An Improved Common Weight DEA-Based Methodology for Manufacturing Technology Selection

Nazli Goker and E. Ertugrul Karsak

***Abstract*— Advanced manufacturing technologies have been widely used due to the competitive market forces and the rapid advances in computer and engineering sciences while their evaluation and selection require a complex decision making process with a large number of alternatives and performance attributes. This paper proposes an improved common weight data envelopment analysis based approach for manufacturing technology selection problem considering multiple inputs and multiple outputs. Comparative analyses of the results of a numerical example addressed in earlier studies are given in order to illustrate the robustness of the proposed decision methodology, which provides better weight dispersion and an improved discriminating power in ranking flexible manufacturing system (FMS) alternatives. The proposed approach does not require an arbitrary discriminating parameter, assures to identify the most efficient FMS via solving a single mixed integer linear programming model, and provides better dispersion for input and output weights.**

***Index Terms*— Common-weight DEA-based models, manufacturing technology selection, decision analysis, discriminating power, mathematical models.**

I. Introduction

DATA envelopment analysis (DEA) is a mathematical programming-based decision making tool, which deals with decision problems that require taking into consideration multiple inputs and multiple outputs for evaluating the relative efficiency of decision making units (DMUs) without a priori information about the importance of inputs and outputs [1-2]. Traditional DEA models provide performance assessment with information whether evaluated DMUs are efficient or not, however, they also possess several shortcomings. First, these models must be solved n times to compute the efficiency scores of all DMUs, where n is the number of DMUs to be evaluated. Second, they do not utilize common attribute weights for performance assessment of DMUs that allow the DMUs to identify input and output weights in their own favor to maximize their respective efficiency scores, which may yield results being far from practical. Moreover, conventional DEA models assume that all DMUs with the efficiency score of 1 are dichotomized as "efficient", whereas the DMUs with efficiency score less than 1 are named "inefficient". In other words, since all efficient DMUs obtain the efficiency score of 1, traditional DEA models are likely to fail to provide an adequate discriminating power [1].

In order to avoid subjective evaluation of DMUs to determine input and output weights as well as providing computational savings, common-weight DEA-based models can be considered. Thus, the discriminating power, which limits the selection of input and output weights in favor of respective DMUs, can be improved. A number of approaches have been proposed over the past decade for common-weight DEA-based models. Karsak and Ahiska [1] proposed a common-weight minimax efficiency approach to compute the efficiencies of DMUs with a single formulation, and included a discriminating parameter to the formulation to obtain a single efficient DMU. They used this model to solve a robot selection problem by considering a single input and multiple outputs. Amin and Emrouznejad [3] presented a formulation for obtaining the maximum value of non-Archimedean infinitesimal ϵ without requiring a linear programming model to be solved. They applied this model to the same robot selection problem addressed in [1]. Karsak and Ahiska [2] developed another common-weight minimax efficiency model to identify the best performing DMU for cases with multiple inputs and multiple outputs. Karsak and Ahiska [4] improved their earlier model by implementing a bisection search algorithm to determine values for discriminating parameter, k, in a robust manner for single input and multiple outputs problems involving both cardinal and ordinal data. Sun et al. [5] suggested two programming models and employed them for evaluating Asian lead frame firms and flexible manufacturing systems. They proposed two alternative models, namely the one that considers the virtual ideal unit as the reference object and another one that considers the virtual anti-ideal unit as the reference object, respectively.

Recently, several authors have used mixed integer linear programming models for common-weight efficiency assessment. Foroughi [6] employed mixed integer linear programming and proposed a minimax efficiency model by eliminating discriminating parameter, k, and applied it to solve the robot selection problem. Toloo [7] extended a linear programming model and reached the single best efficient DMU by offering a mixed integer linear programming model for problems with multiple inputs and multiple outputs. The author also proposed a special formulation for non-Archimedean infinitesimal ϵ. Toloo [8]

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developed another mixed integer linear programming model, however, for single input and multiple outputs case this time. The model assures to identify the single most efficient DMU. More recently, Toloo [9] suggested a mixed integer linear programming model without requiring a non-Archimedean infinitesimal ϵ. The author calculated super-efficiency scores by considering weight values greater than or equal to unity.

