Developing and analyzing the customer pyramid via data envelopment analysis
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Abstract
As customers are the most important asset of companies, they must manage relationships with customers and consider it as an opportunity. Prioritizing the customers is one of the most important marketing activities that must be conducted to build an appropriate relationship with customers. Appropriate classification and ranking are impressive in companies’ interaction with their customers. Ranking and classifying customers into different categories takes place to improve marketing performance. Appropriate classification of customers leads the organizations to the desire target markets. To analyze the customer’s value, some approaches were used in the past that the most important methods are based on regression and artificial intelligence techniques. Previous methods which have been introduced can hardly be applied in real world situation because they are very complex and they need complex mathematical knowledge and software. To overcome these shortcomings, this paper proposed an application of data envelopment analysis (DEA), slack based measure (SBM) model and Super SBM model to measure the value of customers. Applying the above mentioned models, the customers were evaluated, classified and ranked and the customers who were most useful to the company were identified. In the end, customer pyramid was constructed by the customer values.

Keywords: Customer, customer pyramid, performance evaluation, data envelopment analysis, slack based measure.
1. Introduction

In recent years many organizations have realized the need to become more customers facing with increased global competition (Christopher, 2003). Due to the increasing competition in the markets, today businesses are increasingly feeling the need to effectively manage their relationship with customers. On the other hand, Competitive advantage is realized based on three factors: (1) the firm’s marketing strategy, (2) implementation of this strategy and (3) the industry context. An important component of firm’s marketing strategy is relationships, relationships with customers, channel members and with competitors (Sudarshan, 1995 and Kanagal, 2009). Competitive Marketing Strategy has relationship marketing as one of the key functionality in enhancing business performance. Relationship marketing is defined as the identification, establishment, maintenance, enhancement, modification and termination of relationships with customers to create value for customers and profit for organization by a series of relational exchanges that have both a history and a future (Kanagal, 2009). Consequently, customer relationship management (CRM) has risen to the agenda of many organizational strategies. Definitions of CRM are wide ranging, one view of CRM is the utilization of customer related information or knowledge to deliver relevant products or services to customers (Levine, 2000 and Christopher, 2003). Galbreath and Rogers define CRM as the activities that a business performs to identify, qualify, acquire, develop and retain increasingly loyal and profitable customers by delivering the right product or service, to the right customer, through the right channel, at the right time and the right cost (Galbreath and Rogers, 1999).

As already mentioned one view of CRM is the utilization of customer related information. But, what do managers need to know about their customers and how is that information used to develop a complete CRM perspective? As the foregoing discussion illustrates, the measurement of customer profitability is a significant topic in its own right and is linked to the management of customer relationships (Gupta et al., 2001, Rust et al., 2001, Zeithaml et al., 2001, Mulhern, 1999 and Ryals, 2003). One way that some companies use an improved focus on CRM is through the establishment or consideration of splitting the marketing manager job into two parts: one for customer acquisition and another one for customer retention (Winer, 2001). Anderson and Narus (2004) believe that customer retention is a more effective business strategy than continuously trying to acquire new customers in order to replace the defecting ones (Noorizadeh et al., 2013 and Anderson and Narus, 2004). It is often said that the cost to acquire a new customer is five times greater than the cost of retaining an existing one, and therefore firms should spend more money on customer retention (Pfeifer, 2005). As Garland (2005) addresses, while companies may want to treat all customers with superior service, they find it neither practical nor profitable to meet all the customers’ expectations. At the same time, customers with the least profitable segments can be avoided, or at least investments in those segments can be reduced (Garland, R. 2005 and Van Raaij, 2005). Overall, the company should provide the proper incentives and discounts or special services for efficient customers to ensure that when the other competitors appear, they can remain loyal to it (Ju-Fang, and Kun-Yuan 2008). Prioritizing customers and classifying them into different clusters is the purpose of improving the performance of the marketing strategies and increasing the market share. There is a need to allocate company resources to the customers that generate the most profits for the company (Noorizadeh et al., 2013).
To analyze the customer’s value, some approaches were used in the past. Reinartz and Kumar (2002) propose a framework for customer segmentation. Their customer segmentation concept is a 2x2 matrix based upon profitability and customer tenure. This produces four different types of customer classification; butterflies, true friends, strangers and barnacles. Recognizing the importance of profits, Zeithaml et al., (2001) worked on the customer pyramid concept. They mainly focused on the top of the pyramid - those consumers with the highest lifetime customer value (LCV). By dividing the customer pyramid into four sections called customer profitability tiers, they identified the best and most profitable customers, and labeled them as “Platinum” or “Gold”. In contrast, those with lower to very low LCVs, gain the value labels “Iron and Lead”. In contrast, those with lower to very low LCVs gain the value labels “Iron and Lead” (Zeithaml et al., 2001 and Noorizadeh et al., 2013). The customer pyramid is a tool for managers to strengthen the link between service quality and profitability, and often allocation of scarce resources, in order to maximize profitability. The goal is to use the customers value analysis and customers pyramid to separate customers that will provide the most long-term profits from those that are currently hurting profits. This allows the manager to “fire” customers that are too costly to serve relative to the revenues being produced (Winer, 2001). The customer pyramid provides the framework for the development of the customer loyalty. Moving a customer from being satisfied to being loyal can create powerful, sustainable business impact. Moreover, Pitta et al., (2006), Gee et al., (2008), Leverin and Liljander (2006), Yu and Cai (2007) and Ju-Fang and Kun Yuan (2008), emphasize the customer segmentation as an important tool in marketing process. However, they did not propose any practical and mathematical approach to deal with the customer value analysis problem.

