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Technology Selection Based on Decision Maker Preference Information

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ABSTRACT

Technology selection is an important part of management of technology. We use some basic principles from data envelopment analysis (DEA) in order to extract the necessary information for selection the optimal technology and ranking of a number of technologies. The traditional data envelopment analysis (DEA) model does not include a decision maker's (DM) preference structure while measuring relative efficiency, with no or minimal input from the DM. To incorporate the DM's preference information in DEA, various techniques have been proposed. An interesting method to incorporate preference information, without necessary prior judgment, is the use of an interactive decision making technique that encompasses both DEA and multi-objective linear programming (MOLP). This paper applies an interactive approach in order to obtain the DM's preference information in order to detect the most efficient technology. This approach is able to find the most efficient technology interactively by DM without solving the model n times (one linear programming (LP) for each DMU) and therefore allows the user to get faster results. At first one new MOLP model is introduced and then it is shown that solving this MOLP interactively is always feasible and capable to rank the most efficient one. To illustrate the model capability, the proposed methodology is applied to 27 robots borrowed from Khouja (1995).

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INTRODUCTION

The selection of technologies is one of the most challenging decision-making areas that the management of a company encounters. It is difficult because the number of technologies is increasing and the technologies are becoming more and more complex. However, efficient technologies could create significant competitive advantages for a company in a complex business environment. The aim of technology selection is to obtain new know-how, components, and systems which will help the company produce more competitive products and services and develop more effective processes, or create completely new solutions. New technologies also offer opportunities for both product differentiation and totally new businesses. Technology is both a great possibility and a threat to companies at the same time. A company can waste its competitive advantage by investing in poor alternatives at the wrong time or by investing too much in the right ones. Industrial enterprises are faced with complex and multi-criteria decision problems in technology assessment and selection. However, technology selection is a core technology management process, where the company has to make a choice between a numbers 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.

Khouja (1995) proposed a decision model for technology selection problems using a two-phase procedure. Baker and Talluri (1997) proposed an alternate methodology for technology selection using DEA. They addressed some of the shortcomings in the methodology suggested by Khouja (1995) and presented a more robust analysis based on cross-efficiencies in DEA. Archer and Ghasemzadeh (1999) suggested an integrated framework to provide decision support for project portfolio selection. Lee and Kim (2000) 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 (2001) described an integrated approach of interdependent information system project selection using Delphi method, ANP, and goal programming (GP). Kim and Emery (2000) addressed the quantitative methodology for determining possible implementable solutions to project selection problems. Mohamed and McCowan (2001)

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addressed the issue of combining both monetary and non-monetary aspects of an investment option. Badri *et al*. (2001) attempted to present a comprehensive model that includes all the suggested factors that appeared in separate studies. Their model is based on GP. Malladi and Min (2005) showed how an analytic hierarchy process (AHP) model could be utilized to select the optimal access technology for a rural community under a multiple number of criteria. Hajeeh and Al-Othman (2005) used AHP to select the most appropriate technology for seawater desalination. Shehabuddeen *et al*. (2006) focused on the experience of operational zing of a framework for technology selection. Talluri and Yoon (2000) introduced advanced manufacturing technology selection process. Talluri *et al*. (2000) proposed a framework, which is based on the combined application of DEA and non-parametric statistical procedures, for the selection of Flexible Manufacturing Systems (FMSs). Yurdakul (2004) introduced a combined model of the Analytical Hierarchy Process (AHP) and Goal Programming (GP), to consider multiple objectives and constraints simultaneously. Parkan and Wu (1999) demonstrated the use of and compare some of the current MADM and performance measurement methods through a robot selection problem borrowed from Khouja (1995). But, Wang (2006) offered comments on Parkan and Wu (1999) based on an examination of their proposed OCRA method. Sarkis and Talluri (1999) introduced an application of DEA that considers both cardinal and ordinal data, for the evaluation of alternative FMS. The DEA models proposed integrate both qualitative and quantitative data. The initial DEA model is based on the works of Cook *et al*. (1996).

The traditional data envelopment analysis (DEA) model does not include a decision maker's (DM) preference structure while measuring relative efficiency, with no or minimal input from the DM. To incorporate DM's preference information in DEA, various techniques have been proposed. An interesting method to incorporate preference information, without necessary prior judgment, is the use of an interactive decision making technique that encompasses both DEA and multi-objective linear programming (MOLP). In this paper, at first one new MOLP model is introduced and then we will use Zionts_Wallenius (Z_W) method to reflecting the DM's preferences in the process of assessing relative efficiency and performance parameter weights. To illustrate the model capability- it is shown that solving this MOLP interactively is always feasible and capable to rank the best technology- the proposed methodology is applied to 27 robots borrowed from Khouja (1995).