This work proposes a common weight DEA-based approach for manufacturing technology selection problem by improving the decision model developed by Karsak and Ahiska [2]. Rapid advances in computer and engineering sciences have enabled a high range of available manufacturing technologies to be implemented in the industry. In the competitive market, the firms are willing to incorporate advanced manufacturing technologies into their manufacturing processes in order to increase product quality, while obtaining labor savings, faster production and delivery, etc. [10]. A comprehensive analysis requires a high number of manufacturing technology alternatives and numerous performance indicators to be included in the decision framework due to the complexity of the decision making process for evaluating and selecting manufacturing technologies [1].

The proposed decision framework guarantees to identify the most efficient manufacturing technology through solving a single mixed integer linear programming model. Furthermore, it does not require an arbitrary k value to improve discriminating power and provides better distribution among input and output weights. In order to illustrate its robustness, the developed methodology is applied to a numerical example addressed in Karsak and Ahiska [2] and Sun et al [5].

The paper is organized as follows. Section 2 gives a concise treatment of DEA approach. Section 3 delineates the proposed improved model and its advantages. Subsequent section provides two comparative evaluations to illustrate the robustness of the proposed approach. Concluding remarks and future research directions are outlined in the last section.

II. DATA ENVELOPMENT ANALYSIS

Data envelopment analysis (DEA) is a linear programming based decision technique designed specifically to measure relative efficiency using multiple inputs and outputs without *a priori* information regarding which inputs and outputs are the most important in determining an efficiency score. DEA considers n decision making units (DMUs) to be evaluated, where each DMU consumes varying amounts of m different inputs to produce s different outputs.

The relative efficiency of a DMU is defined as the ratio of its total weighted output to its total weighted input. In mathematical programming terms, this ratio, which is to be maximized, forms the objective function for the particular DMU being evaluated. A set of normalizing constraints is required to reflect the condition that the output to input ratio of every DMU be less than or equal to unity. The mathematical programming problem is then represented as

$$\max E_{j_0} = \frac{\sum_r u_r y_{rj_0}}{\sum_i v_i x_{ij_0}}$$

subject to (1)

$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1, \quad \forall j,$$

$$u_r, v_i \ge \varepsilon, \quad \forall r, i.$$

where E_{j_0} is the efficiency score of the evaluated DMU (j_0), u_r is the weight assigned to output r, v_i is the weight assigned to input i, y_{rj} denotes amount of output r produced by the jth DMU, x_{ij} denotes amount of input i used by the jth DMU, and ε is an infinitesimal positive number. The weights in the objective function are chosen to maximize the value of the DMU's efficiency ratio subject to the "less-than-unity" constraints. These constraints ensure that the optimal weights for the DMU in the objective function do not denote an efficiency score greater than unity either for itself or for the other DMUs. A DMU attains a relative efficiency rating of 1 only when comparisons with other DMUs do not provide evidence of inefficiency in the use of any input or output.

The fractional program is not used for actual computation of the efficiency scores due to its intractable nonlinear and nonconvex properties [11]. Rather, the fractional program is transformed to an ordinary linear program given below that is computed separately for each DMU, generating n sets of optimal weights.

$$\max E_{j_0} = \sum_r u_r y_{rj_0}$$

subject to (2)

$$\sum_i v_i x_{ij_0} = 1$$

$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \le 0, \quad \forall j,$$

$$u_r, v_i \ge \varepsilon, \quad \forall r, i.$$

In order to eliminate the unrealistic weight dispersion and improve the poor discriminating power of DEA, a number of approaches have been proposed aiming at weight restriction, which enforces some frontiers or other constraints on weights [1]. Another widely used mathematical technique to improve the discriminating power of DEA is cross-efficiency analysis [12].

On the other hand, minimax and minsum efficiency measures do not give favorable consideration to the evaluated DMU unlike the conventional DEA model. Minimax efficiency minimizes maximum deviation from efficiency [13]. The minimax efficiency model can be represented as follows:

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$$\min M$$

subject to (3)

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad \forall j,$$
$$M - d_j \geq 0, \quad \forall j,$$
$$u_r, v_i, d_j \geq 0, \quad \forall r, i, j.$$

where d_j is the deviation from efficiency for DMU_j, (i.e. $d_j = 1 - E_j$ when E_j is the efficiency score of DMU_j), and M is the maximum deviation from efficiency.

