Expert Systems with Applications 39 (2012) 12358–12370

Contents lists available at SciVerse ScienceDirect

Expert Systems with Applications

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

An intelligent decision support system for forecasting and optimization of complex personnel attributes in a large bank

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ARTICLE INFO

Keywords:
Decision support system
Personnel efficiency
Data mining
Data envelopment analysis
ANN
K-Means algorithm
Optimization

ABSTRACT

Developing decision support system (DSS) can overcome the issues with personnel attributes and specifications. Personnel specifications have greatest impact on total efficiency. They can enhance total efficiency of critical personnel attributes. This study presents an intelligent integrated decision support system (DSS) for forecasting and optimization of complex personnel efficiency. DSS assesses the impact of personnel efficiency by data envelopment analysis (DEA), artificial neural network (ANN), rough set theory (RST), and K-Means clustering algorithm. DEA has two roles in this study. It provides data to ANN and finally it selects the best reduct through ANN results. Reduct is described as a minimum subset of features, completely discriminating all objects in a data set. The reduct selection is achieved by RST. ANN has two roles in the integrated algorithm. ANN results are basis for selecting the best reduct and it is used for forecasting total efficiency. Finally, K-Means algorithm is used to develop the DSS. A procedure is proposed to develop the DSS with stated tools and completed rule base. The DSS could help managers to forecast and optimize efficiencies by selected attributes and grouping inferred efficiency. Also, it is an ideal tool for careful forecasting and planning. The proposed DSS is applied to an actual banking system and its superiorities and advantages are discussed.

1. Introduction

Generally, data mining is the process of analyzing and summarizing data from different viewpoints into valuable information. This area presents new theories and methods for processing large volumes of data and has obtained noteworthy consideration among researchers. Several immeasurable influences and complex relationships among attributes impact efficiency in organizations. Rough set theory (RST) proposed by Pawlak, is one of the techniques for the identification and recognition of common patterns in data (Pawlak, 1982, 1991). This technique has found applications in knowledge discovery from data bases, data mining, fault diagnosis, machine learning, knowledge acquisition, expert systems and decision support systems (Błaszczyński, Greco, & Słowiński, 2007; Fan, Liu, & Tzeng, 2007; Inuiguchi & Miyajima, 2007). It is also used to study uncertainty (Beynon & Peel, 2001; Lili & Zhi, 2001; Ton Su & Hsu, 2006; Ziarko, 1993), prediction (Becerra-Fernandez, Zanakis, & Walczak, 2002; Kusiak & Tseng, 2000; Sanchis, Segovia, Gil, Heras, & Vilar, 2007), service organizations (Chou, Cheng, & Chang, 2007; Hassanien, 2007; Kowalczyk & Slisser, 1997; Sikder & Gangopadhyay, 2007; Tsumoto, 1997), financial firms (Ravi Kumar & Ravi, 2007; Ruhe, 1996; Shyng, Wang, Tzeng, & Wu, 2007), and scheduling problems (Liu, Chen, Wu, & Li, 2006; Triantaphyllou, Liao, & Iyengar, 2002).

Efficiency is a key concept for financial institutions. As personnel specifications have greatest impact on efficiency, they can help us designing work environments for maximizing efficiency. Providing information on multiple input and output factors are a complicated and time consuming procedure. Developing expert system in this situation is hard. So, available attributes must be reduced. Rough set theory is a candidate for this. At the present, the study on rough set theory is focusing on feature selection techniques with much success. Stefanowski and Slowinski have studied rough sets as a tool for feature selection by studying attribute dependencies (Stefanowski & Slowinski, 1997). Kusiak and Tseng have proposed two independent algorithms for accurate feature selection in medical, industrial and engineering case studies (Kusiak, Kern, Kernstine, & Tseng, 2000; Kusiak & Tseng, 2000). Others like Xia and Wu discusses feature extraction technique of rough set theory for supplier selection to select best suppliers according to different tangible and intangible attributes (Xia & Wu, 2007). Moreover, there are some other application of rough set theory to feature selection in customer relationship management (Tseng & Huang, 2007), product quality evaluation (Zhai, Khoo, & Fok, 2002) and healthcare (Xiangyang, Jie, Jensen, & Xiaojun, 2006). However, existing heuristic rough set approaches to feature selection are insufficient at finding optimal reductions. On the other hand, it is

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http://dx.doi.org/10.1016/j.eswa.2012.04.056

not feasible to search for optimal in even in average sized datasets. Therefore, the combination of this method by other robust data mining tools may help practitioners to go further into feature selection to obtain more accurate results.

In this paper, a new DSS approach for feature selection and forecasting and optimization of personnel efficiency amongst various branches within a large bank is introduced. It is accomplished by integration of Data Mining tools (RST, ANN, MLP, GA, and CVTT), DEA and K-Means algorithm is proposed. By using ANN and DEA, the integrated approach decides on which feature subsets (reducts) produced by rough set theory are more important to decision making procedure. ANN and DEA have too many applications in engineering case studies (Al-Omari & Al-Jarrah, 2004; Azadeh, Amalnick, Ghaderi, & Asadzadeh, 2007; Azadeh, Ghaderi, Anvari, & Saberi, 2006; Azadeh, Ghaderi, Anvari, & Saberi, 2007; Azadeh, Ghaderi, Anvari, Saberi, & Izadbakhsh, 2006; Azadeh, Ghaderi, & Izadbakhsh, 2007; Azadeh, Ghaderi, & Sohrabkhani, 2007; Azadeh, Ghaderi, Tarverdian, & Saberi, 2006; Azadeh, Ghaderi, Tarverdian, & Saberi, 2007; Fonseca & Navaresse, 2002).