In order to do so, the remainder of this paper is structured as follows. In Section 2 we introduce some basic concepts such as DEA, MOLP and Zionts and Wallenius (1976) approach. In Section 3 we discuss the idea for technology selection interactively and in the end we bring one empirical illustration for discussed method in section 4. Finally, section 5 gives concluding remarks.

2. Conceptual background and application domain:

2.1. The basic DEA model:

Assume we have **n** decision making units (DMU) each consuming **m** inputs to produce **p** outputs. Let $X \in R_+^{m\times n}$ and $Y \in R_+^{p\times n}$ be the matrices, consisting of nonnegative elements, containing the observed input and output measures for the DMUs. We denote by $\mathbf{x_j}$ (the jth column of **X**) the vector of inputs consumed by DMU_j, and by $\mathbf{x_{ij}}$ the quantity of input **i** consumed by DMU_j. A similar notation is used for outputs.

In data envelopment analysis (DEA) context, the PPS is defined as a set T= {(y, x)| **y** can be produced from **x**} $=\{(y,x) \mid x \ge X\lambda, y \le Y\lambda, \lambda \in \Lambda\}$.

In the case of the CCR- model (Charnes *et al*. (1978)) $\Lambda = R_+^n$ and in the case of the BCC- model (Banker *et al*. (1984)) $\Lambda = \{\lambda \mid \sum_{i=1}^{n} \lambda_i = 1, \lambda \in R_+^n\}$.

In data envelopment analysis, we are interested in recognizing efficient DMUs, which are defined as a subset of points of the set **T** satisfying the efficiency condition defined below:

Definition 1:

A solution $(Y\lambda^*, X\lambda^*) = (y^*, x^*),\ \lambda^* \in \Lambda$, is efficient if there does not exist another $(y,x) \in T$ such that $y \ge y^*, x \le x^*$, and $(y,x) \ne (y^*,x^*)$.

Definition 2:

A point $(y^*,x^*) \in T$ is weakly efficient if there does not exist another $(y,x) \in T$ such that $y > y^*, x < x^*$.

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2.2. Multiple Objectives Linear Programming:

The MOLP problem can be written:

$$(MOLP)\ V_{\max} Cx \qquad s.t. \qquad x \in X = \{x \in R^n \mid Ax = b, x \geq 0\},$$

Where **C** and **A** are $k \times n$ and $m \times n$ matrices, respectively, $b \in R^m$ and $V_{\max}$ represents the vector of maximization. Since there is usually no point which simultaneously optimizes all the objectives, the concept of efficiency, below, is used.

Definition 3:

$\bar{x} \in X$ is efficient (not dominated) iff there does not exist another $x \in X$ such that $Cx \geq C\bar{x}, Cx \neq C\bar{x}$.

Definition 4:

$\bar{x} \in X$ is weakly efficient iff there does not exist another $x \in X$ such that $Cx > C\bar{x}$.

The aim of MOLP approaches is to identify the set of efficient points. For this purpose, there are many different methods in the literature. One of these methods is an interactive programming method proposed by Zionts and Wallenius (1978). Here, we briefly introduce it.

2.3. An interactive programming method for solving MOLP problems:

It is assumed that the utility function U is a linear function of the objective function variables $u_i = f_i(x), i = 1, 2, ..., p,$ but the precise weights in such a function are not known explicitly. The so called Zionts-Wallenius method, first, chooses an arbitrary set of positive multipliers or weights, $\gamma_i \geq \varepsilon$ satisfying $\sum_{i=1}^{p} \gamma_i = 1$, and generates a composite objective function or utility function using these multipliers. The composite objective function is then optimized to produce an extreme efficient solution x^* to the problem.

The continuation of the procedure is essentially the same as the simplex method except that here the DM chooses a nonbasic variable to enter the basis at each iteration. Due to the fact that the utility function being used is assumed not to be known explicitly, the set of all nonbasic variables may be divided into two subsets:

(1) Those nonbasic variables which, when introduced into the basis, lead to efficient adjacent extreme points in the space of the u variables.

(2) Those nonbasic variables which, when introduced into the basis, do not lead to efficient adjacent extreme points in the space of the u variables.

