A Hybrid DEA-Adaboost Model in Supplier Selection for Fuzzy Variable and Multiple Objectives

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Abstract: Supplier selection is a critical multi-criteria decision making problem for supply chain management. With the emergence of big data, there is an urgent need for data-driven decision making methods. A hybrid DEA-Adaboost model is proposed to meet the challenge. The proposed model is split into the DEA and the learner. The fuzzy multi-objective DEA is used to build the expert database, which contains the appropriate and inappropriate suppliers. The learner is trained by Adaboost from the expert database. Thus, the DEA and derived learner are combined as the hybrid model to reduce the time consumption and computational complexities for suppliers selection. The simulation results demonstrate that the proposed model improves the accuracy compared with other two approaches.

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1. INTRODUCTION

The supplier selection plays an important role in successful logistic and supply chain management, which has been studied extensively for decades. Various decision making approaches have been introduced to handle the problem such as data envelopment analysis (DEA), mathematical programming and analytic hierarchy process (Charnes et al. (1978); Chai et al. (2013)).

The most prevalent approach is DEA. DEA is a linear non-parametric programming methodology, which calculates the efficiency of each decision making unit (DMU) according to various inputs and outputs (Charnes et al. (1978)). Braglia and Petroni (2000) used DEA to help purchasing managers choose the best supplier based on their overall performance. DEA has been investigated deeply in recent years. The main challenges in realizing appropriate supplier selection are threefold, namely meeting environmental requirement, dealing with fuzzy data and considering multiple objectives.

The environmental criteria was led into the supplier selection for the growing environmental requirement (Govindan et al. (2015)). Kumar and Jain (2010) proposed a unified green DEA for green supplier selection using carbon footprint monitoring, and this model can encourage suppliers to cut down their carbon footprints in order to survive the competition.

However, the data may not always be available. To alleviate this problem, the notion of fuzzy numbers which describe uncertain information was introduced to DEA and DEA was expanded to fuzzy DEA. Tseng et al. (2009) proposed an integrated model which used AHP, fuzzy multi-criteria and DEA to determine the business performance. Puri and Yadav (2014) proposed a fuzzy DEA model with fuzzy input and output data to overcome the limitations in the existing DEA model.

Multi-objective programming was introduced for suppliers selection by Weber et al. (1993). Wu et al. (2010) applied a fuzzy multi-objective programming model to suppliers selection. The selected suppliers were affected when considering qualitative criteria. This model also evaluated and improved supplier selection decisions in an uncertain supply chain environment.

A DEA model, that consists of n DMUs, for finding the efficiency score of a sample should be calculated in n times. This process is time-consuming for decision-makers in cases where the number of DMUs is large and increases the computational complexities of solving the linear programming (Fallahpour et al. (2016)).

With the emergence of Big Data, there is a great technological explosion(Chen and Zhang (2014)). Intelligent transportation logistics have already become highly data-driven facing the data tsunami (Zhang et al. (2011)). Machine learning is an alternative methodology for the big data challenge.

Hence, it is very attractive to combine DEA with machine learning approaches to develop an hybrid model, in order to reduce the time consumption and computational complexities. Wu (2009) attempted to integrate DEA with other two techniques, i.e, neural network(NN) and decision tree(DT), for assessing supplier performance. Jiang et al. (2013) proposed a DEA-SVM model with the purpose of classifying the suppliers into four categories. Hu et al. (2016) combine DEA and two data mining algorithms,
decision model and SVM, to build a hybrid model. The hybrid model is for the feasibility and effectiveness classification. The aforementioned hybrid DEA and machine learning models improve the accuracy rate and reduce the computation complexity in general.

Recently, adaptive boosting (AdaBoost) learning method has been successfully applied to a lot of classification problems (Khammar et al. (2005); Assareh et al. (2012)). The AdaBoost is an ensemble algorithm, which is in conjunction with different weak learning algorithms, in order to improve the performance.

In this paper, we combine AdaBoost with DEA to establish the hybrid model for supplier selection. The hybrid model selects the appropriate suppliers more exactly, and selects the less inappropriate suppliers.

The rest of this paper is organized as follows. Section II presents the hybrid DEA-Adaboost model in detail. Section III introduces the simulation parameters, results and analyses. Section IV provides conclusion of the paper.

2. SYSTEM MODEL

In this section, the hybrid model is built as shown in Fig. 1. First, the scores of every supplier are acquired in multi-criteria. Then a fuzzy multi-objective DEA is applied to obtain the appropriate and inappropriate suppliers, so the expert database is developed. Next, the expert is used to train the learner by Adaboost. Finally, the hybrid DEA-AdaBoost model is obtained.

