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Selecting the Best Flexible Manufacturing System Supplier in the Presence of Dual-Role Factors: A Decision Model Based on the Worst Practice Frontier DEA and Common Set of Weights

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Abstract: Technology selection, as a multi criteria decision making problem, is known as a difficult task for managers and decision makers (DMs). Among the methods used in the history of technology selection, Data Envelopment Analysis (DEA), as a multiple criteria decision making tool, has been frequently used. In traditional use of DEA for technology selection, considering dual-role factors whose classification as input or output is in doubt, has been presented. However the models used in the literature which consider dual-role factors are based on the Best Practice Frontier (BPF) models. These models use the best possible weights for the inputs and outputs of the particular Decision Making Units (DMUs) to calculate the efficiency score of them. The present paper discusses the disadvantages of using BPF-DEA in the selection of technologies. In addition, the original Worst Practice Frontier (WPF) DEA is developed to consider dual-role factors. Moreover, to derive a complete ranking among all the DMUs and avoid unrealistic weighting scheme in the original WPF-DEA, a solution based on the Common Set of Weights (CSW) has been proposed. A numerical example demonstrates the application of the proposed method.

Key words: Technology selection · Data envelopment analysis · Worst practice frontier · Common set of weights · Dual-role factor.

INTRODUCTION

The selection of technologies is one of the most challenging decision making areas the management of a company encounters. It is difficult to clarify the right technology alternatives because the number of technologies is increasing and the technologies are becoming more and more complex. Technology selection can significantly influence the whole company and its core competencies, as well as people's working modes [1]. According to Farzipoor Saen [2] technology selection is a core technology management process, where the company has to make a choice between a number of distinct technology alternatives. Selecting the right technology is always a difficult task for decision makers. Technologies have varied strengths and weaknesses which require careful assessment by the purchasers. Technology selection models help decision maker choose between evolving technologies. The reason for a special focus on technology selection is due to the complexity of their evaluation which includes strategic and operational characteristics. Gregory [3] has proposed that management of technology is comprised of five generic processes: identification, selection, acquisition, exploitation and protection. Among these processes, technology selection is defined as involving the choice of technologies that should be supported and promoted. Some approaches have been proposed for technology selection in the past.

Chan, *et al*. [4] presented a technology selection algorithm to quantify both tangible and intangible benefits in fuzzy environment. Specially, it describes an application of the theory of fuzzy sets to hierarchical structural analysis and economic evaluations. A two phase procedure is proposed by Hsu, *et al*. [5] for technology selection. The first stage utilizes Fuzzy

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Delphi method to obtain the critical factors of the regenerative technologies by interviewing the foregoing experts. In the second stage, Fuzzy Analytic Hierarchy Process (FAHP) is applied to find the importance degree of each criterion as the measurable indices of the regenerative technologies. To help enterprises economically and effectively implement remanufacturing, Jiang, *et al*. [6] presented the usage of Analytic Hierarchy Process (AHP) for selecting remanufacturing technology. Hajeeh and Al-Othman [7] used AHP to select the most appropriate technology for seawater desalination. Lee and Kim [8] presented a methodology using Analytic Network Process (ANP) and zero one goal programming (ZOGP) for information system projects selection problems that have multiple criteria and interdependence property. Lee and Kim [9] described an integrated approach of interdependent information system project selection using Delphi method, ANP and goal programming. To select Computer-Integrated Manufacturing (CIM) technologies, IC [10] used Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method and Design of Experiment (DOE) to identify critical selection attributes and their interactions of all these cases by fitting a polynomial to the experimental data in a multiple linear regression analysis. Farzipoor Saen [11] proposed a new use of Artificial Neural Networks (ANNs) for technology selection. He showed how the model can be used in the presence of both continuous and categorical data.

