# Resolution Method for Mixed Integer Linear Multiplicative-Linear Bilevel Problems Based on Decomposition Technique 

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#### Abstract

I In this paper, we propose an algorithm base on decomposition technique for solving the mixed integer linear multiplicative-linear bilevel problems. In fact, this algorithm is an application of the algorithm given by G. K. Saharidis et al for the case in which the first level objective function is linear multiplicative. We use properties of quasi-concave of bilevel programming problems and decompose the initial problem into two subproblems named $R M P$ and $S P$. The lower and upper bound provided from the $R M P$ and $S P$ are updated in each iteration. The algorithm converges when the difference between the upper and lower bound is less than an arbitrary tolerance. In conclusion, some numerical examples are presented in order to show the efficiency of algorithm.


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decomposition, Multiplicative programming, Karush-Kuhn-Tucker optimality conditions.

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## 1. Introduction

Bilevel programming problems are a special kind of decision processes involving two decision makers with a hierarchical structure in which the upper level decision maker is called the leader and the lower level decision maker is called the follower; additionally, the constraint region of the upper level optimization problem is implicitly determined by the lower level optimization problem. In general, Bilevel problems consist of determining a vector $x=\left(x_{1}, x_{2}\right) \in \mathbb{R}^{n}$ such that [10]:

[^0]\[

$$
\begin{array}{cc} 
& \min _{\left(x_{1}, x_{2}\right) \in S} f_{1}\left(x_{1}, x_{2}\right) \\
\text { s.t } & x_{2} \in \arg \min _{\nu \in S\left(x_{1}\right)} f_{2}\left(x_{1}, \nu\right) \tag{1}
\end{array}
$$
\]

where $x_{1} \in \mathbb{R}^{n_{1}}$ and $x_{2} \in \mathbb{R}^{n_{2}}$ are the variables controlled by the upper level and the lower level decision makers, respectively; $f_{1}, f_{2}: \mathbb{R}^{n} \Rightarrow \mathbb{R}, n=n_{1}+n_{2} ; S \subset \mathbb{R}^{n}$ defines the common constraint region and $S\left(x_{1}\right)=\left\{x_{2} \in \mathbb{R}^{n_{2}}:\left(x_{1}, x_{2}\right) \in S\right\}$. The most approaches and algorithms proposed for solving bilevel problems have focused on the linear case of this problem such as the KuhnTucker approach [3, 13], the Kth-best algorithm [9], the penalty function approach [31], the branch-and-bound algorithm [4, 13], then, some scholars such as Bilias and Karwan [8] and Bard [1, 2] extended them. Important decision making problems may involve decisions in both discrete and continuous variables. For example, a chemical engineering design problem may involve discrete decisions regarding the existence of chemical process units in addition to decisions in continuous variables, such as temperatures or pressures. Problems in this class, involving both discrete and continuous decision variables are mixed integer BLPP. Note that real world problems often involve nonlinear terms, resulting in mixed integer nonlinear BLPP [19]. Bilevel programming problems are NP hard [16], and discrete nonlinear bilevel problems are harder to solve, so despite numerous applications of them in real world, there have been alittle attention in bilevel problems involving discrete decisions and even less attention in case both nonlinear and discrete. For the solution of the integer linear BLPP, a branch and bound method has been developed by Moore and Bard [22] and For the solution of the mixed integer BLPP, another branch and bound technique is developed by Wen and Yang [30]. Cutting plane and parametric solution approaches have been developed by Dempe [15].Global optimization for solving mixed integer bilevel problems has been developed by Floudas [19]. Also, the few algorithms have been published for the nonlinear problem by Shi et al.[26], Bialas and Karwan [8] and Hansen et al.[20]. One of techniques for solving bilevel problems, is the reformulation techniques that have been developed for solving the nonlinear or quadratic bilevel problems; it transform the bilevel problem into a single level problem, for example by replacing the KarushKuhnTucker optimality conditions instead the inner problem and considering them as constraints of the upper level problem, the bilevel problem is transformed into a single level problem. Therefore, instead of solving the bilevel problem directly, it is transformed into a single level problem to be solved. Shi et al.[26], Bialas and Karwan [8] use the KKT optimality conditions for replacing the inner problem and hence they use different forms of branch and bound algorithm for solving of the reformulated problem. In this paper, that is an application from the algorithm presented in reference [25], we consider the class of bilevel problems in which the upper level objective function $f_{1}$ is linear multiplicative, the lower level one $f_{2}$ is linear and the common constraint region $S$ is a bounded polyhedron thus feasible conditions such as conditions expressed in reference [25] but optimality conditions change. The algorithm is based on Benders decomposition technique which uses Karush-Kuhn-Tucker optimality conditions. The only assumption of the proposed algorithm is that although integer variables could appear in both levels of problem, they should be controlled by the upper optimization problem. Then at each iteration of the algorithm, the $S P$ gives a new valid cut to the $R M P$ which converges to the optimal solution. If the $R M P$ optimality condition is not satisfied by the solution obtained by $S P$, the $R M P$ sends the updated information to the $S P$ which produces another cut for $R M P$
and the algorithm continues until the $R M P$ optimality condition is satisfied [25]. The paper is organized as follows. After having defined the problem in section 2 , an algorithm for solving mixed integer linear multiplicative-linear bilevel problems is offered in section 3. Further, in section 4, the numerical experiments are presented.

