2013

Direct mailing decisions based on the worst and best practice cross-efficiency evaluations

Mahdi Mahdiloo

University of Wollongong, mahdim@uow.edu.au

Abdollah Noorizadeh

Lappeenranta University of Technology

Reza Farzipoor Saen

Islamic Azad University

Publication Details

Mahdiloo, M., Noorizadeh, A. & Saen, R. Farzipoor. (2013). Direct mailing decisions based on the worst and best practice cross-efficiency evaluations. *International Journal of Business Information Systems*, 14 (2), 182-201.

Research Online is the open access institutional repository for the University of Wollongong. For further information contact the UOW Library:
research-pubs@uow.edu.au

Direct mailing decisions based on the worst and best practice cross-efficiency evaluations

Abstract

The problem argued in the literature of direct mailing decisions generally contains three parts: 1) forecasting customers' future purchase/non-purchase responses; 2) evaluating the effectiveness of various strategies for increasing customers purchase responses; 3) prioritising the customers in terms of their values. A significant body of the literature has been dedicated to the first two components, and in particular, to purchase/non-purchase prediction modelling. However, in the current paper, we do not address these two components, but rather we focus on the third component. To this end, data envelopment analysis (DEA) technique and particularly cross-efficiency formulation of the best practice frontier Charnes, Cooper and Rhodes (CCR) (Charnes et al., 1978) (BPF-CCR) is used to determine those customers who should be put on the first priorities of marketing mailing list. In addition, the cross-efficiency formulation of worst practice frontier CCR (WPF-CCR) is developed to exclude the worst customers from mailing list and save the mailing expenses for the best practice ones. Using a numerical example, the application of the proposed model is demonstrated. Copyright 2013 Inderscience Enterprises Ltd.

Disciplines

Business

Publication Details

Mahdiloo, M., Noorizadeh, A. & Saen, R. Farzipoor. (2013). Direct mailing decisions based on the worst and best practice cross-efficiency evaluations. *International Journal of Business Information Systems*, 14 (2), 182-201.

Direct mailing decisions based on the worst and best practice cross-efficiency evaluations

Mahdi Mahdiloo

Griffith Business School,
Gold Coast Campus,
Griffith University,
QLD 4222, Australia
E-mail: mahdi.mahdiloo@griffithuni.edu.au

Abdollah Noorizadeh

Department of Industrial Management,
Lappeenranta University of Technology,
P.O. Box: 20, 53851 Lappeenranta, Finland
E-mail: ab.noorizadeh@gmail.com

Reza Farzipoor Saen*

Department of Industrial Management,
Faculty of Management and Accounting,
Karaj Branch, Islamic Azad University,
P.O. Box: 31485-313, Karaj, Iran
Fax: 0098 (263) 4418156
E-mail: farzipour@yahoo.com
*Corresponding author

Abstract: The problem argued in the literature of direct mailing decisions generally contains three parts: 1) forecasting customers' future purchase/non-purchase responses; 2) evaluating the effectiveness of various strategies for increasing customers purchase responses; 3) prioritising the customers in terms of their values. A significant body of the literature has been dedicated to the first two components, and in particular, to purchase/non-purchase prediction modelling. However, in the current paper, we do not address these two components, but rather we focus on the third component. To this end, data envelopment analysis (DEA) technique and particularly cross-efficiency formulation of the best practice frontier Charnes, Cooper and Rhodes (CCR) (Charnes et al., 1978) (BPF-CCR) is used to determine those customers who should be put on the first priorities of marketing mailing list. In addition, the cross-efficiency formulation of worst practice frontier CCR (WPF-CCR) is developed to exclude the worst customers from mailing list and save the mailing expenses for the best practice ones. Using a numerical example, the application of the proposed model is demonstrated.

Keywords: direct mailing; data envelopment analysis; worst practice frontier; WPF; best practice frontier, BPF; cross-efficiency.

Reference to this paper should be made as follows: Mahdiloo, M., Noorizadeh, A. and Saen, R.F. (2013) 'Direct mailing decisions based on the worst and best practice cross-efficiency evaluations', *Int. J. Business Information Systems*, Vol. 14, No. 2, pp.182–201.

Biographical notes: Mahdi Mahdiloo is a PhD candidate in the Institute for Integrated and Intelligent Systems at Griffith University, Australia. He has several publications in industrial and operations management journals including the *Journal of Industrial and Management Optimisation*, *International Journal of Operational Research*, *International Journal of Information and Decision Sciences*, *International Journal of Productivity and Quality Management*, *International Journal of Logistics Systems and Management*, *International Journal of Services and Operations Management* and *International Journal of Modelling in Operations Management*. His research interests include operations research, data envelopment analysis, supplier selection and customer value analysis.

Abdollah Noorizadeh is an MSc student in the Department of Industrial Management, Lappeenranta University of Technology, Finland. He has several publications in industrial and operations management journals including the *Journal of Industrial and Management Optimisation*, *International Journal of Operational Research*, *International Journal of Information and Decision Sciences*, *International Journal of Productivity and Quality Management*, *International Journal of Logistics Systems and Management*, *International Journal of Services and Operations Management* and *International Journal of Modelling in Operations Management*. His research interests include operations research, data envelopment analysis, supplier selection and customer value analysis.

Reza Farzipoor Saen is an Associate Professor at the Department of Industrial Management, Islamic Azad University, Karaj Branch in Iran. In 2002, he obtained his PhD in Industrial Management from Islamic Azad University, Science and Research Branch in Iran. He has published over 96 refereed papers in many prestigious journals, such as *Expert Systems with Applications*, *Int. J. of Production Economics*, *Annals of Operations Research*, *Journal of the Operational Research Society*, *European Journal of Operational Research*, *Journal of Industrial and Management Optimization*, *Applied Mathematics and Computation*, *Applied Mathematical Modelling*, *Int. J. Advanced Manufacturing Technology*, *Int. J. Applied Management and Technology*, *Asia Pacific Management Review*, etc. His research interests include data envelopment analysis, operations management, supply chain management, and marketing research.

1 Introduction

Satisfaction of customers is an important factor for long-term successful business relationships (Kim, 2008) and mostly depends on post-purchase decisions rather than the first-time use (Kim et al., 2009). This concept is widely discussed in psychology, marketing, management, and information system literature (Cyr, 2008) and is defined and

measured through the comparison between expected service and product quality and real level of service and product quality that customer perceives from the exchange (Kim, 2012). On the other hand, as most companies want to efficiently use their marketing resources, marketers realised that segmentation should guarantee that better customers are separated from other customers. The purpose of separating the profitable segments of customers from the non-profitable ones is to be able to distinguish marketing strategies among these different segments. With the appearance of targeted direct mail or internet marketing and since it is now both organisationally and economically possible to efficiently support a larger number of marketing segments, targeted marketing campaigns are developed. However, the problem of what segments to distinguish and what strategies to take towards the different segments grows considerably in such an environment (Jonker et al., 2004). Jonker et al. (2006) argue that both in business-to-business and in consumer markets, direct mailings are important tools to communicate with customers. Direct mailings allow for a personalised way of addressing a customer. Information about past purchase behaviour can be used to make offers that match the needs of the customers.