Many researchers and consultants have developed scoring models based on regression-type models in order to predict customers’ future behavior (see, e.g. Baesens et al., 2002, Berry and Linoff, 2004, Bolton, 1998 and Malthouse, 1999). Regression method requires a mathematical function which is based on the dependent variable estimated by the independent variables. The above mentioned and other regression assumptions often increase the complexity of the problem.

Moutinho et al., (1994) predict customers’ responses using artificial neural networks (ANN). Using ANN and Genetic Algorithm (GA) simultaneously were proposed by Kim et al., (2005) to predict households interested in purchasing an insurance policy for recreational vehicles (RVs). Crone et al., (2006) have used neural networks (NN) method for direct marketing optimization. In order to assess the value of a company's customers in Taiwan, Huang et al., (2009) used the K-means and fuzzy C-means clustering method. In particular, its performance is sensitive to its complexity, determined by the number of synapses or weight parameters. If a network is more complex than the problem at hand or the available data set requires, then the network learns not only the underlying function, but also the noise peculiar to the finite training data set (Noorizadeh et al., 2013).

For the first time Mahdiloo et al., (2011) have suggested data envelopment analysis to analyze customer value analysis. They have used Cross-Efficiency (CE) and Analytic Hierarchy Process (AHP) for customer value analysis. But they used radial model that can create some problems e.g. radial models ignore the inputs and outputs slack. To this end, we use a combination of the Slack based measure (SBM) model (Tone, 2001) and Super SBM model (Tone, 2002) to overcome the problems mentioned above.
Using the results of the SBM and Super SBM models and based on the work of Zeithaml et al., (2001) a customer pyramid is constructed.

Briefly, this paper applies an application of data envelopment analysis (DEA) to measure the value of customers and to make customer pyramid. In order to distinguish between expectations and needs of profitable and unprofitable customers and to allocate marketing investments among them, customers are compared with each other and ranked in a customer value pyramid.

The remainder of this paper presents reviews of relevant literature in The Customer Pyramid and Data envelopment analysis areas in second section, and the following section describes the methodology of this paper and Case study, respectively. Concluding remarks are discussed in Section 4.

2. Material and methods

Traditionally, marketers have been trained to acquire customers, either new ones who have not bought the product category before or those who are currently competitors’ customers. This has required heavy doses of mass advertising and price-oriented promotions to customers and channel members. Today, the tone of the conversation has changed from customer acquisition to retention. This requires a different mindset and a different and new set of tools (Winer, 2001). The customer pyramid model is one of conceptual tools for customer classification that is used for prioritizing customer. This concept is explained in the following:

2.1. The Customer Pyramid

In this section, we illustrate a framework that is called the Customer Pyramid (see Figure 1) that contains four levels. This framework includes the following four tiers.

- The Platinum Tier describes the company's most profitable customers, typically those who are heavy users of the product, not overly price sensitive, willing to invest in and try new offerings, and are committed to the firm.