## 2. Linear Multiplicative-Linear Bilevel Problem [7]

Using the common notation in bilevel programming, the LMLB problem can be stated as follow:

$$
\begin{align*}
& \min _{x_{1}} \quad\left(\alpha+c_{1}^{t} x\right)\left(\beta+c_{2}^{t} x\right) \\
& = \\
& \min _{x_{2}} \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
& \text { S.t. }\left\{\begin{array}{c}
A_{1} x_{2}+A_{2} x_{2} \leqslant b \\
x_{1} \geqslant 0, x_{2} \geqslant 0
\end{array}\right. \tag{2}
\end{align*}
$$

where $A_{1} \in M_{m \times n_{1}} ; A_{2} \in M_{m \times n_{2}} ; b, d_{2}, c_{22}, c_{21}, c_{12}, c_{11}$ are vectors of conformal dimension; $c_{1}=\left(c_{11}, c_{12}\right), c_{2}=\left(c_{21}, c_{22}\right) ; \alpha, \beta$ are scalars and $\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right)>0,\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)>0$, for all $x=\left(x_{1}, x_{2}\right) \in S$, the polyhedron defined by the constraints. We assume that $S$ is a nonempty and bounded polyhedron of full dimension in $\mathbb{R}^{n_{1}}$. Let $S_{1}$ be the projection of $S$ onto $\mathbb{R}^{n 1}$. For each $x_{1} \in S_{1}$, a feasible solution to the $L M L B$ problem is obtained by solving the following linear programming problem [10]:

$$
\begin{align*}
& \min _{x_{2}} \quad d_{2} x_{2} \\
& \text { S.t. }\left\{\begin{array}{c}
A_{1} x_{1}+A_{2} x_{2} \leqslant b \\
x_{1} \geqslant 0, x_{2} \geqslant 0
\end{array}\right. \tag{3}
\end{align*}
$$

Let $P\left(x_{1}\right)$ be the set of optimal solutions to (3), we assume that $P\left(x_{1}\right)$ is nonempty and singleton. Ref.[2] show the difficulties which may arise when $P\left(x_{1}\right)$ is not singlevalued. The feasible region of problem (2), called inducible region, is implicitly defined as follows:

$$
I R=\left\{\left(\overline{x_{1}}, \overline{x_{2}}\right): \overline{x_{1}} \geqslant 0, \overline{x_{2}} \in P\left(\overline{x_{1}}\right)\right\}
$$

Let us consider the following linear multiplicative problem:

$$
\begin{align*}
& \min _{x_{1}, x_{2}}\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
& \text { S.t. }\left\{\begin{array}{l}
A_{1} x_{1}+A_{2} x_{2} \leqslant b \\
x_{1} \geqslant 0, x_{2} \geqslant 0
\end{array}\right. \tag{4}
\end{align*}
$$

If an optimal solution $\left(\tilde{x_{1}}, \tilde{x_{2}}\right)$ of (4) pertains to $I R$, then it is an optimal solution of the $L M L B$ problem. We used the following results.
Lemma 2.1 [11] The inducible region of the quasiconcave bilevel programming problem (1) is a piecewise linear.
Theorem 2.2 [11] There is an extreme point of the constraint region $S$ which is an optimal solution to the quasiconcave bilevel programming problem (1).

## 3. Theoretical background of the proposed algorithm

In the sequel, we used the following notations:
Index:

- $l$ denotes the number of extreme rays of the dual slave problem;
- $p$ denotes the number of extreme rays of the dual slave problem with $z=z_{1}$;
- $k$ denotes the number of extreme rays of the dual slave problem with $z=z_{2}$;
- $r$ denotes the number of extreme rays of the dual slave problem with $z=z_{n}$;
- $i$ denotes the number of extreme points of the dual slave problem with $z=z_{1}$;
- $j$ denotes the number of extreme points of the dual slave problem with $z=z_{2}$;
- $t$ denotes the number of extreme points of the dual slave problem with $z=z_{n}$.

Auxiliary decision variables:

- $v_{m}=1$ if the $m t h$ constraint is active otherwise takes the value of zero;
- $u_{m}$ dual value of the $m t h$ constraint;
- $w_{m}$ Lagrangian multiplier mth constraint.

Parameter:

- $M$ big value number.

Vector symboles:
$\mathbb{R}^{f_{1}+f_{2}+f_{3}+\ldots}=\mathbb{R}^{f_{1}} \cup \mathbb{R}^{f_{2}} \cup \mathbb{R}^{f_{3}} \cup \mathbb{R}^{\cdots}$
$b_{1} \in \mathbb{R}^{b_{1}}, b_{2} \in \mathbb{R}^{b_{2}}, x \in X \subset \mathbb{R}^{x}, y \in Y \subset \mathbb{R}^{y}, s \in S \subset \mathbb{R}^{b_{1}+b_{2}}$,
$u \in U \subset \mathbb{R}^{b_{1}+b_{2}}, v \in V \subset \mathbb{R}^{b_{1}+b_{2}}$
$z \in Z\{0,1\} \subset \mathbb{R}^{z}, b v \in Z\{0,1\} \subset \mathbb{R}^{v}, h \in H \subset \mathbb{R}^{h}$
$w_{1} \in W_{1} \subset \mathbb{R}^{w_{1}}, w_{2} \in W_{2} \subset \mathbb{R}^{w_{2}}, w_{3} \in W_{3} \subset \mathbb{R}^{w_{3}}, w_{4} \in W_{4} \subset \mathbb{R}^{w_{4}}$
$c_{1} \in \mathbb{R}^{x}, c_{2} \in \mathbb{R}^{y}, c_{3} \in \mathbb{R}^{z}$
$F_{1}, F_{2}: X \times Y \times Z \Rightarrow \mathbb{R}^{1}$
$A_{1} \in \mathbb{R}^{b_{1} \times x}, B_{1} \in \mathbb{R}^{b_{1} \times y}, E_{1} \in \mathbb{R}^{b_{1} \times z}, Q_{1} \in \mathbb{R}^{b_{1} \times b_{1}}, C_{1}=I \in \mathbb{R}^{h \times h}$
$A_{2} \in \mathbb{R}^{b_{2} \times x}, B_{2} \in \mathbb{R}^{b_{2} \times y}, E_{2} \in \mathbb{R}^{b_{2} \times z}, Q_{2} \in \mathbb{R}^{b_{2} \times b_{2}}, C_{2}=I \in \mathbb{R}^{h \times h}$
$c_{T}=\left[\begin{array}{c}c_{1} \\ 0 \\ 0\end{array}\right], c^{T} \in \mathbb{R}^{c}=\mathbb{R}^{x+y+z}, D=\left[\begin{array}{lll}A_{1} & B_{1} & Q_{1} \\ A_{2} & B_{2} & Q_{2}\end{array}\right], D \in \mathbb{R}^{D}=\mathbb{R}^{\left(b_{1}+b_{2}\right) \times\left(x+y+b_{1}+b_{2}\right)}$
$b=\left[\begin{array}{l}b_{1} \\ b_{2}\end{array}\right], b \in \mathbb{R}^{b}=\mathbb{R}^{b_{1}+b_{2}}, g=\left[\begin{array}{l}x \\ y \\ s\end{array}\right], g \in \mathbb{R}^{g}=\mathbb{R}^{x+y+b_{1}+b_{2}}, E=\left[\begin{array}{l}E_{1} \\ E_{2}\end{array}\right], E \in \mathbb{R}^{E}=\mathbb{R}^{b_{1}+b_{2}}$
$c^{\prime T}=\left[\begin{array}{l}0 \\ 0 \\ 0 \\ 0\end{array}\right], c^{\prime T} \in \mathbb{R}^{c^{\prime}}=\mathbb{R}^{x+y+z+h}, D^{\prime}=\left[\begin{array}{llll}A_{1} & B_{1} & Q_{1} & C_{1} \\ A_{2} & B_{2} & Q_{2} & C_{2}\end{array}\right]$
$D^{\prime} \in \mathbb{R}^{D^{\prime}}=\mathbb{R}^{\left(b_{1}+b_{2}\right) \times\left(x+y+h+b_{1}+b_{2}\right)}$
$g^{\prime}=\left[\begin{array}{l}x \\ y \\ s \\ h\end{array}\right], g^{\prime} \in \mathbb{R}^{g^{\prime}}=\mathbb{R}^{x+y+h+b_{1}+b_{2}}$