Bernroider and Stix [12] proposed a new, conceptual approach, named profile distance method, to support information system selection problems. By combining the basic concept of the popular utility scoring and ranking technique with Data Envelopment Analysis (DEA), they recognized their appealing benefits while making up for a number of their limitations. Farzipoor Saen [13] proposed a model that ranks the most appropriate technologies in the conditions that both ordinal and cardinal factors are present. Sarkis and Talluri [14] introduced an application of DEA that considers both cardinal and ordinal data, for the evaluation of alternative flexible manufacturing systems (FMSs). Talluri and Yoon [15] introduced advanced manufacturing technology selection process. They proposed a combination of a cone-ratio DEA model and a new methodological extension in DEA, while allowing for the incorporation of preferences of decision makers. Farzipoor Saen [16] discussed the selection of technologies when some factors play the role of both inputs and outputs simultaneously. He proposed the use of DEA and considered "amount of personnel education hours by the FMS supplier" as a dual role factor.

However, the model used by Farzipoor Saen [16] is a type of Best Practice Frontier (BPF) DEA model which uses the set of most favorable weights for the DMU under evaluation in the sense that it maximizes the efficiency ratio scale. In this situation, DMUs are free to choose which outputs and inputs to emphasize and due to unrealistic weighting scheme of BPF–DEA, it is common to have many DMUs that are relatively efficient. In addition, since each DMU has its own set of weights, some factors might be disregarded in favor of others by putting all of weight on a single output and input. The present paper proposes the use of Worst Practice Frontier (WPF) DEA model and Common Set of Weights (CSW) simultaneously as a remedy for these two problems. As Liu and Chen [17] address, the BPF–DEA establishes a best-practice frontier based on the best observed performance and evaluates the efficiency of each DMU relative to this frontier, while the 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 purpose of WPF model is to find the worst efficient DMUs (the efficient DMUs at being bad) and it picks out distressed firms based on how efficient they are at being bad. The weighting mechanism of DEA in WPF is in a way that gives the highest possible weights to those inputs and outputs that DMU under evaluation has weak performance on them. By doing this, DMUs are evaluated in a more strict and pessimistic way. Since BPF-DEA and WPF-DEA use different weighting system for the evaluation of DMUs, the Decision Maker (DM) can face different rankings in two different scenarios. For instance, there might be a DMU in BPF-DEA which is selected as the best performer but it is known as a weak DMU in WPF-DEA. In this situation, the present paper proposes the Dms to rely on the ranking results of WPF-DEA, because WPF-DEA evaluates the DMUs in a stricter environment and with the worst possible weights. When a DMU is able to show itself as a good performer in a worst case scenario, the DM can easily accept this DMU as the best choice of selection.

The concept of WPF-DEA was first introduced by Paradi, *et al*. [18]. 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*. [18], Shuai and Li [19] 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 unfavorable (worst-case) scenario, Liu and Chen [17] 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 [20] used the concept of chance-constrained programming to develop a WPF-CCR model and also its deterministic equivalent. For customers scoring, Noorizadeh, *et al*. [21] considered payments delay of customers as an undesirable output and incorporated it into the best and worst practice DEA models. In particular, they proposed to use the BPF-DEA to recognize good customers. Also, the WPF-DEA is applied to find bad customers and save the marketing expenses for the best practice ones.

Another step which the present paper proposes for the improvement of Farzipoor Saen [16] is the use of CSW which was first introduced by Roll *et al*. [22] One of the ways to derive CSW is to run a DEA model, find the weights for different factors and take the average. Using the averaged weights for all DMUs, there will be a complete ranking among all DMUs and the used DEA model will not suffer from unrealistic weighting scheme any more. Roll and Golany [23] proposed three common-weights methods, including the one of maximizing the average efficiency of all DMUs. Ganley and Cubbin [24] suggested the potential use of the common weights for ranking DMUs. They considered the common weights for all the units, by maximizing the sum of efficiency ratios of all the units, in order to rank each unit. Doyle [25] averaged the weights derived by different DMUs as the common weights to calculate the final efficiencies of all DMUs. To evaluate the relative efficiency of a set of power plants, where the members of a given subset of the decision making units are experiencing similar circumstances, usage of a set of common weights across all members of that subset is proposed by Cook and Zhu [26]. Liu and Peng [27] proposed a method to find one common set of weights for the performance indices of only efficient DMUs. Then these efficient DMUs are ranked according to the efficiency score weighted by the common set of weights.

Therefore, the purpose of this paper is to propose a type of CSW-WPF-dual-role factor for selecting the best FMS supplier.

The approach presented in this paper has some distinctive contributions.

