D_5} = 0.732$, $g_{\lambda}^{(4)}(\{C_{10}, C_{11}, C_{12}, C_{13}\}) = 1$			
$g_{\lambda}^{(1)}(\{C_{10}\}) = 0.166$	$g_{\lambda}^{(2)}(\{C_{10}, C_{11}\}) = 0.326$	$g_{\lambda}^{(3)}(\{C_{10}, C_{11}, C_{12}\}) = 0.696$	
$g_{\lambda}^{(1)}(\{C_{11}\}) = 0.133$	$g_{\lambda}^{(2)}(\{C_{10}, C_{12}\}) = 0.486$	$g_{\lambda}^{(3)}(\{C_{10}, C_{11}, C_{13}\}) = 0.557$	
$g_{\lambda}^{(1)}(\{C_{12}\}) = 0.266$	$g_{\lambda}^{(2)}(\{C_{10}, C_{13}\}) = 0.366$	$g_{\lambda}^{(3)}(\{C_{10}, C_{12}, C_{13}\}) = 0.748$	
$g_{\lambda}^{(1)}(\{C_{13}\}) = 0.166$	$g_{\lambda}^{(2)}(\{C_{11}, C_{12}\}) = 0.442$	$g_{\lambda}^{(3)}(\{C_{11}, C_{12}, C_{13}\}) = 0.696$	
	$g_{\lambda}^{(2)}(\{C_{11}, C_{13}\}) = 0.326$		
	$g_{\lambda}^{(2)}(\{C_{12}, C_{13}\}) = 0.486$		

Note: $g_{\lambda}^{(i)}(\{C_{1th}, ..., C_{ith}\})$denotes that the fuzzy measure includes i elements (dimensions/criteria) in its measurement.

Table 7
DANP weights and performance scores of the five companies.

DANP weights	Alternatives (companies)						
	w^{C}	w^{L}	A	B	C	D	E
$D_1=016$							
C_1	0.09	0.56	10	8	9	7	5
C_2	0.07	0.44	3	7	8	6	2
$D_2=0.18$		0.18					
C_3	0.08	0.44	9	8	5	7	7
C_4	0.10	0.56	8	7	2	6	7
$D_3=0.23$							
C_5	0.05	0.22	5	5	1	7	6
C_6	0.05	0.22	3	6	5	1	5
C_7	0.07	0.30	7	8	4	5	4
C_8	0.06	0.26	6	7	5	8	6
$D_4=0.20$							
C_9	0.20	1.00	6	3	8	4	4
$D_5=0.22$							
C_{10}	0.05	0.23	6	3	10	5	4
C_{11}	0.04	0.18	7	9	5	2	8
C_{12}	0.08	0.36	9	8	5	3	8
C_{13}	0.05	0.23	6	9	3	4	5

Note: w^{L} denotes local weight; for example, the local weight of $C_1=0.09\ /\ 0.16=0.56$.

Table 8
Final performance scores and ranking results.

Companies	*A*	*B*	*C*	*D*	*E*
SAW	6.68*	6.28	5.70	5.01	5.25
(Rank)	(1)	(2)	(3)	(5)	(4)
Fuzzy integral	6.11	5.81	5.01	4.56	4.80
(Rank)	(1)	(2)	(3)	(5)	(4)

* Note: The final performance score for the *j*th company (SAW) is calculated by $\sum_{i=1}^{13} w_i^C p_{ij}$; see Table 7.

