

On the solution of Large Scale Bi-Level Linear Vector Optimization Problems through TOPSIS

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Abstract- In this paper, we extend TOPSIS (Technique for Order Preference by Similarity Ideal Solution) for solving Large Scale Bi-level Linear Vector Optimization Problems (LS-BL-LVOP). In order to obtain a compromise (satisfactory) solution to the LS-BL-LVOP problems using the proposed TOPSIS approach, a modified formulas for the distance function from the positive ideal solution (PIS) and the distance function from the negative ideal solution (NIS) are proposed and modeled to include all the objective functions of both the first and the second levels. An interactive decision making algorithm for generating a compromise (satisfactory) solution through TOPSIS approach is provided where the first level decision maker (FLDM) is asked to specify the relative importance of the objectives. Finally, a numerical example is given to clarify the main results developed in the paper.

Keywords- Decision making; Vector Optimization Problems; Bi-level programming; TOPSIS; block angular structure; large scale programming; fuzzy programming.

1. INTRODUCTION:

The increasing complexity of modern-day society has brought new problems involving very large numbers of variables and constraints. Due to the high dimensionality of the problems, it becomes difficult to obtain optimal solutions for such large scale programming (LSP) problems. Fortunately, however, most of the LSP problems arising in application almost always have a special structure that can be exploited. One familiar structure is the block angular structure to the constraints that can be used to formulate the subproblems [31, 47, 56].

After the publication of the Dantzig-Wolfe decomposition method [31], the subsequent works on large scale linear and nonlinear programming problems with block angular structure have been numerous (see f. i. [13, 15, 16, 18, 34, 35, 40, 49, 54]).

The decentralized planning has been recognized as an important decision-making problem. It seeks to find a simultaneous compromise among the various objective functions of the different divisions. Bi-level programming, a tool for modeling decentralized decisions, consists of the objective(s) of the leader at its first level and that is of the follower at the second level. The decision-maker at each level attempts to optimize his individual objective, which usually depends in part on the variables controlled by the decision-maker at the other levels and their final decisions

are executed sequentially where the upper-level decision-maker makes his decision firstly. The research and applications concentrated mainly on bi-level programming (see f. i. [3, 4, 7, 9, 12, 19, 20, 22, 23, 24, 25, 27, 36, 37, 38, 52, 58, 59]).

TOPSIS was first developed by C. L. Hwang and K. Yoon [42] for solving a multiple attribute decision making problem. It is based upon the principle that the chosen alternative should have the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS). The single criterion of the shortest distance from the given goal or the PIS may be not enough to decision makers. In practice, we might like to have a decision which not only makes as much profit as possible, but also avoids as much risk as possible. A similar concept has also been pointed out by M. Zeleny [62], Lia *et al.* [45] extended the concept of TOPSIS to develop a methodology for solving multiple objective decision making (MODM) problems. After the publication of TOPSIS approach [42, 45], the subsequent works in this area of optimization have been numerous (see f. i. [1, 2, 5, 6, 8, 11, 14, 17, 18, 21, 28, 29, 30, 33]).

Abo-Sinna and Abou-El-Enien [5] extend the TOPSIS approach to solve large scale multiple objective decision making problems with block angular structure. Also, they [8] extend the TOPSIS approach to solve large scale multiple objective decision making problems under fuzzy

environment. Recently, Baky and Abo-Sinna [21] proposed a TOPSIS algorithm for bi-level multiple objective decision making problems.

In this paper, we extend TOPSIS for solving LS-BL-LVOP, we further extended the concept of TOPSIS [Lia et al. (45)] for LS-BL-LVOP.

In the following section, we will give the formulation of LS-BL-LVOP with block angular structure for which the Dantzig-Wolfe decomposition method has been successfully applied. The family of d_p -distance and its normalization is discussed in section 3. The TOPSIS approach is presented in section 4. By use of TOPSIS, we will propose an interactive algorithm for solving LS-BL-LVOP in section 5. We will also give a numerical example in section 6 for the sake of illustration. Finally, concluding remarks will be given in section 7.

2. FORMULATION OF A LS-BL-LVOP:

Consider there are two levels in a hierarchy structure with a first - level decision maker (FLDM) and a second - level decision maker (SLDM). Let the LS-BL-LVOP problem of the following block angular structure :

$$\begin{aligned} & \text{Maximize}_{X_{I_1}} F_{I_1}(X_{I_1}, X_{I_2}) \\ & = \text{Maximize}_{X_{I_1}} (f_{I_1 1}(X_{I_1}, X_{I_2}), \dots, f_{I_1 k_{I_1}}(X_{I_1}, X_{I_2})) \end{aligned}$$

where X_{I_2} solves second level
[SLDM]

$$\begin{aligned} & \text{Maximize}_{X_{I_2}} F_{I_2}(X_{I_1}, X_{I_2}) \\ & = \text{Maximize}_{X_{I_2}} (f_{I_2 1}(X_{I_1}, X_{I_2}), \dots, f_{I_2 k_{I_2}}(X_{I_1}, X_{I_2})) \end{aligned}$$

subject to ---(1)

$$\begin{aligned} X \in M = \{X \in R^n : \sum_{j=1}^q A_j X_j \leq b_o, \\ D_j X_j \leq b_j, \\ X_j \geq 0, j=1, 2, \dots, q, q > 1\} \end{aligned}$$

where

- k : the number of objective functions,
- k_{I_1} : the number of objective functions of the FLDM
- k_{I_2} : the number of objective functions of the SLDM
- n_{I_1} : the number of variables of the FLDM
- n_{I_2} : the number of variables of the SLDM
- q : the number of subproblems,
- m : the number of constraints,
- n : the number of variables,
- n_j : the number of variables of the j^{th} subproblem, $j=1, 2, \dots, q$,
- m_o : the number of the common constraints represented

$$\text{by } \sum_{j=1}^q A_j X_j \leq b_o,$$

- m_j : the number of independent constraints of the j^{th} subproblem represented by $D_j X_j \leq b_j, j=1, 2, \dots, q$.
 - A_j : an $(m_o \times n_j)$ coefficient matrix,
 - D_j : an $(m_j \times n_j)$ coefficient matrix,
 - b_o : an m_o -dimensional column vector of right-hand sides of the common constraints whose elements are constants,
 - b_j : an m_j -dimensional column vector of independent constraints right-hand sides whose elements are the constants of the constraints for the j^{th} subproblem, $j=1, 2, \dots, q$,
 - C_{ij} : an n_j -dimensional row vector for the j^{th} subproblem in the i^{th} objective function,
 - R : the set of all real numbers,
 - X : an n -dimensional column vector of variables,
 - X_j : an n_j -dimensional column vector of variables for the j^{th} subproblem, $j=1, 2, \dots, q$,
 - X_{I_1} : an n_{I_1} -dimensional column vector of variables of the FLDM,
 - X_{I_2} : an n_{I_2} -dimensional column vector of variables of the SLDM,
 - $K = \{1, 2, \dots, k\}$
 - $N = \{1, 2, \dots, n\}$,
 - $R^n = \{X = (x_1, x_2, \dots, x_n)^T : x_i \in R, i \in N\}$.
- If the objective functions are linear, then the objective function can be written as follows:

$$f_i(X) = \sum_{j=1}^q f_{ij} = \sum_{j=1}^q C_{ij} X_j, \quad i=1, 2, \dots, k \quad \text{--- (2)}$$

3. SOME BASIC CONCEPTS OF DISTANCE MEASURES:

The compromise programming approach [39, 46, 61, 62] has been developed to perform MODM problem, reducing the set of nondominated solutions. The compromise solutions are those which are the closest by some distance measure to the ideal one.