- This is the first time that FMS supplier is selected by a WPF-DEA model.
- For the first time, the concepts of CSW and dual-role factors are discussed together.
- For the first time a single model which is equipped with the characteristics of CSW, WPF and dual-role factor is developed for selecting the best FMS supplier.

This paper proceeds as follows. Section 2 introduces the proposed method which is used to selects FMS suppliers. A numerical example and concluding remarks are given in Sections 3 and 4 respectively.

Proposed Model: In this paper, DEA, as a nonparametric and multiple criteria decision making tool, is used to select the best FMS supplier. DEA was first introduced by Charnes, Cooper and Rhodes (CCR) [28] and it is a linear programming based methodology that uses multiple inputs and multiple outputs to calculate efficiency scores. In order to construct worst practice efficiency frontier, Model (1) is proposed by Liu and Chen [27] as WPF-CCR model. The purpose of this model is to evaluate the efficiency of DMUs using the worst possible weights. The nomenclatures used in this paper are presented in Table 1.

$$min\ h_A = \frac{\sum_{r=1}^{R} \mu_r y_{rd}}{\sum_{i=1}^{I} v_i x_{id}}$$

$$\frac{\sum_{r=1}^{R} \mu_r y_{rk}}{\sum_{i=1}^{I} v_i x_{ik}} \geq 1 \quad k = 1,\ldots,K \tag{1}$$

$v_i \geq 0, \quad i = 1,2,\ldots,I,$
$\mu_r \geq 0, \quad r = 1,2,\ldots,R.$

To see how bad a DMU is performing, the objective function should be minimized. Since the DMU is evaluated in the worst-case scenario, the outcome of this model can be considered as the ‘worst efficiency’. Therefore, in WPF-CCR, we call the units on the worst-practice frontier as the ‘worst efficient’ DMUs. Model (2) is the linear form of Model (1).

Table 1: The nomenclatures

DMU_d	:	The decision making unit under investigation
K	:	The set of DMUs (FMS suppliers)
$k = 1,\ldots,K$		Collection of DMUs
$I = 1,\ldots,R$		The set of outputs
$i = 1,\ldots,I$		The set of inputs
y_{rd}	:	rth output of the DMU_d
x_{id}	:	ith input of the DMU_d
μ_r	:	The weight for rth output
v_i	:	The weight for ith input
y_{rk}	:	The rth output of DMU_k
x_{ik}	:	The ith input of DMU_k
w_d	:	Level of dual-role factor of DMU_d
w_k	:	Level of dual-role factor of DMU_k
γ	:	The weight for dual-role factor when it is treated on the output side
β	:	The weight for dual-role factor when it is treated on the input side

$$
\begin{aligned}
min\ h_B &= \sum_{r=1}^{R} \mu_r y_{rd} \\
&s.t. \\
&\sum_{i=1}^{I} v_i x_{id} = 1, \\
&\sum_{r=1}^{R} \mu_r y_{rk} - \sum_{i=1}^{I} v_i x_{ik} \geq 0 \qquad k = 1,\ldots,K
\end{aligned} \tag{2}
$$

$v_i \geq 0, \quad i = 1,2,\ldots I,$
$\mu_r \geq 0, \quad r = 1,2,\ldots,R$

Now consider a situation where members k of a set of K DMUs are to be evaluated in terms of R outputs $Y_k = (y_{rk})^R_{r=1}$ and I inputs $X_k = (x_{ik})^I_{i=1}$. In addition, assume that a particular factor is held by each DMU in the amount w_k and serves as both an input and output factor. Model (3) is the WPF model which can consider dual-role factors. We call this model WPF-dual-role model (for more details on the development of dual-role factors in DEA, please see Cook *et al*. [29].

$$
\begin{aligned}
min\ h_C &= \sum_{r=1}^{R} \mu_r y_{rd} + \gamma w_d - \beta w_d \\
&s.t. \\
&\sum_{i=1}^{I} v_i x_{id} = 1, \\
&\sum_{r=1}^{R} \mu_r y_{rk} + \gamma w_k - (\sum_{i=1}^{I} v_i x_{ik} + \beta w_k) \geq 0 \quad k = 1,\ldots,K
\end{aligned}
$$

$v_i \geq 0, \quad i = 1,2,\ldots,I$
$\mu_r \geq 0, \quad r = 1,2,\ldots,R.$
$\gamma \geq 0,$
$\beta \geq 0.$

The $(v^*,\mu^*,\gamma^*,\beta^*)$ obtained as an optimal solution for (3) results in a set of most unfavorable weights for the DMU_d in the sense of minimizing the ratio scale. Each DMU is assigned a set of most unfavorable weights with values that may vary from one DMU to another. The worst efficiency derived by Model (3) is not less than 1. Outcome of model (3) is an efficiency score equal to one to WPF efficient DMUs and more than one to WPF inefficient DMUs.