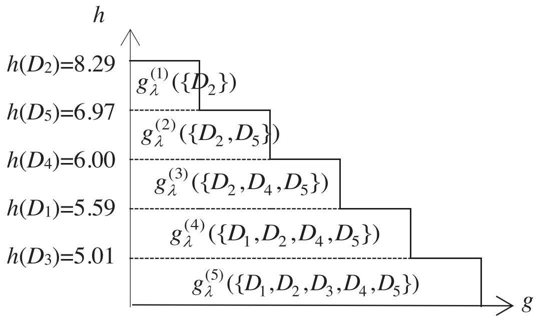


Fig. 5. Illustration of the fuzzy integral on the 5 dimensions for company *A*
Note: In this case, $(C)\int hdg = [h(D_2) - h(D_5)] \times g_\lambda^{(1)}(\{D_2\}) + [h(D_5) - h(D_4)] \times g_\lambda^{(2)}(\{D_4, D_5\}) + [h(D_4) - h(D_1)] \times g_\lambda^{(3)}(\{D_2, D_4, D_5\})$ $+[h(D_1) - h(D_3)] \times g_\lambda^{(4)}(\{D_1, D_2, D_4, D_5\}) + h(D_3) \times 1$=6.11 in Table 8.

Table 9
Improvement priority by saw and λ-measure for company *B*.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
P_{C_i}	8	7	8	7	5	6	7	8	3	3	9	8	9
w^G (DANP)	0.09	0.07	0.08	0.10	0.05	0.05	0.07	0.06	0.20	0.05	0.04	0.08	0.05
$P_{C_i} \times w_{C_i}^{G\_DANP}$	0.72	0.49	0.64	0.70	0.25	0.30	0.49	0.48	0.60	0.15	0.36	0.64	0.45
(Priority criteria)					(2nd)	(3rd)				(1st)			
w^G (λ-measure)	0.09	0.02	0.09	0.03	0.03	0.01	0.02	0.10	0.20	0.07	0.07	0.02	0.01
$P_{C_i} \times w_{C_i}^{G\_\lambda}$	0.75	0.16	0.75	0.21	0.15	0.08	0.13	0.82	0.60	0.20	0.60	0.16	0.11
(Priority criteria)						(1st)	(3rd)						(2nd)

Note: $w_{C_i}^{G\_DANP}$ and $w_{C_i}^{G\_\lambda}$ denote the global weights of the *i*th criterion according to the DANP and λ-measure, respectively.
Note: λ-measure was collected and transformed from the questionnaires.

The aggregated performance score (Table 8) obtained using the fuzzy integral aggregator might require additional explanation. The criteria performance scores within each dimension should be aggregated before determining the final performance score. For company *A*, consider the case of C_1 and C_2 in D_1 as an example: Because the performance score on C_1 is higher than that on C_2, the fuzzy integral integrated performance score in D_1 should be $(10-3)\times 0.37+3\times 1=5.59$. Similarly, the fuzzy integral aggregated performance scores for D_2, D_3, D_4, and D_5 are 8.29, 5.01, 6.00, and 6.97, respectively. Because the aggregated dimensional performance scores reflect the order $h(D_2) > h(D_5) > h(D_4) > h(D_1) > h(D_3)$, the final performance score obtained using the fuzzy integral can be presented as shown in Fig. 5. Although the SAW and fuzzy integral aggregators indicated the same ranking result (i.e., $A \succ B \succ C \succ E \succ D$), the focus of this study was on FP diagnosis for supporting the improvement of FP. For example, the improvement priorities for company *B*, which are based on SAW and the λ-measure, are presented in Table 9 for comparison.

From Table 9, we can learn that the top three improvement priorities for company *B* obtained by using the additive-type (i.e., $\{C_{10}, C_5, C_6\}$) and nonadditive-type (i.e., $\{C_6, C_{13}, C_7\}$) aggregators differ. Moreover, the top priority (i.e., the lowest weighted performance score based on λ-measure) for company *B* to improve is C_6 (*ΔEquity*), which belongs to D_3 (*Operational Efficiency*). According to the INRM (Fig. 3), within dimension D_3, both C_5 (*NCost*) and C_8 (*CapInvest*) would have influences on C_6. The other four dimensions also have direct influences on D_3. Company *B* can thus identify the systematic cause–effect influence relations among the core attributes to devise improvement plans.