The point $f_i(X^*) = \sum_{j=1}^q f_{ij}(X^*)$ in the criteria space is called the ideal point (reference point). As the measure of "closeness", d_p -metric is used. The d_p -metric defines the distance between two points, $f_i(X) = \sum_{j=1}^q f_{ij}(X)$ and $f_i(X^*) = \sum_{j=1}^q f_{ij}(X^*)$ (the reference point) in k -dimensional space [50] as:

$$\begin{aligned} d_p &= \left(\sum_{i=1}^k w_i^p (f_i^* - f_i)^p \right)^{\frac{1}{p}} \\ &= \left(\sum_{i=1}^k w_i^p \left(\sum_{j=1}^q f_{ij}^* - \sum_{j=1}^q f_{ij} \right)^p \right)^{\frac{1}{p}} \quad \text{--- (3)} \end{aligned}$$

where $p \geq 1$.

Unfortunately, because of the incommensurability among objectives, it is impossible to directly use the above distance family. To remove the effects of the incommensurability, we need to normalize the distance family of equation (3) by using the reference point [41, 42] as :

$$d_p = \left(\sum_{i=1}^k w_i^p \left(\frac{\sum_{j=1}^q f_{ij}^* - \sum_{j=1}^q f_{ij}}{\sum_{j=1}^q f_{ij}^*} \right)^p \right)^{1/p} \quad \text{--- (4)}$$

where $p \geq 1$.

To obtain a compromise solution for the Large Scale Vector Optimization problems (LSVOP) of the following form ,

$$\begin{aligned} & \text{Maximize } [f_1(X), f_2(X), \dots, f_k(X)] \\ & \text{subject to} \quad \text{--- (5)} \end{aligned}$$

$$\begin{aligned} X \in M = \{X \in R^n : \sum_{j=1}^q A_j X_j \leq b_o, \\ D_j X_j \leq b_p, \\ X_j \geq 0, j=1, 2, \dots, q, q > 1\} \end{aligned}$$

The global criteria method [41] for large scale problems uses the distance family of equation (4) by the ideal solution being the reference point. The problem becomes how to solve the following auxiliary problem :

$$\text{Minimize}_{x \in M} d_p = \left(\sum_{i=1}^k w_i^p \left(\frac{\sum_{j=1}^q f_{ij}(X^*) - \sum_{j=1}^q f_{ij}(X)}{\sum_{j=1}^q f_{ij}(X^*)} \right)^p \right)^{1/p} \quad \text{--- (6)}$$

where X^* is the PIS and $p = 1, 2, \dots, \infty$.

Usually, the solutions based on PIS are different from the solutions based on NIS. Thus, both PIS(f^*) and NIS(f^-) can be used to normalize the distance family and obtain [18]:

$$d_p = \left(\sum_{i=1}^k w_i^p \left(\frac{\sum_{j=1}^q f_{ij}^* - \sum_{j=1}^q f_{ij}}{\sum_{j=1}^q f_{ij}^* - \sum_{j=1}^q f_{ij}^-} \right)^p \right)^{1/p} \quad \text{--- (7)}$$

where $p \geq 1$.

In this study, we further extended the concept of TOPSIS to obtain a compromise (satisfactory) solution for LS-BL-LVOP problems. Also, in this paper, an algorithm of generating compromise (satisfactory) solutions of LS-BL-LVOP has been presented. It is based on the decomposition algorithm of LSVOP with block angular structure via TOPSIS approach, [5]. This algorithm has few features, (i) it combines both LS-BL-LVOP and TOPSIS approach to obtain TOPSIS's compromise solution of the problem, (ii) it can be efficiently coded. (iii) it was found that the decomposition based method generally met with better results than the traditional simplex-based methods. Especially, the efficiency of the

decomposition-based method increased sharply with the scale of the problem. Finally, an illustrative numerical example clarified the various aspects of both the solution concept and the proposed algorithm.

4. TOPSIS for LS-BL-LVOP :

Consider the following LS-BL-LVOP problem with block angular structure:
[FLDM]

$$\begin{aligned} & \text{Maximize/Minimize}_{X_{I_1}} F_{I_1}(X_{I_1}, X_{I_2}) \\ & = \text{Maximize/Minimize}_{X_{I_1}} \left(f_{I_1,1}(X_{I_1}, X_{I_2}), \dots, f_{I_1, k_{I_1}}(X_{I_1}, X_{I_2}) \right) \end{aligned}$$

where X_{I_2} solves second level

[SLDM]

$$\begin{aligned} & \text{Maximize/Minimize}_{X_{I_2}} F_{I_2}(X_{I_1}, X_{I_2}) \\ & = \text{Maximize/Minimize}_{X_{I_2}} \left(f_{I_2,1}(X_{I_1}, X_{I_2}), \dots, f_{I_2, k_{I_2}}(X_{I_1}, X_{I_2}) \right) \end{aligned}$$

subject to --- (8)

$X \in M$

where

$\sum_{j=1}^q f_{tj}(X)$: Objective Function for Maximization, $t \in K_1 \subset K$,
 $\sum_{j=1}^q f_{vj}(X)$: Objective Function for Minimization, $v \in K_2 \subset K$.

4-1. Phase (I):

Consider the FLDM problem of the LS-BL-LVOP Problem (8):

[FLDM]

$$\begin{aligned} & \text{Maximize/Minimize}_{X_{I_1}} F_{I_1}(X_{I_1}, X_{I_2}) \\ & = \text{Maximize/Minimize}_{X_{I_1}} \left(f_{I_1,1}(X_{I_1}, X_{I_2}), \dots, f_{I_1, k_{I_1}}(X_{I_1}, X_{I_2}) \right) \end{aligned}$$

subject to --- (9)

$X \in M$

where

$\sum_{j=1}^q f_{tj}(X)$: Objective Function for Maximization, $t \in K_1 \subset K$,
 $\sum_{j=1}^q f_{vj}(X)$: Objective Function for Minimization, $v \in K_2 \subset K$.

In order to use the distance family of equation (7) to resolve problem (9), we must first find PIS(f^*) and NIS(f^-) which are [18, 45]:

$$F^* = \underset{x \in M'}{\text{Maximize (or Minimize)}} \sum_{j=1}^q F_{tj}(X) \left(\text{or } \sum_{j=1}^q F_{vj}(X) \right),$$

$$\forall t(\text{and } v) \text{ --- (10a)}$$

$$F^- = \underset{x \in M'}{\text{Minimize (or Maximize)}} \sum_{j=1}^q F_{tj}(X) \left(\text{or } \sum_{j=1}^q F_{vj}(X) \right),$$

$$\forall t(\text{and } v) \text{ --- (10b)}$$

where $K = K_1 \cup K_2$.

$$f^{*FLDM} = (f_1^{*FLDM}, f_2^{*FLDM}, \dots, f_{k_1}^{*FLDM})$$

and

$$f^{-FLDM} = (f_1^{-FLDM}, f_2^{-FLDM}, \dots, f_{k_1}^{-FLDM})$$

are the individual positive (negative) ideal solutions for the FLDM.