Denote the first subset of variables as efficient variables and the second subset as inefficient variables. In the process of finding a set of efficient variables from the set of nonbasic variables, firstly, w_{ij} values must be estimated based on implicit information around the optimal solution which is at hand. These w_{ij} values represent the decrease in objective function u_i due to some specified increase in x_j. For estimating w_{ij} values, the following model is solved for each nonbasic variable x_j:

$$\begin{aligned} &\max \quad xj \\ &\text{s.t. } x \in X = \left\{x \in \mathbb{R}_+^n \middle| a_i x = b_i,\ i=1,2,...,m\right\} \end{aligned} \tag{1}$$

Suppose that $\bar{x}$ is an optimal solution of the above model. Then we compute the value of the w_{ij} $i = 1, 2, ..., p,$ as follows:

$$w_{ij} = \frac{f_i(x^*) - f_i(\bar{x})}{\bar{x}_j} \tag{2}$$

After estimation of w_{ij} values, the following model is solved for each nonbasic variable x_l:

$$\begin{aligned} Min \quad & \sum_{i=1}^{p} w_{il}\gamma_i \\ s.t. \quad & \sum_{i=1}^{p} w_{il}\gamma_i \geq 0 \quad j \neq l, j \in N\,BV \\ & \sum_{i=1}^{p} \gamma_i = 1 \\ & \gamma_i \geq 0 \qquad i=1,2,..., p \end{aligned} \tag{3}$$

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Where NBV is the set of nonbasic variables.

Test 1 If the optimal value of model (3) is negative, the variable x_l is efficient,

Test 2 If the optimal value of model (3) is nonnegative, the variable x_l is not efficient,

Test 3 There will be at least one positive w_{ij} and at least one negative w_{ij} for any efficient variable x_j. If all values of w_{ij} for the variable x_j are positive, it indicates that x_j is not an efficient variable. Hence it is not necessary to solve model (3) for x_j.

Now for each variable of a subset of efficient variables, the DM is asked: Here is a trade. Are you willing to accept a decrease in objective function u_1 of w_{1j}, a decrease in objective function u_2 of w_{2j}, · · ·, and a decrease in objective function u_p of w_{pj}? Respond yes, no or indifferent to the trade.

If the responses are all" no" for all efficient variables, terminate the procedure and take γ_i's as the bast set of weights. Otherwise, using the DM's responses, we construct constraints to restrict the choice of the weights γ_i to be used in finding a new efficient solution.
For each yes response construct an inequality of the form

$$\sum_{i=1}^{p} w_{ij}\gamma_i \le -\varepsilon. \tag{4}$$

For each no response, construct an inequality of the form

$$\sum_{i=1}^{p} w_{ij}\gamma_i \ge \varepsilon. \tag{5}$$

For each response of indifference, construct an equality of the form

$$\sum_{i=1}^{p} w_{ij}\gamma_i = 0. \tag{6}$$

A feasible solution to the following set of constraints is found:
All previously constructed constraints of the form (4), (5), (6) and

$$\sum_{i=1}^{p} \gamma_i = 1$$
$$\gamma_i \ge \varepsilon \qquad i=1,2,..., p.$$

The process is then repeated by the resulting set of γ_i's and optimization of composite objective function to produce a new extreme efficient solution to the problem. In this manner, convergence to an overall optimal solution with respect to the DM's implicit utility function is assured and finally, overall optimal solution of γ_i's the weights of objective functions with respect to the DM's implicit utility function. Therefore optimal value of γ_i's can be used for construction of utility function U as a linear function of the objective function variables $u_i = f_i(x), i = 1, 2, ...,$ p.

3. The idea:

Starting with a set of feasible technologies, the decision maker would like to select the one that provides the best combination of the performance parameters. A procedure that identifies technologies which provide the best combination of specifications on the performance parameters and somehow incorporate the decision-maker's preferences into the analysis is now needed. Khouja (1995) suggested using DEA to identify the best

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technologies. For manufacturing technologies, he treated performance parameters for which higher values were preferred as outputs and performance parameters for which lower values were preferred as inputs. If only performance parameters for which higher values are considered, which is the case for pure benefit analysis and comparison, an input value of 1 can be assumed for every technology. The DMUs correspond to the technologies which have to be evaluated.

The traditional data envelopment analysis (DEA) model does not include a decision maker's (DM) preference structure while measuring relative efficiency, with no or minimal input from the DM. To incorporate DM's preference information in DEA, various techniques have been proposed. An interesting method to incorporate preference information, without necessary prior judgment, is the use of an interactive decision making technique that encompasses both DEA and multi-objective linear programming (MOLP). In this paper, at first one new MOLP model is introduced and then we will use Zionts_Wallenius (Z_W) method to reflecting the DM's preferences in the process of assessing relative efficiency and performance parameter weights.