Next, we consider the following problem for the mixed integer linear multiplicative-linear bilevel problem:

$$
P_{1}:\left\{\begin{array}{l}
\min _{x_{1}, x_{2}, z} \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
\text { St. } \min _{x_{2}} \quad d_{2} x_{2} \\
\text { St. } \\
A_{1} x_{1}+B_{1} x_{2}+E_{1} z \leqslant b_{1} \\
A_{2} x_{1}+B_{2} x_{2}+E_{2} z \leqslant b_{2} \\
x_{1}, x_{2} \geqslant 0 \quad z \in\{0,1\}
\end{array}\right.
$$

Note that constraints can be considered in the upper level and also, binary variable can be considered in the objective function of the upper level problem.
We get the following problem by fixing binary variables:

$$
P_{2}:\left\{\begin{array}{l}
\min _{x_{1}} \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
S t . \\
\min _{x_{2}} \quad d_{2} x_{2} \\
S t . \\
A_{1} x_{1}+B_{1} x_{2} \leqslant b_{1}-E_{1} \bar{z} \Rightarrow w_{1} \\
A_{2} x_{1}+B_{2} x_{2} \leqslant b_{2}-E_{2} \bar{z} \Rightarrow w_{2} \\
\quad-x_{1} \leqslant 0 \Rightarrow w_{3} \\
\quad-x_{2} \leqslant 0 \Rightarrow w_{4}
\end{array}\right.
$$

The problem $P_{2}$ can be transformed to a mixed integer multiplicative problem using $K K T$ optimality conditions and the active constraints strategy [18] as following:

$$
P_{3}:\left\{\begin{array}{l}
\min \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
\text { St. } \\
A_{1} x_{1}+B_{1} x_{2} \leqslant b_{1}-E_{1} \bar{z} \\
A_{2} x_{1}+B_{2} x_{2} \leqslant b_{2}-E_{2} \bar{z} \\
w_{1}-M b v_{1} \leqslant 0, \quad w_{2}-M b v_{2} \leqslant 0 \\
w_{3}-M b v_{3} \leqslant 0, \quad w_{4}-M b v_{4} \leqslant 0 \\
\left(b_{1}-E_{1} \bar{z}\right)-A_{1} x_{1}-B_{1} x_{2}-M\left(1-b v_{1}\right) \leqslant 0 \\
\left(b_{2}-E_{2} \bar{z}\right)-A_{2} x_{1}-B_{2} x_{2}-M\left(1-b v_{2}\right) \leqslant 0 \\
x_{2}-M\left(1-b v_{3}\right) \leqslant 0, x_{1}-M\left(1-b v_{4}\right) \leqslant 0 \\
w_{1} A_{1}+w_{2} A_{2}-w_{4}=0 \\
w_{1} B_{1}+w_{2} B_{2}-w_{3}=-d_{2} \\
x, y, w_{1}, w_{2}, w_{3}, w_{4} \geqslant 0 \quad b v_{1}, b v_{2}, b v_{3}, b v_{4} \in\{0,1\}
\end{array}\right.
$$

From the solution of $P_{3}$, we find active constraints, so we can replace $L M L B$ problem with active constraints plus remainder constraints and the first level objective function, and transform the problem $P_{1}$ to the following linear multiplicative problem:

$$
P_{4}:\left\{\begin{array}{l}
\min \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
\text { St. } \\
A_{1} x_{1}+B_{1} x_{2}=b_{1}-E_{1} \bar{z} \\
A_{2} x_{1}+B_{2} x_{2} \leqslant b_{2}-E_{2} \bar{z} \\
x_{1}, x_{2} \geqslant 0
\end{array}\right.
$$

From reformulated the problem $P_{4}$, we have:

$$
P_{5}:\left\{\begin{array}{l}
\min \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
S t . \\
A_{1} x_{1}+B_{1} x_{2}+Q_{1} s=b_{1}-E_{1} \bar{z} \\
A_{2} x_{1}+B_{2} x_{2}+Q_{2} s=b_{2}-E_{2} \bar{z} \\
x_{1}, x_{2}, s \geqslant 0
\end{array}\right.
$$

where $Q_{1}, Q_{2}$ are matrices that all the their elements are equal to zero except the elements in the diagonal that correspond to non-active constraints and are equal to 1 . We reformulate the problem $P_{5}$ to $P_{5}^{\prime}$ using the notations of nomenclature:

$$
P_{5}^{\prime}:\left\{\begin{array}{l}
\min \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
S t . \\
\quad D g=b-E \bar{z} \\
g \geqslant 0
\end{array}\right.
$$