Using the PIS and the NIS for the FLDM, we obtain the following distance functions from them, respectively:

$$d_p^{PISFLDM} = \left(\sum_{t \in K_1} W_t^p \left(\frac{\sum_{j=1}^q f_{tj}^{*FLDM} - \sum_{j=1}^q f_{tj}^{FLDM}(X)}{\sum_{j=1}^q f_{tj}^{*FLDM} - \sum_{j=1}^q f_{tj}^{-FLDM}} \right)^p + \sum_{v \in K_2} W_v^p \left(\frac{\sum_{j=1}^q f_{vj}^{FLDM}(X) - \sum_{j=1}^q f_{vj}^{*FLDM}}{\sum_{j=1}^q f_{vj}^{-FLDM} - \sum_{j=1}^q f_{vj}^{*FLDM}} \right)^p \right)^{1/p} \text{ --- (11a)}$$

$$\mu_1(X) = \begin{cases} 1, & \text{if } d_p^{PIS}(X) < (d_p^{PIS})^*, \\ 1 - \frac{d_p^{PIS}(X) - (d_p^{PIS})^*}{(d_p^{PIS})^- - (d_p^{PIS})^*}, & \text{if } (d_p^{PIS})^- \geq d_p^{PIS} \geq (d_p^{PIS})^* \text{ --- (13a)} \\ 0, & \text{if } d_p^{PIS}(X) > (d_p^{PIS})^-, \end{cases}$$

$$\mu_2(X) = \begin{cases} 1, & \text{if } d_p^{NIS}(X) > (d_p^{NIS})^*, \\ 1 - \frac{d_p^{NIS}(X) - (d_p^{NIS})^-}{(d_p^{NIS})^* - (d_p^{NIS})^-}, & \text{if } (d_p^{NIS})^- \leq d_p^{NIS} \leq (d_p^{NIS})^* \text{ --- (13b)} \\ 0, & \text{if } d_p^{NIS}(X) < (d_p^{NIS})^-, \end{cases}$$

where

$$(d_p^{PIS})^* = \underset{x \in M'}{\text{Minimize}} d_p^{PIS}(X) \text{ and the solution is } X^{PIS},$$

$$(d_p^{NIS})^* = \underset{x \in M'}{\text{Maximize}} d_p^{NIS}(X) \text{ and the solution is } X^{NIS},$$

$$(d_p^{PIS})^- = d_p^{PIS}(X^{NIS}) \text{ and } (d_p^{NIS})^- = d_p^{NIS}(X^{PIS}).$$

and

$$d_p^{NISFLDM} = \left(\sum_{t \in K_1} W_t^p \left(\frac{\sum_{j=1}^q f_{tj}^{FLDM}(X) - \sum_{j=1}^q f_{tj}^{-FLDM}}{\sum_{j=1}^q f_{tj}^{FLDM} - \sum_{j=1}^q f_{tj}^{-FLDM}} \right)^p + \sum_{v \in K_2} W_v^p \left(\frac{\sum_{j=1}^q f_{vj}^{-FLDM} - \sum_{j=1}^q f_{vj}^{FLDM}(X)}{\sum_{j=1}^q f_{vj}^{-FLDM} - \sum_{j=1}^q f_{vj}^{*FLDM}} \right)^p \right)^{1/p} \text{ --- (11b)}$$

where $w_i = 1, 2, \dots, k$, are the relative importance (weights) of objectives, and $p = 1, 2, \dots, \infty$.

In order to obtain a compromise solution for the FLDM, we transfer the FLDM of problem (9) into the following bi-objective problem with two commensurable (but often conflicting) objectives [18, 45]:

$$\text{Minimize } d_p^{PISFLDM}(X), \text{ Maximize } d_p^{NISFLDM}(X)$$

$$\text{subject to } X \in M \text{ --- (12)}$$

where $p = 1, 2, \dots, \infty$.

Since these two objectives are usually conflicting to each other, we can simultaneously obtain their individual optima. Thus, we can use membership functions to represent these individual optima. Assume that the membership functions $(\mu_1(X))$ and $(\mu_2(X))$ of two objective functions are linear. Then, based on the preference concept, we assign a larger degree to the one with shorter distance from the PIS for $\mu_1(X)$ and assign a larger degree to the one with farther distance from NIS for $\mu_2(X)$. Therefore, as shown in figure (1), $\mu_1(X) \equiv \mu_{d_p^{PISFLDM}}(X)$ and $\mu_2(X) \equiv \mu_{d_p^{NISFLDM}}(X)$ can be obtained as the following (see [26, 43, 44, 53, 55, 63]):

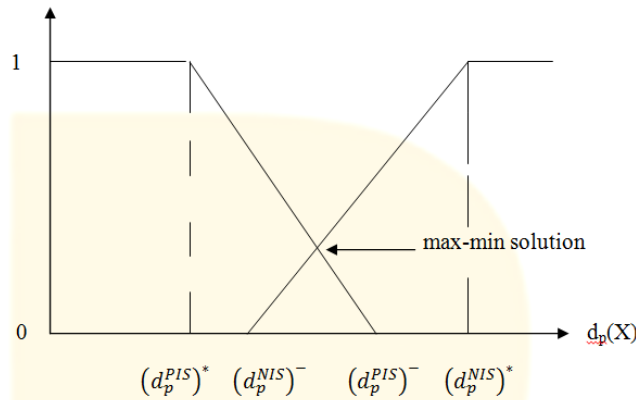


Figure 1. The membership functions of $\mu_1(X)$ and $\mu_2(X)$

Now, by applying the max-min decision model which is proposed by R. E. Bellman and L. A. Zadeh [26] and extended by H. -J. Zimmermann [63], we can resolve problem (12). The satisfying decision of the FLDM of the LS-BL-LVOP Problem, $X^{*FLDM} = (X_{I_1}^{*FLDM}, X_{I_2}^{*FLDM})$, may be obtained by solving the following model:

$$\mu_D(X^{*FLDM}) = \text{Maximize}_{X \in M} \{ \text{Min.}(\mu_1(X), \mu_2(X)) \} \quad (14)$$

Finally, if $\delta^{FLDM} = \text{Minimize}(\mu_1(X), \mu_2(X))$, the model (14) is equivalent to the form of Tchebycheff model (see [32]), which is equivalent to the following model:

$$\text{Maximize } \delta^{FLDM}, \quad \text{--- (15a)}$$

$$\mu_{I_1i}(x_{I_1i}) = \begin{cases} \frac{x_{I_1i} - (X_{I_1i}^{*FLDM} - \tau_i^L)}{\tau_i^L}, & \text{if } x_{I_1i}^{*FLDM} - \tau_i^L \leq x_{I_1i} \leq x_{I_1i}^{*FLDM} \\ \frac{(X_{I_1i}^{*FLDM} + \tau_i^R) - x_{I_1i}}{\tau_i^R}, & \text{if } x_{I_1i}^{*FLDM} \leq x_{I_1i} \leq x_{I_1i}^{*FLDM} + \tau_i^R, \quad i = 1, 2, \dots, n_{I_1}, \quad \text{--- (16)} \\ 0, & \text{if otherwise,} \end{cases}$$

It may be noted that, the decision maker may desire to shift the range of x_{I_1i} . Following Pramanik & Roy [51] and Sinha [57], this shift can be achieved.

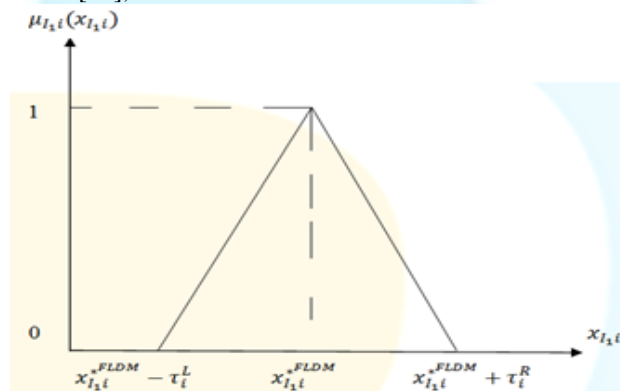


Figure 2: The membership function of the decision variable x_{I_1i}

subject to

$$\mu_1(X) \geq \delta^{FLDM} \quad \text{--- (15b)}$$

$$\mu_2(X) \geq \delta^{FLDM} \quad \text{--- (15c)}$$

$$X \in M, \quad \delta^{FLDM} \in [0,1] \quad \text{--- (15d)}$$

where δ^{FLDM} is the satisfactory level for both criteria of the shortest distance from the PIS and the farthest distance from the NIS. It is well known that if the optimal solution of (15) is the vector $(\delta^{*FLDM}, X^{*FLDM})$, then X^{*FLDM} is a nondominated solution [41,60] of (12) and a satisfactory solution [46] of the FLDM problem (9).

