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A combined goal programming and inverse DEA method for target setting in mergers

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ABSTRACT

This paper suggests a novel method to deal with target setting in mergers using goal programming (GP) and inverse data envelopment analysis (InvDEA). A conventional DEA model obtains the relative efficiency of decision making units (DMUs) given multiple inputs and multiple outputs for each DMU. However, the InvDEA aims to identify the quantities of inputs and outputs when efficiency score is given as a target. This study provides an effective method that allows decision makers to incorporate their preference in target setting of a merger for saving specific input(s) or producing certain output(s) as much as possible. The proposed method is validated through an illustrative application in banking industry.

1. Introduction

Restructuring decision making units (DMUs) in the form of mergers and acquisitions (M&As) is a useful strategic corporation for extending the production capabilities of merging units. Effective mergers may lead to saving money, boosting profits, upscaling, and freeing up abundant resources. With the aim of improving the chances for more successful M&As, Weber and Dholakia (2000) suggested a two-phase approach in order to identify, value, and prioritize opportunities for marketing synergy based on the proposed or consummated acquisition.

Bernad, Fuentelsaz, and Gómez (2010) assessed the effects of M&As on the long-run productivity of savings banks in Spain. The authors found out that due to ineffective mergers the productivity of only half of the mergers has been improved during 1986–2004. Asimakopoulos and Athanasoglou (2013) dealt with the impact of announced M&As on European banks' stock in a period of 15 years.

Data envelopment analysis (DEA) is a successful method which has been widely used for mergers performance evaluation in different areas (Emrouznejad & Yang, 2018; Gattoufi, Amin, & Emrouznejad, 2014; Liu, Lu, Lu, & Lin, 2013). Fried, Lovell, and Yaisawarng (1999) considered a sample of 6000 credit unions and used the DEA method in order to investigate the impact of mergers on credit union service provision. In other words, their study concerns the successful/unsuccessful mergers issues as well as potential benefits of mergers for the member of acquiring/acquired credit unions. Bogetoft and Wang (2005) utilized the DEA approach for estimating the potential gains from merging agricultural extension offices in Denmark with the aim of decomposing the potential gains into technical efficiency, size, and harmony indices. Johnes and Yu (2008) applied four DEA models on a real dataset involving 109 top Chinese higher education institutions to verify how efficient these institutes are in producing research. Lozano and Villa (2010) formulated a pair of DEA models to provide a pre-merger planning tool for minimizing post-merger input cost and maximizing post-merger profit. In contrast to the former model which assumes the input processes are known, in the latter model it is assumed that the output prices are known. It is also shown that the proposed models are apt for in-market horizontal mergers. Førsund, Grosskopf, and Margaritis (2011) provided a framework for optimal coalition formation to demonstrate the applicability of DEA in building and solving coalition models. Halkos and Tzeremes (2013) suggested a bootstrapped DEA procedure to pre-calculate and pre-evaluate the short-run operating efficiency gains of 45 possible bank M&As in the Greek banking from 2007 to 2001. Shi, Li, Emrouznejad, Xie, and Liang (2018) constructed a merger production possibility set to formulate a new two-stage cost efficiency model with the aim of estimating and decomposing the potential gains from M&As. A case study of top 20 most competitive Chinese City Commercial Banks was taken as an example to illustrate the potential application of their method.

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Based on their research, there are many benefits for the proposed merged banks which are obtained from technical and harmony efficiency. Their results also indicated that the scale effect works against the merger which points out that it is not favorable for a full-scale merger. Wanke, Maredza, and Gupta (2017) suggested a network DEA approach for evaluating the determinants of M&A in South African banks based on bank type and origin variables.