The problem $P_{2}$ (and $P_{3}$ ) should have at least a non-empty solution set for $z$, so we cannot choose the variable $z$ arbitrarily, thus we add $-c_{1} h$ and $-c_{2} h$ to active constraints and non-active constraints of the $P_{2}$ problem, respectively. Also we use $K K T$ conditions and the active constraints strategy that due to problem $P_{3}^{\prime}$ which gives the best feasible solution minimizing the auxiliary variables $h$.

$$
P_{3}^{\prime}: \begin{cases}\min \quad h \\ \text { St. } & \\ & A_{1} x_{1}+B_{1} x_{2}-C_{1} h \leqslant b_{1}-E_{1} \bar{z} \\ A_{2} x_{1}+B_{2} x_{2}-C_{2} h \leqslant b_{2}-E_{2} \bar{z} \\ w_{1}-M b v_{1} \leqslant 0, \quad w_{2}-M b v_{2} \leqslant 0 \\ w_{3}-M b v_{3} \leqslant 0, \quad w_{4}-M b v_{4} \leqslant 0 \\ \left(b_{1}-E_{1} \bar{z}\right)-A_{1} x_{1}-B_{1} x_{2}+C_{1} h-M\left(1-b v_{1}\right) \leqslant 0 \\ & \left(b_{2}-E_{2} \bar{z}\right)-A_{2} x_{1}-B_{2} x_{2}+C_{2} h-M\left(1-b v_{2}\right) \leqslant 0 \\ x_{2}-M\left(1-b v_{3}\right) \leqslant 0, x_{1}-M\left(1-b v_{4}\right) \leqslant 0, h-M\left(1-b v_{5}\right) \leqslant 0 \\ w_{1} A_{1}+w_{2} A_{2}-w_{4}=0 \\ & -w_{1} C_{1}-w_{2} C_{2}-w_{5}=0 \\ w_{1} B_{1}+w_{2} B_{2}-w_{3}=-c_{2} \\ x_{1}, x_{2}, w_{1}, w_{2}, w_{3}, w_{4}, w_{5} \geqslant 0 \quad b v_{1}, b v_{2}, b v_{3}, b v_{4}, b v_{5} \in\{0,1\}\end{cases}
$$

We transform $P_{3}^{\prime}$ to $P_{5}^{\prime \prime}$ like transformed process $P_{3}$ to $P_{5}^{\prime}$, so we have:

$$
P_{5}^{\prime \prime}:\left\{\begin{array}{l}
\max \quad c^{\prime} g^{\prime} \\
S t . \\
D^{\prime} g^{\prime}=b-E \bar{z} \\
g^{\prime} \geqslant 0
\end{array}\right.
$$

The necessary and sufficient condition for existence at least a non-empty solution for $z$ is given by lemma of Farkas and Minkowski:

Lemma 3.1 [14] [Farkas and Minkowski] Let $A \in \mathbb{R}^{m, n}$ and $b \in \mathbb{R}^{m}$. Then there exists a vector $x=\left(x_{1}, \ldots, x_{n}\right) \geqslant 0$ satisfying $A x=b$ if and only if for each $u \in \mathbb{R}^{m}$ with $u A \geqslant 0$ it also holds that $u b \geqslant 0$.

If we correspond to each constraint $i$ of $P_{5}^{\prime \prime}$ a dual variable $u_{i}$, then the Lemma of Farkas and Minkowski states:
The problem $P_{5}^{\prime \prime}$ has a solution $g^{\prime} \geqslant 0$ if and only if $u(b-E \bar{z}) \leqslant 0$ for all $u$ which $u D^{\prime} \leqslant 0$ holds.
We should notice that for each $z$ the matrix $D^{\prime}$ is different based on the values of matrix $Q$. That means that the matrix $D^{\prime}$ is related to the value of $z$, so it can be stated as $D^{\prime}(z)[25]$.

Theorem 3.2 [20] [Minkowski and Weyl] A convex cone $C$ is polyhedral if and only if it is finitely generated, that is, the cone is generated by a finite number of vectors $b_{1}, \ldots, b_{m}$.

For each $z$ the cone $U(z)=\left\{u: u D^{\prime}(z) \leqslant 0\right\}$ is a polytope, so, in view of theorem (3.1), the cone $U(z)$ has a finite number of generators as $u_{1}^{z}, \ldots, u_{l}^{z}$. First, we considered the problem for $z \in\{0,1\}$. Now we extend the problem and consider it for nonnegative integer values $z_{1}, \ldots, z_{n}$. The necessary and sufficient conditions of the Farkas and Minkowski Lemma for each $z_{1}, \ldots, z_{n}$, then, is equivalent to the following system of inequalities:

$$
\begin{aligned}
& \text { if } z=z_{1} \Longrightarrow\left\{\begin{array}{l}
u_{1}^{z_{1}}\left(b-E z_{1}\right) \leqslant 0 \\
u_{2}^{z_{1}}\left(b-E z_{1}\right) \leqslant 0 \\
\cdots \cdots \cdots \\
u_{p}^{z_{1}}\left(b-E z_{1}\right) \leqslant 0
\end{array}\right. \\
& \text { if } z=z_{2} \Longrightarrow\left\{\begin{array}{l}
u_{1}^{z_{2}}\left(b-E z_{2}\right) \leqslant 0 \\
u_{2}^{z_{2}}\left(b-E z_{2}\right) \leqslant 0 \\
\cdots \cdots \cdots \\
u_{K}^{z_{2}}\left(b-E z_{2}\right) \leqslant 0
\end{array}\right. \\
& \text { if } z=z_{n} \Longrightarrow\left\{\begin{array}{r}
u_{2}^{z_{n}}\left(b-E z_{n}\right) \leqslant 0 \\
u_{2}^{z_{n}}\left(b-E z_{n}\right) \leqslant 0 \\
\cdots \cdots \cdots \\
u_{R}^{z_{n}}\left(b-E z_{n}\right) \leqslant 0
\end{array}\right.
\end{aligned}
$$

Now, consider the following quadratic programming problem:

$$
\min \quad \frac{1}{2} x^{t} H x+d^{t} x
$$

S.t.