Similarly, minsum efficiency is to minimize the total deviation from efficiency [13]. The resulting model is as

$$\min \sum_{j=1}^{n} d_j$$

subject to (4)

$$\sum_{i=1}^{m} v_i x_{ij_0} = 1,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad \forall j,$$
$$u_r, v_i, d_j \geq 0, \quad \forall r, i, j.$$

III. Proposed Decision Methodology

Over the past decade, common-weight DEA-based models have been proposed in order to avoid the limitations of traditional DEA models. These models provide a common evaluation for all DMUs and do not necessitate subjective assessment to determine input and output weights. Hence, the discriminating power is improved that restricts the selection of input and output weights in favor of respective DMUs [1]. This study introduces a common-weight DEA-based approach for problems with multiple inputs and multiple outputs by enhancing the model developed by Karsak and Ahiska [2]. The minimax efficiency model addressed in [2] for evaluating alternatives with multiple inputs and outputs is as follows:

$$\min M$$

subject to (5)

$$M - d_j \geq 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1,$$
$$u_r, v_i, d_j \geq 0, \quad \forall r, i, j.$$

For the case of obtaining more than one efficient DMU by solving Formulation (5), Karsak and Ahiska [2] suggested the following common-weight model for identifying the best DMU.

$$\min M - k \sum_{j \in EF} d_j$$

subject to (6)

$$M - d_j \geq 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1,$$
$$u_r, v_i, d_j \geq 0, \quad \forall r, i, j.$$

where k ϵ (0,1] is a discriminating parameter whose value is to be determined by the analyst, and EF is the set of minimax efficient DMUs that are obtained by using Formulation (5).

The methodology proposed by Karsak and Ahiska [2] provides an improved discriminating power and computation savings compared with conventional DEA models. However, this methodology also has several limitations. First, it requires a decision analyst to determine the value of k subjectively. Second, the final evaluation in their proposed approach may yield lower efficiency scores for some minimax efficient DMUs compared with other DMUs that are considered to be inefficient according to Formulation (5).

The first step of the proposed approach includes a non-Archimedean infinitesimal ϵ as a lower bound to input and output weights in Formulation (5). The resulting multiple inputs and multiple outputs model is as follows:

$$\min \theta$$

subject to (7)

$$\theta - d_j \geq 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1,$$
$$u_r, v_i \geq \varepsilon, \quad \forall r, i,$$
$$d_j \geq 0, \quad \forall j.$$

where θ refers to the maximum deviation from efficiency.

When there exist multiple efficient DMUs with respect to Formulation (7), the model proposed for obtaining a single efficient DMU is as follows:

$$\min \theta$$

subject to (8)

$$\theta - d_j \geq 0, \quad \forall j,$$
$$\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} + d_j = 0, \quad \forall j,$$

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$$\sum_{r=1}^{s} u_r + \sum_{i=1}^{m} v_i = 1,$$
$$d_j + z_j M \geq \varepsilon, \quad j \in EF,$$
$$\sum_{j \in EF} z_j = 1,$$
$$z_j \in \{0,1\}, \quad j \in EF,$$
$$u_r, v_i \geq \varepsilon, \quad \forall r, i,$$
$$d_j \geq 0, \quad \forall j.$$

where M is a sufficiently large positive number and z_j is a binary variable. Unlike the earlier model developed by Karsak and Ahiska [2], the proposed approach does not require a discriminating parameter k to find the most efficient DMU, guarantees to have one single efficient DMU and provides better dispersion for input and output weights. The resulting efficiency rankings are consistent with the discrimination between efficient and inefficient DMUs in Formulation (7).

IV. NUMERICAL ILLUSTRATION

This section illustrates the application of the proposed methodology through a numerical example given in Karsak and Ahiska [2] and Sun et al. [5]. Comparative results are analyzed in order to demonstrate the robustness of the proposed decision methodology.