In addition, in the event that company *B* intends to improve C_6, the plausible performance improvement rates obtained by using SAW and the fuzzy integral method for aggregating the results would not be identical. Table 10 presents the final

Table 10
Performance score improvement rate of company B on C_6.

Aggregators	$C_6=6$	$C_6=7$	$C_6=8$	$C_6=9$	$C_6=10$
SAW	6.28	6.33	6.38	6.43	6.48
Improvement rate^{SAW}		[a]0.80%	1.59%	2.39%	3.18%
Fuzzy integral	5.81	5.88	5.93	5.96	5.99
Improvement rate^{FI}		1.20%	2.07%	2.58%	3.10%
[b]Differences of improvement rates		0.40%	0.48%	0.19%	-0.08%

[a] Note: For example, when $C_6=7$, the improvement rate=(6.33–6.28)/6.28×100%=0.80% according to the SAW aggregator.
[b] Note: Differences of improvement rates=(Improvement rate^{FI} - Improvement rate^{SAW}).

performance scores of company B and the corresponding improvement rates (C_6 improved from 7 to 10) for the two types of aggregators.

If the performance score of C_6 (of company B) was improved from 6 to 9, the improvement rates obtained using the fuzzy integral would outperform those obtained using SAW. The difference in the improvement rate would decrease from 0.48% to 0.19% for an improvement in C_6 from 8 to 9. The management of company B should be aware of this type of nonlinear incremental result when evaluating the cost (or resources) involved in attaining different levels of improvement.

6. Concluding remarks

In this study, a hybrid approach for the FP diagnosis of life insurance companies was proposed. The attribute reduction and implicit knowledge retrieval capabilities of DRSA helped induct rough financial knowledge from historical data in the first stage. In the next stage, a hybrid decision model constructed using the DANP and fuzzy integral methods was used to refine the rough financial knowledge in two ways: (1) the cause–effect influence relations among the core dimensions or criteria were identified using the DEMATEL technique and (2) the initial influential weight of each core dimension or criterion was evaluated and the synergy effects among the core set were measured.

The present study enhances the previous research by providing a more detailed discussion of how to retrieve and refine knowledge regarding FP improvements. Furthermore, the commonly observed additive-type aggregation approach can be adjusted and enhanced to measure the plausible synergy effects among the criteria and dimensions. This possibility was overlooked and underexplored by previous financial studies, which mainly relied on statistical analyses (see Introduction), and MCDM studies (such as those studies based on AHP and ANP methods). The findings of this research not only contribute to the integration or combination of heterogeneous methodologies in modeling, but also provide practical insights for life insurance companies.

Although this study presents an approach for acquiring rough knowledge for FP improvement guidance for the life insurance industry, it has several limitations. First, only operational and financial indicators were considered in the modeling. Future research could incorporate other dimensions (e.g., marketing) to enrich the findings. Second, the rough machine learning mechanism used in the first stage is based on the assumption that historical patterns will reoccur in the near future. Third, the adopted fuzzy measure depends on the subjective judgments of the invited experts; the average opinions of the experts were used for calculating the parameters in the fuzzy integral model. Because the domain experience and knowledge of the invited experts are crucial to the modeling of a decision model, a plausible variance could be caused by different experts. Despite these limitations, future research has two potential directions. First, on the modeling side, the concept of intuitionistic fuzzy relations [4-5] could be integrated with fuzzy integrals for improving the decision model. Second, on the application side, collaboration for evaluating plausible improvement plans by using the proposed approach could be undertaken with a financial institution.

Acknowledgments

We are grateful for the valuable opinions and suggestions from the Editor-in-Chief Prof. Pedrycz and Reviewers, which have helped us improve this study in many aspects; also, the funding supports from the Ministry of Science and Technology of Taiwan under the grant numbers MOST-104-2410-H-305-052-MY3 and MOST-104-2410-H-034-064 are appreciated.