$$
A x \leqslant b
$$

where $H$ is symmetric and positive semidefinite, so that the objective function is convex. Then, the dual problem be written as follows[5]:

$$
\max \quad-\frac{1}{2} x^{t} H x-b^{t} u
$$

S.t.

$$
\begin{aligned}
& H x+A^{t} u=-d \\
& u \geqslant 0
\end{aligned}
$$

It is clear that linear multiplicative programming problem is a special type of quadratic programming problem, so we can reformulate $P_{5}^{\prime}$ as follows:
$P_{6}:\left\{\begin{array}{c}\min \quad\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\ \quad=\frac{1}{2}\left(x_{1} x_{2}\right)\left(\begin{array}{cc}2 c_{11} c_{21} & c_{11} c_{22}+c_{12} c_{21} \\ c_{11} c_{22}+c_{12} c_{21} & 2 c_{12} c_{22}\end{array}\right)\binom{x_{1}}{x_{2}} \\ \quad+\left(\alpha c_{21}+\beta c_{11} \alpha c_{22}+\beta c_{12}\right)\binom{x_{1}}{x_{2}}+\alpha \beta\end{array}\right\} \begin{gathered}\text { St. } \quad \begin{array}{c}D g=b-E \bar{z} \\ g \geqslant 0\end{array}\end{gathered}$
where,

$$
H=\left(\begin{array}{cc}
2 c_{11} c_{21} & c_{11} c_{22}+c_{12} c_{21} \\
c_{11} c_{22}+c_{12} c_{21} & 2 c_{12} c_{22}
\end{array}\right)
$$

and $d^{t}=\left(\alpha c_{21}+\beta c_{11} \alpha c_{22}+\beta c_{12}\right)$,
With suppose existence at least a non-empty solution for the problem $P_{3}$ for given $z=\bar{z}$, the dual of $P_{6}$ can be written as folows:

$$
P_{6} \text { dual }: \begin{cases}\max & -\frac{1}{2} x^{t} H x-(b-E \bar{z})^{t} v+\alpha \beta \\ \text { S.t. } & H x+A^{t} v \leqslant-d \\ & v \text { of any sign, } x \geqslant 0\end{cases}
$$

where $v$ is the vector of dual variables of the constraints of the problem $P_{6}$. Constraints of $P_{6}$ make a convex polytope, so by using the duality theorem, problem $P_{6}$ can be rewritten as:

$$
\begin{gathered}
\max \left\{-\frac{1}{2} x^{t} H x-(b-E z)^{t} v+\alpha \beta:\left(H x+A^{t} v\right)(z) \leqslant-d\right\} \\
z \in \mathbb{R}^{Z} \text { where } Z=\left\{z_{1}, z_{2}, \ldots, z_{n}\right\}
\end{gathered}
$$

This maximum is obtained at the vertex of each polytope $V(z)=\left\{(x, v): H x+A^{t} v(z) \leqslant-d\right\}$.
Assuming that $V(z)$ is non-empty for all $z$, we denote by $\left(\left(x_{1}^{z_{1}}, v_{1}^{z_{1}}\right), \ldots,\left(x_{I}^{z_{1}}, v_{I}^{z_{1}}\right)\right), \ldots,\left(\left(x_{1}^{z_{n}}, v_{1}^{z_{n}}\right), \ldots,\left(x_{T}^{z_{n}}, v_{T}^{z_{n}}\right)\right)$ the vertices of the polytope $V(z)$ where $z \in\left\{z_{1}, z_{2}, \ldots, z_{n}\right\}$ [25]. Then $P_{6}$ can be written:

$$
\left\{\begin{array}{c}
\max _{i=1, \ldots, I}\left\{-\frac{1}{2}\left(x_{i}^{z_{1}}\right)^{t} H x_{i}^{z_{1}}\left(b-E z_{1}\right)^{t} v_{i}^{z_{1}}+\alpha \beta\right\} \\
\max _{k=1, \ldots, K}\left\{-\frac{1}{2}\left(x_{k}^{z_{n}}\right)^{t} H x_{k}^{z_{n}}\left(b-E z_{n}\right)^{t} v_{k}^{z_{n}}+\alpha \beta\right\}
\end{array}\right.
$$

These maximization is equivalent to the following nonlinear problem:

$$
\left\{\begin{array}{c}
\min \quad \xi \\
S t . \\
-\frac{1}{2}\left(x_{1}^{z_{1}}\right)^{t} H x_{1}^{z_{1}}\left(b-E z_{1}\right)^{t} v_{1}^{z_{1}}+\alpha \beta \leqslant \xi \\
\quad \cdots \\
-\frac{1}{2}\left(x_{I}^{z_{1}}\right)^{t} H x_{I}^{z_{1}}\left(b-E z_{1}\right)^{t} v_{I}^{z_{1}}+\alpha \beta \leqslant \xi \\
-\frac{1}{2}\left(x_{1}^{z_{2}}\right)^{t} H x_{1}^{z_{2}}\left(b-E z_{2}\right)^{t} v_{1}^{z_{2}}+\alpha \beta \leqslant \xi \\
\ldots \\
-\frac{1}{2}\left(x_{J}^{z_{2}}\right)^{t} H x_{J}^{z_{2}}\left(b-E z_{2}\right)^{t} v_{J}^{z_{2}}+\alpha \beta \leqslant \xi \\
\ldots \\
-\frac{1}{2}\left(x_{1}^{z_{n}}\right)^{t} H x_{1}^{z_{n}}\left(b-E z_{n}\right)^{t} v_{1}^{z_{n}}+\alpha \beta \leqslant \xi \\
\ldots \\
-\frac{1}{2}\left(x_{T}^{z_{n}}\right)^{t} H x_{T}^{z_{n}}\left(b-E z_{n}\right)^{t} v_{T}^{z_{n}}+\alpha \beta \leqslant \xi
\end{array}\right.
$$