In contrast to the conventional DEA models which measure the relative efficiency scores of units, the InvDEA models determine the required inputs and outputs for a given efficiency target. The InvDEA approach is a sort of multiobjective problem where there are multiple objective functions and each objective function gives a goal to be achieved. Goal programming (GP), firstly used by Charnes, Cooper, and Ferguson (1955), is an approach for solving multiobjective problems with the aim of minimizing the unwanted deviations from the set of goals. There are two main algorithms for solving GP that are based on representing the multiple goals by a single objective function: weights (non-preemptive) and lexicographic (preemptive) methods. In the former method, a single objective function is presented as the sum of weighted functions representing the goals of the problem. The latter method starts by ordering the goals and then optimizing the model using one objective function at a time such that the optimum objective value with a higher priority is never degraded by an objective function with a lower priority. Sherali and Soyster (1983) proved that in the linear case the optimal solution of the preemptive problem leads to a set of optimal weights for the non-preemptive problem, such that any optimal solution to the non-preemptive problem is optimal to the preemptive problem and vice versa. Contreras (2011) suggested a DEA-based approach for the aggregation of preferences in GP. Bae and Lee (2012) integrated GP and imprecise DEA methods for providing a framework of risk evaluation and risk allocation in operations of Korean Army helicopters.

Recently, Amin and Al-Muharrami (2018), Amin, Emrouznejad, and Gattoufi (2017), Gattoufi et al. (2014) have studied the application of InvDEA in mergers. Gattoufi et al. (2014) utilized the InvDEA approach in M&A analysis for determining the required quantities of inputs and outputs from the merging entities. The input orientation InvDEA model proposed in Gattoufi et al. (2014) determines the quantities of inputs that can be saved by a merger whereas the output ordination model identifies additional outputs that can be produced for a given efficiency target. It should be noted that the InvDEA method in Gattoufi et al. (2014) fails to set the target for a merger when decision maker has priority in saving specific input(s) or wants to produce certain output(s).

More precisely, the InvDEA model in Gattoufi et al. (2014) neglects to include the nature of the inputs and their degree of complexity. For instance, human resources are inputs that are the least easy to manage and hence requiring more attention from the decision maker. It also fails to include the specific context of the application and its peripherals in the process of target setting, e.g., manufacturing, service, academia, etc. which may suggest managerial approaches that should be more accommodating. Under such practical considerations, a target setting should be flexible enough to cope with external and internal constraints.

To fill this gap, we extend a novel method which indeed is a combination of GP and InvDEA approaches. We take a case study of banking industry as an example to illustrate the potential application of the suggested method.

The rest of this paper is organized as follows. A literature review in merging using InvDEA is provided in Section 2. The next section deals with extending an InvDEA method for target setting using GP. In Section 4, we use a real data set involving 42 banks in Gulf Cooperation Council (GCC) (Persian Gulf) countries to illustrate the efficacy and effectiveness of the proposed method. Finally, concluding remarks and managerial implications are given in Section 5.

2. Merging using InvDEA

Assume there are n DMUs each uses m semi-positive inputs and produces s semi-positive outputs. Let us denote x_{ij} and y_{rj}, respectively, as the ith input and the rth output of the jth DMU ($i=1, \ldots, m;\ r=1, \ldots s;\ j=1, \ldots, n$). Consider a merger with two merging DMU_k and DMU_l for producing a new merged entity.

To the best of our knowledge, the first InvDEA model for target setting of mergers is suggested by Gattoufi et al. (2014). According to their input-oriented model, the merged entity preserves the entire outputs and keeps the minimum levels of inputs from each merging DMUs that allows it to reach a given efficiency target. Let α_{ik} and α_{il} be the levels of the ith input from the merging DMU_k and DMU_l, respectively, that is kept by the merged entity M. The input orientation InvDEA model proposed in Gattoufi et al. (2014) is as below:

$$
\begin{aligned}
&\min \sum_{i=1}^{m} (\alpha_{ik} + \alpha_{il}) \\
&\text{s.t.} \\
&\sum_{j \in F} x_{ij}\lambda_j + (\alpha_{ik} + \alpha_{il})\lambda_M - \bar{\theta}(\alpha_{ik} + \alpha_{il}) \le 0 \quad && i = 1, \ldots, m \\
&\sum_{j \in F} y_{rj}\lambda_j + (y_{rk} + y_{rl})\lambda_M \ge (y_{rk} + y_{rl}) && r = 1, \ldots, s \\
&\sum_{j \in F} \lambda_j + \lambda_M = 1 \\
&0 \le \alpha_{ij} \le x_{ij} && j = k, l; i = 1, \ldots, m \\
&\lambda_j \ge 0 && \forall j \in F \cup \{M\}
\end{aligned}
\tag{1}
$$