Appendix A. (supplementary calculations of DEMATEL)

1. In Step 4, form initial average influence matrix **A** in Table A.1.
2. Refer to (8)–(9) in Step 5 and normalize A to obtain the direct influence relation matrix **D** (Table A.2).
3. Refer to (10) in Step 6 for obtaining the total influence relation matrix **T** (Table A.3).
4. Refer to (11)–(15) in Steps 7 and 8, to obtain the normalized $\mathbf{T}_D^N$ (Table A.4)

Table A.1
Initial influence average matrix **A**.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0.00	2.88	1.25	1.50	1.13	3.25	2.00	3.13	0.88	2.25	2.00	1.00	1.50
C_2	1.50	0.00	1.38	1.38	1.00	2.25	1.75	1.50	1.50	1.50	0.25	0.25	1.25
C_3	0.50	1.75	0.00	3.13	3.25	1.25	2.63	2.00	2.75	0.75	0.25	3.00	1.50
C_4	1.00	1.50	1.75	0.00	2.75	2.00	3.00	2.00	3.75	0.50	0.50	3.50	1.00
C_5	1.75	1.50	2.75	3.50	0.00	1.63	3.25	1.50	3.25	0.75	0.75	3.75	0.75
C_6	2.00	0.75	0.25	0.25	0.50	0.00	1.75	1.50	0.75	1.25	1.75	1.25	1.25
C_7	2.13	0.75	2.00	1.75	2.00	1.75	0.00	1.75	1.75	2.75	2.00	2.50	1.38
C_8	2.00	1.75	1.25	0.75	2.25	1.75	3.50	0.00	1.50	3.75	3.25	3.25	3.00
C_9	1.25	2.50	1.25	3.13	1.88	1.38	3.25	1.88	0.00	1.75	1.25	3.88	1.50
C_{10}	2.25	1.00	1.25	1.25	2.00	1.75	3.50	2.75	1.50	0.00	3.50	3.75	3.25
C_{11}	2.75	0.75	1.50	1.25	2.00	2.00	4.00	3.63	1.75	2.50	0.00	3.75	3.75
C_{12}	2.75	0.75	2.25	2.50	3.00	1.75	3.13	3.25	2.75	2.00	1.75	0.00	1.00
C_{13}	1.00	0.25	0.75	0.25	0.75	1.75	2.50	3.13	0.75	2.88	2.75	2.38	0.00

Table A.2
Direct influence relation matrix **D**.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}
C_1	0.000	0.084	0.036	0.044	0.033	0.095	0.058	0.091	0.026	0.066	0.058	0.029	0.044
C_2	0.044	0.000	0.040	0.040	0.029	0.066	0.051	0.044	0.044	0.044	0.007	0.007	0.036
C_3	0.015	0.051	0.000	0.091	0.095	0.036	0.077	0.058	0.080	0.022	0.007	0.088	0.044
C_4	0.029	0.044	0.051	0.000	0.080	0.058	0.088	0.058	0.109	0.015	0.015	0.102	0.029
C_5	0.051	0.044	0.080	0.102	0.000	0.047	0.095	0.044	0.095	0.022	0.022	0.109	0.022
C_6	0.058	0.022	0.007	0.007	0.015	0.000	0.051	0.044	0.022	0.036	0.051	0.036	0.036
C_7	0.062	0.022	0.058	0.051	0.058	0.051	0.000	0.051	0.051	0.080	0.058	0.073	0.040
C_8	0.058	0.051	0.036	0.022	0.066	0.051	0.102	0.000	0.044	0.109	0.095	0.095	0.088
C_9	0.036	0.073	0.036	0.091	0.055	0.040	0.095	0.055	0.000	0.051	0.036	0.113	0.044
C_{10}	0.066	0.029	0.036	0.036	0.058	0.051	0.102	0.080	0.044	0.000	0.102	0.109	0.095
C_{11}	0.080	0.022	0.044	0.036	0.058	0.058	0.117	0.106	0.051	0.073	0.000	0.109	0.109
C_{12}	0.080	0.022	0.066	0.073	0.088	0.051	0.091	0.095	0.080	0.058	0.051	0.000	0.029
C_{13}	0.029	0.007	0.022	0.007	0.022	0.051	0.073	0.091	0.022	0.084	0.080	0.069	0.000

Table A.3
Total influence relation matrix **T**.