The basic concept of the bi-level programming technique is that the FLDM sets his/her goals and/or decisions with possible tolerances which are described by membership functions of fuzzy set theory. According to this concept, let τ_i^L and $\tau_i^R, i = 1, 2, \dots, n_{I_1}$ be the maximum acceptable negative and positive tolerance (relaxation) values on the decision vector considered by the FLDM, $X_{I_1}^{*FLDM} = (x_{I_11}^{*FLDM}, x_{I_12}^{*FLDM}, \dots, x_{I_1n_{I_1}}^{*FLDM})$. The tolerances give the SLDM an extent feasible region to search for the satisfactory solution. If the feasible region is empty, the negative and positive tolerances must be increased to give the SLDM an extent feasible region to search for the satisfactory solution, [11, 51, 57]. The linear membership functions (Figure 2) for each of the n_{I_1} components of the decision vector $(x_{I_11}^{*FLDM}, x_{I_12}^{*FLDM}, \dots, x_{I_1n_{I_1}}^{*FLDM})$ controlled by the FLDM can be formulated as:

4-2. Phase (II):

The SLDM problem can be written as follows:

[SLDM]

$$\begin{aligned} & \text{Maximize}_{X_{I_2}} F_{I_2}(X_{I_1}, X_{I_2}) \\ & = \text{Maximize}_{X_{I_2}} (f_{I_21}(X_{I_1}, X_{I_2}), \dots, f_{I_2k_{I_2}}(X_{I_1}, X_{I_2})) \end{aligned} \quad \text{--- (17)}$$

subject to

$X \in M$

where

$\sum_{j=1}^q f_{tj}(X)$: Objective Function for Maximization,

$t \in K_1 \subset K$,

$\sum_{j=1}^q f_{vj}(X)$: Objective Function for Minimization,

$v \in K_2 \subset K$.

In order to use the distance family of equation (7) to resolve problem (17), we must first find PIS(f^*) and NIS(f^-) which are [18, 45]:

$$f^{*SLDM} = \begin{aligned} & \text{Maximize (or Minimize)} \sum_{j=1}^q f_{tj}(X) \text{ (or } \sum_{j=1}^q f_{vj}(X)), \\ & x \in M \\ & \forall t \text{ (and } v) \text{ --- (18-a)} \end{aligned}$$

$$f^{-SLDM} = \begin{aligned} & \text{Minimize (or Maximize)} \sum_{j=1}^q f_{tj}(X) \text{ (or } \sum_{j=1}^q f_{vj}(X)), \\ & x \in M \\ & \forall t \text{ (and } v) \text{ --- (18-b)} \end{aligned}$$

where $K = K_1 \cup K_2$.

$f^{*SLDM} = (f_1^{*SLDM}, f_2^{*SLDM}, \dots, f_{k_{12}}^{*SLDM})$ and $f^{-SLDM} = (f_1^{-SLDM}, f_2^{-SLDM}, \dots, f_{k_{12}}^{-SLDM})$ are the individual positive (negative) ideal solutions for the SLDM. In order to obtain a compromise (satisfactory) solution to the LS-BL-LVOP using TOPSIS approach, the distance family of (7) to represent the distance function from the positive ideal solution, $d_p^{PIS^{BL}}$, and the distance function from the negative ideal solution, $d_p^{NIS^{BL}}$, can be proposed, in this paper, for the objectives of the FLDM and the SLDM as follows:

$$d_p^{PIS^{BL}} = \left(\sum_{t \in K_1} w_t^p \left(\frac{\sum_{j=1}^q f_{tj}^{*FLDM} - \sum_{j=1}^q f_{tj}^{FLDM}(X)}{\sum_{j=1}^q f_{tj}^{*FLDM} - \sum_{j=1}^q f_{tj}^{-FLDM}} \right)^p + \sum_{v \in K_2} w_v^p \left(\frac{\sum_{j=1}^q f_{vj}^{FLDM}(X) - \sum_{j=1}^q f_{vj}^{*FLDM}}{\sum_{j=1}^q f_{vj}^{-FLDM} - \sum_{j=1}^q f_{vj}^{*FLDM}} \right)^p \right)^{1/p} + \sum_{t \in K_1} w_t^p \left(\frac{\sum_{j=1}^q f_{tj}^{*SLDM} - \sum_{j=1}^q f_{tj}^{SLDM}(X)}{\sum_{j=1}^q f_{tj}^{*SLDM} - \sum_{j=1}^q f_{tj}^{-SLDM}} \right)^p + \sum_{v \in K_2} w_v^p \left(\frac{\sum_{j=1}^q f_{vj}^{SLDM}(X) - \sum_{j=1}^q f_{vj}^{*SLDM}}{\sum_{j=1}^q f_{vj}^{-SLDM} - \sum_{j=1}^q f_{vj}^{*SLDM}} \right)^p \text{ --- (19a)}$$

And

$$d_p^{NIS^{BL}} = \left(\sum_{t \in K_1} w_t^p \left(\frac{\sum_{j=1}^q f_{tj}^{FLDM}(X) - \sum_{j=1}^q f_{tj}^{-FLDM}}{\sum_{j=1}^q f_{tj}^{*FLDM} - \sum_{j=1}^q f_{tj}^{-FLDM}} \right)^p + \sum_{v \in K_2} w_v^p \left(\frac{\sum_{j=1}^q f_{vj}^{-FLDM} - \sum_{j=1}^q f_{vj}^{FLDM}(X)}{\sum_{j=1}^q f_{vj}^{-FLDM} - \sum_{j=1}^q f_{vj}^{*FLDM}} \right)^p \right)^{1/p} + \sum_{t \in K_1} w_t^p \left(\frac{\sum_{j=1}^q f_{tj}^{SLDM}(X) - \sum_{j=1}^q f_{tj}^{-SLDM}}{\sum_{j=1}^q f_{tj}^{*SLDM} - \sum_{j=1}^q f_{tj}^{-SLDM}} \right)^p + \sum_{v \in K_2} w_v^p \left(\frac{\sum_{j=1}^q f_{vj}^{-SLDM} - \sum_{j=1}^q f_{vj}^{SLDM}(X)}{\sum_{j=1}^q f_{vj}^{-SLDM} - \sum_{j=1}^q f_{vj}^{*SLDM}} \right)^p \text{ --- (19b)}$$

where $w_i = 1, 2, \dots, k$, are the relative importance (weights) of objectives, and $p = 1, 2, \dots, \infty$. In order to obtain a compromise solution, we transfer problem (8) into the following bi-objective problem with two commensurable (but often conflicting) objectives [18, 45]:

$$\begin{aligned} & \text{Minimize } d_p^{PIS^{BL}}(X), \text{ Maximize } d_p^{NIS^{BL}}(X) \\ & \text{subject to } \text{--- (20)} \\ & X \in M \end{aligned}$$

where $p = 1, 2, \dots, \infty$.