In this paper, data envelopment analysis (DEA), as a non-parametric and multiple criteria decision making tool, is used to model customers direct mailing decisions. 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. The efficiency score for each decision making unit (DMU) is defined as a weighted sum of outputs divided by the weighted sum of inputs, where all efficiencies are restricted to a range from 0 to 1. Wong and Wong (2008) listed some of the features of DEA as follows:

- DEA is an effective tool for evaluating the relative value of DMUs in the presence of multiple performance measures.
- DEA is able to address the complexity arising from the lack of a common scale of measurement.
- In DEA, there is no prior need to the existence of a particular production function for weighting and aggregating inputs or outputs.
- The objectivity stemming from DEA weighting variables during the optimisation procedure frees the analysis from subjective estimates and randomness. This increases the acceptability of its results by affected parties.

The above inherent features of DEA make it suitable to be used as a tool for prioritising of customers.

By using DEA, customers are classified into two groups of good and bad customers. Ju-Fang and Kun-Yuan (2008) defined these two groups of customers as follows: Good customers are those who follow a good business practice and keep long-term business relationships with a corporation. These kinds of customers are able to bring the profits to the corporation. However, other customers are not loyal to the corporation and often buy products and services from another supplier, lured by lower prices. These types of customers have a negative impact on the corporation as it is not profitable. When the corporation realises this point, it will be able to pay more attention to the former. In the following section, a brief literature regarding customers scoring and segmentation is presented.

This paper proceeds as follows. Section 2 reviews the state of the art. Section 3, introduces the proposed model. Numerical example and conclusion remarks are discussed in Sections 4 and 5, respectively.

2 Literature review

Importance of customer relationship management (CRM), customer value analysis and customer segmentation is frequently discussed in direct marketing literature (Fan and Zhang, 2009; Kim and Lee, 2007; Kim and Gupta, 2009; Tsekouropoulos et al., 2012; Nour, 2012). Many researchers and consultants have developed ‘scoring models’ based on regression-type models in order to predict customers’ future behaviour (e.g., Malthouse, 2003; Malthouse and Blattberg, 2005; Parr Rud, 2001). Gönül and Shi (1998) declare that the scenario of a typical customers’ scoring model begins with developing of a customer response model, e.g., estimating a multiple regression or a logit/probit equation where the left-hand side is a discrete dependent variable for purchase/non-purchase. The independent variables are typically composed of purchase history variables usually RFM (recency, frequency, and monetary value of the purchase amount) triplet. According to Gönül and Shi (1998), recency stands for elapsed time since the last purchase, frequency refers to the number of purchases in the past or proportion of purchases over a period of time, and monetary value is the amount spent so far or average amount per purchase so far. Weng et al. (2006) studied applying RFM for customers’ analysis. Colombo and Jiang (1999) focused on a stochastic RFM model to determine a ranking of marketing research customers considering their expected contribution or lifetime value. Aaker et al. (2001) used a linear statistical method such as logistic regression to model response based on test of random sample of customers from the complete list. To overcome the limitations of logistic regression, other approaches such as ridge regression (Malthouse, 1999), and hazard function models (Gönül et al., 2000) have been proposed. Fader et al. (2005) presented a model that connects the well-known RFM paradigm with customer lifetime value (CLV). The stochastic model used in their paper is based on the Pareto framework to capture the flow of transactions over time and a gamma-gamma submodel for spending per transaction. Deichmann et al. (2002) investigated the use of a multiple adaptive regression splines (MARS), together with logistic regression in the context of modelling direct response. They showed that the MARS model outperforms the logistic model in general. McCarty and Hastak (2007) applied logistic regression, as well as a decision tree algorithm and RFM to their two direct marketing datasets. Huang et al. (2009) applied K-means method, fuzzy C-means clustering method, and bagged clustering algorithm to the analysis of customer value for an outfitter in Taipei, Taiwan. Their study concludes that bagged clustering algorithm outperforms the other two methods.

Moutinho et al. (1994) predicted bank customers’ responses using artificial neural network (ANN). Kim et al. (2005) proposed an approach that uses ANNs guided by genetic algorithms (GAs) to the prediction of households interested in purchasing an insurance policy for recreational vehicles (RVs). The trained model is then used to rank the potential customers with regard to their purchase probability. For customers’ credit (CC) rating prediction, Huang et al. (2004) applied a learning method based on statistical learning theory, support vector machines (SVM) together with back

propagation neural networks (BNN). Holmbom et al. (2011) used self-organising map (SOM) and identified profitable and unprofitable customers. The gained knowledge from this process is used to develop marketing strategies. Aeron et al. (2010) reviewed applications of different statistical and data mining techniques for CLV. They used CLV as a metric to optimal resource allocation among customers.

Recently, Mahdiloo et al. (2011) proposed the use of DEA method for customer value analysis. To evaluate peer appraisal value of customers instead of their self appraisal, they used cross-efficiency evaluation. They also used analytic hierarchy process (AHP) to determine the lower and upper bounds of inputs and outputs weights, and imposing them to proposed cross-efficiency model, constrained the feasible region of the optimal weights.

The present paper also uses worst practice frontier (WPF) and best practice frontier (BPF) DEA to model direct mailing decisions. The BPF-DEA is used to pick out good customers for direct mailing. The WPF-DEA is used to identify bad customers and exclude them from mailing list. The BPF-DEA models evaluate each customer (DMU) with a set of most favourable weights of performance indices. As Liu and Chen (2009) address, the efficient DMUs obtained from these kinds of models construct an efficient (best practice) frontier. Therefore, BPF-DEA can be used to identify good performers in the most favourable scenario. The WPF-DEA model is formulated for identifying the bad performers in the worst-case scenario. While BPF-DEA establishes a best-practice frontier based on the best observed performance and evaluates the efficiency of each DMU relative to this frontier, WPF-DEA establishes a worst-practice frontier based on the worst observed performance, and the efficiency score of a DMU that does not lie on the frontier is evaluated relative to a linear combination of the worst efficient DMUs.