	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9	C_{10}	C_{11}	C_{12}	C_{13}	r_i^C
C_1	0.10	0.15	0.12	0.13	0.13	0.19	0.21	0.21	0.13	0.18	0.16	0.18	0.14	2.02
C_2	0.11	0.05	0.10	0.10	0.10	0.14	0.15	0.12	0.11	0.11	0.08	0.11	0.10	1.37
C_3	0.11	0.12	0.09	0.19	0.20	0.14	0.23	0.18	0.19	0.13	0.10	0.24	0.13	2.05
C_4	0.13	0.11	0.14	0.11	0.19	0.16	0.24	0.18	0.21	0.12	0.11	0.25	0.12	2.07
C_5	0.16	0.12	0.17	0.20	0.12	0.16	0.25	0.17	0.20	0.13	0.12	0.26	0.12	2.20
C_6	0.12	0.06	0.06	0.07	0.08	0.07	0.14	0.12	0.08	0.11	0.11	0.13	0.10	1.26
C_7	0.16	0.09	0.15	0.15	0.17	0.15	0.16	0.18	0.16	0.18	0.16	0.22	0.14	2.07
C_8	0.19	0.13	0.15	0.14	0.20	0.18	0.29	0.16	0.17	0.24	0.21	0.27	0.21	2.54
C_9	0.15	0.14	0.14	0.19	0.17	0.15	0.25	0.19	0.12	0.16	0.14	0.26	0.14	2.21
C_{10}	0.20	0.12	0.15	0.16	0.19	0.18	0.29	0.24	0.17	0.14	0.22	0.29	0.21	2.56
C_{11}	0.21	0.11	0.16	0.16	0.20	0.20	0.32	0.28	0.18	0.22	0.14	0.30	0.23	2.72
C_{12}	0.20	0.11	0.17	0.19	0.22	0.17	0.27	0.24	0.20	0.19	0.17	0.18	0.15	2.45
C_{13}	0.12	0.07	0.10	0.09	0.12	0.14	0.21	0.20	0.11	0.18	0.17	0.20	0.09	1.80
s_i^C	1.96	1.39	1.70	1.88	2.07	2.03	3.03	2.47	2.03	2.09	1.88	2.89	1.90	

Table A.4
Normalized dimensional influence matrix $\mathbf{T}_D^N$.

	D_1	D_2	D_3	D_4	D_5	r_i^D
D_1	0.10	0.11	0.16	0.12	0.13	0.62
D_2	0.12	0.13	0.19	0.20	0.15	0.79
D_3	0.13	0.14	0.16	0.15	0.17	0.75
D_4	0.15	0.16	0.19	0.12	0.18	0.80
D_5	0.14	0.15	0.22	0.17	0.19	0.87
s_i^D	0.64	0.69	0.92	0.76	0.82	