Considering these inequalities and the inequalities have been obtained for existence at least solution set, the following formulation is acquireed:

$$
\left\{\begin{array}{l}
\min \quad \xi \\
S t . \\
-\frac{1}{2}\left(x_{1}^{z_{1}}\right)^{t} H x_{1}^{z_{1}}\left(b-E z_{1}\right)^{t} v_{1}^{z_{1}}+\alpha \beta \leqslant \xi \\
-\frac{1}{2}\left(x_{I}^{z_{1}}\right)^{t} H x_{I}^{z_{1}}\left(b-E z_{1}\right)^{t} v_{I}^{z_{1}}+\alpha \beta \leqslant \xi \\
\cdots \\
-\frac{1}{2}\left(x_{1}^{z_{n}}\right)^{t} H x_{1}^{z_{n}}\left(b-E z_{n}\right)^{t} v_{1}^{z_{n}}+\alpha \beta \leqslant \xi \\
\cdots \cdots \\
-\frac{1}{z_{2}}\left(x_{T}^{z_{n}}\right)^{t} H x_{T}^{z_{n}}\left(b-E z_{n}\right)^{t} v_{T}^{z_{n}}+\alpha \beta \leqslant \xi \\
u_{1}^{z_{1}}\left(b-E z_{1}\right) \leqslant 0 \\
\ldots \ldots \\
u_{p}^{z_{1}}\left(b-E z_{1}\right) \leqslant 0 \\
\ldots \ldots \\
u_{1}^{z_{n}}\left(b-E z_{n}\right) \leqslant 0 \\
u_{R}^{z_{n}}\left(b-E z_{n}\right) \leqslant 0 \\
\xi \in(-\infty,+\infty)
\end{array}\right.
$$

Which is equivalent to the following problem $\left(P_{7}\right)$ and is named master problem (MP):

$$
M P: P_{7}\left\{\begin{array}{l}
\min \xi \\
S t . \\
-\frac{1}{2}\left(x_{1}^{z_{1}}\right)^{t} H x_{1}^{z_{1}}(b-E z)^{t} v_{1}^{z_{1}}+\alpha \beta \leqslant \xi \\
-\frac{1}{2}\left(x_{I}^{z_{1}}\right)^{t} H x_{I}^{z_{1}}(b-E z)^{t} v_{I}^{z_{1}}+\alpha \beta \leqslant \xi \\
-\frac{1}{2}\left(x_{1}^{z_{n}}\right)^{t} H x_{1}^{z_{n}}(b-E z)^{t} v_{1}^{z_{n}}+\alpha \beta \leqslant \xi \\
\cdots \cdots \\
-\frac{1}{2}\left(x_{T}^{z_{n}}\right)^{t} H x_{T}^{z_{n}}(b-E z)^{t} v_{T}^{z_{n}}+\alpha \beta \leqslant \xi \\
u_{1}^{z_{1}}(b-E z) \leqslant 0 \\
\cdots \cdots \\
u_{p}^{z_{1}}(b-E z) \leqslant 0 \\
u_{1}^{z_{n}}(b-E z) \leqslant 0 \\
\cdots \cdots \\
u_{R}^{z_{n}}(b-E z) \leqslant 0 \\
z \in\{0,1\}, \xi \in(-\infty,+\infty)
\end{array}\right.
$$

At each stage of the algorithm, only some constraints of $P_{7}$ are known explicitly which gives a problem named Restricted Master Problem (RMP) and involves a subset of the constraints of $P_{7}$ (Master Problem). Let $(\bar{z}, \bar{\xi})$ be an optimal solution of $R M P, \bar{\xi}$ is a lower bound of optimal $\xi^{*}$ such that $\bar{\xi} \leqslant \xi^{*}$. An upper bound can be obtained by the resolution of $P_{4}$ or $P_{2}$ (which is a restricted form of the initial $M I B L P)$. The upper bound $(U B)$ is updated when a lower bound is obtained of the current $P_{4}$ (or $P_{2}$ ) compared with the current $U B$. Sufficient condition for the $(\bar{z}, \bar{\xi})$ to be an optimal solution of $P_{7}$ is that the $U B-L B \leqslant \epsilon$ because the $R M P$ is a relaxation of the original problem whereas the $S P$ represent a restriction [25]. In each iteration of the algorithm, three cases can be arised:
(1) (Production of feasibility cut)

The optimal value of dual $P_{5}$ is unbounded. The Simplex algorithm is applied to dual $P_{5}^{\prime \prime}$ and produces an extreme ray $\bar{u}$ such that $\bar{u}(b-E \bar{z})>0$ and $\bar{u} D^{\prime} \leqslant 0$. Thus the constraint $\bar{u}(b-E \bar{z}) \leqslant 0$ does not hold for the current solution $\bar{z}$ of $R M P$ and so it is not a solution of $P_{7}$. The constraints $\bar{u}(b-E \bar{z}) \leqslant 0$ must be added to $R M P$ to form a new $R M P$ [25].
(2) (Production of integer exclusion cut)

The optimal value of dual is finite and $-\frac{1}{2} x^{t} H x-(b-E \bar{z})^{t} v+\alpha \beta-\xi \leqslant$ 0 . So with adding this constraint to $R M P$, the optimal value does not change. If the optimality condition is not satisfied, the algorithm continues by changing the current integer solution using the following cut:

$$
\sum_{i \in P} z_{i}-\sum_{j \in Q} z_{j} \leqslant|P|-1
$$

where $P$ is the set of indices of variables that equals to 1 , i.e. $P=\{i$ : $\left.z_{i}^{*}=1\right\}$. Similarly $Q$ is the set of indices of variables that equals to 0 , i.e. $Q=\left\{j: z_{j}^{*}=0\right\}$. By adding this constraint to $R M P$, integer optimal solution of problem change and is produced new $S P$.
(3) (Production of optimality cut)

The optimal value of dual $P_{5}$ is bounded but

$$
-\frac{1}{2} x^{t} H x-(b-E \bar{z})^{t} v+\alpha \beta-\xi>0
$$

So the constraint $-\frac{1}{2} x^{t} H x-(b-E \bar{z})^{t} v+\alpha \beta-\xi \leqslant 0$ be added to $P_{7}$ and a new $R M P$ be made.