2.1 Data acquisition

Assuming there is an enterprise with the need of choosing the optimal supplier among several candidates. First, the score of suppliers are acquired with multi-criteria. In this study, the two dimension criteria are considered as follows.

The input dimension are divided into the following categories.

- Economic criteria are technology capability (TC) and financial capability (FC).
- Environmental criterion is environmental cost (EC).
- Social criterion is the cost of work safety and labor health (SC).

The output dimension are divided into the following categories.

- The number of shipments to arrive on time (NOT).
- The number of bills received from suppliers without errors (NB).

Two separated questionnaires are developed to assess supplier capabilities.

2.2 The expert database

After getting the score of each supplier under various criteria, a novel fuzzy multi-objective DEA approach Zhou et al. (2016) has been implemented to select the appropriate suppliers. The efficiency of a DMU was defined as the ratio of output value to input value. It indicates the capability of a supplier.

\[
E_{ij} = \frac{\beta_1 y_{ij} + \ldots + \beta_m y_{mj}}{\alpha_1 x_{ij} + \ldots + \alpha_m x_{mj}}
\]

where \(\alpha_k\) is the weight of input \(k\), \(\beta_k\) is the weight of output \(k\), \(x_{kj}\) is the amount of input \(k\) in DMU \(j\), \(y_{kj}\) is the amount of output \(k\) from DMU \(j\).

The effectiveness of a DMU was defined as the ratio of output values to the ideal predetermined goals. It expresses how much a supplier can meet its predetermined goals.

\[
E_{2j} = \frac{\beta_1 y_{ij} + \ldots + \beta_m y_{mj}}{\chi_1 g_{ij} + \ldots + \chi_m g_{mj}}
\]

where \(g_{kj}\) is the predetermined goal of output \(k\) from DMU \(j\), \(\chi_k\) is the weight of \(k\)th predetermined goal.

When considering both efficiency and effectiveness, the multi-objective DEA model is constructed.

Then in view of the uncertain data \(\xi\) in practical, it is justifiable to lead type-2 fuzzy variable \(\xi = (r_1, r_2, r_3)\) into the model. But in this way, the model cannot be solved like a mathematical model. Consequently, two following steps are adopted to handle the problem.

**Step 1** A critical value reduction method Qin et al. (2011) is applied to transform a type-2 fuzzy variable into a type-1 fuzzy variable.

Let \(\xi\) be an regular fuzzy variable. The critical value (CV) of \(\xi\), denoted by \(CV[\xi]\), is defined as

\[
CV[\xi] = \sup_{\alpha \in [0, 1]} [\alpha \land Cr\{\xi \geq \alpha\}]
\]

Let \(\xi\) be a type-2 triangular fuzzy variable defined as \(\xi = (r_1, r_2, r_3; \theta_1, \theta_r)\), where \(r_1, r_2, r_3\) are three real values and \(\theta_1, \theta_r \in [0, 1]\) are two fuzzy parameters. Using the CV reduction method, the reduction \(\xi\) has the following possibility distribution:

\[
\mu_{\xi}(x) = \begin{cases} 
(1+\theta_1)(r_1-x), & \text{if } x \in \left[0, \frac{r_1 + r_2}{2}\right] \\
(1-\theta_1)\frac{r_2-r_1+2\theta_2(x-r_1)}{r_2-r_1+2\theta_2(r_2-r_1)}, & \text{if } x \in \left[\frac{r_1 + r_2}{2}, \frac{r_1 + r_3}{2}\right] \\
-\theta_1\frac{r_2-r_1+2\theta_2(x-r_1)}{r_2-r_1+2\theta_2(r_2-r_1)}, & \text{if } x \in \left[\frac{r_1 + r_3}{2}, \frac{r_2 + r_3}{2}\right] \\
(1+\theta_r)(r_3-x), & \text{if } x \in \left[\frac{r_2 + r_3}{2}, \frac{r_3 + r_4}{2}\right] \\
(1-\theta_r)\frac{r_3-r_2+2\theta_3(x-r_2)}{r_3-r_2+2\theta_3(r_3-r_2)}, & \text{if } x \in \left[\frac{r_3 + r_4}{2}, \frac{r_3 + r_5}{2}\right] \\
-\theta_r\frac{r_3-r_2+2\theta_3(x-r_2)}{r_3-r_2+2\theta_3(r_3-r_2)}, & \text{if } x \in \left[\frac{r_3 + r_5}{2}, \frac{r_4 + r_5}{2}\right] \\
0, & \text{otherwise}
\end{cases}
\]

After the step 1, \(\bar{\xi} = (r_1, r_2, r_3; \theta_1, \theta_r)\) with three fuzzy values are reduced to \(\mu_{\xi}(x)\).
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