The example problem evaluates 12 FMS alternatives considering two inputs that are "capital and operating cost" and "floor space needed", and four outputs, namely "qualitative improvement", "improvement in WIP", "improvement in # of tardy" and "improvement in yield". Input and output data regarding FMS alternatives are given in Table 1.

TABLE I
INPUT AND OUTPUT DATA FOR 12 FLEXIBLE MANUFACTURING SYSTEMS

	Data					
FMS (j)	Input 1	Input 2	Output1	Output2	Output3	Output4
1	17.02	5	42	45.3	14.2	30.1
2	16.46	4.5	39	40.1	13	29.8
3	11.76	6	26	39.6	13.8	24.5
4	10.52	4	22	36	11.3	25
5	9.5	3.8	21	34.2	12	20.4
6	4.79	5.4	10	20.1	5	16.5
7	6.21	6.2	14	26.5	7	19.7
8	11.12	6	25	35.9	9	24.7
9	3.67	8	4	17.4	0.1	18.1
10	8.93	7	16	34.3	6.5	20.6
11	17.74	7.1	43	45.6	14	31.1
12	14.85	6.2	27	38.7	13.8	25.4

Karsak and Ahiska [2] normalized the data and employed their minimax efficiency formulation. Thus, normalized data are used in order to provide a consistent comparative evaluation with Karsak and Ahiska [2].

The classical DEA model results in seven efficient FMSs which are FMS_1, FMS_2, FMS_4, FMS_5, FMS_6, FMS_7 and FMS_9. The minimax efficiency formulation developed by Karsak and Ahiska [2] yields three efficient FMSs which are FMS_1, FMS_5 and FMS_7. Subsequently, FMS_5 becomes the single efficient FMS after having solved three additional linear programs until increasing discriminating parameter k to 0.3 with a step size of 0.1. Besides, FMS_1 and FMS_7, which are identified as minimax efficient by Formulation (5) in Karsak and Ahiska [2], are ranked in the seventh and third places, eventually. Formulation (7) results in three efficient FMSs that are FMS_1, FMS_5 and FMS_7, and by solving Formulation (8), FMS_1 ranks first, however FMS_5 and FMS_7 rank second as listed in Table II. Hence, the proposed model results in consistent Formulation (8) rankings of the FMSs with minimax efficient FMSs in Formulation (7) unlike the earlier models developed by Karsak and Ahiska [2]. In addition, Formulation (8) does not necessitate an arbitrary k value to be determined for ranking FMSs.

TABLE II
RANKINGS WITH RESPECT TO EFFICIENCY SCORES OF FMSs FOR $\epsilon = 0.000001$

FMS (j)	DEA	Formulation (5) in [2]	Formulation (6) in [2]	Formulation (7)	Formulation (8)
1	1	1	7	1	1
2	1	7	8	7	7
3	9	4	2	4	4
4	1	8	5	8	8
5	1	1	1	1	2
6	1	5	4	5	5
7	1	1	3	1	2
8	10	9	6	9	9
9	1	10	10	10	10
10	11	11	9	11	11
11	8	6	10	6	6
12	12	12	10	12	12

Sun et al. [5] proposed two mathematical programming models for performance ranking of FMSs, and used input and output data given in Table 1. Initially, they developed the following linear programming model.

$$\min \sum_{j=1}^{n} d_j$$

subject to (9)

$$\sum_{i=1}^{m} v_i x_{ij} - d_j = \sum_{r=1}^{s} u_r y_{rj}, \quad \forall j,$$
$$\sum_{i=1}^{m} v_i x_{\min} = 1,$$
$$\sum_{r=1}^{s} u_r y_{\max} = 1,$$
$$u_r, v_i \geq \varepsilon, \quad \forall r, i,$$
$$d_j \geq 0, \quad \forall j.$$

Sun et al. [5] stated that the optimal weights calculated by Formulation (9) may not be unique, and different software may yield different optimal weights. In order to improve the usefulness of this formulation, they proposed the following non-linear programming model.