Since these two objectives are usually conflicting to each other, we can simultaneously obtain their individual

optima. Thus, we can use membership functions to represent these individual optima. Assume that the membership functions $(\mu_3(X)$ and $\mu_4(X))$ of two objective functions are linear. Then, based on the preference concept, we assign a larger degree to the one with shorter distance from the PIS for $\mu_3(X)$ and assign a larger degree to the one with farther distance from NIS for $\mu_4(X)$. Therefore, as shown in figure (3), $\mu_3(X) \equiv \mu_{d_p^{PIS^{BL}}}(X)$ and $\mu_4(X) \equiv \mu_{d_p^{NIS^{BL}}}(X)$ can be obtained as the following (see [26, 43, 44, 53, 55, 63]):

$$\mu_3(X) = \begin{cases} 1, & \text{if } d_p^{PIS^{BL}}(X) < (d_p^{PIS^{BL}})^*, \\ 1 - \frac{d_p^{PIS^{BL}}(X) - (d_p^{PIS^{BL}})^*}{(d_p^{PIS^{BL}})^- - (d_p^{PIS^{BL}})^*}, & \text{if } (d_p^{PIS^{BL}})^- \geq d_p^{PIS^{BL}}(X) \geq (d_p^{PIS^{BL}})^*, \\ 0, & \text{if } d_p^{PIS^{BL}}(X) > (d_p^{PIS^{BL}})^-, \end{cases} \text{ --- (21a)}$$

$$\mu_4(X) = \begin{cases} 1, & \text{if } d_p^{NISBL}(X) > (d_p^{NISBL})^*, \\ 1 - \frac{(d_p^{NISBL})^* - d_p^{NISBL}(X)}{(d_p^{NISBL})^* - (d_p^{NISBL})^-}, & \text{if } (d_p^{NISBL})^- \leq d_p^{NISBL}(X) \leq (d_p^{NISBL})^*, \\ 0, & \text{if } d_p^{NISBL}(X) < (d_p^{NISBL})^-, \end{cases} \quad (21b)$$

where

$$\begin{aligned} (d_p^{PISBL})^* &= \text{Minimize}_{X \in M} d_p^{PISBL}(X) \text{ and the solution is } X^{PISBL}, \\ (d_p^{NISBL})^* &= \text{Maximize}_{X \in M} d_p^{NISBL}(X) \text{ and the solution is } X^{NISBL}, \\ (d_p^{PISBL})^- &= d_p^{PISBL}(X^{NISBL}) \text{ and } (d_p^{NISBL})^- = d_p^{NISBL}(X^{PISBL}). \end{aligned}$$

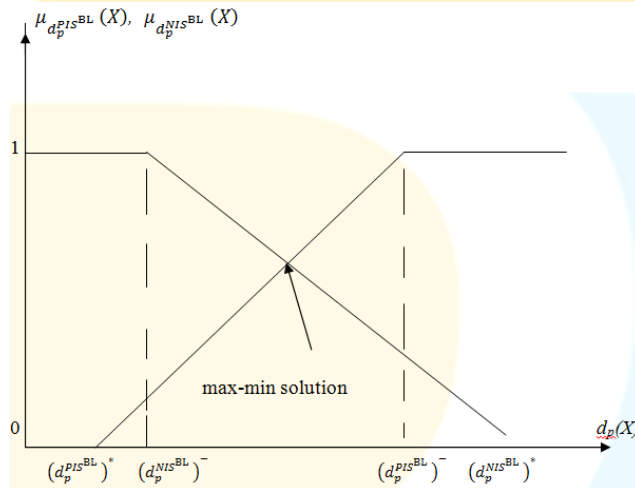


Figure 3: The membership functions of $\mu_{d_p^{PISBL}}(X)$ and $\mu_{d_p^{NISBL}}(X)$

Now, by applying the max-min decision model which is proposed by R. E. Bellman and L. A. Zadeh [26] and extended by H. -J. Zimmermann [63], we can resolve problem (20). The satisfactory solution of the LS-BL-LMOP Problem, X^{*BL} , may be obtained by solving the following model:

$$\mu_D(X^{*BL}) = \text{Maximize}_{X \in M} \{ \text{Min}(\mu_3(X), \mu_4(X)) \} \quad (22)$$

Finally, if $\delta^{BL} = \text{Minimize}(\mu_3(X), \mu_4(X))$, the model (22) is equivalent to the form of Tchebycheff model (see [32]), which is equivalent to the following model:

$$\text{Maximize } \delta^{BL}, \quad (23a)$$

subject to

$$\mu_3(X) \geq \delta^{BL}, \quad (23b)$$

$$\mu_4(X) \geq \delta^{BL}, \quad (23c)$$

$$\frac{x_{i_1i} - (X_{i_1i}^{*FLDM} - \tau_i^L)}{\tau_i^L} \geq \delta^{BL}, i = 1, 2, \dots, n_{i_1} \quad (23d)$$

$$\frac{(X_{i_1i}^{*FLDM} + \tau_i^R) - x_{i_1i}}{\tau_i^R} \geq \delta^{BL}, i = 1, 2, \dots, n_{i_1} \quad (23e)$$

$$x \in M, \quad \delta^{BL} \in [0,1], \quad (23f)$$

where δ^{BL} is the satisfactory level for both criteria of the shortest distance from the PIS and the farthest distance from the NIS. It is well known that if the optimal solution of (23) is the vector (δ^{*BL}, X^{*BL}) , then X^{*BL} is a nondominated solution of (20) and a satisfactory solution for the LS-BL-LMOP problem.

5. THE INTERACTIVE ALGORITHM OF TOPSIS FOR SOLVING LS-BL-LVOP:

Thus, we can introduce the following interactive algorithm to generate a set of satisfactory solutions for the LS-BL-LVOP:

The algorithm (Alg-I):

Phase (I):

Step 1. Construct the PIS payoff table of problem (9) by using the decomposition algorithm [31], and obtain $f^{*FLDM} = (f_1^{*FLDM}, f_2^{*FLDM}, \dots, f_{k_{i_1}}^{*FLDM})$ the individual positive ideal solutions.

Step 2. Construct the NIS payoff table of problem (9) by using the decomposition algorithm, and obtain $f^{-FLDM} = (f_1^{-FLDM}, f_2^{-FLDM}, \dots, f_{k_{i_1}}^{-FLDM})$ the individual negative ideal solutions.

Step 3. Use equations (10 & 11) and the above steps (1 & 2) to construct $d_p^{PISFLDM}$ and $d_p^{NISFLDM}$.

Step 4. Transform problem (9) to the form of problem (12).

Step 5. (I) Ask the FLDM to select $p = p^* \in \{1, 2, \dots, \infty\}$,
(II) Ask the FLDM to select $w_i = w_i^*$,
 $i = 1, 2, \dots, k_{i_1}$, where $\sum_{i=1}^{k_{i_1}} w_i = 1$,

Step 6. Use steps (3 & 5) to compute $d_p^{PISFLDM}$ and $d_p^{NISFLDM}$.

Step 7. Construct the payoff table of problem (12):
At $p = 1$, use the decomposition algorithm [31].
At $p \geq 2$, use the generalized reduced gradient method, [47, 48], and obtain:

$$\begin{aligned} d_p^{-FLDM} &= ((d_p^{PISFLDM})^-, (d_p^{NISFLDM})^-), \\ d_p^{*FLDM} &= ((d_p^{PISFLDM})^*, (d_p^{NISFLDM})^*). \end{aligned}$$

Step 8. Construct problem (15) by using the membership functions (13).

Step 9. Solve problem (15) to obtain $(\delta^{*FLDM}, X^{*FLDM})$.