We form PPS by Variable Return to Scale with these DMUs and then an MOLP problem is proposed that objective functions are same decision variables which decision variables are same inputs and outputs components. With this model, our purpose is to find a feasible solution of the input-output vectors of the PPS, which simultaneously maximizes all outputs and minimizes all inputs.
The MOLP problem is as follows:

$$\begin{aligned} &\min\ x \\ &\max\ y \\ \text{s.t.}\ & X\lambda \le x \\ & Y\lambda \ge y \\ & 1\lambda = 1 \\ & \lambda \ge 0 \end{aligned}$$

Or in the other form:

$$\begin{aligned} &\max\{-x_1, -x_2, ..., -x_m, y_1, y_2, ..., y_p\} \\ &s.t \qquad (x_1, ..., x_m, y_1, ..., y_p\} \in T_v \end{aligned} \tag{7}$$

Where T_v is Productive Possibility Set (PPS) by Variable Return to Scale (VRS).

After we solve this problem with Zionts and Wallenius (1976) approach, one of the results of this approach is efficient solution (x^*, y^*), because this solution is belong to the PPS and it has attained interactively with DM; We consider this solution as a most efficient DMU. The other result is γ^q as our known set of weights for objective functions. Science inputs and outputs components are same objective functions; we assume these weights as weights of inputs and outputs and we are able to obtaining the efficiency score of other DMUs. Since parameters and technologies are considered as inputs (or outputs) and DMUs, respectively, we assume most efficient DMU as the best technology and γ^q as the weight of performance parameters. Briefly, based on DEA and MOLP concepts, this paper investigates how the set of parameter weights and relative efficiency for technology selection problems is determined according to DM's preferences.

4. Numerical example:

For illustration purposes, the technology selection approach proposed in this paper is used for robot selection. The data set for this example is partially taken from Khouja (1995) and contains specifications on 27 industrial robots. The specifications are on repeatability in millimeters, speed in meters per second, payload capacity in kilograms, and cost in \$10,000. The data set is shown in Table1.

At present we have 27 DMUs correspond to the technologies which have to be evaluated. The inputs and outputs correspond to the performance parameters to be minimized and maximized respectively. Cost and Repeatability were used in some sense as inputs for the DEA model. Load capacity and velocity were considered as outputs. Hence, there are 27 DMUs that each DMU consumes varying amount of 2 different inputs to produce 2 different outputs. We consider the produced PPS by these DMUs. we form model (7) with this PPS and then we use Zionts_Wallenius (Z_W) method to reflecting the DM's preferences in the process of assessing relative efficiency and performance parameter weights.

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Table 1: Related attributes for 27 robots.

Robot No.	Cost ($10,000)	Repeatability (mm)	Load capacity (kg)	velocity (m/s)
1	7.20	0.150	60.0	1.35
2	4.80	0.050	6.0	1.10
3	5.00	1.270	45.0	1.27
4	7.20	0.025	1.5	0.66
5	9.60	0.250	50.0	0.05
6	1.07	0.100	1.0	0.30
7	1.76	0.100	5.0	1.00
8	3.20	0.100	15.0	1.00
9	6.72	0.200	10.0	1.10
10	2.40	0.050	6.0	1.00
11	2.88	0.500	30.0	0.90
12	6.90	1.000	13.6	0.15
13	3.20	0.050	10.0	1.20
14	4.00	0.050	30.0	1.20
15	3.68	1.000	47.0	1.00
16	6.88	1.000	80.0	1.00
17	8.00	2.000	15.0	2.00
18	6.30	0.200	10.0	1.00
19	0.94	0.050	10.0	0.30
20	0.16	2.000	1.5	0.80
21	2.81	2.000	27.0	1.70
22	3.80	0.050	0.9	1.00
23	1.25	0.100	2.5	0.50
24	1.37	0.100	2.5	0.50
25	3.63	0.200	10.0	1.00
26	5.30	1.270	70.0	1.25
27	4.00	2.030	205.0	0.75

Iteration NO.1:

We first arbitrarily choose a set of weights $\gamma^1 = (0.25, 0.25, 0.25, 0.25)$ for the composite objective function. The composite objective function is then optimized to produce an extreme efficient solution x^* to the problem. So optimal solution for this problem is:
$X^1 = (x_1^1,\ x_2^1, y_1^1, y_2^1)$=(4.00, 2.030, 205.0, 0.75) and $\lambda_{27} = 1$.

