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Ranking Irrigation Planning Alternatives Using Data Envelopment Analysis

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Abstract. Application of Data Envelopment Analysis (DEA) as a Multicriterion Decision Making (MCDM) methodology is tested for Sri Ram Sagar Project, Andhra Pradesh, India to select the suitable irrigation planning alternative. Three different criterion functions of DEA, namely minimizing deviation variable D_j (Min D_j), minimizing maximum deviation (Minmax), and minimizing the sum of deviations $\sum D_j$ (Minsum) are applied for the same DEA constraint set. These criterion functions are evaluated under the framework of Multi Objective Linear Programming (MOLP). Highest efficiency rated irrigation planning alternative is chosen to be the best for each of the above criterion functions. The results are compared with those obtained by discrete MCDM methods, PROMETHEE and EXPROM. It is found that ranks obtained by DEA are reasonably close to those obtained by the above mentioned MCDM methods, PROMETHEE and EXPROM.

Key words: data envelopment analysis (DEA), irrigation planning, ranking methods

Introduction

Water resources are becoming scarce day by day due to ever increasing demands from various sectors such as irrigation, drinking water, municipal and industrial. Good number of conflicting objectives are existing in the irrigation sector itself, as plans for irrigation development differ appreciably, depending on the relative importance given to each objective. For example, a plan for achievement of a single objective, net benefits, often may make it unsuitable for socio-economic factors, such as labour employment, primary food needs of the community etc. For developing countries, the above objectives are equally important in addition to net benefits (Loucks *et al.*, 1981). This necessitated development and selection of compromise alternatives for sustainable irrigation planning and development.

Data Envelopment Analysis (DEA) is becoming prominent as an alternative methodology for Multicriterion Decision Making (MCDM) analysis due to the following advantages (1) Multiple inputs and multiple outputs can be used effectively, while ascertaining efficiency and a specific production function is not required (Diaz *et al.*, 2004) (2) Decision Maker doesn't need prior information about weights of the inputs and outputs (3) For each planning alternative (from now on termed as Decision Making Unit, DMU) efficiency is compared to that of an ideal operating unit, rather than to the average performance (4) Most of the MCDM techniques require numerous parameters, which are difficult to be determined precisely requiring extensive sensitivity analysis. On the other hand, main limitation is that standard formulation of DEA creates a separate linear program for each DMU. This will be computationally intensive when the number of DMUs is large.

Stewart (1996) has differentiated DEA from MCDM with reference to their goals. According to him, DEA is suitable for situations where the goal is to determine the productive efficiency of a system or decision making unit, by comparing how well these units convert inputs to outputs, while MCDM models are suitable for problems of ranking and selecting from a set of alternatives that have conflicting objectives. Li and Reeves (1999) discussed the drawbacks in DEA, namely, weak discriminating power between alternatives and unrealistic weight distribution. They discussed about causes and improvements in solution methodology to minimize those difficulties. Adler *et al.* (2002) extensively reviewed the ranking methods of DEA. Diaz *et al.* (2004) tested DEA for 35 irrigation districts of Andalusia, Southern Spain for three inputs, namely irrigated surface area in hectares, labour in annual working units, and total volume of water applied to an irrigation district in hectare m^3 and output being agricultural production in Euros. They used Baker, Charnes and Cooper model of DEA and concluded that DEA is found to be a highly useful technique to find the efficiency of each irrigation district. Limitations of DEA such as non consideration of random error of data are also reported in their study. However, they used only one criterion in their study.

Numerous MCDM methods are employed in water resources field for different problems, namely river basin planning (Gershon and Duckstein, 1983; Ko *et al.*, 1994), hydropower generation (Duckstein *et al.*, 1989), ground water planning (Duckstein *et al.*, 1994), and Irrigation planning (Raju and Kumar, 1999). Most of the techniques employed in the above studies require prior information of the criteria, in addition to numerous parameters for taking a decision. A detailed description of MCDM methods is available in Pomerol and Romero (2000).