where λ_j is the intensity variable, $\bar{\theta}$ is the given efficiency target for the merged entity M, and F is the set of available peers in the post-merger evaluation process. In general, two possible cases for a merger may arise: (1) **Surviving:** the acquiring DMU continues to operate in the market under its former name; and (2) **Consolidating:** where both merging DMUs integrate into a new entity under a new name. Hence, based on the form of the merger, F may involve either DMU_k, DMU_l or neither of them.

Note that although model (1) is a nonlinear programming problem due to the terms $(\alpha_{ik}+\alpha_{il})\lambda_M$, an easy way to turn it to the following linear model is removing λ_M by relaxing M from the set of its peers:

$$
\begin{aligned}
&\min \sum_{i=1}^{m} (\alpha_{ik} + \alpha_{il}) \\
&\text{s.t.} \\
&\sum_{j \in F} x_{ij}\lambda_j + (\alpha_{ik} + \alpha_{il})\bar{\theta} \le 0 \quad && i = 1, \ldots, m \\
&\sum_{j \in F} y_{rj}\lambda_j \ge (y_{rk} + y_{rl}) && r = 1, \ldots, s \\
&\sum_{j \in F} \lambda_j = 1 \\
&0 \le \alpha_{ij} \le x_{ij} && j = k, l; i = 1, \ldots, m \\
&\lambda_j \ge 0 && \forall j \in F \cup \{M\}
\end{aligned}
\tag{2}
$$

Moreover, the following nonlinear model which is, in fact, the output orientation of InvDEA model is built by Gattoufi et al. (2014):

$$\begin{aligned}
&\max \sum_{r=1}^{s} \beta_r \\
&\text{s.t.} \\
&\sum_{j\in F} x_{ij}\lambda_j + (x_{ik}+x_{il})\lambda_M \le (x_{ik}+x_{il}) && i=1,\dots,m \\
&\sum_{j\in F} y_{rj}\lambda_j + (y_{rk}+y_{rl}+\beta_r)\lambda_M \\
&\qquad -(y_{rk}+y_{rl}+\beta_r)\bar{h} \ \ge 0 && r=1,\dots,s \\
&\sum_{j\in F}\lambda_j + \lambda_M = 1 \\
&\beta_r \ge 0 && r=1,\dots,s \\
&\lambda_j \ge 0 && \forall j\in F\cup\{M\} \qquad (3)
\end{aligned}$$

where the decision variable β_r corresponds to the rth output ($r=1, \dots, s$) of the merged entity. The model obtains the additional levels of outputs which should be produced by the merged entity in comparison to the outputs of the merging DMUs for reaching the given efficiency target $\bar{h}$. Analogous to the input orientation, the nonlinear model (3) can be turned to the following linear model:

$$\begin{aligned}
&\max \sum_{r=1}^{s} \beta_r \\
&\text{s.t.} \\
&\sum_{j\in F} x_{ij}\lambda_j \le (x_{ik}+x_{il}) && i=1,\dots,m \\
&\sum_{j\in F} y_{rj}\lambda_j - (y_{rk}+y_{rl}+\beta_r)\bar{h} \ \ge 0 && r=1,\dots,s \qquad (4) \\
&\sum_{j\in F}\lambda_j = 1 \\
&\beta_r \ge 0 && r=1,\dots,s \\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned}$$

Note that the linear InvDEA models (2) and (4) may suffer from the infeasibility issue when the merged entity M falls outside the pre-merger production possibility set (PPS). The following section proposes a combined method for target setting in mergers using goal programming and InvDEA approaches.

