

# Discrete Linear Bilevel Programming Problems Using Transformation

Anuradha Sharma

(Associate Professor Delhi University,India)

**Abstract**—In this paper an algorithm is developed to solve the integer linear bilevel programming (ILBP) problem. The ILBP is transferred into a single level programming which can be solved by the algorithm proposed here. This algorithm deals by changing the randomly generated initial population into an initial population satisfying the constraints to improve the efficiency of the algorithm to deal with the constrains.

**Keywords**- Linear functios; bilevel programming; Integer programming; genetic algorithm; Kuhn-Tucker conditions.

## I. INTRODUCTION

The mathematical programming models deal with single decision maker and single objective function which are used for centralized planning systems. Bilevel programming deals with decision processes involving two decision makers with a hierarchical structure. The first level decision maker is termed as the “Leader” and the decision maker at the second level pertains to the objective of “follower”. Each decision maker optimizes its own objective function and/or is affected by actions .of planner. Integer Linear bilevel programming (ILBP) problem is a special case of bilevel programming problems in which the objective functions as well as constraints are all linear, and it can be formulated as follows[3]:

$$(ILBP). \quad \max f(x,y) = p_1x + q_1y.$$

Where, y solves

$$\max g(x,y)=p_2x+q_2.y$$

$$s.t. \quad A_1x+A_2.y \leq b;$$

$x, y \geq 0$ ,  $x, y$  integers

where  $f, g$  : the objective functions of leader-follower;  $x$  is an  $n_1$ -dimensional column vector (variables under control of first level) and  $y$  is an  $n_2$ -dimensional column vector (variables under control of second level);  $p_1, p_2$  are  $n_1$ -dimensional row vectors,  $q_1$  and  $q_2$  are  $n_2$ -dimensional row vectors;  $A_1$  is  $m \times n_1$ -matrix and  $A_2$  is  $m \times n_2$ -matrix and  $b$  is an  $m$ -dimensional column vector. We assume that  $S$  defined by common constraints is nonempty and bounded

$$(ILBP) \max f(x, y) = p_1 x + q_1 y$$

where  $y$  solves

$$\max g(x, y) = p_2 x + q_2 y \quad (1)$$

$$\text{s.t. } A_1 x + A_2 y \leq b,$$

$$x, y \geq 0,$$

$$x, y \text{ integers}$$

where  $f, g$  are the objective functions of the leader and follower, respectively;  $x$  is an  $n_1$  dimensional column vector (variables under the control of first level) and  $y$  is an  $n_2$  dimensional column vector (variables under the control of second level);  $p_1$  and  $p_2$  are  $n_1$ -dimensional row vectors,  $q_1$  and  $q_2$  are  $n_2$ -dimensional row vectors;  $A_1$  is  $m \times n_1$  matrix and  $A_2$  is  $m \times n_2$  matrix ;and  $b$  is an  $m$ -dimensional column vector. We assume that the polyhedron  $S$  defined by the common constraints is nonempty and bounded.

Many researchers tackled the ILBP problem by presenting both theoretical results and application [4],[5]. The algorithmic approaches developed so far for ILBP problem can be classified into four categories[5]

- (1) meta-heuristic approach;
- (2) KT conditions .approach;
- (3) fuzzy criterion approach;

## (4) vertex.enumeration approach

The ILBP is neither continuous everywhere nor convex because the objective function of the first level problem is decided by the solution function of the second level problem which is neither linear nor differential. J. F. Bard [1] proved that ILBP is a NP-Hard problem. The algorithms proposed include genetic algorithms [2], [5], [7], simulated annealing algorithms [9], particle swarm optimization (PSO) [6] etc.

In this study, algorithm is developed/proposed for ILBP problem. DE proposed by Storn and Price[10] optimized real valued multi-modal objective functions. Besides its good convergence properties the algorithm is very simple to implement and finds solution to the problem.

## II. ALGORITHMIC DEVELOPMENT

The algorithm proposed in this paper is a parallel direct search method which utilizes NP dimensional parameter vectors

$$p_i^G = (p_{i1}^G \ p_{i2}^G \ \dots \ p_{iD}^G) \quad i=1,2,\dots, NP$$

as a population for each generation G. To be more precise, the basic approach in the algorithm [8],[10] is described in the following steps :

Step1: The initial vector population is chosen randomly from within a user-defined range and should cover the entire parameter space.

Step2: *Mutation*. In this step, the mutated vectors ( $i = 1, 2, \dots, NP$ ) are generated according to

$$g_i^{G+1} = p_{r1}^G + F \cdot (p_{r2}^G - p_{r3}^G) \quad (3)$$

with random indexes  $r1, r2, r3 \in \{1, 2, \dots, NP\}$ , integer, mutually different and  $F > 0$ . The randomly chosen integers  $r1, r2$  and  $r3$  are also chosen to be different from the running index  $i$ , so that NP must be greater or equal to four to allow for this condition. Weighting factor  $F \in [0, 2]$  is a real and constant factor which controls the amplification of the differential variation  $(p_{r2}^G - p_{r3}^G)$ .