In the present study, DEA is employed to select the suitable irrigation planning alternative for demonstrating its use as an alternative methodology to MCDM, as more number of methodologies enhances the selection process (Duckstein *et al.*, 1994). The multiobjective irrigation planning problem, tackled earlier by Raju and Kumar (1999), has been used for the present analysis. As against the previous studies reported above, the present study is the first application of DEA for irrigation planning. Irrigation planning alternatives that were generated by three stage procedure (Raju and Kumar, 1999), were evaluated by three DEA criterion functions, as against only one criterion function considered in Diaz *et al.* (2004). Results of DEA are compared with those of discrete MCDM methods, PROMETHEE and

EXPROM obtained in their study. More details of PROMETHEE and EXPROM are available in Brans *et al.* (1986), Diakoulaki and Koumoutsos (1991).

Data Envelopment Analysis

Data Envelopment Analysis considers systems approach, in which the relationship between all inputs and outputs are taken into account simultaneously yielding a more consistent measure of efficiency. The weights used for each irrigation planning alternative, hereinafter called Decision Making Unit (DMU), are those which maximize the ratio between the weighted output and the weighted input. If the relative efficiency of a set of DMUs, performing the same function is to be evaluated, those DMUs should use the same type of input to produce the same type of output. The efficiency score of a DMU varies from 0 to 1. A DMU with an efficiency score of 1 is considered to be most efficient. Efficient DMUs achieve greater output per unit input than those achieved by the inefficient DMUs. If efficiency of a DMU is 1, no other DMU is more efficient than that DMU and the weights adopted can be considered as the optimal weights. If efficiency is less than 1, there can be other DMUs that may be more efficient. Detailed description of DEA is available in Stewart (1996), Li and Reeves (1999), Sarkis (2000). DEA methodology suggested by Li and Reeves (1999) is used in the present study and is briefly explained below.

DEA criterion function 1 (DEA classical model)

Minimizing Deviation Variable D_j (Min D_j): A solution is considered efficient if and only if the deviation variable D_j, corresponding to the solution that optimizes the criterion function 1, is zero or close to zero. The smaller the value of D_j, the more efficient the DMU.

$$\text{Min } D_j \tag{1}$$

DEA criterion function 2 (Minmax model)

Minimizing maximum deviation M (Minmax): Decision Making Unit, j, is Minmax efficient if and only if the value of D_j, corresponding to the solution that minimizes the criterion function 2, is zero or close to zero.

$$\text{Min } M \tag{2}$$

DEA criterion function 3 (Minsum model)

Minimizing the sum of deviations (Minsum): Decision Making Unit j is Minsum efficient if and only if the value of D_j, corresponding to the solution that minimizes the criterion function 3, is zero or close to zero.

$$\text{Min} \sum_{j=1}^{n} D_j \tag{3}$$

Subject to

$$\sum_{i=1}^{m} V_i X_{ij} = 1 \tag{4}$$

$$\sum_{r=1}^{s} U_r Y_{rj} - \sum_{i=1}^{m} V_i X_{ij} + D_j = 0 \quad \text{for } j = 1 \text{ to } n \tag{5}$$

$$M - D_j \geq 0 \quad \text{for } j = 1 \text{ to } n \tag{6}$$

$$U_r, V_i, D_j \geq 0 \quad \text{for all } r, i \text{ and } j \tag{7}$$

Where j = DMU index, $j = 1, \ldots, n$; r = Output index, $r = 1, \ldots s$; i = Input index, $i = 1, \ldots, m$; Y_{rj} = Value of the rth output for the jth DMU; X_{ij} = Value of the ith input of the jth DMU; U_r = Weight of the rth output; V_i = Weight of the ith input; D_j = Deviation from efficiency of the jth DMU; M = Maximum quantity among all deviation variables D_j $(j = 1, 2, \ldots, n)$