The concept of WPF-DEA is introduced in Paradi et al. (2004). They showed how worst practice DEA analysis, aimed at identifying the companies that are efficient at being bad, can be used to identify worst performers. Following Paradi et al. (2004), Shuai and Li (2005) proposed a hybrid approach that predicts the failure of firms based on the past business data, combining rough set approach and worst practice DEA. To identify bad performers such as bankrupt firms in the most unfavourable (worst-case) scenario, Liu and Chen (2009) proposed the radial WPF-CCR model in which the 'worst efficient' DMUs construct a worst-practice frontier. In addition, to identify bad performers along with slack variables they formulated another model called WPF slacks-based measure (SBM). Azadi and Farzipoor Saen (2011) used the concept of chance-constrained programming to develop a WPF-CCR model and also its deterministic equivalent.

However, all the papers which discuss concept of WPF, suffer from some limitations. Since, in traditional WPF-DEA, all DMUs are free to choose which outputs and inputs to emphasise, it is common to have many DMUs that are relatively worst (WPF) efficient. In addition, since each DMU has its own set of weights, all of its weight might be put on a single output and input which cause an unrealistic weighting scheme among DMUs. To overcome these problems, the cross-efficiency method introduced by Sexton et al. (1986) and developed by Doyle and Green (1994) is a good alternative. Cross-efficiency is a powerful extension of DEA that not only provides a complete ranking among the best and worst performing DMUs but also eliminates unrealistic weighting schemes among all DMUs. Anderson et al. (2002) argue that, cross evaluation often offers two main advantages. Firstly, it usually creates a unique ordering among the DMUs. With cross evaluation, since each DMU is rated not only by its own weighting scheme, but also by the schemes of the others, the amalgamation of weighting schemes creates a unique

ordering in practice. Secondly, cross evaluation appears to eliminate unrealistic weighting schemes that might be used by the DMUs. According to Anderson et al. (2002), under a cross evaluation, once the DMU has chosen weighting scheme which has been applied to all DMUs, the efficiency value given to each DMU is set aside forming a cross-efficiency matrix. Once the matrix is filled, each DMU has not only its own self evaluation but also the peer evaluations it has received via the other DMUs in the sample. The average across self and peer evaluations represents a DMU's cross-efficiency value. A DMU which has a high cross-efficiency value has, therefore, passed a more rigorous test since it can not only make itself look good but is considered efficient by the majority of its peers. The above discussions made by Anderson et al. (2002) make it more reasonable and motivate us to model the cross-efficiency formulation of WPF-CCR developed by Liu and Chen (2009).

In summary, none of the abovementioned references consider WPF-DEA in the context of peer evaluation. A technique that can deal with WPF-DEA and BPF-DEA in the peer evaluation form is needed to better model such situation. To the best of knowledge of authors, there is no reference that discusses direct mailing decisions by WPF/BPF cross-efficiency evaluation. Authors believe that this paper has a significant contribution to an important and very much under-researched topic.

3 Proposed model

To evaluate customers for direct mailing, we use the pair of BPF-CCR cross-efficiency model and WPF-CCR cross-efficiency model.

3.1 BPF-CCR cross-efficiency model

Model (1) is the input-oriented CCR model which evaluates the relative efficiency of DMU under evaluation (DMU_d). Table 1 shows the used nomenclatures in this paper.

Table 1 Nomenclatures

DMU_d :	the decision making unit under evaluation
$j = 1, \dots, n$	collection of DMUs (customers)
$r = 1, \dots, k$	the set of outputs
$i = 1, \dots, m$	the set of inputs
y_{rd} :	r th output of DMU_d
y_{rj} :	r th output of DMU_j
x_{id} :	i th input of the DMU_d
x_{ij} :	i th input of DMU_j
μ_r :	the weight for r th output
ν_i :	the weight for i th input
E_{dj} :	shows the relative best practice efficiency of DMU_j with optimal weights for inputs and outputs of DMU_d
E_{dd} :	is the self evaluation best practice efficiency score of DMU_d
E'_{dj} :	shows the relative worst practice efficiency of DMU_j with optimal weights for inputs and outputs of DMU_d
E'_{dd} :	is the self evaluation worst practice efficiency score of DMU_d

$$\begin{aligned}
E_{dd} &= \max h_A = \sum_{r=1}^k \mu_r y_{rd} \\
\text{s.t.} \quad & \sum_{i=1}^m v_i x_{id} = 1, \\
& \sum_{r=1}^k \mu_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \leq 0, \quad j = 1, \dots, n \\
& v_i \geq 0, \quad i = 1, 2, \dots, m \\
& \mu_r \geq 0, \quad r = 1, 2, \dots, k.
\end{aligned} \tag{1}$$

For each DMU_{*d*}, in Model (1), we can obtain a set of optimal weights (multipliers) (μ_r^* , v_i^*). Using these set of weights, the cross-efficiency for any DMU_{*j*} ($j = 1, \dots, n$), is then calculated as below (Sexton et al., 1986):

$$E_{dj} = \frac{\sum_{r=1}^k \mu_r^* y_{rj}}{\sum_{i=1}^m v_i^* x_{ij}}, \quad d, j = 1, 2, \dots, n \tag{2}$$

where E_{dj} shows the relative efficiency of DMU_{*j*} with optimal weights for inputs and outputs of DMU_{*d*}. One could compute the average of the efficiencies in each column to get a measure of how the DMUs associates with the column are rated by the rest of the DMUs. Good operating practices more likely to be exhibited by relatively efficient DMUs offering high average efficiencies in their associated columns in the cross-efficiency matrix. Since Model (1) is run n times for n DMUs, each DMU gets n efficiency scores, which construct an $n \times n$ matrix, called cross-efficiency matrix. For DMU_{*j*} ($j = 1, \dots, n$), the average of all E_{dj} ($d = 1, \dots, n$), can be used as the efficiency measure and is referred to as its cross-efficiency score. The average is as below:

$$\bar{E}_j = \frac{1}{n} \sum_{d=1}^n E_{dj} \tag{3}$$

The non-uniqueness of the DEA optimal weights possibly reduces the usefulness of cross-efficiency. To overcome this problem, Doyle and Green (1994) suggested the use of aggressive and benevolent cross evaluation. The BPF cross-efficiency is aggressive/benevolent in the sense that it selects a set of weights which not only maximise the efficiency of DMU_{*d*}, but also minimise/maximise the efficiencies of all other DMUs in some sense. Model (4) shows the aggressive form of the BPF-CCR model.

$$\begin{aligned}
\text{Min } h_B &= \mu_r \sum_{j \neq d} y_{rj} \\
\text{s.t.} \quad & \sum_{r=1}^k \mu_r y_{rj} - \left(\sum_{i=1}^m v_i x_{ij} \right) \leq 0, \quad j = 1, 2, \dots, n \\
& v_i \sum_{j \neq d} x_{ij} = 1, \\
& \sum_{r=1}^k \mu_r y_{rd} - E_{dd}^* \left(\sum_{i=1}^m v_i x_{id} \right) = 0 \\
& v_i \geq 0, \quad i = 1, 2, \dots, m \\
& \mu_r \geq 0, \quad r = 1, 2, \dots, k.
\end{aligned} \tag{4}$$

where E_{dd} is the efficiency of DMU_d obtained by Model (1). Note that the benevolent formulation has the same set of constraints except that the objective function is maximised.