Reference

[1] E.I. Altman, Financial ratios, discriminant analysis and the prediction of corporate bankruptcy, J. Finance 23 (4) (1968) 589–609.
[2] E.I. Altman, in: Predicting Financial Distress of Companies: Revisiting the Z-Score and ZETA Models. Stern School of Business, New York University, 2000, pp. 9–12.
[3] S. Angilella, S. Mazzù, The financing of innovative SMEs: a multicriteria credit rating model, Eur. J. Operat. Res. 244 (2) (2015) 540–554.
[4] K. Atanassov, Index Matrices: Towards an Augmented Matrix Calculus, vol. 573, Springer, 2014.
[5] K. Atanassov, G. Pasi, R. Yager, Intuitionistic fuzzy interpretations of multi-criteria multi-person and multi-measurement tool decision making, Int. J. Syst. Sci. 36 (14) (2005) 859–868.
[6] J. Błaszczyński, S. Greco, B. Matarazzo, R. Słowiński, M. Szelag, jMAF-dominance-based rough set data analysis framework, in: A. Skowron, Z. Suraj (Eds.), Rough Sets and Intelligent Systems-Professor Zdzisław Pawlak in Memoriam, Springer, 2013, pp. 185–209.
[7] P.L. Brockett, L.L. Golden, J. Jang, C. Yang, A comparison of neural network, statistical methods, and variable choice for life insurers' financial distress prediction, J. Risk Insur. 73 (3) (2006) 397–419.
[8] S. Canbas, A. Cabuk, S.B. Kilic, Prediction of commercial bank failure via multivariate statistical analysis of financial structures: the Turkish case, Eur. J. Operat. Res. 166 (2) (2005) 528–546.
[9] Y. Cao, Aggregating multiple classification results using Choquet integral for financial distress early warning, Expert Syst. Appl. 39 (2) (2012) 1830–1836.
[10] C.H. Chiu, T.M. Choi, Supply chain risk analysis with mean-variance models: a technical review, Ann. Operat. Res. 240 (2016) 489–507.
[11] J. Dai, Q. Xu, Attribute selection based on information gain ratio in fuzzy rough set theory with application to tumor classification, Appl. Soft Comput. 13 (1) (2013) 211–221.
[12] Y. Demyanyk, I. Hasan, Financial crises and bank failures: a review of prediction methods, Omega 38 (5) (2010) 315–324.
[13] M.D. Fethi, F. Pasiouras, Assessing bank efficiency and performance with operational research and artificial intelligence techniques: a survey, Eur. J. Operat. Res. 204 (2) (2010) 189–198.
[14] J.Greco Figueira, Ehrgott S., M. (eds.), Multiple Criteria Decision Analysis: State of the Art Surveys, vol. 78, Springer Science & Business Media, 2005.
[15] A. Gabus, E. Fontela, World Problems, an Invitation to Further Thought Within the Framework of DEMATEL, Battelle Geneva Research Center, Geneva, Switzerland, 1972.
[16] İ. Gölcük, A. Baykasoğlu, An analysis of DEMATEL approaches for criteria interaction handling within ANP, Expert Syst. Appl. 46 (2016) 346–366.
[17] M. Grabisch, The application of fuzzy integrals in multicriteria decision making, Eur. J. Operat. Res. 89 (3) (1996) 445–456.
[18] S. Greco, B. Matarazzo, R. Slowinski, Multicriteria classification by dominance-based rough set approach, Handbook of Data Mining and Knowledge Discovery, Oxford University Press, New York, 2002.
[19] S. Greco, B. Matarazzo, R. Slowinski, Rough approximation of a preference relation by dominance relations, Eur. J. Operat. Res. 117 (1) (1999) 63–83.
[20] W.R.J. Ho, C.L. Tsai, G.H. Tzeng, S.K. Fang, Combined DEMATEL technique with a novel MCDM model for exploring portfolio selection based on CAPM., Expert Syst. Appl. 38 (1) (2011) 16–25.
[21] C.W. Hsu, T.C. Kuo, S.H. Chen, A.H. Hu, Using DEMATEL to develop a carbon management model of supplier selection in green supply chain management, J. Cleaner Product. 56 (2013) 164–172.
[22] S.K. Hu, Y.C. Chuang, Y.F. Yeh, G.H. Tzeng, Combining hybrid MADM with fuzzy integral for exploring the smart phone improvement in M-Generation, Int. J. Fuzzy Syst. 14 (2) (2012) 204–214.
[23] J.J. Huang, G.H. Tzeng, C.S. Ong, Two-stage genetic programming (2SGP) for the credit scoring model, Appl. Math. Comput. 174 (2) (2006) 1039–1053.
[24] C. Hung, J.H. Chen, A selective ensemble based on expected probabilities for bankruptcy prediction, Expert Syst. Appl. 36 (3) (2009) 5297–5303.