For any DMU$_j$, efficiency score $E_j = 1 - D_j \cdot D_j$ values may vary depending on the criterion function chosen. It is more difficult for a DMU$_j$ to achieve minmax or minsum efficiency than to achieve classical DMU$_j$ efficiency. If DMU$_j$ is minmax or minsum efficient, it must also be DEA efficient because by definition minmax and minsum efficiency requires $d_j = 0$. However, if DMU$_j$ is DEA efficient it may or may not be minmax or minsum efficient, because $d_j = 0$ does not necessarily imply that M or $\sum d_j$ is minimized. It is inferred that minmax and minsum criteria yield less efficient DMU$_j$ than classical DEA. Li and Reeves (1999) observed that M and $\sum D_j$ are functions of all deviation variables and each deviation variable is related to a constraint minimizing M or $\sum D_j$ which is equivalent to imposing tighter constraints on weight variables due to which weight flexibility is restricted. It is concluded from their study that Minmax and Minsum criteria yield less efficient DMUs. The above mentioned criterion functions are evaluated under the framework of Multi Objective Linear Programming (MOLP).

Case Study

The above methodology is applied to the case study of Sri Ram Sagar Project (SRSP), Andhra Pradesh, India used earlier in Raju and Kumar (1999). The culturable command area (CCA) of the project is 178,100 ha. The main crops grown in the command area are paddy, maize, sorghum, groundnut, vegetables, pulses, chillies and sugarcane. There is a practice of double cropping to utilise the available land more effectively. Three irrigation planning objectives, namely net benefits, agricultural production, and labour employment are considered in the present study. All the three objectives are of maximizing type and are mutually conflicting in nature. Analytic Hierarchy Process (AHP) method is employed to assess weights of each objective (Saaty and Gholamnezhad, 1982). Net benefits are given higher importance (0.5613), followed by agricultural production (0.3124) and labour employment (0.1263). It is inferred from the above analysis that the objective of net benefits is given top priority followed by agricultural production and labour employment in that order. These three objectives are subject to the following irrigation planning constraints (these are different from DEA constraints i.e., Equations (4)–(7)): continuity equation, land and water requirements of crops, ground water withdrawals, water quality, canal capacity restrictions, minimum and maximum reservoir storages, crop diversification, downstream water requirements, labour and fertiliser availability, etc. In the planning model, the stochastic nature of inflows is considered through chance constrained programming (Raju, 1995). Mathematical modelling of the three conflicting objectives with the corresponding constraints are explained in Appendix-1. A three stage procedure is employed (Raju and Kumar, 1999) to formulate the payoff matrix and then selection of the best alternative is made. In stage 1 optimization of each irrigation planning objective, namely labour employment, agricultural production, and net benefits is performed using a Linear Programming (LP) algorithm that gives the upper and lower bounds of each objective. In stage 2, Constraint method of multi objective optimization is employed to generate 37 nondominated irrigation planning alternatives. These are reduced to a manageable subset of six, using cluster analysis. In stage 3, two MCDM methods, PROMETHEE and EXPROM are applied to select the best compromise irrigation planning alternative. Brief description of these two methods is presented in Appendix-2. An irrigation management expert (Former Director, Water and land management, training and research institute, Andhra Pradesh, India) has been consulted for the decision making process. The weights mentioned above are further used in PROMETHEE and EXPROM while computing Multicriterion Preference Index and Total Preference Index respectively to obtain the ranking pattern.

Table I(a) shows the results of the two stage procedure and presents 6 compromise irrigation planning alternatives, i.e. payoff matrix of DMUs for the 3 objectives namely labour employment, agricultural production, and net benefits. Table I(b) shows the corresponding normalized payoff matrix. In the present study, the six DMUs presented in Table I(b) are evaluated by DEA methodologies and ranks obtained are compared with those obtained by PROMETHEE and EXPROM.