In situations where relative dominance among the DMUs is to be evaluated, the aggressive formulation is more appropriate than the benevolent formulation. The aggressive formulation aims to maximise the own efficiency and minimise that of other DMUs, so it is suitable to the scenario where one DMU prefers to discriminate against other DMUs. Otherwise, the benevolent formulation aims to maximise the efficiencies of its own and other DMUs, so it is not as discriminatory as the aggressive formulation (Wu et al., 2009).

3.2 WPF-CCR cross-efficiency model

Now to find those customers who should be excluded from the mailing list, the formulation of the WPF-CCR model given by Liu and Chen (2009) is presented as below.

$$\begin{aligned}
E_{dd}^* &= \min h_c = \sum_{r=1}^k \mu_r y_{rd} \\
\text{s.t.} \quad & \sum_{i=1}^m v_i x_{id} = 1, \\
& \sum_{r=1}^k \mu_r y_{rj} - \sum_{i=1}^m v_i x_{ij} \geq 0, \quad j = 1, \dots, n \\
& v_i \geq 0, \quad i = 1, 2, \dots, m \\
& \mu_r \geq 0, \quad r = 1, 2, \dots, k.
\end{aligned} \tag{5}$$

The (v^*, u^*) obtained as an optimal solution for (5) results in a set of most unfavourable weights for the DMU_d in the sense of minimising the ratio scale. Each DMU is assigned a set of most unfavourable weights with values that may vary from one DMU to another. The worst efficiency derived by Model (5) is not less than 1. The DMUs with efficiency score of 1 are considered efficient at being bad.

In order to create a unique ordering among the worst practice DMUs and to eliminate unrealistic weighting schemes in Model (5), we develop the cross-efficiency form of WPF-CCR. The WPF cross-efficiency is aggressive/benevolent in the sense that it selects a set of weights which not only minimise the efficiency of DMU_d , but also minimise/maximise the efficiencies of all other DMUs in some sense. Model (6) shows the benevolent form of WPF-CCR model.

$$\begin{aligned}
 \text{Max } h_B &= \mu_r \sum_{j \neq d} y_{rj} \\
 \text{s.t.} \quad & \sum_{r=1}^k \mu_r y_{rj} - \left(\sum_{i=1}^m v_i x_{ij} \right) \geq 0, \quad j \neq d, \\
 & v_i \sum_{j \neq d} x_{ij} = 1, \\
 & \sum_{r=1}^k \mu_r y_{rd} - E_{dd}^* \left(\sum_{i=1}^m v_i x_{id} \right) = 0 \\
 & v_i \geq 0, \quad i = 1, 2, \dots, m \\
 & \mu_r \geq 0, \quad r = 1, 2, \dots, k.
 \end{aligned} \tag{6}$$

where E_{dd}' is the WPF efficiency of DMU_d obtained by Model (5). Note that the aggressive formulation has the same set of constraints except that the objective function is minimised.

Now by using the optimal weights (μ_r^*, v_i^*) for each DMU_d in Model (6) the WPF cross-efficiency for any DMU_j ($j = 1, \dots, n$), is then calculated as below:

$$E'_{dj} = \frac{\sum_{r=1}^k \mu_r^* y_{rj}}{\sum_{i=1}^m v_i^* x_{ij}}, \quad d, j = 1, 2, \dots, n \tag{7}$$

Note that, since the aggressive formulation in WPF-CCR aims to minimise the own efficiency and minimise that of other DMUs, so it is not suitable to the scenario where one DMU prefers to discriminate against other DMUs. Otherwise, the benevolent formulation aims to minimise the efficiency of its own and maximise the efficiency of other DMUs, so it can discriminate the efficiencies furthest. In summary, in BPF-CCR the aggressive form and in WPF-CCR, the benevolent formulation of cross-efficiency is used.

However, one may argue that, we can easily use only the BPF-CCR cross-efficiency to recognise both the good and bad performers. In other words, we can easily call customers with high BPF-CCR cross-efficiency as good performers and those customers with low BPF-CCR cross-efficiency as bad performers. Here using a simple hypothetical numerical example, this question is answered. Table 2 shows 10 DMUs which are using two inputs to produce two outputs.

The efficiency results of BPF-CCR shows that the worst DMU is DMU₁₀ with the efficiency score of 0.1646. But the efficiency scores of WPF-CCR show that DMUs 2, 6 and 8 with the WPF efficiency of 1 are more efficient than DMU₁₀ at being bad. Cooper et al. (2000) pointed out that, the set of optimal weights for the DMU under evaluation in BPF model is actually the set of most favourable weights for the DMU under evaluation in the sense that it maximises the efficiency ratio scale. As Liu and Chen (2009) argue, the original DEA can be considered to identify good performers in the most favourable scenario. Therefore, BPF selects potentially distressed firms by measuring how inefficient they are at being good, while WPF picks out distressed firms based on how efficient they are at being bad. Consider DMU₉ and its weighting scheme in both the BPF and WPF scenarios. This DMU has the largest and smallest values for the x_1 and x_2 , respectively. The optimal weights of inputs for DMU₉ in BPF-CCR is $v_1^* = 0$ and $v_2^* = 1$. While in WPF-CCR, the weights of inputs are $v_1^* = 0.0714$ and $v_2^* = 0$. Since in BPF, the purpose is to maximise the efficiency of DMU₉, it completely disregards x_{19} (the biggest x_{1j}) to emphasise x_{29} (the smallest x_{2j}). While in WPF the purpose is to minimise the efficiency of DMU₉, it completely eliminates x_{29} to emphasise x_{19} . Therefore, both the BPF/WPF models which are regarded to maximise/minimise the efficiency of DMU under evaluation should be used along with each other. However, to avoid any DMU to eliminate some inputs or outputs from its self evaluation, the peer evaluation of both WPF and BPF models should be used.

Table 2 Dataset for hypothetical numerical example

DMU	y_1	y_2	x_1	x_2	BPF-CCR efficiency	WPF-CCR efficiency
1	4	5	1	3	1	3.5194
2	3	1	14	2	0.2201	1
3	5	2	5	5	0.4219	2.2837
4	7	3	6	9	0.3663	1.7855
5	8	7	7	7	0.4821	2.8372
6	2	9	8	8	0.2813	1
7	4	8	1	2	1	5.9070
8	5	1	12	11	0.1865	1
9	12	4	14	1	1	4
10	3	5	7	8	0.1646	1.0552

Similar to the maverick index in the cross-efficiency evaluation suggested by Doyle and Green (1994) and the false positive index (FPI) defined by Baker and Talluri (1997), we propose the following false negative index (FNI) for measuring the false negativeness of the DMUs.

$$\text{FPI} = \frac{E_{dd} - E_{jd}}{E_{jd}} \times 100 \quad (8)$$

$$\text{FNI} = \frac{E'_{dd} - E'_{jd}}{E'_{jd}} \times 100 \quad (9)$$

The higher FPI, the more false positive is DMU_d . As well, the more negative FNI, the more false negative is DMU_d . Figure 1 depicts the above mentioned discussions graphically.