[25] K. Ishii, M. Sugeno, A model of human evaluation process using fuzzy measure, int. J. Man-mach. Stud. 22 (1) (1985) 19–38.
[26] R.L. Keeney, H. Raiffa, Decisions with Multiple Objectives: Preferences and Value Trade-Offs, Cambridge University Press, 1993.
[27] Y.C. Ko, H. Fujita, G.H. Tzeng, An extended fuzzy measure on competitiveness correlation based on WCY, Knowl.-Based Syst. 37 (2013) 86–93.
[28] P.R. Kumar, V. Ravi, Bankruptcy prediction in banks and firms via statistical and intelligent techniques–A review, Eur. J. Operat. Res. 180 (1) (2007) 1–28.
[29] G.V. Karels, A.J. Prakash, Multivariate normality and forecasting of business bankruptcy, J. Bus. Finance Account. 14 (4) (1987) 573–593.
[30] W.Y. Lin, Y.H. Hu, C.F. Tsai, Machine learning in financial crisis prediction: a survey, IEEE Trans. Syst. Man Cybern. Part C: Appl. Rev. 42 (4) (2012) 421–436.
[31] J.J.H. Liou, G.H. Tzeng, A dominance-based rough set approach to customer behavior in the airline market, Inf. Sci. 180 (11) (2010) 2230–2238.
[32] J.J.H. Liou, Y.C. Chuang, G.H. Tzeng, A fuzzy integral-based model for supplier evaluation and improvement, Inf. Sc. 266 (2014) 199–217.
[33] R. Malhotra, D. Malhotra, Differentiating between good credits and bad credits using neuro-fuzzy systems, Eur. J. Operat. Res. 136 (1) (2002) 190–211.
[34] A. Mardani, Jusoh, E.K. Zavadskas, Fuzzy multiple criteria decision-making techniques and applications–Two decades review from 1994 to 2014, Expert Syst. Appl. 42 (8) (2015) 4126–4148.
[35] H. Markowitz, Portfolio Selection: Efficient Diversification of Investments, Wiley, New York, 1959.
[36] T. Murofushi, M. Sugeno, An interpretation of fuzzy measures and the Choquet integral as an integral with respect to a fuzzy measure, Fuzzy Sets Syst. 29 (2) (1989) 201–227.
[37] C.S. Ong, J.J. Huang, G.H. Tzeng, Building credit scoring models using genetic programming, Expert Syst. Appl. 29 (1) (2005) 41–47.
[38] Y.P. Ou Yang, M.H. Shieh, G.H. Tzeng, A VIKOR technique based on DEMATEL and ANP for information security risk control assessment, Inf. Sci. 232 (2013) 482–500.
[39] Z. Pawlak, Rough sets, Int. J. Comput. Inf. Sci. 11 (5) (1982) 341–356.
[40] K.H. Peng, G.H. Tzeng, A hybrid dynamic MADM model for problem-improvement in economics and business, Technol. Econ. Dev. Econ. 19 (4) (2013) 638–660.
[41] T.L. Saaty, What is the Analytic Hierarchy Process?, Springer, 1988.
[42] T.L. Saaty, Decision Making with Dependence and Feedback: The Analytic Network Process, vol. 4922, RWS Publications, Pittsburgh, 1996.
[43] P. Sevastjanov, D. Ludmila, Stock screening with use of multiple criteria decision making and optimization, Omega 37 (3) (2009) 659–671.
[44] M. Shaverdi, I. Ramezani, R. Tahmasebi, A.A.A. Rostamy, Combining fuzzy AHP and fuzzy TOPSIS with financial ratios to design a novel performance evaluation model, Int. J. Fuzzy Syst. 18 (2) (2016) 248–262.
[45] K.Y. Shen, G.H. Tzeng, DRSA-based neuro-fuzzy inference systems for the financial performance prediction of commercial banks, Int. J. Fuzzy Syst. 16 (2) (2014) 173–183.
[46] K.Y. Shen, G.H. Tzeng, A decision rule-based soft computing model for supporting financial performance improvement of the banking industry, Soft Comput. 19 (4) (2015) 859–874.
[47] K.Y. Shen, G.H. Tzeng, Fuzzy inference enhanced VC-DRSA model for technical analysis: Investment decision aid, Int. J. Fuzzy Syst. 17 (3) (2015) 375–389.
[48] K.Y. Shen, G.H. Tzeng, A new approach and insightful financial diagnoses for the IT industry based on a hybrid MADM model, Knowl.-Based Syst. 85 (2015) 112–130.
[49] K.Y. Shen, G.H. Tzeng, Contextual improvement planning by fuzzy-rough machine learning: a novel bipolar approach for business analytics, Int. J. Fuzzy Syst. (2016) in press, doi:10.1007/s40815-016-0215-8.
[50] K.Y. Shen, M.R. Yan, G.H. Tzeng, Combining VIKOR-DANP model for glamor stock selection and stock performance improvement, Knowl.-Based Syst. 58 (2014) 86–97.
[51] P.H. Sherrod, DTREG predictive modeling software, http://www.dtreg.com; accessed in 2015.