As for DM's judgments we continue the other steps of iteration one. In the end of this iteration we have γ^2 = (0.35, 0.17, 0.20, 0.28) .

Iteration NO. 2:

We form the composite objective function with γ^2= (0.35, 0.17, 0.20, 0.28), and then we solve this problem. Then the optimal solution is $X^2 = (x_1^2,\ x_2^2,\ \ y_1^2, y_2^2)$=(4.00, 2.030, 205.0, 0.75) and $\lambda_{27} = 1$.

In the end of this iteration the all of w^j are not attractive trade-off (i.e., response of no). Because the responses are all "no" for all efficient variables, we terminate the procedure, and we take γ^2 as the best set of weights for objective functions and $X^2 = (x^*, y^*)$ as the efficient solution for model (7).

Because this point is belong to the PPS and it has attained interactively by DM; we consider this point as a most efficient DMU. So at present we have
$DMU_{27} = (x^*,\ y^*)$=(4.00, 2.030, 205.0, 0.75) as a most efficient DMU and γ^2 that is common set of weights for inputs and outputs.

We consider γ^2 as $\gamma^2 = (\overset{*}{v},\ \overset{*}{u}) = (\overset{*}{v}_1, \overset{*}{v}_2, \overset{*}{u}_1, \overset{*}{u}_2)$=(0.35, 0.17, 0.20, 0.28) in which $\overset{*}{v}_i$ is weight for $\overset{*}{x}_i$ (i=1, 2) and $\overset{*}{u}_j$ is weight for $\overset{*}{y}_j$ (j=1, 2).

Since most efficient DMU is an input-output vector preferred to all other possible input-output vectors and as for concept of BCC-efficiency, we have

$$\frac{\sum_{r=1}^{p} \overset{*}{u}_r \overset{*}{y}_{r27} + u_O^*}{\sum_{i=1}^{m} \overset{*}{v}_i \overset{*}{x}_{i27}} = 1 \qquad (8)$$

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So we have $\sum_{r=1}^{p} \overset{*}{u}_r \overset{*}{y}_{r27} - \sum_{i=1}^{m} \overset{*}{v}_i \overset{*}{x}_{i27} + u_0^* = 0$.

Notice that $u^{*t} y - v^{*t} x + u_o^* = 0$ is one supporting hyperplan that passing through the most efficient DMU in which $(\overset{*}{v}, \overset{*}{u})$ is gradient vector for this hyperplan.

Now for obtaining the efficiency of each DMU, at first by use equation (8) u_0^* is obtained and then for example $DMU_o = (x_o, y_o)$ we compute:

$$\theta = \frac{\sum_{r=1}^{p} u_r^* y_{ro}^* + u_o^*}{\sum_{i=1}^{m} v_i^* x_{io}^*} \tag{9}$$

where $(\overset{*}{v}, \overset{*}{u})$ have obtained formerly. Solving (9) for each DMU gives the following efficiency scores and ranking of DMUs shown in Table 2.

Table 2: New BCC-I efficiency scores of DMUs.

Rank	DMU	BCC-I efficiency score
1	27	1
2	16	2.5825
3	26	2.8945
4	1	3.3940
5	15	4.2276
6	5	4.2807
7	3	4.4284
8	14	6.4510
9	11	6.4872
10	10	6.9415
11	17	11.9677
12	8	12.3786
13	12	15.2244
14	13	17.3773
15	25	17.8813
16	9	18.1329
17	18	18.2912
18	19	19.0990
1 9	10	27.2388
20	2	27.2901
21	7	31.3265
22	23	62.3741
23	24	62.4397
24	4	86.6112
25	20	76.0704
26	22	88.7030
27	6	140.3396

Conclusion:

This paper started with the motivation for determining the best technology and developed a new MOLP model. Using the proposed model, decision maker is able to find best technology by solving only one MOLP, so user can get faster results. The merits of the proposed formulation compared with DEA-based approaches that have previously been used for finding the best technology can be listed as follows. First, by solving this MOLP problem interactively, decision-maker’s preferences into the analysis are incorporated. Second, this formulation allows the computation of the efficiency scores of all technologies by a single formulation, i.e. all technologies are evaluated by a common set of weights. Third, this approach is capable for situation in which return to scale is variable. Finally to illustrate the model capability it is applied to 27 robots borrowed from Khouja (1995).

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