Figure 1 Flow chart of the proposed model

4 Numerical example

In order to demonstrate the application of the proposed approach for customers scoring, the dataset for this study is partially taken from Mahdiloo et al. (2011). These customers work as the wholesalers of the company. Average of payment period (PP) and marketing expenses (ME) are considered as inputs. The outputs utilised in this study are CC (in terms of US dollar), customers' profitability (CP) (in terms of US dollar), payments on due date (PD), and recency value (R). PD is a qualitative criterion. Therefore for this qualitative variable each customer is rated on a 5-point scale, where the particular point on the scale is chosen through a consensus on the part of executives within the organisation. Also recency value is calculated as the average of elapsed days between customers' two purchases. Notice that, this value is considered as output. Gönül and Shi (1998) argue that it is better to save the mailing dollars for customers in the medium and

high recency ranges in order to keep top-of-the mind awareness and not lose them to competitors when they need to replace the product. For example, if a customer has recently made a purchase (for example, in the last 5 months) then the response probability is still high even without mail. However, if a customer has not bought in 15 months or longer then a catalogue is necessary to activate the customer. If a customer has not bought in 60 months a response is likely but it is still necessary to send mail in order to realise a purchase and bring down the recency to one. Table 3 depicts customers' attributes and the dataset for this example. Tables 4 and 5 show the matrices of BPF and WPF cross-efficiency, respectively.

Table 3 Related attributes for 18 customers

Customer (DMU)	Inputs		Outputs			
	PP	ME	CC	CP	PD	R
1	7.12	3,200	4,500,000	53,598	3	30
2	6.11	3,220	5,800,000	54,458	5	25
3	15	1,200	5,000,000	43,152	5	43
4	60.31	1,900	5,000,000	41,563	3	20.4
5	75	1,770	5,000,000	35,033	3	37.8
6	39.9	1,100	2,500,000	27,668	3	18
7	7.11	2,500	3,000,000	40,987	5	14
8	4.74	800	4,500,000	34,000	5	35
9	75.4	2,100	2,650,000	39,879	1	51
10	45.3	1,300	3,000,000	29,683	1	23.7
11	32.7	1,900	4,500,000	39,000	3	49.8
12	44.12	2,800	5,000,000	41,000	1	52
13	78	3,100	3,400,000	21,988	3	45
14	14.94	700	3,100,000	22,000	5	22.3
15	5.8	1,450	4,100,000	40,876	5	19
16	74.32	1,600	3,700,000	33,000	1	43
17	7.48	650	2,700,000	31,000	3	17
18	15	2,550	3,000,000	23,000	5	38.2

Customers' scores derived by different approaches are shown in Table 6. Using BPF-CCR, customers 2, 8, 14, and 17 are efficient and other customers are inefficient. Using WPF-CCR, customers 1, 4, 6, 7, 9, 10, 12, 13, and 16 are recognised as worst efficient customers. Both the WPF and BPF models are not able to distinguish between the worst and best customers with the efficiency score of 1. The BPF model has an objective function to maximise the efficiency score of each DMU. Therefore, it finds the most possible weights for the inputs and outputs weights. The WPF model tries to put the DMU under evaluation on the worst efficient frontier. It determines the worst possible weight for the factors and finds the worst possible efficiency score. Columns 3 and 5 in Table 6 show the averages of BPF cross-efficiency and WPF cross-efficiency scores, respectively. Therefore, using peer evaluation technique all the customers are completely ranked.

Table 4 Matrix of BPF cross-efficiency

Customer (DMU)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	0.8819	1.0000	0.4243*	0.1037	0.0717	0.1050	0.7085	1.0000	0.0814	0.0996	0.1798	0.1396	0.0440	0.2222	0.9215	0.0687	0.6016	0.2170
2	0.7117	1.0000	0.3569	0.0707	0.0510	0.0835	0.7325	1.0000	0.0420	0.0548	0.1251	0.0734	0.0379	0.2635	0.8966	0.0364	0.4751	0.2669
3	0.3521	0.3465	0.8398	0.4519	0.4709	0.5410	0.3256	1.0000	0.4721	0.5091	0.5101	0.3632	0.2054	0.7369	0.5784	0.5154	0.9998	0.2426
4	0.3480	0.3730	0.8124	0.4998	0.4774	0.5317	0.3305	1.0000	0.3756	0.4966	0.4631	0.3359	0.1759	0.7548	0.6119	0.4615	0.9993	0.2112
5	0.2500	0.3202	0.7407	0.4678	0.5022	0.4040	0.2133	1.0000	0.2243	0.4103	0.4211	0.3175	0.1950	0.7873	0.5027	0.4111	0.7385	0.2092
6	0.3163	0.3503	0.7889	0.4312	0.4037	0.5423	0.3648	1.0000	0.3287	0.4053	0.4096	0.2530	0.1631	0.8680	0.6278	0.3625	0.9999	0.2446
7	0.7118	1.0001	0.3569	0.0707	0.0510	0.0835	0.7325	1.0000	0.0420	0.0548	0.1251	0.0734	0.0379	0.2635	0.8967	0.0364	0.4751	0.2669
8	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
9	0.2143	0.1775	0.8190	0.2454	0.4881	0.3740	0.1280	1.0000	0.5551	0.4167	0.5991	0.4245	0.3318	0.7282	0.2995	0.6143	0.5978	0.3424
10	0.3522	0.3466	0.8396	0.4520	0.4708	0.5411	0.3257	0.9998	0.4719	0.5092	0.5099	0.3630	0.2052	0.7367	0.5786	0.5152	1.0000	0.2424
11	0.2143	0.1775	0.8190	0.2454	0.4881	0.3740	0.1280	1.0000	0.5551	0.4167	0.5991	0.4245	0.3318	0.7282	0.2995	0.6143	0.5978	0.3424
12	0.2143	0.1775	0.8191	0.2454	0.4882	0.3741	0.1280	1.0000	0.5551	0.4167	0.5991	0.4245	0.3318	0.7282	0.2995	0.6143	0.5978	0.3424
13	0.2143	0.1775	0.8191	0.2454	0.4881	0.3740	0.1280	1.0000	0.5551	0.4167	0.5991	0.4245	0.3318	0.7282	0.2995	0.6143	0.5978	0.3424
14	0.1312	0.2174	0.5833	0.2211	0.2373	0.3818	0.2800	0.8750	0.0667	0.1077	0.2211	0.0500	0.1355	1.0000	0.4828	0.0875	0.6462	0.2745
15	0.8819	1.0000	0.4267	0.1059	0.0722	0.1069	0.7151	1.0000	0.0815	0.1009	0.1797	0.1395	0.0432	0.2238	0.9313	0.0688	0.6117	0.2136
16	0.2143	0.1775	0.8191	0.2454	0.4881	0.3740	0.1280	1.0000	0.5551	0.4167	0.5991	0.4245	0.3318	0.7282	0.2995	0.6143	0.5978	0.3424
17	0.4288	0.4364	0.7397	0.3289	0.2591	0.3556	0.4137	1.0000	0.2698	0.3290	0.3873	0.2835	0.1176	0.5529	0.6925	0.2572	1.0000	0.2124
18	0.5683	0.5571	0.3872	0.0458	0.0678	0.0612	0.2721	1.0000	0.0905	0.0702	0.2046	0.1577	0.0778	0.2037	0.4487	0.0775	0.3088	0.3449