After selecting the best reduct, construction of DSS is initiated. At first, K-Means algorithm is used for grouping efficiency values. Then, the preferred ANN is executed with arbitrary values of inputs. With proposed rule base, the position of this output is determined in available groups and a new group is constructed.

This study is an extension of a previous study by Azadeh, Saberi, Reza, and Leili (2011). Furthermore the previous study presented an integrated data envelopment analysis-artificial neural network-rough set algorithm for assessment of personnel efficiency. However, this study presents a DSS approach based on previous approaches and K-Means algorithm for optimization of personnel attributes. Moreover, the intelligent DSS approach utilizes data envelopment analysis (DEA), and data mining tools including rough set theory (RST), artificial neural network (ANN), cross validation test technique (CVTT), and K-Means algorithm for forecasting and optimization of personnel efficiency. The paper is organized as follows: DEA, ANN, RST and CVTT are discussed in the first section. The methodology or the intelligent DSS is discussed in the second section. Third section explains the details of experimentations and results of DSS. Section four deals with the execution of K-Means algorithm which is the core of DSS. Finally, last section presents the conclusions of this study.

1.1. Data envelopment analysis

DEA is a non-parametric method that uses linear programming to calculate the efficiency in a given set of decision-making units (DMUs). The DMUs that make up a frontier envelop, the less efficient firms and the relative efficiency of the firms is calculated in terms of scores on a scale of 0–1, with the frontier firms receiving a score of 1. DEA models can be input or output oriented and can be specified as constant returns to scale (CRS) or variable returns to scale (VRS).

1.2. Basic models of DEA

The original fractional CCR model (1) evaluates the relative efficiencies of n DMUs ($j = 1,\ldots,n$), each with m inputs and s outputs denoted by $x_{1j}, x_{2j}, \ldots, x_{mj}$ and $y_{1j}, y_{2j}, \ldots, y_{sj}$, respectively (Charnes, Cooper, & Rhodes, 1978). This is done so by maximizing the ratio of weighted sum of output to the weighted sum of inputs:

$$\begin{aligned}
&\text{Max} \quad \theta = \frac{\sum_{r=1}^{S} u_r y_{ro}}{\sum_{r=1}^{m} v_i x_{io}},\\
&\text{s.t.} \quad \frac{\sum_{r=1}^{S} u_r y_{rj}}{\sum_{r=1}^{m} v_i x_{ij}} \le 1, \quad j = 1,\ldots,n, \quad r = 1,\ldots,s,\\
&u_r,\ v_i \ge 0, \quad i = 1,\ldots,m, \quad r = 1,\ldots,s.
\end{aligned} \tag{1}$$

In model (1), the efficiency of DMU_o is θ_o and u_r and v_i are the factor weights. However, for computational convenience the fractional programming model (1) is re-expressed in linear program (LP) form as follows:

$$\begin{aligned}
&\text{Max} \quad \theta = \sum_{r=1}^{s} u_r y_{r0},\\
&\text{s.t.} \quad \sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad j = 1,\ldots,n,\\
&\qquad \sum_{i=1}^{m} v_i x_{io} = 1,\\
&\qquad u_r,\ v_i \ge \varepsilon, \quad i = 1,\ldots,m, \ \ r = 1,\ldots,s,
\end{aligned} \tag{2}$$

where ε is a non-Archimedean infinitesimal introduced to ensure that all the factor weights will have positive values in the solution. The model (3) evaluates the relative efficiencies of n DMUs ($j = 1,\ldots,n$), respectively, by Minimizing inputs when outputs are constant. The dual of linear program (LP) model for input oriented CCR is as follows:

$$\begin{aligned}
&\text{Min} \quad \theta,\\
&\text{s.t.} \quad \theta x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i = 1,\ldots,m,\\
&\qquad y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \quad r = 1,\ldots,s,\\
&\qquad \lambda_j \ge 0.
\end{aligned} \tag{3}$$

The output oriented CCR model is as follows:

$$\begin{aligned}
&\text{Max} \quad \theta,\\
&\text{s.t.} \quad x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i = 1,\ldots,m,\\
&\qquad \theta y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \quad r = 1,\ldots,s,\\
&\qquad \lambda_j \ge 0,
\end{aligned} \tag{4}$$

If $\sum \lambda_j = 1 (j = 1,\ldots,n)$ is added to model (3), the BCC model is obtained which is input oriented and its return to scale is variable. The calculations provide a maximal performance measure using piecewise linear optimization on each DMU with respect to the closest observation on the frontier. The linear programming system for the BCC input-oriented model is given in expression (5), and the output-oriented model in expression (6) (refer to Charnes et al. (1994) for more detail (Charnes et al., 1978).

$$\begin{aligned}
&\text{Min} \quad \theta,\\
&\text{s.t.} \quad \theta x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i = 1,\ldots,m,\\
&\qquad y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj} \quad r = 1,\ldots,s,\\
&\qquad \sum_{j=1}^{n} \lambda_j = 1,\\
&\qquad \lambda_j \ge 0, \quad j = 1,\ldots,n,
\end{aligned} \tag{5}$$

$$\begin{aligned}
&\text{Max} \quad \theta,\\
&\text{s.t.} \quad x_{io} \ge \sum_{j=1}^{n} \lambda_j x_{ij}, \quad i = 1,\ldots,m,\\
&\qquad \theta y_{ro} \le \sum_{j=1}^{n} \lambda_j y_{rj}, \quad r = 1,\ldots,s,\\
&\qquad \sum_{j=1}^{n} \lambda_{j=1},\\
&\qquad \lambda_j \ge 0, \quad j = 1,\ldots,n.
\end{aligned} \tag{6}$$