Results and Discussion

The DEA model proposed by Li and Reeves (1999) is used to rank the DMUs under each DEA criterion function. Labour employment and agricultural production are taken as inputs and net benefits as the output. Six DMUs obtained after stage

Table I. (a) Payoff matrix and (b) Normalized payoff matrix

DMU	Irrigation planning objectives: Labour employment (million man days)	Agricultural production (million tons)	Net benefits (million rupees)
(a) Payoff matrix			
1	35.250	0.77718	1152.00
2	36.300	0.77250	1301.80
3	38.490	0.76386	1439.50
4	40.331	0.74119	1586.50
5	43.239	0.66374	1599.40
6	45.500	0.58989	1478.70
(b) Normalized payoff matrix	V1	V2	U1
1	0.7747	1.0000	0.7202
2	0.7978	0.9939	0.8139
3	0.8459	0.9828	0.9000
4	0.8863	0.9536	0.9919
5	0.9503	0.8540	1.0000
6	1.0000	0.7590	0.9245

2 (Table I(b)) are considered for the Data Envelopment Analysis (Sarkis, 2000). Data is normalized and converted into the form of mathematical expression of DEA (Equations (1)–(7)). A sample mathematical expression for DMU1 is presented in Appendix-3. Among these 6 DMUs, efficient DMUs are obtained by DEA methodology with corresponding weights of inputs and output. Results under each DEA criterion function are briefly explained below.

DEA CRITERION FUNCTION 1 (DEA CLASSICAL MODEL)

Minimizing deviation variable D_j (Min D_j) is used as the criterion function for optimization and subjected to constraints given in Equations (4)–(7) (from now on termed as DEA constraints). Results are presented in Table II showing weights, efficiency scores, and ranking pattern of the 6 DMUs. It is observed that DMUs 4–6 are showing efficiency score of 1. An interesting point is that the weights of the agricultural production of DMUs 1 to 4 are zero indicating that there is no contribution of agricultural production towards net benefits, which may not be realistic. In other words, the problem of unrealistic weight distribution refers to the situation where some DMUs can be rated as efficient because they have extremely large weights in a single output and/or extremely small weights in a single input while these extreme weights are practically unreasonable or undesirable as observed in the present case (Li and Reeves, 1999). DMUs 5 and 6 are having efficiency

Table II. Results for criterion function 1: Minimizing deviation variable D_j (DEA classical model)

DMU	Wt. of labour employment	Wt. of agricultural production	Wt. of net benefits	Efficiency	Rank
1	1.2907	0.0000	1.1534	0.8307	4
2	1.2534	0.0000	1.1200	0.9116	3
3	1.1821	0.0000	1.0563	0.9507	2
4	1.1281	0.0000	1.0081	1.0000	1
5	0.7136	0.3767	1.0000	1.0000	1
6	0.2491	0.9892	1.0816	1.0000	1

score of 1 and a reasonable weight distribution i.e., in this case weights of labour employment and agricultural production are having significant values (other than zero) which indicate that both the criteria are contributing to the net benefits. It may be inferred from Table II that this methodology could not effectively discriminate the DMUs and is showing unrealistic weight distribution for DMUs 1 to 4. The problem of unrealistic weights can be minimized by weight restriction i.e., keeping a minimum value for the weights used in the model.

DEA CRITERION FUNCTION 2 (MINMAX MODEL)

Results are presented in Table III showing weights, efficiency scores and ranking pattern of the 6 DMUs. In this approach, all the DMUs are showing reasonable weight distribution and the discrimination among DMUs is reasonably good. The weights of agricultural production are considerably low compared to those for the other two criteria, whereas weights for net benefits and labour employment are closer. DMU 4 is found to be the best (highest efficiency score of 1).