Notes: *0.4243 represents the cross-efficiency score of customer #3 in terms of optimal weights of customer #1

**italics numbers in the leading diagonal are the simple efficiencies.

Table 5 Matrix of WPF cross-efficiency

Customer (DMU)	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18
1	1.0000	1.3359	4.2037	1.4757	1.9898	2.4589	1.5390	5.8929	1.3137	1.2554	2.1143	1.0000	1.2320	5.9859	2.7958	1.5179	4.0977	1.9005
2	1.0000	1.0353	3.2270	1.2977	1.7488	1.8297	1.0000	4.1027	1.6552	1.5247	1.9680	1.2675	1.0000	3.4395	1.8791	1.8387	3.1533	1.2374
3	1.0000	1.0353	3.2270	1.2977	1.7488	1.8297	1.0000	4.1027	1.6552	1.5247	1.9680	1.2675	1.0000	3.4395	1.8791	1.8387	3.1533	1.2374
4	12.4566	12.0965	8.4749	1.0000	1.4900	1.3337	5.8213	21.8298	1.9997	1.5467	4.5024	3.4844	1.7100	4.4128	9.6847	1.7105	6.7190	7.5289
5	11.0642	13.2779	6.3897	1.0000	1.0283	1.2354	8.4606	17.0825	1.1652	1.0919	2.8653	2.0332	1.0026	3.9388	11.3834	1.0000	6.6933	5.2202
6	9.6659	11.7232	5.9030	1.0000	1.0940	1.0000	5.3987	15.8372	1.0898	1.1149	2.8611	2.2618	1.0270	3.3100	9.0160	1.0696	5.3534	4.5746
7	1.6741	1.3864	6.3988	1.9173	3.8136	2.9221	1.0000	7.8125	4.3367	3.2555	4.6805	3.3163	2.5922	5.6888	2.3399	4.7991	4.6703	2.6751
8	1.1931	1.1248	3.2983	1.4875	1.8920	1.8988	1.0000	3.9638	1.9934	1.8821	2.1527	1.5298	1.0000	2.9079	1.8825	2.1884	3.3717	1.1084
9	31.7697	61.7021	25.1333	3.7506	3.0160	5.6692	53.0239	79.5358	1.0000	1.6645	6.9174	1.7090	2.9075	25.2343	65.0000	1.0145	30.2406	25.1333
10	8.5978	11.3278	7.4056	1.0000	1.1539	1.4250	8.5280	20.0794	1.1405	1.0000	3.1377	1.9465	1.2400	5.5192	12.1029	1.0000	7.1791	6.6371
11	1.0000	1.3644	3.7075	1.6711	1.9533	2.1787	1.3543	5.2036	1.0000	1.3385	1.8502	1.0000	1.0000	5.0499	2.6124	1.4163	3.7557	1.4785
12	2.6250	4.3478	11.6667	4.4211	4.7458	7.6364	5.6000	17.5000	1.3333	2.1538	4.4211	1.0000	2.7097	20.0000	9.6552	1.7500	12.9231	5.4902
13	26.7041	31.6176	10.2051	2.4447	1.6570	2.4599	20.4496	25.4454	1.8762	2.3244	4.2308	3.2965	1.0000	5.2237	25.0005	1.5751	14.7017	5.4393
14	1.3546	1.2277	3.5035	1.0000	1.3385	1.2874	1.0000	4.7984	1.5801	1.3629	2.2262	1.6181	1.0009	2.6815	1.9706	1.5385	3.1737	1.4805
15	1.0000	1.0353	3.2270	1.2977	1.7488	1.8297	1.0000	4.1027	1.6552	1.5247	1.9680	1.2675	1.0000	3.4395	1.8791	1.8387	3.1533	1.2374
16	30.3135	57.9779	23.4980	3.5474	2.8389	5.3073	49.5260	74.0576	1.0000	1.6291	6.5303	1.7130	2.7104	23.3701	60.7090	1.0000	28.3802	23.2871
17	1.0000	1.1040	3.3786	1.0000	1.3870	1.3838	1.0000	4.8091	1.2608	1.1363	1.9640	1.2582	1.0007	3.4949	1.9976	1.3533	2.9666	1.5234
18	1.1976	1.4952	3.6222	2.1789	2.4289	1.9466	1.0000	4.8477	1.2200	1.9914	2.1124	1.5818	1.0000	3.7929	2.3555	2.0743	3.5235	1.0673

Table 6 The average of cross-efficiency scores related to WPF and BPF

<i>Customer (DMU)</i>	<i>BPF-CCR</i>	<i>Average of BPF cross-efficiency</i>	<i>WPF-CCR</i>	<i>Average of WPF cross-efficiency</i>
1	0.8819	0.3892	1	8.0342
2	1	0.4353	1.0353	12.0119
3	0.8398	0.6329	3.2270	7.5817
4	0.4998	0.2487	1	1.8215
5	0.5022	0.3098	1.0283	2.0596
6	0.5423	0.3115	1	2.5351
7	0.7325	0.3363	1	9.3167
8	1	0.9930	3.9638	17.8335
9	0.5551	0.2957	1	1.5708
10	0.5092	0.2906	1	1.6290
11	0.5991	0.3740	1.8502	3.2484
12	0.4245	0.2596	1	1.8084
13	0.3318	0.1721	1	1.4518
14	1	0.5697	2.6815	7.2738
15	0.9313	0.5370	1.8791	12.4524
16	0.6143	0.3316	1	1.6957
17	1	0.6581	2.9666	8.1783
18	0.3449	0.2588	1.0673	5.4587