Model (3) which ranks DMUs based on the worst possible weights, is more reliable than BPF models which rank DMUs based on the best possible weights. However, the DMUs in Model (3) are again completely free to choose their own optimal weights. This might allow some DMUs to show their performance unrealistically bad. To avoid this problem, we propose the simultaneous use of CSW method introduced by Roll *et al*. [22] and WPF-dual-role model. The CSW procedure consists the steps presented in Table 2.

The outcome of (8) is an efficiency score more than1. In this procedure, the DMUs are not allowed to reach a WPF efficiency score of 1 using their own unrealistic weighting schemes. Since the weights used by DMUs in WPF model are the worst possible weights to minimize the efficiency score of them, by applying the average of the weights, the efficiency score derived by (8) cannot be less than efficiency score of WPF model.

Numerical Example: In order to show how the proposed procedure is applicable in the FMS technology selection problem, we use the dataset presented in Farzipoor Saen [16]. The FMS selection problem addressed in Farzipoor Saen [16] involves the evaluation of relative efficiency of 15 FMS alternatives with respect to attributes including 'lead time reduction' and 'amount of personnel education hours by the FMS supplier (AH)', which are considered in some sense as outputs. The inputs utilized in this paper are 'capital and operating cost', 'required floor space' and 'AH' which are considered in some sense as input. AH constitutes both output and input. Note that these measures are not exhaustive by any means, but frequently used in FMS's performance evaluation. In an application of this methodology, decision-makers must carefully identify appropriate inputs and outputs to be used in the decision making process. Table 3 shows the inputs, outputs and dual-role factor amount for the 15 FMS suppliers.

As the first step, Model (3) is used to evaluate FMS suppliers. The results of this evaluation are shown in Table 4.

Table 2: The procedure of the proposed CSW

Step 1: Run Model (3).

Step 2: Find the set of optimal weights (multipliers) from the previous step.

Step 3: Find v_i^*, μ_r^* γ*and β* as follows:

$$v_i^* = \frac{\sum_{k=1}^{K} v_{ik}}{K}, \quad i = 1,2,...I, \tag{4}$$

$$\mu_r^* = \frac{\sum_{k=1}^{K} \mu_{rk}}{K}, \quad r = 1,2,...R, \tag{5}$$

$$\gamma^* = \frac{\sum_{k=1}^{K} \gamma k}{K}, \tag{6}$$

$$\beta^* = \frac{\sum_{k=1}^{K} \beta k}{K}. \tag{7}$$

Where v_i^*, μ_r^*, γ* and β* are the average of the optimal weights for x_{ik}, y_{rk}, w_k (when it is treated on the output side) and w_k (when it is treated on the input side) vectors, respectively.

Step 4: Run (8) and determine the WPF-CSW efficiency scores of DMUs.

$$E_k = \frac{\sum_{r=1}^{R} \mu_r^* \gamma_{rk} + y^* w_k - \beta^* w_k}{\sum_{i=1}^{I} v_i^* x_{ik}}, \quad k = 1,2,...,K. \tag{8}$$

Table 3: Related attributes for 15 FMS suppliers

	Inputs		Dual-role factor	Output
FMS supplier (DMU)	Required floor space (m2) x_{1k}	Capital and operating cost (million \$) x_{2k}	AH x_k	Lead time Reduction (%) y_{1k}
1	650	3.9	60	40
2	730	5.8	100	18
3	680	3.7	90	22
4	425	5.1	75	65
5	510	6.3	115	35
6	630	3.7	105	20
7	550	5.7	135	25
8	720	5.1	120	40
9	475	6.0	80	13
10	780	6.7	90	15
11	490	4.2	85	41
12	760	3.8	90	24
13	850	6.3	65	38
14	550	4.1	110	18
15	530	5.5	125	55