Table III. Results for criterion function 2: Minmax model

DMU	Wt. of labour employment	Wt. of agricultural production	Wt. of net benefits	Efficiency	Rank
1	1.1461	0.1120	1.1319	0.8153	6
2	1.1173	0.1092	1.1034	0.8981	4
3	1.0615	0.1037	1.0483	0.9435	3
4	1.0208	0.0997	1.0081	1.0000	1
5	0.9673	0.0945	0.9553	0.9553	2
6	0.9309	0.0909	0.9193	0.8499	5

Table IV. Results for criterion function 3*:* Minsum model

DMU	Wt. of labour employment	Wt. of agricultural production	Wt. of net benefits	Efficiency	Rank
1	0.7676	0.4052	1.0756	0.7747	5
2	0.7561	0.3991	1.0594	0.8623	3
3	0.7327	0.3868	1.0266	0.9240	2
4	0.7194	0.3798	1.0081	1.0000	1
5	0.7136	0.3767	1.0000	1.0000	1
6	1.0000	0.0000	0.8936	0.8261	4

DEA CRITERION FUNCTION 3 (MINSUM MODEL)

Results are presented in Table IV showing weights, efficiency scores and ranking pattern of the 6 DMUs. Weight of agricultural production is zero in the case of DMU 6. In this case, DMUs 5 and 4 got the rank of 1, with the same efficiency score of 1.

FINAL RANKING AND SPEARMAN RANK CORRELATION COEFFICIENT

Table V shows the ranking patterns obtained by Min D_j, Minmax, Minsum criterion functions and by PROMETHEE and EXPROM. It is observed that DMUs 4, 5 are given either first or second ranking by all the approaches. Spearman rank correlation coefficient (R), which is useful to determine the measure of association between ranks obtained by two different approaches, is used in the present study (Gibbons, 1971). Spearman R values of 1, 0 and -1 represent perfect association, no association and perfect disagreement respectively between the approaches. Table VI presents R values. Low value of R is observed between min D_j approach and PROMETHEE and EXPROM. This may be due to tie for ranking of three DMUs 4, 5 and 6 (which are having ranking of 1) in Min D_j approach. R values vary from 0.3428 to 0.7142 in this case. Spearman R values between Minmax & Minsum

Table V. Rankings obtained by different methodologies

DMU	Min D_j	Minmax	Minsum	PROMETHEE	EXPROM
1	4	6	5	6	6
2	3	4	3	5	5
3	2	3	2	4	3
4	1	1	1	2	2
5	1	2	1	1	1
6	1	5	4	3	4

Table VI. Spearman rank correlation coefficient (R) values

	Min D_j	Minmax	Minsum	PROMETHEE	EXPROM
Min D_j	1	0.3428	0.7142	0.5142	0.4571
Minmax		1	0.8571	0.7714	0.8857
Minsum			1	0.6857	0.8000
PROMETHEE				1	0.9428
EXPROM					1

and Minmax & EXPROM are 0.8571 and 0.8857 respectively. Highest R value of 0.9428 is observed between PROMETHEE and EXPROM. Results indicate that Minmax is suitable for the present planning problem due to its discriminating ability between DMUs and reasonable and realistic weight distribution as compared to the other two approaches.

Conclusions

The present study demonstrates the use of Data Envelopment Analysis (DEA) as an alternative methodology for MCDM for ranking irrigation planning alternatives. The following conclusions are drawn from this study:

(i) Three different DEA criterion functions, namely Minimizing deviation variable D_j, Minmax and Minsum are employed. Minmax is found to be suitable for the present case study due to its discriminating ability between DMUs and reasonable and realistic weight distribution as compared to the other two criterion functions.
(ii) It is observed that DMUs 4 and 5 are given either first or second position by both DEA and MCDM approaches.
(iii) Spearman rank correlation coefficients are found to be very useful to assess the correlation between different ranking patterns. Ranking pattern obtained by Minmax is reasonably closer to that of EXPROM with an R value of 0.8857.

Data Envelopment Analysis thus offers a useful methodology for ranking irrigation planning alternatives with mutually conflicting objectives, especially because this method evaluates each alternative independently, with independent set of weights.

Appendix-1

Mathematical modelling of the three conflicting objectives with the corresponding constraints is briefly explained below.