Step10. Ask the FLDM to select the maximum negative and positive tolerance values τ_i^L and τ_i^R , $i = 1, 2, \dots, n_{I_1}$ on the decision vector $X_{I_1}^{*FLDM} = (x_{I_1 1}^{*FLDM}, x_{I_1 2}^{*FLDM}, \dots, x_{I_1 n_{I_1}}^{*FLDM})$,

Phase (II):

Step 11. Construct the PIS payoff table of problem (17) by using the decomposition algorithm [31], and obtain $f^{*SLDM} = (f_1^{*SLDM}, f_2^{*SLDM}, \dots, f_{k_{I_2}}^{*SLDM})$ the individual positive ideal solutions.

Step 12. Construct the NIS payoff table of problem (17) by using the decomposition algorithm, and obtain $f^{-SLDM} = (f_1^{-SLDM}, f_2^{-SLDM}, \dots, f_{k_{I_2}}^{-SLDM})$ the individual negative ideal solutions.

Step 13. Use equations (18 & 19) and the above steps (11 & 12) to construct $d_p^{PIS^{BL}}$ and $d_p^{NIS^{BL}}$.

Step 14. Transform problem (8) to the form of problem (20).

Step 15. Ask the FLDM to select $w_i = w_i^*$, $i = 1, 2, \dots, k$, where $\sum_{i=1}^k w_i = 1$,

Step 16. Use steps (5-1, 13, 15) to compute $d_p^{PIS^{BL}}$ and $d_p^{NIS^{BL}}$.

Step 17. Construct the payoff table of problem (20):
At $p=1$, use the decomposition algorithm [31],
At $p \geq 2$, use the generalized reduced gradient method, [47, 48], and obtain:

$$d_p^{-BL} = ((d_p^{PIS^{BL}})^-, (d_p^{NIS^{BL}})^-),$$

$$d_p^{*BL} = ((d_p^{PIS^{BL}})^*, (d_p^{NIS^{BL}})^*).$$

Step 18. Use equations (16 and 21) to construct problem (23).

Step 19. Solve problem (23) to obtain (δ^{*BL}, X^{*BL}) .

Step 20. If the DM is satisfied with the current solution, go to step 21. Otherwise, go to step 5.

Step 21. Stop.

6. AN ILLUSTRATIVE NUMERICAL EXAMPLE:

Consider the following LS-BL-LVOP problem with block angular structure:

[FLDM]
Maximize $f_{11}(X) = 2x_1 + 4x_2$ --- (24a)

Minimize $f_{12}(X) = x_1 - 2x_2$ --- (24b)

where x_1 solves the second level

[SLDM]
Maximize $f_{21}(X) = 2x_1 + 5x_2$ --- (24c)

Minimize $f_{22}(X) = 2x_1 - 4x_2$ --- (24d)

subject to

$x_1 + x_2 \leq 5$, --- (24e)

$x_1 \leq 2$, --- (24f)

$x_2 \leq 4$, --- (24g)

$x_1, x_2 \geq 0$ --- (24h)

Solution:

Obtain PIS and NIS payoff tables for the FLDM of the LS-BL-LVOP Problem (24).

Table (1) : PIS payoff table for the FLDM of problem (24)

	f_{11}	f_{12}	x_1	x_2
Maximize $f_{11}(X)$	18*	-7	1	4
Minimize $f_{12}(X)$	16	-8*	0	4

PIS: $f^{*FLDM} = (18, -8)$

Table (2) : NIS payoff table for the FLDM of problem (24)

	f_{11}	f_{12}	x_1	x_2
Minimize $f_{11}(X)$	0 ⁻	0	0	0
Maximize $f_{12}(X)$	4	2 ⁻	2	0

NIS: $f^{-FLDM} = (0, 2)$

Next, compute equation (11) and obtain the following equations:

$$d_p^{PIS^{FLDM}} = \left[w_1^p \left(\frac{18 - f_{11}(X)}{18 - 0} \right)^p + w_2^p \left(\frac{f_{12}(x) - (-8)}{2 - (-8)} \right)^p \right]^{1/p}$$

$$d_p^{NIS^{FLDM}} = \left[w_1^p \left(\frac{f_{11}(X) - 0}{18 - 0} \right)^p + w_2^p \left(\frac{2 - f_{12}(x)}{2 - (-8)} \right)^p \right]^{1/p}$$

Thus, problem (12) is obtained. In order to get numerical solutions, assume that $w_1^p = w_2^p = 0.5$ and $p=2$,

Table (3) : PIS payoff table of problem (12), when $p=2$.

	$d_2^{PIS^{FLDM}}$	$d_2^{NIS^{FLDM}}$	x_1	x_2
Min. $d_2^{PIS^{FLDM}}$	0.0365*	0.5677 ⁻	0.5339	4
Max. $d_2^{NIS^{FLDM}}$	0.05 ⁻	0.6592*	1	4

$d_2^{*FLDM} = (0.0365, 0.6592)$, $d_2^{-FLDM} = (0.05, 0.6577)$.

Now, it is easy to compute (15) :

Maximize δ^{FLDM}

subject to

$x_1 + x_2 \leq 5$, $x_1 \leq 2$, $x_2 \leq 4$, $x_1, x_2 \geq 0$,

$$\left(\frac{d_2^{PIS^{FLDM}}(X) - 0.0365}{0.0135} \right) \geq \delta^{FLDM},$$

$$\left(\frac{0.6592 - d_2^{NIS^{FLDM}}(X)}{0.0015} \right) \geq \delta^{FLDM},$$

$\delta^{FLDM} \in [0, 1]$.

The maximum “satisfactory level” ($\delta^{FLDM}=1$) is achieved for the solution $X_1^{*FLDM}=1$, $X_2^{*FLDM}=1$ and $(f_{11}, f_{12}) = (18, -8)$. Let the FLDM decide $X_1^{*FLDM}=1$ with positive tolerance $\tau^R = 0.5$ (one sided membership function [21, 52, 58]).

Obtain PIS and NIS payoff tables for the SLDM of the LS-BL-LMOP Problem (24).

Table (4) : PIS payoff table for the SLDM of problem (24)

	f_{21}	f_{22}	x_1	x_2
Maximize $x_2 f_{21}(X)$	23*	-10	1	4
Minimize $x_2 f_{22}(X)$	20	-12*	0	4

PIS: $f^{*SLDM}=(23, -12)$

Table (5) : NIS payoff table for the SLDM of problem (24)

	f_{21}	f_{22}	x_1	x_2
Minimize $x_2 f_{21}(X)$	0 ⁻	0	0	0
Maximize $x_2 f_{22}(X)$	6	4 ⁻	2	0

NIS: $f^{-SLDM}=(0, 4)$

Next, compute equation (19) and obtain the following equations:

$$d_p^{PIS^{BL}} = \left[w_1^p \left(\frac{18 - f_{11}(X)}{18 - 0} \right)^p + w_2^p \left(\frac{f_{12}(x) - (-8)}{2 - (-8)} \right)^p + w_3^p \left(\frac{23 - f_{21}(X)}{23 - 0} \right)^p + w_4^p \left(\frac{f_{22}(X) - (-12)}{4 - (-12)} \right)^p \right]^{1/p}$$

$$d_p^{NIS^{BL}} = \left[w_1^p \left(\frac{f_{11}(X) - 0}{18 - 0} \right)^p + w_2^p \left(\frac{2 - f_{12}(x)}{2 - (-8)} \right)^p + w_3^p \left(\frac{f_{21}(X) - 0}{23 - 0} \right)^p + w_4^p \left(\frac{4 - f_{22}(X)}{4 - (-12)} \right)^p \right]^{1/p}$$

Thus, problem (20) is obtained. In order to get numerical solutions, assume that $w_1^p=w_2^p=w_3^p=w_4^p=0.25$ and $p=2$,

Table (6) : PIS payoff table of problem (20), when $p=2$.