3. Target setting using goal programming

In this section, we extend the method of Gattoufi et al. (2014) by employing the well-known GP approach for both input and output orientations. The proposed method in this study would guide decision makers to save specific inputs or to produce specific output(s).

For the input orientation, we propose the following preemptive GP model:

$$\begin{aligned}
&\min P_1\left(d_1^+\right) \\
&\vdots \\
&\min P_p\left(d_p^+\right) \\
&\text{s.t.} \\
&\sum_{j\in F} x_{ij}\lambda_j + (\alpha_{ik}+\alpha_{il})\bar{\theta} \le 0 && i=1,\dots,m \\
&\sum_{j\in F} y_{rj}\lambda_j \ \ge (y_{rk}+y_{rl}) && r=1,\dots,s \\
&\sum_{j\in F}\lambda_j = 1 \\
&\alpha_{ij} + d_{ij}^- - d_{ij}^+ = g_{ij} && \forall i\in P,\ \ j\in\{k,l\} \\
&0 \le \alpha_{ij} \le x_{ij} && j\in\{k,l\},\ \ i=1,..,m \\
&d_{ij}^-, d_{ij}^+ \ge 0 && j\in\{k,l\},\ \ i=1,..,m \\
&\lambda_j \ge 0 && \forall j\in F \qquad (5)
\end{aligned}$$

where g_{ij} is the goal to the ith input of DMU$_j$($j \in \{k, l\}$), and d_{ij}^- and d_{ij}^+ are negative and positive deviational variables, respectively. Here, the set of prioritized inputs are indexed in P and therefore there are $p=|P|$ prioritized objective functions, where $P_e(d_e^+)$ indicates the eth important objective function, $e=1, \dots, p$. For instance, if we assume the second input of DMU$_k$ has the highest priority then the first objective function of the above model will be d_{2k}^+. The proposed InvDEA preemptive GP model (5), minimizes positive deviational variables because in input orientation the objective is to save the inputs as much as possible, or equivalently using the minimum levels of existing inputs by the merged entity. Nevertheless, the goals g_{ij} can be any value within the interval $[0, x_{ij}]$ for any $j \in \{k, l\}$, $i=1, \dots, m$.

It is worth nothing that the inverse DEA model for target setting of mergers can be solved via a single objective function obtained from the sum of weighted functions representing the goals of the problem or if the decion maker wants to prioritize the target setting, to cut (or save) the first important resource as much as possible then the second resource, and so on, in this case, the proposed GP InvDEA is the most appropprite approach.

Analogously, the output orientation model aims to produce some additional outputs while keeping the entire inputs of merging DMUs. Now, assume a scenario that the merged entity aims to give priority to specific outputs indexed in Q. We propose the following preemptive GP model for the output orientation.

$$\begin{aligned}
&\min P_1\left(d_{r_1}^-\right) \\
&\vdots \\
&\min P_q\left(d_{r_q}^-\right) \\
&\text{s.t.} \\
&\sum_{j\in F} x_{ij}\lambda_j \le (x_{ik}+x_{il}) && i=1,\dots,m \\
&\sum_{j\in F} y_{rj}\lambda_j - (y_{rk}+y_{rl}+\beta_r)\bar{h} \ge 0 && r=1,\dots,s \\
&\sum_{j\in F}\lambda_j = 1 \\
&\beta_r + d_r^- - d_r^+ = g_r && \forall r\in Q \\
&\beta_r \ge 0 && r=1,\dots,s \\
&\lambda_j \ge 0 && \forall j\in F \qquad (6)
\end{aligned}$$

As shown, there are q prioritized objective functions all minimizing the negative deviational variables. The goals are given by the decision maker and can be any nonnegative value. Nevertheless, the preemptive GP model (6) attempts to achieve the prioritized goals as much as possible. It considers the first objective function and minimizes the negative deviational variable $d_{i_1}^-$. This is followed by minimizing the second important function by keeping the first achieved goal and finally solving the last objective function by keeping the first $q-1$ achieved goals.