OBJECTIVE 1: MAXIMIZATION OF NET BENEFITS

The net benefits (BEM) from the irrigated and unirrigated areas under different crops are obtained by subtracting the costs of surface water, ground water, fertilizer and labour from the gross revenue from different crops. Maximization of net benefits can be expressed as

$$\text{Max BEM} = \sum_{i=1}^{16} B_i A_i - P_{\text{sw}} \sum_{t=1}^{12} R_t - P_{\text{gw}} \sum_{t=1}^{12} \text{GW}_t - \sum_{f=1}^{3}\sum_{i=1}^{16} F_{fi} A_i P_f - P_l \sum_{t=1}^{12}\sum_{i=1}^{16} L_{\text{it}} A_i \tag{A.1}$$

in which i = Crop index [1 = Paddy(s), 2 = Maize(s), 3 = Sorghum(s), 4 = Groundnut(s), 5 = Vegetables(s), 6 = Pulses(s), 7 = Paddy(srf), 8 = Groundnut(srf), 9 = Paddy(w), 10 = Groundnut(w), 11 = Pulses(w), 12 = Maize(w), 13 = Sorghum(w), 14 = Vegetables(w), 15 = Chillies(w), 16 = Sugarcane(ts)]; s = Summer; w = Winter; ts = Two season; srf = Summer rainfed; t = Monthly index; f = Fertilizer index; A_i = Area of crop i (ha); B_i = gross return per ha from ith crop (Rs); P_{sw} = Unit surface water cost (Rs/Mm^3); R_t = Monthly canal water releases (Mm^3); P_{gw} = Unit ground water cost (Rs/Mm^3); GW$_t$ = Monthly ground water requirement (Mm^3); F_{fi} = Quantity of fertilizer of type f for crop i (tons/ha); P_f = Unit cost of fertilizer type f (Rs); P_l = Unit wage rate (Rs); L_{it} = Labour-days required for each hectare of crop i in month t; Rs = Rupees in Indian currency.

OBJECTIVE 2: MAXIMISATION OF AGRICULTURAL PRODUCTION

Total Agricultural production (PRM) of all the crops are to be maximised to get the maximum yield from the cropped area.

$$\text{Max PRM} = \sum_{i=1}^{16} Y_i A_i \tag{A.2}$$

where Y_i = Yield of ith crop (tons/ha).

OBJECTIVE 3: MAXIMIZATION OF LABOUR EMPLOYMENT

The total labour employed (LAM) under all the crops for the whole year is maximized to increase the level of their economic status and can be expressed as

$$\text{Max LAM} = \sum_{t=1}^{12}\sum_{i=1}^{16} L_{\text{it}} A_i \tag{A.3}$$

The above three objectives are subject to the following constraints (which are different from DEA constraints):

a) Continuity Equation
The monthly continuity equation for the reservoir storage (Mm^3) is expressed as

$$S_{t+1} = S_t + Q_t - EV_t - R_t - RDS_t - OSR_t \tag{A.4}$$

where S_{t+1} = End of month reservoir storage volume; Q_t = Monthly net inflow volume; EV_t = Monthly net evaporation volume; RDS_t = Downstream requirements; OSR_t = Spilled volume. By incorporating the stochasticity in the inflow terms, the above equation changes to

$$\Pr(S_{t+1} - S_t + EV_t + R_t + RDS_t + OSR_t = Q_t) \geq \alpha \tag{A.5}$$

$$S_{t+1} - S_t + EV_t + R_t + RDS_t + OSR_t \leq q_t^{\alpha} \tag{A.6}$$

where q_t^{α} is the inverse of the cumulative distribution function of inflows at dependable level α, Pr is the probability operator.

b) Crop Land Requirements
The total area allocated for different crops in a particular season should be less than or equal to the culturable command area (*CCA*).

$$\sum_i A_i \leq CCA; \quad i = 1, 2, 3, 4, 5, 6, 7, 8, 15, 16 \text{ for summer crops} \tag{A.7}$$

$$\sum_i A_i \leq CCA; \quad i = 9, 10, 11, 12, 13, 14, 15, 16 \text{ for winter crops} \tag{A.8}$$