Table 7 False positiveness and negativeness of the customers

<i>Customer (DMU)</i>	<i>FPI</i>	<i>FNI</i>
1	126.5827	−87.5533
2	129.7389	−91.3813
3	32.6965	−57.4369
4	100.9646	−45.1006
5	62.1163	−50.0734
6	74.0753	−60.5543
7	117.7717	−89.2666
8	0.7004	−77.7735
9	87.7433	−36.3393
10	75.2086	−38.6116
11	60.1883	−43.0405
12	63.5391	−44.7025
13	92.8239	−31.1210
14	75.5402	−63.1352
15	73.4099	−84.9101
16	85.2240	−41.0289
17	51.9624	−63.7257
18	33.2699	−80.4485

Table 7 displays the results of FNI and FPI for all the customers. Customer #8 with the highest average of BPF cross-efficiency is the one with the lowest average of FPI value. On the other hand, the worst customer, customer #13, has the highest negative value of FNI. To indicate the importance of the developed WPF cross evaluation, consider customer #1 which is the worst efficient customer in the model proposed by Liu and Chen (2009) (Model 5). However, in the proposed model in this paper (WPF cross-efficiency), customer #1 with the -87.5533 of FNI, is assumed as one of the most negatively false scored customers.

The final ranking of customers, according to their BPF cross-efficiency and WPF cross-efficiency are depicted in Table 8.

Table 8 Ranking of customers

<i>Customer (DMU)</i>	<i>BPF cross-efficiency</i>	<i>WPF cross-efficiency</i>
1	7	13
2	6	16
3	3	12
4	17	6
5	12	7
6	11	8
7	9	15
8	1	18
9	13	2
10	14	3
11	8	9
12	15	5
13	18	1
14	4	11
15	5	17
16	10	4
17	2	14
18	16	10

Based on the ranking results, the direct mailing planners can allocate most of the marketing investments on those customers which are highly ranked by BPF cross-efficiency. As well, based on WPF cross-efficiency ranking, the planners can exclude 10% to 30% (proposed by Bauer, 1988) of worst efficient customers from mailing list.

5 Concluding remarks

As part of relationship marketing programmes, marketing executives are taking advantage of vast quantities of customer data newly available. Models commonly used in the direct marketing arena to predict response to mailings and other forms of direct

marketing promotions (including e-mail and targeted Internet) are increasingly being used to up-sell or cross-sell customers who contact companies through call centres (Ha et al., 2005).

In this paper, we used DEA as a multiple-criteria decision making tool to evaluate customers and to find good customers (who should be put on the top ranges of mailing list) and bad customers (who should be excluded from mailing list). We demonstrated that for direct mailing modelling, the BPF and WPF models should be used. Since, in traditional DEA models, free hand is given when deciding for each DMU which outputs and inputs to emphasise, many different avenues are present by which a DMU can appear efficient. Therefore, it is common to have many DMUs that are relatively efficient. In addition, since each DMU has its own set of weights, all of its weights might be put on a single output and input. While this is permissible, it may not be realistic. Therefore, to solve these limitations, the BPF-CCR cross-efficiency model is used to find good performers. As well, the WPF-CCR cross-efficiency is developed to find bad performers. In summary, the contributions of this paper are as follows:

- the proposed model does not demand weights from the decision maker
- the paper makes a sufficient contribution to the practice of operations research and it is the first study, which proposes advanced DEA model for customers' direct mailing modelling
- the WPF and BPF models are used along with each other and in a logical way
- using the developed cross-efficiency formulation of conventional WPF-CCR model not only provides a complete ranking among the bad performing DMUs, but also eliminates unrealistic weighting schemes among them.

The problem considered in this study is at initial stage of investigation and further researches can be done based on the results of this paper. Similar research can be repeated in the presence of imprecise data, stochastic data, and generally speaking, evaluating the customers direct mailing decisions under uncertainty. Another practical extension to the methodology includes the case that preferences of decision makers can be incorporated into the proposed model by restricting the feasible region.

Acknowledgements

The authors wish to thank the anonymous reviewer for the valuable suggestions and comments which improved the quality of this paper.

References

- Aaker, D.A., Kumar, V. and Day, G.S. (2001) *Marketing Research*, John Wiley & Sons, New York.
- Aeron, H., Kumar, A. and Janakiraman, M. (2010) 'Application of data mining techniques for customer lifetime value parameters: a review', *International Journal of Business Information Systems*, Vol. 6, No. 4, pp.514–529.
- Anderson, T. R., Hollingsworth, K. and Inman, L. (2002) 'The fixed weighting nature of a cross-evaluation model', *Journal of Productivity Analysis*, Vol. 17, No. 3, pp.249–255.