- The Gold Tier differs from the Platinum Tier in that profitability levels are not as high, perhaps because the customers want price discounts that limit margins. They might not be as loyal to the firm even though
they are heavy users in the product category—they might minimize risk by working with multiple vendors rather than just the focal company.

• The Iron Tier contains customers that provide the volume needed to utilize the firm's capacity but whose spending levels, loyalty, and profitability are not substantial enough for special treatment.

• The Lead Tier consists of customers that are costing the company money. They demand more attention than they are due given their spending and profitability, and they are sometimes problem customers—complaining about the firm to others and tying up the firm's resources.

The specific factors vary across industries, but the Customer Pyramid is a rich and robust concept across most industries and categories. For example, it can be used successfully by companies selling directly to consumers, to intermediaries (such as retail, wholesale and professional channels of distribution), and to other businesses (Zeithaml et al., 2001).

2.2. Data envelopment analysis
In this paper, data envelopment analysis (DEA) as a nonparametric and multiple criteria decision making tool is used. DEA was first introduced by Charnes, Cooper, and Rhodes (CCR) in 1978 and is a linear-programming-based methodology that uses multiple inputs and multiple outputs to calculate efficiency scores (Charnes et al., 1978). The efficiency score for each decision making unit (DMU) is defined as a weighted sum of outputs divided by a weighted sum of inputs, where all efficiencies are restricted to a range from 0 to 1. To avoid the potential difficulty in assigning these weights among various DMUs, a DEA model computes weights that give the highest possible relative efficiency score to a DMU while keeping the efficiency scores of all DMUs less than or equal to the one under the same set of weights (19). DEA is a robust, standardized and transparent methodology. Furthermore, it enjoys additional positive features which make it a tool so suitable for prioritizing the customers. The advantages of DEA are as (Liu et al., 2000):

. DEA is an effective tool for evaluating the relative efficiency of DMUs in the presence of multiple performance measures.

. DEA is able to address the complexity that arises from the lack of a common scale of measurement. It allows the management to analyze simultaneously a relatively large number of inputs and outputs measured on different scales.

. The objectivity stemming from DEA weighting variables during the optimization procedure frees the analysis from subjective estimates and randomness. This increases the acceptability of its results by affected parties (Noorizadeh et al., 2013).

In applying classical DEA models, two problems often occur, the weakness of distinction and another unrealistic distribution weight between the inputs and output. The weakness of distinction occurs when the total number of units under assessment is not sufficiently larger than number of inputs and outputs. In this case the classical models of many decision units are identified as efficient. The problem of the weight of non-logical model occurs when a model assigned very small or large weights to inputs and outputs.
Hashemi et al. (2014). We use a combination of the Slack based measure (SBM) model (Tone, 2001) and Super SBM model (Tone, 2002) to overcome the above mentioned problems.

Suppose there are n DMUs associated with m inputs and s outputs. Let $x_{ij}$ denote the ith input of DMU$_{j}$ and $y_{rj}$ denote rth output of DMU$_{j}$. Assume that all data are positive, i.e., $x_{ij}, y_{rj} > 0$ for all possible $i = 1, ..., m; y = 1, ..., s; j = 1, ..., n$. The production possibility set $P$ spanned by all DMUs is defined as

$$P = \{(x_1, ..., x_m, y_1, ..., y_s) | x_i \geq \sum_{j=1}^{n} \lambda_{j} x_{ij}, i = 1, ..., m, y_r \leq \sum_{j=1}^{n} \lambda_{j} y_{rj}, r = 1, ..., s\} \quad (1)$$

Tone (2001) proposed the following SBM model to evaluate the efficiency of DMU$_{o}$

$$\text{Min} \rho \ 1 - (1/m) \sum_{i=1}^{m} \left( s_i^- / x_{io} \right) / 1 + (1/s) \sum_{r=1}^{s} \left( s_r^+ / y_{ro} \right), \quad (2)$$

subject to:

$$\sum_{j=1}^{n} \lambda_{j} x_{ij} + s_i^- = x_{io}, \quad i = 1, ..., m,$$

$$\sum_{j=1}^{n} \lambda_{j} y_{rj} - s_r^+ = y_{ro}, \quad r = 1, ..., s,$$

$$s_i^- \geq \rho, \quad i = 1, ..., m,$$

$$s_r^+ \geq \rho, \quad r = 1, ..., s,$$

$$\lambda_j \geq \rho, \quad j = 1, ..., n.$$

Tone (2001) defines that a DMU is SBM-efficient if $s_i^- = s_r^+ = 0$ for all $i$ and $r$. Or equivalently, a DMU is SBM-efficient if $\rho = 0$. The linear programming equivalent of (2) is as follows:

$$\text{Min} \tau \ t - (1/m) \sum_{i=1}^{m} \left( S_i^- / x_{io} \right), \quad (3)$$

subject to:

$$t + (1/s) \sum_{r=1}^{s} \left( S_r^+ / y_{ro} \right) = 1,$$

$$\sum_{j=1}^{n} \Lambda_j x_{ij} + S_i^- = x_{io}, \quad i = 1, ..., m,$$

$$\sum_{j=1}^{n} \Lambda_j y_{rj} - S_r^+ = y_{ro}, \quad r = 1, ..., s,$$

$$S_i^- \geq \rho, \quad i = 1, ..., m,$$

$$S_r^+ \geq \rho, \quad r = 1, ..., s,$$

$$\Lambda_j \geq \rho, \quad j = 1, ..., n.$$
Note that the choice $t > 0$ means that the transformation is reversible. Thus let an optimal solution of (LP) be $\left( \tau^*, t^*, \Lambda^*, S^x^*, S^z^* \right)$. We then have an optimal solution of (2) defined by:

$$\left( \rho^* = \tau^*, \lambda = \Lambda^*/t^*, s^x^* = S^x^*/t^*, s^z^* = S^z^*/t^* \right)$$

For a SBM-efficient DMUo, Tone (2002) proposed the following model (Super SBM) to identify its super-efficiency:

$$\text{Min} \delta = \left( 1/m \right) \sum_{i=1}^{m} \left( \bar{x}_i / x_{io} \right) \left/ \left( 1/s \right) \sum_{r=1}^{s} \left( \bar{y}_r / y_{ro} \right) \right., \quad (4)$$

subject to

$$\sum_{j=1,z_o}^{n} \lambda_j x_{ij} \leq \bar{x}_i, \quad i = 1, \ldots, m,$$

$$\sum_{j=1,z_o}^{n} \lambda_j y_{rj} \geq \bar{y}_r, \quad r = 1, \ldots, s,$$

$$\bar{x}_i \geq x_{io}, \quad i = 1, \ldots, m,$$

$$\bar{y}_r \geq \circ, \bar{y}_r \leq y_{ro}, \quad r = 1, \ldots, s,$$

$$\lambda_j \geq \circ, \quad j = 1, \ldots, n, j \neq o.$$

If we employ model (4) to evaluate an inefficient DMU, the efficiency will be 1. In other words, inefficient DMUs cannot be discriminated by Super SBM.

Let us introduce $\phi \in R^m$ and $\psi \in R^s$ such that

$$\bar{x}_i = x_{io} (1 + \phi_i), i = 1, \ldots, m, \quad \bar{y}_r = y_{ro} (1 + \psi_r), r = 1, \ldots, s.$$

Then, this problem can be equivalently stated in terms of $\phi$ and $\psi$ and $\lambda$ as follows:

$$\text{Min} \delta = 1 + \left( 1/m \right) \sum_{i=1}^{m} \phi_i \left/ \left( 1 - 1/s \right) \sum_{r=1}^{s} \psi_r \right., \quad (5)$$

subject to

$$\sum_{j=1,z_o}^{n} \lambda_j x_{ij} - x_{io} \phi_i \leq x_{io}, \quad i = 1, \ldots, m,$$

$$\sum_{j=1,z_o}^{n} \lambda_j y_{rj} + y_{ro} \psi_r \geq y_{ro}, \quad r = 1, \ldots, s,$$

$$\phi_i \geq 0, \quad i = 1, \ldots, m,$$

$$\psi_r \geq \circ, \quad r = 1, \ldots, s,$$

$$\lambda_j \geq \circ, \quad j = 1, \ldots, n, j \neq o.$$
The fractional program (5) can be transformed into a linear programming problem using the Charnes-Cooper transformation as:

\[
\begin{align*}
\min \tau &= t + \left(1/m\right) \sum_{i=1}^{m} \Phi_i, \\
\text{s.t.} \quad & t - \left(1/s\right) \sum_{r=1}^{s} \Psi_r = 1 \\
& \sum_{j=1,x,0}^{n} \Lambda_j x_{ij} - x_{io} \Phi_i \leq t x_{io}, \quad i = 1, \ldots, m, \\
& \sum_{j=1,x,0}^{n} \Lambda_j y_{rj} + y_{ro} \Psi_r \geq t y_{ro}, \quad r = 1, \ldots, s, \\
& \Phi_i \geq 0, \quad i = 1, \ldots, m, \\
& \Psi_r \geq 0, \quad r = 1, \ldots, s, \\
& \Lambda_j \geq 0, \quad j = 1, \ldots, n, j \neq o.
\end{align*}
\]