The following theorem verifies the feasibility of the suggested models.

Theorem 1. : *The input- and output-oriented InvDEA preemptive GP models (5) and (6) are feasible for any predetermined goals when the InvDEA models (2) and (4) are feasible.*

Proof. : An easy computation shows that any feasible solution in model (2) can be extended to a feasible solution to model (5) by calculating the corresponding negative and positive deviational variables. Similarly, any feasible solution to model (4) can be used to obtain a feasible solution to model (6). ■

It is easy to observe that similar to the InvDEA model in Gattoufi et al. (2014), the proposed InvDEA model in Amin and Al-Muharrami (2018) also fails to prioritize resources in target setting of mergers. Therefore, both the original inverse DEA model (Gattoufi et al., 2014) and its extension to deal with negative data (Amin & Al-Muharrami, 2018) have the same drawback and therefore the proposed GP InvDEA method in this paper can be applied for the mergers with negative data.

4. Application

In this section, we use the dataset introduced in Gattoufi et al. (2014). The dataset consists of active banks in the GCC countries, a political and economic alliance of six countries in the Persian Gulf, i.e., the United Arab Emirates, Saudi Arabia, Qatar, Oman, Kuwait, and Bahrain. There are 42 GCC banks each with two inputs, interest expenses (x_1) and non-interest expenses (x_2), along with two outputs, interest income (y_1) and non-interest income (y_2), as shown in Gattoufi et al. (2014) and replicated in Appendix A.

In an input orientation scenario, both x_1 and x_2 inputs can be the priority of the merger. The merged entity new bank would be bigger; therefore, usually bigger banks charge higher interest rates for loans and less interest rate for deposits. So, their interest expenses will be less. This is true in reality. Also, non-interest expenses will be less than the combination of the two merging banks by reducing redundant departments.

To illustrate the validity of the new method, let us start with the input orientation. Similar to Gattoufi et al. (2014), let us consider two merger cases. The first case is a merger between banks B_{02} and B_{03}. Table 3 in Gattoufi et al. (2014) shows different target settings for the inputs of the merged bank by considering different efficiency targets. Let us assume the merged bank is interested in being fully efficient. Moreover, assume the merged bank would like to give its preference to interest expenses of B_{02}, followed by interest expenses of B_{03}, then non-interest expenses of B_{02} and finally non-interest expenses of B_{03}. Therefore, the proposed input-oriented InvDEA GP model becomes as follows:

$$\begin{aligned}
&\min P_1\left(d_{12}^+\right)\\
&\min P_2\left(d_{13}^+\right)\\
&\min P_3\left(d_{22}^+\right)\\
&\min P_4\left(d_{23}^+\right)\\
&\text{s.t.}\\
&\sum_{j\in F} x_{ij}\lambda_j - (\alpha_{i2}+\alpha_{i3}) \le 0 && i=1,2\\
&\sum_{j\in F} y_{rj}\lambda_j \ \ge (y_{r2}+y_{r3}) && r=1,2\\
&\sum_{j\in F}\lambda_j = 1\\
&\alpha_{12}+d_{12}^- - d_{12}^+ = 65\\
&\alpha_{13}+d_{13}^- - d_{13}^+ = 100\\
&\alpha_{22}+d_{22}^- - d_{22}^+ = 200\\
&\alpha_{23}+d_{23}^- - d_{23}^+ = 55\\
&0\le \alpha_{ij}\le x_{ij} && i\in\{1,2\},\ \ j\in\{2,3\}\\
&d_{ij}^-, d_{ij}^+ \ge 0 && i\in\{1,2\},\ \ j\in\{2,3\}\\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned} \tag{7}$$

The optimal value of the first prioritized linear programming model is $d_{12}^+ = 1.06953$ which means the target for the interest expenses of B_{02} would be $\alpha_{12}^* = 66.06653$. From the definition, α_{12}^* is the amount of the interest expenses of B_{02} which will be kept by the merged bank after the merger. Now, we keep the optimal value of the first LP model and solve the second prioritized LP model as follows:

Table 1
Target setting by two methods; input orientation.