	$d_2^{PIS^{BL}}$	$d_2^{NIS^{BL}}$	x_1	x_2
Min. $d_2^{PIS^{BL}}$	0.0292*	0.4709 ⁻	0.5340	4
Max. $d_2^{NIS^{BL}}$	0.04 ⁻	0.4727*	1	4

$$d_2^{*BL}=(0.0292, 0.4727), d_2^{-BL}=(0.04, 0.4709).$$

Now, it is easy to compute (23) :

Maximize δ^{BL}

subject to

$$x_1 + x_2 \leq 5, x_1 \leq 2, x_2 \leq 4, x_1, x_2 \geq 0,$$

$$\left(\frac{d_2^{PIS^{BL}}(X) - 0.0292}{0.04 - 0.0292} \right) \geq \delta^{BL},$$

$$\left(\frac{0.4727 - d_2^{NIS^{BL}}(X)}{0.4727 - 0.4709} \right) \geq \delta^{BL},$$

$$\left(\frac{(1 + 0.5) - x_1}{0.5} \right) \geq \delta^{BL}$$

$$\delta^{BL} \in [0,1] .$$

The maximum “satisfactory level” ($\delta^{BL}=1$) is achieved for the solution $X_1^{*BL}=1$, $X_2^{*BL}=1$.

7. CONCLUSION

In this paper, a TOPSIS approach has been extended to solve LS-BL-LVOP . The LS-BL-LVOP using TOPSIS approach provides an effective way to find the compromise (satisfactory) solution of such problems. In order to obtain a compromise (satisfactory) solution to the LS-BL-LVOP using the proposed TOPSIS approach, a modified formulas for the distance function from the PIS and the distance function from the NIS are proposed and modeled to include all objective functions of both the first and the second levels. Thus, the bi-objective problem is obtained which can be solved by using membership functions of fuzzy set theory to represent the satisfaction level for both criteria and obtain TOPSIS, compromise solution by a second-order compromise. The max-min operator is then considered as a suitable one to resolve the conflict between the new criteria (the shortest distance from the PIS and the longest distance from the NIS). An interactive TOPSIS algorithm for solving these problems are also proposed. An illustrative numerical example is given to demonstrate the proposed TOPSIS approach and the interactive algorithm.

REFERENCES

- [1] Afshar A., Mariño M. A., Saadatpour M. and Afshar A., Fuzzy TOPSIS Multi-Criteria Decision Analysis Applied to Karun Reservoirs System, *Water Resour Manage* , 25 (2011) 545–563.
- [2] Abo-Sinna M. A., " Extensions of the TOPSIS for multiobjective Dynamic Programming Problems under Fuzziness", *Advances in Modelling & Analysis*, (Series B), Vol. 43, No. 4, pp. 1-24, (AMSE Journals, France), (2000).

- [3] Abo-Sinna M.A., Pareto optimality for bi-level programming problem with fuzzy parameters, *J. Oper. Res. Soc. India (OPSEARCH)* 38 (4) (2001) 372–393.
- [4] Abo-Sinna M.A., A Bi-level non-linear multi-objective decision making under fuzziness, *J. Oper. Res. Soc. India (OPSEARCH)* 38 (5) (2001) 484–495.
- [5] Abo-Sinna M.A., and Abou-El-Enien T. H. M., An Algorithm for Solving Large Scale Multiple Objective Decision Making Problems Using TOPSIS Approach, *Advances in Modelling and Analysis*, (Series A), Vol. 42, No.6, pp. 31-48, (*AMSE Journals, France*), (2005).
- [6] Abo-Sinna M. A. and Amer A. H., Extensions of TOPSIS for multi-objective large-scale nonlinear programming problems, *Applied Mathematics and Computations*, Vol.162, pp. 243-256, (2005).
- [7] Abo-Sinna M.A.,and Baky I.A., A Comparison of two bi-level programming methods in multi-objective programming problems applied to the supply demand interactions in electronic commerce, *Scientific Bulletin, Ain Shams University, Faculty of Engineering*, vol. 40, no. 4 2005, pp. 1189–1213.
- [8] Abo-Sinna M.A.and Abou-El-Enien T. H. M., An Interactive Algorithm for Large Scale Multiple objective Programming Problems with Fuzzy Parameters through TOPSIS approach, *Applied Mathematics and Computation*, Vol. 177, No. 2, pp. 515-527, (*Elsevier, Holland*), (2006).
- [9] Abo-Sinna M.A.,and Baky I.A., Interactive balance space approach for solving bi-level multi-objective programming problems, *AMSE-Model. (B)*. (40) (2006) 43–62. France.
- [10] Abo-Sinna M.A., and Baky I.A., Interactive balance space approach for solving multi-level multi- objective programming problems, *Inform. Sci.* 177 (2007) 3397–3410.
- [11] Abo-Sinna M. A., Amer A. H. and Ibrahim A. S., Extensions of TOPSIS for large scale multi-objective non-linear programming problems with block angular structure, *Applied Mathematical Modelling*, 32(3) (2008), 292-302.
- [12] Abo-Sinna M. A. and Baky I. A., Fuzzy Goal Programming Procedure to Bilevel Multiobjective Linear Fractional Programming Problems, *International Journal of Mathematics and Mathematical Sciences*, pp. 1-15, 2010,
- [13] Abou -El-Enien T. H. M., On Large Scale Linear Vector Optimization Problems with single Parameters in the objective functions, *Advances in Modelling and Analysis*, (D), Vol. 7, No.3, pp. 19-29, (*AMSE Journals, France*), (2002).
- [14] Abou -El-Enien T. H. M. and Abo-Sinna M. A., Extension of TOPSIS for Large Scale Multiple Objective Decision Making Problems under Fuzzy environment, in *the proceeding of the Second International Conference on Informatics and Systems, "INFOS 2004"*, Faculty of Computers & Information, Cairo University, March 6-8, pp. 153-170, *Egypt*, (2004).
- [15] Abou-El-Enien T. H. M., An Algorithm for Parametric Large Scale Integer Linear Multiple Objective Decision Making Problems, *Advances in Modelling and Analysis*, (Series A), Vol. 42, No.4, pp.51-70, (*AMSE Journals, France*), (2005).
- [16] Abou-El-Enien T. H. M. and Saad O. M., On the Solution of a Special Type of Large Scale Linear Fractional Multiple Objective Programming Problems with Uncertain Data", *Applied Mathematical Sciences*, Vol. 4, No. 62, pp. 3095–3105, (*Hikari, Bulgaria*), (2010).
- [17] Abou-El-Enien T. H. M., Interactive TOPSIS Algorithm for a Special Type of Linear Fractional Vector Optimization Problems , *International Journal of Information Technology and Business Management*, Vol. 31, No. 1, pp. 13 – 24, (*ARF, Pakistan*), (2014).
- [18] Abou-El-Enien T. H. M., TOPSIS Algorithms for Multiple Objectives Decision Making : Large Scale Programming Approach, *LAP LAMBERT Academic Publishing*, Germany, (2013).
- [19] Aryanezhad M.B. & Roghanian E., A bi-level linear multi-objective decision making model with interval coefficients for supply chain coordination, *IUST International Journal of Engineering Science*, Vol. 19, No.1-2, 2008, pp. 67-74 *Mathematics & Industrial Engineering Special Issue*
- [20] Baky I . A., Fuzzy goal programming algorithm for solving decentralized bi-level multi-objective programming problems, *Fuzzy Sets and Systems*, 160 (2009), 2701–2713.
- [21] Baky I . A. and Abo-Sinna M. A., TOPSIS for bi-level MODM problems, *Applied Mathematical Modelling*, 37 (2013), 1004-1015.
- [22] Bard J. F., An efficient point algorithm for a linear two-stage optimization problem, *Operations Research*, 31 (1983), 670–684.
- [23] Bard J. F., Coordination of a multidivisional organization through two levels of management, *Omega*, 11 (1983), 457–468.
- [24] Ben-Ayed O., Bi-level linear programming, *Computers and Operations Research*, 20 (1993), 485–501.
- [25] Ben-Ayed O.,and Blair C. E., Computational difficulties of bi-level linear programming, *Operations Research*, 38 (1990), 556–560.