$$\max \sum_{i=1}^{m} v_i^2 + \sum_{r=1}^{s} u_r^2$$

subject to (10)

$$\sum_{j=1}^{n} \left(\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \right) = D^*,$$
$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0, \quad \forall j,$$
$$\sum_{i=1}^{m} v_i x_{\min} = 1,$$
$$\sum_{r=1}^{s} u_r y_{\max} = 1,$$
$$u_r, v_i \geq \varepsilon, \qquad \forall r, i.$$

where D^* is the optimal objective function value of Formulation (9). Alternatively, Sun et al. [5] employed the following linear programming model for manufacturing technology selection problem.

$$\min \sum_{j=1}^{n} \left(\sum_{i=1}^{m} v_i x_{\max} - \sum_{i=1}^{m} v_i x_{ij} \right) + \sum_{j=1}^{n} \left(\sum_{r=1}^{s} u_r y_{rj} - \sum_{r=1}^{s} u_r y_{\min} \right)$$

subject to (11)

$$\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \leq 0, \quad \forall j,$$
$$\sum_{i=1}^{m} v_i x_{\max} = 1,$$
$$\sum_{r=1}^{s} u_r y_{\min} = 1,$$
$$u_r, v_i \geq \varepsilon, \qquad \forall r, i.$$

Sun et al. [5] considered a single input $V_2 > \epsilon$ and two outputs (U_1, $U_4 > \epsilon$) in Formulation (10), and a single input $V_2 > \epsilon$ and a single output $U_4 > \epsilon$ to rank the alternatives in Formulation (11) in their paper, as they determined all the other weights equal to non-Archimedean infinitesimal ϵ. Alternatively, Formulation (8) proposed in this work provides better weight dispersion as shown in Table III. Due to these changes in weights, efficiency scores for assessing alternatives and the resulting rankings turn out to be different in the three approaches. Although Sun et al. [5] identified FMS_2 as the most efficient one, FMS_4 is placed in the top rank according to Formulation (8) proposed in this study. The comparison with respect to efficiency rankings is reported in Table IV. The non-Archimedean infinitesimal ϵ is considered as 0.000001, which is the same value used in Sun et al. [5].

TABLE III
COMPARATIVE EVALUATION OF INPUT AND OUTPUT WEIGHTS

Weight	Formulation (10) in [5]	Formulation (11) in [5]	Formulation (8)
V_1	0.000001	0.000001	0.437726
V_2	0.263157	0.124998	0.283321
U_1	0.000012	0.000001	0.123803
U_2	0.000001	0.000001	0.000001
U_3	0.000001	0.000001	0.063083
U_4	0.032135	0.060605	0.092065

TABLE IV
RANKINGS WITH RESPECT TO EFFICIENCY SCORES OF FMSs FOR $\epsilon = 0.000001$

FMS (j)	DEA	Formulation (10) & Formulation (11) in [5]	Formulation (7)	Formulation (8)
1	1	3	1	2
2	1	1	4	4
3	9	8	6	6
4	1	2	1	1
5	1	4	1	2
6	1	10	7	7
7	1	9	5	5
8	10	6	8	8
9	1	12	11	11
10	11	11	10	10
11	8	5	9	9
12	12	7	11	11

V. CONCLUDING REMARKS

In this work, an improved common-weight DEA-based approach, which can be applied in a straightforward manner for identifying the best performing manufacturing technology considering multiple inputs and multiple outputs, is developed.

The contributions of this research to manufacturing technology selection can be summarized as follows. The proposed model eliminates the need for a discriminating parameter k to determine the best performing manufacturing technology, assures a single efficient manufacturing technology by solving one mixed integer linear programming model, provides better dispersion for input and output weights, and results in consistent rankings with the initial differentiation between efficient and inefficient manufacturing technologies.

Numerical examples provided in earlier studies are employed to demonstrate the robustness of the proposed methodology and the comparative results are analyzed. Future research will focus on incorporating qualitative data into the proposed common-weight decision framework.

One shall note that the common weight decision making methodology proposed in here for evaluating manufacturing technologies is a general purpose decision approach. Thus, implementing the decision methodology presented here for real-world decision making problems in other disciplines may also be the focus of future research.

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