Method	α_{12}^*	α_{13}^*	α_{22}^*	α_{23}^*
GP Model (5)	66.06953	305.2	290	138.2408
InvDEA model (2)	371.27	319.98	0	108.26

$$\begin{aligned}
&\min d_{13}^+\\
&\text{s.t.}\\
&\sum_{j\in F} x_{ij}\lambda_j - (\alpha_{i2}+\alpha_{i3}) \le 0 && i=1,2\\
&\sum_{j\in F} y_{rj}\lambda_j \ \ge (y_{r2}+y_{r3}) && r=1,2\\
&\sum_{j\in F}\lambda_j = 1\\
&\alpha_{12}+d_{12}^- - d_{12}^+ = 65\\
&\alpha_{13}+d_{13}^- - d_{13}^+ = 100\\
&\alpha_{22}+d_{22}^- - d_{22}^+ = 200\\
&\alpha_{23}+d_{23}^- - d_{23}^+ = 55\\
&d_{12}^+ = 1.06953\\
&0\le \alpha_{ij}\le x_{ij} && i\in\{1,2\},\ \ j\in\{2,3\}\\
&d_{ij}^-, d_{ij}^+ \ge 0 && i\in\{1,2\},\ \ j\in\{2,3\}\\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned}$$

The optimal value of the above model is $d_{13}^+ = 205.2$ which means the target for the interest expenses of B_{02} would be $\alpha_{13}^* = 305.2$. Similar to the above model, we solve the remaining two prioritized linear programming problems and obtain the following target setting shown in Table 1.

Table 1 presents the target settings obtained by the GP model (5) proposed in this paper and the InvDEA model (2) in Gattoufi et al. (2014).

As shown in Table 1, the target setting for the interest expenses of B_{02} by the InvDEA model (2) is 371.27 which means a save of $481.239 - 371.27 = 109.969$ million dollars meanwhile the GP model (5) proposed in this paper suggests that this input can be 66.06953. This means that our method significantly reduces the interest expenses, i.e. $481.239 - 66.06953 = 415.17307$ million dollars. Therefore, the proposed method in this paper can save more than 63% of the interest expenses of B_{02}.

It is not realistic to assume that the two inputs in the above application are equal important. In the banking sector, the interest expenses are usually less in value and it is less controllable comparing to the non-interest expenses.

The target seeting for the other efficiency values in Table 1 can be interpreted similarly.

Now, we illustrate the usefulness of GP in the output orientation scenario.

We consider the same merger presented in Gattoufi et al. (2014) for the output orientation scenario. A merger between merging banks B_{02} and B_{03} aiming to generate an efficient merged entity. The decision maker would like to use the post-merger synergy for producing additional outputs. The merged bank would like to reduce the interest expenses as the first priority and then the non-interest expenses. This is shown in the following GP model.

$$\begin{aligned}
&\min P_1\left(d_1^-\right)\\
&\min P_2\left(d_2^-\right)
\end{aligned}$$

$$\begin{aligned}
&\text{s.t.}\\
&\sum_{j\in F} x_{ij}\lambda_j \le (x_{ik}+x_{il}) && i=1,2\\
&\sum_{j\in F} y_{rj}\lambda_j - (y_{rk}+y_{rl}+\beta_r) \ge 0 && r=1,2\\
&\sum_{j\in F} \lambda_j = 1\\
&\beta_1 + d_1^- - d_1^+ = g_1 = 1000\\
&\beta_2 + d_2^- - d_2^+ = g_2 = 4000\\
&\beta_r \ge 0 && r=1,2\\
&d_i^-, d_i^+ \ge 0 && i=1,2\\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned}$$

where $g_1 = 1000$ and $g_2 = 4000$ present, respectively, additional interest and non-interest expenses that is going to be produced after the merger. Nevertheless, an upper bound to these goals can be achieved by utilizing the following linear programming models, for $r = 1,\ 2$, if the decision maker has no idea about the goals.