Step3: To increase the diversity of the perturbed parameter vectors, crossover is introduced. To this end, the trial vector

$$h_i^{G+1} = (h_{i1}^{G+1} \ h_{i2}^{G+1} \ \dots \ h_{iD}^{G+1}) \quad (4)$$

is formed, where

$$h_{ij}^{G+1} = \begin{cases} g_{ij}^{G+1} & , \text{ if } (randb(j) \leq CR) \text{ or } j = rnbr(i) \\ p_{ij}^G & , \text{ otherwise,} \end{cases} \quad (5)$$

In (5),  $randb(j) \in [0, 1]$  is the  $j$ -th evaluation of a uniform random number generator with outcome.  $CR \in [0, 1]$  is the crossover constant which has to be determined by the user.  $rnbr(i) \in \{1, 2, \dots, D\}$  is a randomly chosen index which ensures that  $h_{ij}^{G+1}$  gets at least one parameter from  $g_{ij}^{G+1}$

Step4: To decide whether or not it should become a member of generation  $G+1$ , the trial vector  $g_{ij}^{G+1}$  is compared to the target vector  $p_i^G$  using the greedy criterion.

Step5: Stop the algorithm if the condition is satisfied or iteration number is larger than the maximal iteration number. Then .best generated solution, which can be obtained by the current best vector kept in all iterations in the earliest time: is reported as the solution for the LBP problem by proposed algorithm.

### III. REDUCING ILBP PROBLEM TO A SINGLE LEVEL PROGRAM

At first the ILBP problem can be transferred into a single level programming of the form

$$(P1) \quad \max f(x,y) = p_1 x + q_1 y$$

$$\text{s.t.} \quad A_1 x + A_2 y + u = b;$$

$$z A_2 - v = d_2, ,$$

$$uz = 0, vy = 0,;$$

$$x, y, z, u, v \geq 0.$$

$$x, y \text{ integer}$$

Problem (6) is transformed into the following problem

$$(P2) \quad \max p_1 x$$

$$\text{s.t.} \quad A_1 x = b - A_2 y_1^G - u_1^G;$$

$$z' A_2 - v' = d_2;$$

$$x, z', v' \geq 0; \quad (8)$$

$$x \text{ integer}$$

In problem (8),  $z'$  and  $v'$  are the variables of  $z$  and  $v$  that are greater than or equal to zero. Also,  $A'_2$  is the rows of  $A_2$  which is associated with the variables  $z'$ . Furthermore, problem (8) can be decomposed into two separate problems as follows:

$$(P3) \quad z'A'_2 - v' = d_2$$

$$z', v' \geq 0 \quad (9)$$

$$(P4) \quad \max p_1 x$$

$$\text{s.t. } A_1 x = b - A_2 y_1^G - u_1^G \quad (10)$$

$$x \geq 0$$

Such decomposition is allowed for the problem, because problems (9) and (10) do not have common variables. Problem (9) is solved at first. If problem is infeasible, then the target vector is not achievable; otherwise, problem (10) is solved. If problem is infeasible, then  $p_1^G$  is unaccessible.

#### IV NUMERICAL EXAMPLE

$$\text{Max } -42x + 21y + 72$$

$$\text{Max } -5x - 31y + 23:$$

$$\text{s.t. } 23.2x - 32y \leq 34:$$

$$2x - 3.1y \leq 24:$$

$$13x + 54y \leq 96:$$

$$22.6x + 37y \leq 86:$$

$$54x + 25y \leq 65.2:$$

$$34x + 54y \geq 78:$$

$$x, y \geq 0;$$

The best solution for technique proposed in this paper is given by

$(x^*, y^*) = (17.4545, 10.9091)$  and objective function value is "f = 85.0909" and "g = -50.181".

#### "IV CONCLUSIONS

The presented procedure designs the algorithm for solving ILBP problems in which the optimal solution of the lower level problem is dependent on the upper level problem. The solution approach makes use of simple transformation method which takes up less computational work.

**ACKNOWLEDGEMENTS** : The author is highly grateful to reviewers & referees for their valuable suggestions which helped in the improvement of the paper.

## V. REFERENCES

- [1] J F Bard, J E Falk. *An explicit solution to the multi-level programming problem*. Computers & Operations Research, 1982, 9(1):77–100.
- [2] H I Calvete, C Gale, P M Mateo. *A new approach for solving linear bilevel problems using genetic algorithms*. European Journal of Operational Research, 2008, 188:14–28.
- [3] W Candler, R Townsley. *A linear two-level programming problem*. Computers & Operations Research, 1982, 9:59–76.
- [4] S Dempe. *Annotated bibliography on bilevel programming and mathematical programs with equilibrium constraints*. Optimization, 2003, 52:333–359.
- [5] SR Hejazi, A Memariani, G Jahanshahloo, M M Sepehri. *Linear bilevel programming solution* Computers & Operations Research, 2002, 29:1913–1925.
- [6] R J Kuo, C C Huang. *Application of particle swarm optimization algorithm for solving bi-level linear programming problem*. Computers & Mathematics with Applications, 2009, 58(4) :678–685.
- [7] M S Osman, W F El-Wahed,. *A solution methodology of bi-level linear programming based on genetic algorithm*. Journal of Mathematics and Statistics, 2009, 5(4):352–359.
- [8] K J Pan, H Chen, Y J Tan. *Multi-exponential inversion of  $T_2$  spectrum in NMR based on differential evolution algorithm*. Acta Physica Sinica, 2008, 57(9):5956–5961.
- [9] K H Sahin, A R Cirit. *A dual temperature simulated annealing approach for solving bilevel programming problems*. Computers and Chemical Engineering, 1998, 23:11–25.
- [10] R Storn, K Price. *Differential evolution – a simple and efficient heuristic for global optimization over continuous spaces*. Journal of Global Optimization, 1997, 11:341–359.
- [11] U P Wen, S T Hsu. *Algorithms for solving the mixed integer two-level linear programming problem*. Computers & Operations Research 1990 , 17(2) , 133 – 142.