Let an optimal solution of [LP] be \( (\tau^*, t^*, \Lambda^*, \Phi^*, \Psi^*) \). Then we have an optimal solution of (5) expressed by \( (\delta^* = \tau^*, \lambda^* = \Lambda^*/t^*, \phi^* = \Phi^*/t^*, \psi^* = \Psi^*/t^*) \). Furthermore, the optimal solution of (4) is given by:

\[
\begin{align*}
\bar{x}_{i}^* &= x_{io} (1 + \phi_i^*), i = 1, \ldots, m, \\
\bar{y}_{r}^* &= y_{ro} (1 + \psi_r^*), r = 1, \ldots, s.
\end{align*}
\]

3. Methodology

This research in terms of objective is practical and in terms of methods is descriptive and analytical. For gathering data, both library and field methods are used. The main data for this paper has been gathered through interviews with managers, experts and customers. Various stages of research and data analysis are shown in Fig 2.

According to this method, first we identified the inputs and outputs for customer value analysis and gathered information about inputs and outputs. After that we evaluated customers separately by using of super SBM model with all DMUs. Super-efficient units were categorized as platinum class. In level 4, having removed platinum class, we solved Super SBM model. Super-efficient units were labeled as Gold class. In next level, having removed Platinum and Gold classes, we re-ran Super SBM model. Super-efficient units were labeled as Iron class and inefficient units are labeled as Lead class. To rank these inefficient units, we move to level 6. In level 6, we applied the same data set that we did in level 5. We ranked the Lead class through SBM model. Finally in level 7, we developed customer pyramid using the results of previous levels.
4. Case study

The proposed approach is applied in SADAF TEJARAT Company, a commercial company located in Karaj, Iran. This Company imports hygienic products from Germany and sell them in Iran. This company has a significant number of countrywide distributors which are, in fact, the company’s customers. In this paper, we were evaluating customers’ value for this company. In DEA, careful attention should be paid to the selection of inputs and outputs. In this paper, the selection of the input and outputs was made by marketing managers and discussions with experts in the field of DEA. Based on experts opinion similar to Noorizadeh et al., (2013), Noorizadeh et al., (2011) and Mahdiloo et al., (2011), the inputs and outputs used in our study is defined in Table 1.

<table>
<thead>
<tr>
<th>Inputs</th>
<th>Outputs</th>
</tr>
</thead>
<tbody>
<tr>
<td>$X_1 = \text{Average payment period (PP)}$</td>
<td>$Y_1 = \text{customer’s credit (CC)}$</td>
</tr>
<tr>
<td>$X_2 = \text{Average marketing expenses (ME)}$</td>
<td>$Y_2 = \text{customers’ profitability (CP)}$</td>
</tr>
<tr>
<td>$X_3 = \text{Average Payments delay (PD)}$</td>
<td></td>
</tr>
<tr>
<td>$X_4 = \text{Average purchase return (PR)}$</td>
<td></td>
</tr>
</tbody>
</table>

Average of payment period (PP), marketing expenses (ME), Payment delays (PD) and purchase return (PR) are considered as inputs. Those customers with the smaller values of these four criteria will be the first priorities of marketing investments. Payment delay (PD) of customers is considered as input. If customers do not pay on due date, it can create hidden costs, such as energy costs and transaction costs, which causes difficulties to measure the profitability of customers. Due to the lack of market prices for
the aforementioned indices, we are not able to estimate their costs. Some of the measurement and evaluation difficulties can be overcome by treating these indices as inputs in DEA technique. The outputs with larger values being better utilized in this study are customer’s credit (CC) and customers’ profitability (CP). After that we collect data for inputs and outputs. Table 2 depicts data set for 25 customers.