$$\begin{aligned}
&\max \beta_r\\
&\text{s.t.}\\
&\sum_{j\in F} x_{ij}\lambda_j \le (x_{ik}+x_{il}) && i=1,2\\
&\sum_{j\in F} y_{rj}\lambda_j - (y_{rk}+y_{rl}+\beta_r) \ge 0 && r=1,2\\
&\sum_{j\in F} \lambda_j = 1\\
&\beta_r \ge 0 && r=1,2\\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned}$$

According to the priority, the first linear programming model for the output-oriented GP becomes as follows:

$$\begin{aligned}
&\min d_1^-\\
&\text{s.t.}\\
&\sum_{j\in F} x_{ij}\lambda_j \le (x_{ik}+x_{il}) && i=1,2\\
&\sum_{j\in F} y_{rj}\lambda_j - (y_{rk}+y_{rl}+\beta_r) \ge 0 && r=1,2\\
&\sum_{j\in F} \lambda_j = 1\\
&\beta_1 + d_1^- - d_1^+ = 1000\\
&\beta_2 + d_2^- - d_2^+ = 4000\\
&\beta_r \ge 0 && r=1,2\\
&d_i^-, d_i^+ \ge 0 && i=1,2\\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned}$$

The optimal value of the above model is $d_1^- = 363.4271$ and therefore an achievable additional interest income would be $\beta_1^* = 636.5729$. We keep this level and try to achieve the second goal as much as possible using the following linear programming model:

$$\begin{aligned}
&\min d_2^-\\
&\text{s.t.}\\
&\sum_{j\in F} x_{ij}\lambda_j \le (x_{ik}+x_{il}) && i=1,2\\
&\sum_{j\in F} y_{rj}\lambda_j - (y_{rk}+y_{rl}+\beta_r) \ge 0 && r=1,2\\
&\sum_{j\in F} \lambda_j = 1\\
&\beta_1 + d_1^- - d_1^+ = 1000\\
&\beta_2 + d_2^- - d_2^+ = 4000\\
&d_1^- = 363.4271\\
&\beta_r \ge 0 && r=1,2\\
&d_i^-, d_i^+ \ge 0 && i=1,2\\
&\lambda_j \ge 0 && \forall j\in F
\end{aligned}$$

The target setting obtained by the above model is shown in the following table.

Table 2
Target setting by two methods; output orientation.

Method	β_1^*	β_2^*
GP Model (6)	636.5729	478.8093
InvDEA model (4)	409.24	2009.48

Analogous to the input orientation, the assumption of considering the two outputs equally important is not realistic in banking sector. Interest income is the core main business of banks and it represents the highest source of revenue; therefore, interest income should be given the priority in the target set of a merger. In Table 2, the additional interest income that can be generated by the merger in the proposed GP is greater than that of the standard InvDEA Model (4). In general, the merged bank would be bigger in size and therefore will be charging a higher interest rate for loans and gives less interest rate for deposits. As the result, the interest spread will increase and this fits more with the result of the new proposed method.

The proposed GP method in this paper is able to generate more flexible target setting for mergers, allowing them to prioritize specific resources that are judged more valuable.

5. Concluding remarks and managerial implications

Unlike the standard DEA method, the InvDEA aims at opting the optimal level of required inputs and outputs to get a specific efficiency target. The InvDEA has been successfully implemented in M&A context. The problem of target setting in a merger has been addressed in this paper by considering the existing InvDEA method as a multiobjective problem and then utilizing the GP approach for solving the problem when there is a preference for saving specific resources. The preemptive approach is employed in order to solve the GP model, however, investigating the weight approach for various values of weights would be an interesting research direction. In this direction, decision makers can carry out sensitivity analysis to verify the stability for the importance weights of goals (see Hatami-Marbini and Toloo (2016)). As a result, a combined GP and InvDEA (GP-InvDEA) method is suggested for dealing with mergers target setting problem. The proposed method in this study supports decision makers to save specific inputs from specific merging unit as well as giving priority in producing specific outputs. To be more specific, the GP InvDEA approach, in fact, is a sort of decision support system that supports decision making process.