- [26] Bellman R.E. & Zadeh L.A., Decision-making in fuzzy environment, *Management Science*, B 17(1970) 141-164,
- [27] Candler W., and Townsley R., A linear bi-level programming problems, *Computers and Operations Research*, 9 (1982), 59–76.
- [28] Chen C.T., Extensions of the TOPSIS for group decision-making under environment, *Fuzzy Sets and Systems*, 114 (2000) 1-9.
- [29] Chen M. and Tzeng G., Combining grey relation and TOPSIS concepts for selecting an expatriate host country, *Mathematical and Computer Modelling*, 40(2004) 1473-1490.
- [30] Cheng C., Zhao M., Chau K.W. and Wu X., Using genetic algorithm and TOPSIS for Xinanjiang model calibration with a single procedure, *Journal of Hydrology*, 316(2006),129-140.
- [31] Dantzig G., & Wolfe P., The Decoposition Algorithm for Linear Programming, *Econometric*, 9(4)(1961), 1-9.
- [32] Dauer J.P., and Osman M.S.A., Decomposition of the Parametric Space in Multiobjective Convex Programs using the Generalized Tchebycheff Norm, *Journal of Mathematical Analysis and Applications*, 107(1) (1985), 156-166.
- [33] Deng H., , Yeh C.H.& Willis R. J., Inter-company comparison using modified TOPSIS with objective weights, *Computers & Operations Research*, 17(2000), 963-973.
- [34] El-Sawy A. A., El-Khouly N. A. and Abou -El-Enien T. H. M. , Qualitative and Quantitative Analysis of the stability set of first kind in parametric large scale integer linear programming problems. *Advances in Modelling and Analysis*, (A), Vol. 37, No. 1, pp.1-20, (*AMSE Journals, France*) (2000).
- [35] El-Sawy A. A., El-Khouly N. A. and Abou -El-Enien T. H. M., An Algorithm for Decomposing the Parametric Space in Large Scale Linear Vector Optimization Problems : A Fuzzy Approach, *Advances in Modelling and Analysis*, (C), Vol. 55, No. 2, pp. 1-16, (*AMSE Journals, France*), (2000).
- [36] Emam O. E., A fuzzy approach for bi-level integer non-linear programming problem, *Applied Mathematics and Computation*, 172 (2006) 62-71.
- [37] Emam O. E., Interactive bi-level Multi-Objective Integer non-linear programming problem, *Applied Mathematical Sciences*, Vol. 5, no. 65, 3221-3232, (2011).
- [38] Emam O. E., Interactive approach to bi-level Integer Multi-Objective fractional programming problem, *Applied Mathematics and Computation*, 223(2013)17-24.
- [39] Freimer M., and Yu P. L., Some New Results on Compromise Solutions for Group Decision Problems, *Management Science*, Vol. 22, No. 6, pp. 688-693, (1976).
- [40] Ho J. K., and P.Sundarraaj R., Computational Experience with Advanced Implementation of Decomposition Algorithm for Linear Programming , *Mathematical Programming*, 27(1983), 283-290.
- [41] Hwang C. L., & Masud A. S. M., Multiple Objective Decision Making Methods and Applications, Springer-Verlag, New York, 1979.
- [42] Hwang C. L. and Yoon K., Multiple Attribute Decision Making Methods and Applications: A State-of-the-Art-Survey, Lecture Notes in Economics and Mathematical Systems 186, Springer-Verlag, Berlin, Heidelberg, (1981).
- [43] Kahraman C. (ed), Fuzzy Multi-Criteria Decision Making: Theory and Applications with Recent Developments, Springer, New York, 2008.
- [44] Lai Y. J. and Hwang C.L., Fuzzy Multiple Objective Decision Making: Methods and Applications, Springer-Verlag, Heidelberg, 1994.
- [45] Lai Y. J., Liu T.Y. & Hwang C.L., TOPSIS for MODM, *European Journal of Operational Research*, 76(1994), 486-500.
- [46] Lai Y. J., Hierarchical optimization: A satisfactory solution, *Fuzzy Sets and Systems*, 77 (1996), 321–335.
- [47] Lasdon L. S., Optimization theory for large systems, Macmillan, New York, 1970.
- [48] Lasdon L. S., Waren A. D., & Ratner M.W, GRG2 User's Guide Technical Memorandum, University of Texas, 1980.
- [49] Mulvey J. M., Vanderbei R. J., and Zenios S. A., Robust optimization of large-scale systems, *Operations Research*, 43 (1995), 264–281.
- [50] Nikolsky S. M., A Course of Mathematical Analysis, Mir Publishers, Moscow, USSR, (1987).
- [51] Pramanik S., Kumar Roy T., Fuzzy goal rogramming approach to multilevel programming problems, *Euro. J. Oper. Res.* 176 (2006) 1151–1166.
- [52] Roghanian E., Sadjadi S. J., and Aryanezhad M. B., A probabilistic bi-level linear multi-objective programming problem to supply chain planning, *Applied Mathematics and Computation* 188 (2007) 786–800.
- [53] Sakawa M., Fuzzy Sets and Interactive Multi-objective Optimization, Plenum Press, New York, pp. 7-82, 1993.
- [54] Sakawa M. and Yano H., Fuzzy dual decomposition method for large-scale multiobjective nonlinear programming problems", *Fuzzy Sets and Systems* Vol. 67, Issue 1, pp. 231-240, (1994).

- [55] Sakawa M., Yano H. & Yumine T., An Interactive Fuzzy Satisficing method for multiobjective Linear-Programming Problems and its Application, *IEEE Transactions Systems, Man and Cybernetics*, Vol. SMC-17, No. 4, pp. 654-661, (1987).
- [56] Sakawa M., Large Scale Interactive Fuzzy Multiobjective Programming, Physica-Verlag, A Springer-Verlag, New York, (2000)
- [57] Sinha S., Fuzzy programming approach to multi-level programming problems, *Fuzzy Sets and Syst.* 136 (2003) 189–202.
- [58] Wen U. P., and Hsu S. T., Linear bi-level programming problems—a review, *Journal of the Operational Research Society*, 42 (1991), 125–133.
- [59] White D. J., and Anandalingam G., A penalty function approach for solving bi-level linear programs, *Journal of Global Optimization*, 3 (1993), 393–419.
- [60] Yu P. L. and Zeleny M., The set of all non-dominated solutions in linear cases and a multicriteria decision making, *Journal of Mathematical Analysis and Applications*, 49(1975),430-448.
- [61] Zeleny M., Compromise Programming, in : J.L. Cochrane and M. Zeleny (eds.), *Multiple Criteria Decision Making*, University of South Carolina, Columbia, SC, (1973),262-300.

- [62] Zeleny M., *Multiple Criteria Decision Making*, McGraw-Hill, New York, 1982.
- [63] Zimmermann H.-J., *Fuzzy Sets, Decision Making, and Expert Systems*, Kluwer Academic Publishers, Boston, 1987.

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