To eliminate the impacts of units of measurement, all the inputs and outputs should be normalized (Wang, et al., 2009). Normalized data about inputs and outputs for each customer is shown in Table 2.

| DMU_j | Inputs | | | | Outputs | |
|-------|--------|---|---|---|---|---|---|
|       | X_1    | X_2 | X_3 | X_4 | Y_1  | Y_2  |
| DMU01 | 0.3621 | 0.3571 | 0.1967 | 0.22 | 0.645 | 0.5134 |
| DMU02 | 0.1441 | 0.5714 | 0.082 | 0.0002 | 0.66 | 0.7804 |
| DMU03 | 0.3712 | 0.6607 | 0.3279 | 0.21 | 0.4417 | 0.62 |
| DMU04 | 0.9476 | 0.6607 | 0.3607 | 0.0002 | 0.48 | 1 |
| DMU05 | 0.3895 | 0.5536 | 0.2951 | 0.32 | 0.1333 | 0.2515 |
| DMU06 | 0.0604 | 0.5 | 0.0002 | 0.018 | 0.9667 | 0.9964 |
| DMU07 | 1 | 0.3036 | 1 | 1 | 0.4567 | 0.2549 |
| DMU08 | 0.5625 | 0.6964 | 0.0002 | 0.292 | 0.6283 | 0.5775 |
| DMU09 | 0.4016 | 0.3571 | 0.5082 | 0.632 | 0.4167 | 0.3434 |
| DMU10 | 0.3825 | 0.6786 | 0.1148 | 0.0002 | 0.9833 | 0.607 |
| DMU11 | 0.3585 | 0.6964 | 0.0002 | 0.037 | 0.68 | 0.4544 |
| DMU12 | 0.769 | 0.5 | 0.4918 | 0.2294 | 1 | 0.5446 |
| DMU13 | 0.3953 | 0.3571 | 0.0164 | 0.022 | 0.15 | 0.2966 |
| DMU14 | 0.408 | 0.3036 | 0.1967 | 0.191 | 0.4833 | 0.3647 |
| DMU15 | 0.765 | 0.4286 | 0.4918 | 0.0002 | 0.2667 | 0.2601 |
| DMU16 | 0.5526 | 0.5 | 0.1311 | 0.3548 | 0.4283 | 0.6616 |
| DMU17 | 0.9614 | 1 | 0.5738 | 0.45 | 0.6333 | 0.3642 |
| DMU18 | 0.4845 | 0.6071 | 0.3443 | 0.26 | 0.45 | 0.5983 |
| DMU19 | 0.8859 | 0.5 | 0.4426 | 0.3726 | 0.5417 | 0.4327 |
| DMU20 | 0.3825 | 0.4286 | 0.2295 | 0.0002 | 0.5617 | 0.5376 |
| DMU21 | 0.601 | 0.6964 | 0.0002 | 0.2998 | 0.4667 | 0.4679 |
| DMU22 | 0.5498 | 1 | 0.5902 | 0.3832 | 0.8333 | 0.7111 |
| DMU23 | 0.4208 | 0.6607 | 0.6393 | 0.428 | 0.425 | 0.594 |
| DMU24 | 0.4169 | 0.5 | 0.2623 | 0.218 | 0.4333 | 0.5062 |
| DMU25 | 0.1318 | 0.3214 | 0.0328 | 0.0360; | 0.8 | 0.7978; |

As you know, SBM model (3) cannot give a complete ranking and there are ties among efficient customers. To overcome this problem, this paper used Super SBM (6) evaluation in levels 3, 4 and 5. Super SBM has been considered as a powerful extension of DEA that provides only a unique ordering among the DMUs, also eliminates unrealistic weighting schemes without requiring the elicitation of weight restrictions from application area experts. Thus, we used Models (3) and (6) to derive the customers’ efficiency score and their complete ranking.
Table 3. Customers SBM and Super SBM efficiency scores