- Azadi, M. and Farzipoor Saen, R. (2011) 'Developing a WPF-CCR model for selecting suppliers in the presence of stochastic data', *OR Insight*, Vol. 24, No. 1, pp.31–48.
- Baker, P.C. and Talluri, S. (1997) 'A closer look at the use of data envelopment analysis for technology selection' *Computers & Industrial Engineering*, Vol. 32, No. 1, pp.101–108.
- Bauer, C.L. (1988) 'A direct mail customer purchase model', *Journal of Direct Marketing*, Vol. 2, No. 3, pp.16–24.
- Charnes, A., Cooper, W.W. and Rhodes, E. (1978) 'Measuring the efficiency of decision making units', *European Journal of Operational Research*, Vol. 2, No. 6, pp.429–444.
- Colombo, R. and Jiang, W. (1999) 'A stochastic RFM model', *Journal of Interactive Marketing*, Vol. 13, No. 3, pp.2–12.
- Cooper, W.W., Seiford, L.M. and Tone, K. (2000) *Data Envelopment Analysis: A Comprehensive Text With Models, Applications, References and DEA-solver Software*, Kluwer Academic Publishers, Boston.
- Cyr, D. (2008) 'Modeling web site design across cultures: relationships to trust, satisfaction, and e-loyalty', *Journal of Management Information Systems*, Vol. 24, No. 4, pp.47–72.
- Deichmann, J., Eshghi, A., Haughton, D., Sayek, S. and Teebagy, N. (2002) 'Application of multiple adaptive regression splines (MARS) in direct response modeling', *Journal of Interactive Marketing*, Vol. 16, No. 4, pp.15–27.
- Doyle, J. and Green, R. (1994) 'Efficiency and cross efficiency in DEA: derivations, meanings and the uses', *Journal of the Operational Research Society*, Vol. 45, No. 5, pp.567–578.
- Fader, P., Hardie, B. and Lee, K.L. (2005) 'RFM and CLV: using iso-value curves for customer base analysis', *Journal of Marketing Research*, Vol. 42, No. 4, pp.415–430.
- Fan, B. and Zhang, P. (2009) 'Spatially enabled customer segmentation using a data classification method with uncertain predicates', *Decision Support Systems*, Vol. 47, No. 4, pp.343–353.
- Gönül, F.F., Kim, B.D. and Shi, M. (2000) 'Mailing smarter to catalog customer', *Journal of Interactive Marketing*, Vol. 14, No. 2, pp.2–16.
- Gönül, F. and Shi, M. (1998) 'Optimal mailing of catalogs: a new methodology using estimable structural dynamic programming models', *Management Science*, Vol. 44, No. 9, pp.1249–1262.
- Ha, K., Cho, S. and Maclachlan, D. (2005) 'Response models based on bagging neural networks', *Journal of Interactive Marketing*, Vol. 19, No. 1, pp.17–30.
- Holmbom, A.H., Eklund, T. and Back, B. (2011) 'Customer portfolio analysis using the SOM', *International Journal of Business Information Systems*, Vol. 8, No. 4, pp.396–412.
- Huang, S.C., Chang, E.C. and Wu, H.H. (2009) 'A case study of applying data mining techniques in an outfitter's customer value analysis', *Expert System with Applications*, Vol. 36, No. 3, pp.5909–5915.
- Huanga, Z., Chena, H., Hsua, C. J., Chenb, W.H. and Wu. S. (2004) 'Credit rating analysis with support vector machines and neural networks: a market comparative study', *Decision Support Systems*, Vol. 37, No. 4, pp.543–558.
- Jonker, J.J., Piersma, N. and Van den Poel, D. (2004) 'Joint optimization of customer segmentation and marketing policy to maximize long-term profitability', *Expert Systems with Applications*, Vol. 27, No. 2, pp.159–168.
- Jonker, J.J., Piersma, N. and Potharst, R. (2006) 'A decision support system for direct mailing decisions', *Decision Support Systems*, Vol. 42, No. 2, pp.915–925.
- Ju-Fang, C. and Kun-Yuan, Y. (2008) 'Application of activity-based costing in customer profitability analysis', *Proceedings of the International Seminar on Business and Information Management*, pp.494–497.
- Kim, Y., Street, W.N., Russell, G.J. and Menczer, F. (2005) 'Customer targeting: a neural network approach guided by genetic algorithms', *Management Science*, Vol. 51, No. 2, pp.264–276.

- Kim, E. and Lee, B. (2007) 'An economic analysis of customer selection and leveraging strategies in a market where network externalities exist', *Decision Support Systems*, Vol. 44, No. 1, pp.124–134.
- Kim, D.J. (2008) 'Self-perception-based versus transference-based trust determinants in computer-mediated transactions: a cross-cultural comparison study', *Journal of Management Information Systems*, Vol. 24, No. 4, pp.13–45.
- Kim, H.W. and Gupta, S. (2009) 'A comparison of purchase decision calculus between potential and repeat customers of an online store', *Decision Support Systems*, Vol. 47, No. 4, pp.477–487.
- Kim, D.J., Ferrin, D.L. and Rao, H.R. (2009) 'Trust and satisfaction, two stepping stones for successful e-commerce relationships: a longitudinal exploration', *Information Systems Research*, Vol. 20, No. 2, pp.237–257.
- Kim, D.J. (2012) 'An investigation of the effect of online consumer trust on expectation, satisfaction, and post expectation', *Information Systems and e-Business Management*, Vol. 10, No. 2, pp.219–240.
- Liu, F.H.F. and Chen C.L. (2009) 'The worst-practice DEA model with slack-based measurement', *Computers & Industrial Engineering*, Vol. 57, No. 2, pp.496–505.
- Mahdiloos, M., Noorizadeh, A. and Farzipoor Saen, R. (2011) 'Developing a new data envelopment analysis model for customer value analysis', *Journal of Industrial and Management Optimization*, Vol. 7, No. 3, pp.531–558.
- McCarty, J.A and Hastak, M. (2007) 'Segmentation approaches in data-mining: a comparison of RFM, CHAID, and logistic regression', *Journal of Business Research*, Vol. 60, No. 6, pp.656–662.
- Malthouse, E.C. (1999) 'Ridge regression and direct marketing scoring models', *Journal of Interactive Marketing*, Vol. 13, No. 4, pp.10–23.
- Malthouse, E.C. (2003) 'Scoring models', in Dawn Iacobucci and Bobby Calder (Eds.): *Kellogg on Integrated Marketing*, pp.227–249, John Wiley & Sons, Hoboken, NJ.
- Malthouse, E.C. and Blattberg, R.C. (2005) 'Can we predict customer lifetime value?', *Journal of Interactive Marketing*, Vol. 19, No. 1, pp.2–16.
- Moutinho, L., Curry, B., Davies, F. and Rita, P. (1994) *Neural Network in Marketing*, Routledge, New York.
- Nour, M.A. (2012) 'An integrative framework for customer relationship management: towards a systems view', *International Journal of Business Information Systems*, Vol. 9, No. 1, pp.26–50.
- Paradi, J.C., Asmild, M. and Simak, P.C. (2004) 'Using DEA and worst practice DEA in credit risk evaluation', *Journal of Productivity Analysis*, Vol. 21, No. 2, pp.153–165.
- Parr Rud, O. (2001) *Data Mining Cookbook*, John Wiley & Sons, New York.
- Sexton, T.R., Silkman, R.H. and Hogan, A.J. (1986) 'Data envelopment analysis: critique and extensions', in Silkman, R.H. (Ed.): *Measuring Efficiency: An Assessment of Data Envelopment Analysis*, Chapter 4, pp.73–105, Jossey-Bass, San Francisco.
- Shuai, J.J. and Li, H.L. (2005) 'Using rough set and worst practice DEA in business failure prediction', *Lecture notes on Computer Science*, Vol. 3642, pp.503–510, Springer, Berlin, Heidelberg.
- Tsekouropoulos, G., Andreopoulou, Z., Seretakis, A., Koutroumanidis, T. and Manos, B. (2012) 'Optimising e-marketing criteria for customer communication in food and drink sector in Greece', *International Journal of Business Information Systems*, Vol. 9, No. 1, pp.1–25.
- Weng, S.S., Chiu, R.K., Wang, B.J. and Su, S.H. (2006) 'The study and verification of a mathematical modeling for customer purchasing behavior', *Journal of Computer Information Systems*, Vol. 47, No. 2, pp.46–57.

- Wong, W.P. and Wong, K.Y. (2008) 'A review on benchmarking of supply chain performance measures', *Benchmarking: An International Journal*, Vol. 15, No. 1, pp.25–51.
- Wu, J., Liang, L. and Yang, F. (2009) 'Achievement and benchmarking of countries at the summer Olympics using cross efficiency evaluation method', *European Journal of Operational Research*, Vol. 197, No. 2, pp.722–730.