[52] M. Sugeno, Theory of Fuzzy Integrals and its Applications, Tokyo Institute of Technology, 1974.
[53] Taiwan Insurance Institute, http://ins-info.ib.gov.tw/, accessed in 2015.
[54] T.JSMAA Tervonen, Open source software for SMAA computations, Int. J. Syst. Sci. 45 (1) (2014) 69–81.
[55] S. Tsumoto, Automated extraction of medical expert system rules from clinical databases based on rough set theory, Inf. Sci. 112 (1) (1998) 67–84.
[56] G.H. Tzeng, J.J. Huang, Multiple Attribute Decision Making: Methods and Applications, CRC Press, 2011.
[57] G.H. Tzeng, J.J. Huang, Fuzzy Multiple Objective Decision Making, CRC Press, 2013.
[58] J.J. Wang, J.Z. Wang, Z.G. Zhang, S.P. Guo, Stock index forecasting based on a hybrid model, Omega 40 (6) (2012) 758–766.
[59] Y. Wang, S. Wang, K.K. Lai, A new fuzzy support vector machine to evaluate credit risk, IEEE Trans. Fuzzy Syst. 13 (6) (2005) 820–831.
[60] R.C. West, A factor-analytic approach to bank condition, J. Bank. Finance 9 (2) (1985) 253–266.
[61] C.R. Wu, C.T. Lin, P.H. Tsai, Evaluating business performance of wealth management banks, Eur. J. Operat. Res. 207 (2) (2010) 971–979.
[62] R.R. Yager, On ordered weighted averaging aggregation operators in multicriteria decisionmaking, IEEE Trans. Syst. Man Cybern. 18 (1) (1988) 183–190.
[63] W. Yu, ELECTRE TRI (Aspects Méthodologiques et Manuel D'utilisation), Document- Université de Paris-Dauphine, Lamsade, 1992.
[64] L.A. Zadeh, Fuzzy sets, Inf. Contr. 8 (3) (1965) 338–353.
[65] E.K. Zavadskas, Z. Turskis, Multiple criteria decision making (MCDM) methods in economics: an overview, Technol. Econ. Dev. Econ. 17 (2) (2011) 397–427.
[66] H.J. Zimmermann, Fuzzy Set Theory—and its Applications, Springer Science & Business Media, 2001.
[67] C. Zopounidis, E. Galariotis, M. Doumpos, S. Sarri, K. Andriosopoulos, Multiple criteria decision aiding for finance: an updated bibliographic survey, Eur. J. Operat. Res. 247 (2) (2015) 339–348.