<table>
<thead>
<tr>
<th>DMUj</th>
<th>Efficiency</th>
<th>final ranking</th>
<th>classes</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Level 1</td>
<td>Level 2</td>
<td>Level 3</td>
</tr>
<tr>
<td>DMU1</td>
<td>1</td>
<td>1.2044</td>
<td>-</td>
</tr>
<tr>
<td>DMU2</td>
<td>1.5662</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DMU3</td>
<td>1</td>
<td>1.0535</td>
<td>-</td>
</tr>
<tr>
<td>DMU4</td>
<td>1.0924</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DMU5</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>DMU6</td>
<td>4.4778</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DMU7</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>DMU8</td>
<td>1</td>
<td>1.1158</td>
<td>-</td>
</tr>
<tr>
<td>DMU9</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
<tr>
<td>DMU10</td>
<td>1.1651</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>DMU11</td>
<td>1</td>
<td>2.7329</td>
<td>-</td>
</tr>
<tr>
<td>DMU12</td>
<td>1</td>
<td>1.1185</td>
<td>-</td>
</tr>
<tr>
<td>DMU13</td>
<td>1</td>
<td>1.0824</td>
<td>-</td>
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<tr>
<td>DMU14</td>
<td>1</td>
<td>1</td>
<td>1.2567</td>
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<tr>
<td>DMU15</td>
<td>1</td>
<td>22.4182</td>
<td>-</td>
</tr>
<tr>
<td>DMU16</td>
<td>1</td>
<td>1.0617</td>
<td>-</td>
</tr>
<tr>
<td>DMU17</td>
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<td>1</td>
<td>1</td>
</tr>
<tr>
<td>DMU18</td>
<td>1</td>
<td>1</td>
<td>1.0037</td>
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<td>1</td>
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<td>DMU20</td>
<td>1.0102</td>
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<tr>
<td>DMU21</td>
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<td>1</td>
<td>271.7911</td>
</tr>
<tr>
<td>DMU22</td>
<td>1</td>
<td>1</td>
<td>1.0793</td>
</tr>
<tr>
<td>DMU23</td>
<td>1</td>
<td>1</td>
<td>1.0326</td>
</tr>
<tr>
<td>DMU24</td>
<td>1</td>
<td>1</td>
<td>1.042</td>
</tr>
<tr>
<td>DMU25</td>
<td>1.0711</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

Using Super SBM at first time in level 3 with all DMUs (customers), customers 6, 2, 10, 4, 25 and 20 are efficient respectively and other customers are inefficient. For these Super SBM efficient customers, the company should pay more attention to them, because they are the most useful. The company should provide the appropriate incentives and discounts or special services for them to ensure that when the other competitors appear, they can maintain loyalty to it (Ju-Fang and Kun-Yuan, 2008). After removing the customers 6, 2, 10, 4, 25 and 20, Super SBM model is re-run. Using Super SBM at second time in level 4 with remaining units from previous level, customers 15, 11, 1, 12, 8, 13, 14 and 21 are efficient respectively and other customers are inefficient. After removing the customers 15, 11, 1, 12, 8, 13, 14 and 21, Super SBM model is re-run. Using Super SBM at third time in level 5 with remaining units from previous levels, customers 21, 14, 22, 24, 23 and 18 are efficient respectively and 19, 9, 17, 7 and 5 are inefficient. In level 6, SBM model are just used to rank the remaining units in the level 5. Using SBM, customers 19, 9, 17, 7 and 5 are recognized as the worst inefficient customers. For these inefficient customers who have a long-term cooperation with the company, if it takes all measures not to change the non-profit status into profits, the company can give up them, refuse to provide discounts, reduce or eliminate technical and marketing support so that customers to be fired (Ju-Fang and Kun-Yuan, 2008).
As you can see, total ranking and customers’ classification are shown in columns sixth and seventh of table 3, respectively.

5. Concluding remarks

Prioritizing the customers is one of the most important marketing activities that must be performed. Also ranking and classifying customers into different clusters takes place to improve marketing performance. To analyze the customer’s value, some approaches were used in the past. Previous methods which have been introduced can hardly be applied in real world situation because they are very complex and they need complex mathematical knowledge and software. This paper applies an application of data envelopment analysis (DEA), i.e. Slack based measure (SBM) model to measure the value of customers and to make customer pyramid. In this paper, average of payment period (PP), marketing expenses (ME), Payment delays (PD) and purchase return (PR) are considered as inputs. Those customers with the smaller values of these four criteria will be first priorities of marketing investments. The outputs with larger values being better utilized in this study are customer’s credit (CC) and customers’ profitability (CP). Using Super SBM in level 3 with all DMUs (customers), customers 6, 2, 10, 4, 25 and 20 are efficient. For these Super SBM efficient customers, the company should pay more attention to them, because they are the most useful. Using SBM, customers 19, 9, 17, 7 and 5 are recognized as the worst inefficient customers.

References