Crops of two seasons, namely, Chillies and Sugarcane (indices 15 and 16) are included in both the equations because they occupy the land in both seasons.

c) Water Requirements of Crops
Monthly crop water requirements should not exceed the maximum available water from both surface and ground water sources.

$$\sum_{i=1}^{16} A_i\, CWR_{it} \leq R_t + GW_t \tag{A.9}$$

where CWR_{it} is crop water requirement for unit area of crop i in month t.

d). Canal Capacity Restrictions
The total releases from reservoir should not exceed the canal capacity

$$R_t \leq CC, \quad t = 1, 2, \ldots, 12 \tag{A.10}$$

Discharging capacity of canal can be expressed as m^3/s. In the present study, it is converted into volumetric units, Million cubic meters (Mm^3), to be compatible with releases.

e). Live Storage Restrictions
Reservoir storage volume S_t in any month t should be less than or equal to the maximum live storage capacity of the reservoir.

$$S_t \leq \text{LSP}, \quad t = 1, 2, \ldots, 12 \tag{A.11}$$

Where LSP = Maximum live storage capacity of the reservoir.

The other constraints which are incorporated in the model are crop diversification considerations, downstream water requirements, labour and fertilizer availability, water quality, ground water withdrawals etc (Raju, 1995).

Appendix-2

Promethee. (Preference Ranking Organisation METHod of Enrichment Evaluation) is of outranking nature. When two alternatives a and b are to be compared for any criterion j, they can be expressed in terms of the preference function, which is a function of the difference between the two alternatives a and b and the type of criterion function. Brans *et al.* (1986) proposed six types of criterion functions i.e., usual criterion, quasi criterion, criterion with linear preference, level criterion, criterion with linear preference & indifference area and Gaussian criterion. Indifference and preference thresholds are also defined. Multicriterion preference index (weighted average of the preference functions) can be calculated from which ranking of the alternatives are obtained.

Exprom. is the modified and extended version of PROMETHEE where the relative performance of one alternative over the other is defined by two preference indices, one by weak preference index (based on outranking, i.e., Multicriterion preference index in PROMETHEE) and the other by strict preference index (based on the notion of the ideal and the anti-ideal). The total preference index, i.e., summation of strict and weak (multicriterion) preference indices in the fuzzy environment gives an accurate measure of the intensity of preference of one alternative over the other for all criteria (Diakoulaki and Koumoutsos, 1991).

Appendix-3

Detailed formulation for evaluating DMU for irrigation planning alternative 1 (DMU1).

MIN D1
MIN M
MIN D1+D2+D3+D4+D5+D6
SUBJECT TO
D1+E = 1
0.7747V1 + 1.0000V2 = 1
0.7202U1 − 0.7747V1 − 1.0000V2 + D1 = 0
0.8139U1 − 0.7978V1 − 0.9939V2 + D2 = 0

$$0.9000\text{U1} - 0.8459\text{V1} - 0.9828\text{V2} + \text{D3} = 0$$
$$0.9919\text{U1} - 0.8863\text{V1} - 0.9536\text{V2} + \text{D4} = 0$$
$$1.0000\text{U1} - 0.9503\text{V1} - 0.8540\text{V2} + \text{D5} = 0$$
$$0.9245\text{U1} - 1.0000\text{V1} - 0.7590\text{V2} + \text{D6} = 0$$
$$\text{M} - \text{D1} \geq 0$$
$$\text{M} - \text{D2} \geq 0$$
$$\text{M} - \text{D3} \geq 0$$
$$\text{M} - \text{D4} \geq 0$$
$$\text{M} - \text{D5} \geq 0$$
$$\text{M} - \text{D6} \geq 0$$
$$\text{V1} \geq 0$$
$$\text{V2} \geq 0$$
$$\text{U1} \geq 0$$
$$\text{D1} \geq 0$$
$$\text{D2} \geq 0$$
$$\text{D3} \geq 0$$
$$\text{D4} \geq 0$$
$$\text{D5} \geq 0$$
$$\text{D6} \geq 0$$

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