Table 4: The WPF efficiency score and ranking of FMS suppliers

FMS Supplier	WPF efficiency score	FMS suppliers ranking
1	1.2071	10
2	1.2065	11
3	1.2557	9
4	1.4253	7
5	1.5035	5
6	1.4863	6
7	1.7973	3
8	1.7376	4
9	1	13
10	1	13
11	1.8541	2
12	1.1513	12
13	1	13
14	1.3364	8
15	2.0321	1

Table 5: The weights of inputs, dual-role factor and output for the 15 FMS suppliers

FMS Supplier	v_1	v_2	β	γ	μ
1	0.0015	0	0	0.0201	0
2	0.0014	0	0	0.0095	0.0145
3	0.0015	0	0	0.0102	0.0155
4	0	0.1961	0	0.019	0
5	0	0.1587	0	0.0106	0.0082
6	0.0016	0	0	0.011	0.0167
7	0	0.1707	0	0.0115	0.0097
8	0.0014	0	0	0.0096	0.0147
9	0	0.1667	0	0.0111	0.0087
10	0	0.1444	0	0.0097	0.0082
11	0	0.2381	0	0.0158	0.0124
12	0.0013	0	0	0.0091	0.0139
13	0.0012	0	0	0.0081	0.0124
14	0.0018	0	0.1827	0	1.1909
15	0	0.1818	0	0.0121	0.0094
Average	0.0008	0.0838	0.0122	0.0112	0.089

Model (3) suggested FMS supplier 15 with the WPF efficiency score of 2.0321 as the best choice of selection (please note that, the more WPF efficiency score, the better supplier). The evaluation conducted in this step suffer from two aspects; (a) although Model (3) found the best FMS supplier, it was not able to derive a complete ranking among worst efficient FMS suppliers, i.e. suppliers 9, 10 and 13 whose WPF efficiency score is equal to 1 and (b) since Model (3) allows to DMUs to freely choose their own optimal weights, there might be some FMS suppliers which unrealistically shows themselves as WPF efficient. To overcome these two limitations, in this part, as the second step, we use common set of weights procedure presented in Table 2.

Table 6: The WPF efficiency scores and the ranking results based on the CSW

FMS supplier (DMU)	WPF-CSW Efficiency score	FMS suppliers ranking
1	4.1849	4
2	1.4178	13
3	2.2141	10
4	7.5091	1
5	3.2324	6
6	2.0815	11
7	2.2974	8
8	3.4672	5
9	1.2292	14
10	1.0602	15
11	4.8415	3
12	2.2367	9
13	2.7774	7
14	1.9235	12
15	5.4422	2

To calculate (8), we need to have the optimal amounts of v_i^*, μ_r^*, γ^* and β^* for all DMUs. Therefore, these amounts and their average are depicted in Table 5.

Using the average of v_i^*, μ_r^*, γ^* and β^* the new WPF efficiency score of FMS suppliers named WPF-CSW is calculated and shown in Table 6. Based on the results of this step of evaluation, FMS supplier 4 with the WPF-CSW efficiency score of 7.5091 is selected as the best supplier.

Concluding Remarks: Technology selection is a critical decision that has considerable affect on the profitability and growth of a company in the increasing competitive global environment. Since this selection requires the analysis of a large number of tangible and intangible factors in a decision support environment [4], the present paper proposed an effective multi criteria decision making method to help managers and decision makers. The method is based on the DEA technique and particularly WPF-DEA. We also discussed the presence of some factors which can play the role of both input and output simultaneously. These factors are called dual-role factors in DEA literature. The authors presented how these factors can be modeled in a WPF-DEA model. As the last contribution, the authors used the CSW method with the proposed WPF-dual role factor model to derive a complete and realistic ranking among WPF efficient FMS suppliers. 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. One of the contributions that other researchers can do is to develop the proposed

procedure to consider those factors which are not under control of managers. These factors are known as nondiscretionary factors. To show the importance of this contribution, consider the situation where decision makers consider these factors as discretionary. In this situation, the proposed procedure will unfairly decrease the efficiency of those DMUs which have poorly performed in these particular factors.

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