Although the proposed approach can be utilized in many different activities in many different contexts including supply chain management (Toloo, 2014), information systems (Sowlati, Paradi, & Suld, 2005; Toloo, Nalchigar, & Sohrabi, 2018), data mining (Amin, Gattoufi, & Rezaee Seraji, 2011; Toloo, Sohrabi, & Nalchigar, 2009), and metasearch aggregation (Amin & Emrouznejad, 2011). An illustrative case study of banking industry in the GCC countries is taken as an example to demonstrate the usefulness of our new GP InvDEA method.

It is shown that the target setting obtained by the proposed GP approach allows managers to prioritize more valuable and vital resources.

The approach proposed in this study provides a common framework for future research. Our approach can be developed to other variations of the DEA models such as the non-oriented and non-radial models. Especially, the GP InvDEA model can be used for determining potential candidates for an M&A. In addition, the proposed GP InvDEA method can be extended to solve inverse DEA models in resource allocation.

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Appendix A. GCC 42 banks data and efficiency scores

Bank	Interest expenses	Non-interest expenses	Interest incomes	Non-interest incomes	Technical efficiency scores under VRS
B01	3956.796	1894.426	9001.004	8701.497	1.000
B02	481.239	319.976	974.854	597.726	0.677
B03	305.200	138.600	479.800	252.200	0.640
B04	4710.680	3996.259	12,920.337	6060.768	0.893
B05	1.018	1.282	3.054	0.377	1.000
B06	954.437	1208.703	1991.004	7278.097	1.000
B07	3.965	5.082	13.359	3.003	0.829
B08	14.630	16.863	44.659	14.938	0.738
B09	11.771	6.579	22.952	15.134	0.727
B10	364.920	244.750	923.510	1942.935	1.000
B11	4897.442	2787.181	11,294.607	9363.232	0.939
B12	14.665	8.973	28.124	10.971	0.670
B13	6.077	14.249	26.994	10.207	0.970
B14	397.627	371.535	894.845	1902.878	0.813
B15	661.120	830.166	2325.128	1748.531	0.953
B16	12.125	7.346	33.573	19.530	0.960
B17	1222.026	1049.479	2959.509	2651.546	0.785
B18	931.172	838.346	2460.798	2765.485	0.866
B19	4070.351	2845.498	8377.368	7726.906	0.770
B20	3721.233	858.463	6953.701	2779.716	1.000
B21	16.137	7.080	40.771	22.126	1.000
B22	150.706	132.504	538.754	129.956	1.000
B23	3857.940	2894.374	7439.526	10,239.087	0.910
B24	7994.808	2286.908	14,156.194	11,261.820	1.000
B25	9.689	6.975	22.432	6.032	0.756
B26	3292.736	1953.592	7041.164	3323.973	0.826
B27	402.772	321.189	906.237	775.778	0.678
B28	32.835	21.536	97.679	26.551	0.980
B29	6.737	7.854	18.402	4.504	0.690
B30	531.395	922.040	1672.093	1185.165	0.815
B31	152.510	190.361	685.374	769.898	1.000
B32	1.925	4.581	9.163	5.274	1.000
B33	4.889	6.737	17.402	5.082	0.840
B34	3233.619	2527.414	7959.733	4684.616	0.840
B35	5169.710	5405.975	15,189.609	9830.137	0.871
B36	6802.566	5608.863	19,958.043	15,716.893	1.000
B37	3111.952	2126.013	6895.572	4869.316	0.811
B38	3600.983	1319.711	6547.924	5116.082	0.876
B39	7781.754	8486.425	27,514.033	14,335.679	1.000
B40	4488.666	4531.419	12,157.913	12,380.677	1.000
B41	3188.736	1106.154	5727.009	6194.460	1.000
B42	650.830	307.959	1265.646	441.359	0.780

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