In case where the integer decision variables appear in the upper level objective function as $c_{13} x_{3}, c_{23} x_{3}$ terms, we have:

$$
\begin{aligned}
& \left(\alpha+c_{11} x_{1}+c_{12} x_{2}+c_{13} x_{3}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}+c_{23} x_{3}\right) \\
= & \left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right)+c_{13} x_{3}\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
+ & c_{23} x_{3}\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)+c_{13} c_{23} x_{3}^{2} \\
= & \left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right) \\
+ & x_{3}\left[c_{13}\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right)+c_{23}\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\right]+c_{13} c_{23} x_{3}^{2}
\end{aligned}
$$

If $\left[c_{13}\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right)+c_{23}\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\right]=0$ then we have $\left(\alpha+c_{11} x_{1}+\right.$ $\left.c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right)+c_{13} c_{23} x_{3}^{2}$. Therefore we obtain the following form to objective function of dual $P_{6}$ :

$$
\min _{x_{3}}\left(c_{13} c_{23} x_{3}^{2}+\max _{x_{1}, x_{2}}\left(\alpha+c_{11} x_{1}+c_{12} x_{2}\right)\left(\beta+c_{21} x_{1}+c_{22} x_{2}\right)\right)
$$

the variable $\xi$ in the produced optimality cuts is replaced by $\left(\xi=\xi+c_{13} c_{23} x_{3}^{2}\right) \xi+$ $c_{13} c_{23} x_{3}^{2}$.
Note that when we find dual variables may face with a dual gap then by writing the dual problem we find the value of the gap and add or deduce it to the given cut.

## 4. Examples

Consider the following problem:

$$
\begin{array}{lll}
\min _{x_{1}, x_{2}} & \left(20-x_{1}\right)\left(1+x_{2}\right) \\
\text { S.t. } & \min _{x_{2}} & -30 x_{1}-8 x_{2} \\
& \text { S.t. } & g_{1}: 10 x_{1}+3 x_{2}+8 z \leqslant 75 \\
& & g_{2}: 5 x_{1}+4 z \leqslant 5 \\
& & g_{3}: 5 x_{1}+x_{2}+2 z \leqslant 85 \\
& & z \in\{0,1\}, x_{1}, x_{2} \geqslant 0
\end{array}
$$

This problem is decomposed into the master and slaves problems:

## RMP:

$$
\begin{array}{cc}
\min & F(z, \xi)=\xi \\
\text { S.t. } & -M \leqslant \xi \leqslant M \\
& z \in\{0,1\} \\
& M=235
\end{array}
$$

$$
\begin{array}{cc}
\mathbf{S P}(\overline{\mathbf{z}}): \\
\min & F_{1}\left(x_{1}, x_{2}\right)=\left(20-x_{1}\right)\left(1+x_{2}\right) \\
\text { S.t. } \quad \min \quad F_{2}\left(x_{1}, x_{2}\right)=-30 x_{1}-8 x_{2} \\
& \text { S.t. } 10 x_{1}+3 x_{2} \leqslant 75-8 \bar{z} \\
& 5 x_{1} \leqslant 5-4 \bar{z} \\
& 5 x_{1}+x_{2} \leqslant 85-2 \bar{z} \\
& x_{2}, y_{3} \geqslant 0
\end{array}
$$

In the first, we fix the binary variable with $z=0$ arbitrarily, so we have problem $S P(0)$ :

## $\mathbf{S P}(0)$ :

$$
\begin{array}{cc}
\min & F_{1}\left(x_{1}, x_{2}\right)=\left(20-x_{1}\right)\left(1+x_{2}\right) \\
\text { S.t. } & \min \quad F_{2}\left(x_{1}, x_{2}\right)=-30 x_{1}-8 x_{2}
\end{array}
$$

$$
\text { S.t. } \quad \begin{aligned}
10 x_{1}+3 x_{2} & \leqslant 75 \\
5 x_{1} & \leqslant 5 \\
5 x_{1}+x_{2} & \leqslant 85 \\
x_{2}, y_{3} & \geqslant 0
\end{aligned}
$$

The initial value of the lower and upper bound of the algorithm are $L B=-235$
and $U B=\infty$.

$$
z=1, \xi=-235 \Rightarrow F_{3}(z, \xi)=-235 \Rightarrow L B=-235
$$

By using Kuhn-Tucker method and active set strategy, we obtain the following problem:

$$
\begin{array}{ll}
\min & F_{1}\left(x_{1}, x_{2}\right)=\left(20-x_{1}\right)\left(1+x_{2}\right) \\
\text { S.t. } & g_{1}: 10 x_{1}+3 x_{2} \leqslant 75 \\
& g_{2}: 5 x_{1} \leqslant 5 \\
& g_{3}: 5 x_{1}+x_{2} \leqslant 85 \\
& 10 u_{1}+5 u_{2}+5 u_{3}-u_{4}=30 \\
& 3 u_{1}+u_{3}-u_{5}=8 \\
& u_{1}-M v_{1} \leqslant 0,75-10 x_{1}-3 x_{2}-M\left(1-v_{1}\right) \leqslant 0 \\
& u_{2}-M v_{2} \leqslant 0,5-5 x_{1}-M\left(1-v_{2}\right) \leqslant 0 \\
& u_{3}-M v_{3} \leqslant 0,85-5 x_{1}-x_{2}-M\left(1-v_{3}\right) \leqslant 0 \\
& u_{4}-M v_{4} \leqslant 0, x_{1}-M\left(1-v_{4}\right) \leqslant 0 \\
& u_{5}-M v_{5} \leqslant 0, x_{2}-M\left(1-v_{5}\right) \leqslant 0 \\
& x_{1}, x_{2} \geqslant 0, u_{1}, u_{2}, u_{3}, u_{4}, u_{5} \geqslant 0, v_{1}, v_{2}, v_{3}, v_{4}, v_{5} \in\{0,1\}
\end{array}
$$

The solving of this problem shows that the inducible region of the linear multiplicative-linear bilevel problem is the line: $10 x_{1}+3 x_{2}=75$ : So the first constraint of the linear multiplicative-linear bilevel problem is an active constraint. The associated linear multiplicative problem $(L M P)$ is to the following form:

## LMP:

$$
\begin{gathered}
\min F_{1}\left(x_{1}, x_{2}\right)=\left(20-x_{1}\right)\left(1+x_{2}\right) \\
\text { S.t. } 10 x_{1}+3 x_{2}=75 \Rightarrow w_{1} \\
5 x_{1} \leqslant 5 \Rightarrow w_{2} \\
5 x_{1}+x_{2} \leqslant 85 \Rightarrow w_{3} \\
x_{2}, y_{3} \geqslant 0
\end{gathered}
$$

The optimal solution of $L M P$ is equal to 430.67 (obtained with Lingo) at the point $\left(x_{1}, x_{2}, z\right)=(1,21.66,0)$. Therfore new upper bound is $U B_{\text {new }}=430.67$.

$$
L B=-235, U B=430.67 \quad U B-L B=430.67+235=665.67 \nless 0=\epsilon
$$

The optimality condition is not satisfied and the current $L M P$ produce the first cut. The optimal solution of $P_{5}^{\prime}$ is finite and the constraint $-\frac{1}{2} x^{t} H x-(b-E \bar{z})^{t} v+$ $\alpha \beta-\bar{\xi} \leqslant 0$ is not satisfied, so optimality cut provide. Let $\left(w_{1}, w_{2}, w_{3}\right)$ is the value
of dual variables associated with $L M P$ then we write $L M P$ problem as following:

$$
\begin{gathered}
\max \quad x_{1} x_{2}-75 w_{1}-5 w_{2}-85 w_{3}+20 \\
\text { S.t. } \quad-x_{2}+10 w_{1}+5 w_{2}+5 w_{3}=1 \\
\\
\quad-x_{1}+3 w_{1}+w_{3}=-20 \\
\\
w_{1} \text { of any sign, } w_{2}, w_{3} \geqslant 0
\end{gathered}
$$

The optimal solution is equal to 452.33 at the point $\left(x_{1}, x_{2}, w_{1}, w_{2}, w_{3}\right)=$ $(0,0,-6.67,13.53,0)$ then we have:

$$
w_{1}=-6.67, w_{2}=13.53, w_{3}=0
$$

In this problem the value of dual gap is equal to $a=21.66$. By attention to dual values, we product
$-\frac{1}{2} x^{t} H x-(b-E \bar{z})^{t} v+\alpha \beta-\bar{\xi} \leqslant 0$ cut as following:

$$
\begin{aligned}
& \left(x_{1} x_{2}\right)\left(\begin{array}{cc}
0 & .5 \\
.5 & 0
\end{array}\right)\binom{x_{1}}{x_{2}}-\left(w_{1}, w_{2}, w_{3}\right)\left(\begin{array}{c}
75-8 z \\
5-4 z \\
85-2 z
\end{array}\right)-a+\alpha \beta-\xi \leqslant 0 \\
& \Rightarrow x_{1} x_{2}+18.16 z+432.33+20-21.66-\xi \leqslant 0 \\
& \Rightarrow x_{1} x_{2}+18.16 z+430.67-\xi \leqslant 0
\end{aligned}
$$

This cut is added to the new $R M P$ is produced:

## RMP:

$$
\begin{array}{cc}
\min & F_{3}(\xi)=\xi \\
\text { S.t. } & -M \leqslant \xi \leqslant M \\
& x_{1} x_{2}+18.16 z+430.67-\xi \leqslant 0 \\
& z \in\{0,1\} \\
& M=235
\end{array}
$$

The resolution of the $R M P$ gives a new lower bound $L B_{n e w}=430.67$. Comparison of the $U B$ and the new $L B$ satisfy the $R M P$ optimality condition of the algorithm which it is $\epsilon=0$. The optimal solution of the problem is the point $\left(x_{1}, x_{2}\right)=$ $(1,21.67), z=0$. In this example, the upper bound of slack variables is $M=85$ and it has solution for values $M \geqslant 85$ but may be infeasible for values $M<85$.
An complication in this class of problems is that first level objective function is nonlinear and it product the dual gap; therefore, by writing the dual problem we find the gap value and add or deduce it to the given cut.

## 5. Conclusions

In this paper, an algorithm for solving of the mixed integer linear multiplicativelinear bilevel problem was presented. The algorithm is based on Benders decomposition method and, can be considered as a reformulation algorithm. After decomposing the initial problem, the bilevel problem was solved using from $K K T$ optimality conditions. The presented algorithm decomposes the initial problem to
two subprolem that are named slave problems $(S P)$ and the restricted master problem $(R M P)$. The $R M P$ is a relaxation of the initial problem, so it provides a lower bound for the algorithm in the case of minimization. The $S P$ represents a restriction of the initial problem because they are resulted from the initial problem by fixing the integer variables. Thus, the solution of the SP in each iteration provides an upper bound in the case of minimization. The $R M P$ results the optimal solution after the addition of cuts produced from the $S P$. The convergence condition of the algorithm is satisfied when the difference between the upper and lower bound of the algorithm is less than an arbitrary tolerance.

## References

[1] Bard. J, An efficient point algorithm for a linear two-stage optimization problem, Oper. Res, 31 (4) (1983) 670-684.
[2] Bard. J, Practical Bilevel Optimization, Algorithms and Applications, Kluwer Academic Publishers, Dordrecht, London, 1998. Journal of Scientific and Statistical Computing, 11 (1990) 281-292.
[3] Bard. J and Falk. J, An explicit solution to the multi-level programming problem, J. Computer and Operations Research, 9 (1982) 77-100.
[4] Bard. J and Moore. J. T, A branch-and-bound algorithm for the bilevel programming problem, J. Scientic and Statistical Computing, 11 (1990) 281-292.
[5] Bazaraa. M, Nonlinear Programming, Theory and Algorithms, John Wiley Sons, Inc, New Jesey, (2006).
[6] Bazaraa. M, linear Programming And Network Flows, John Wiley Sons, Inc, New York, (1977).
[7] Benders. J, Partitioning procedures for solving mixed-variables programming problems, Numer. Math, 4 (1962) 238-252.
[8] Bialas. W and Karwan. M, Multilevel linear programming, Technical Report 78-1, State University of NewYork at Buffalo, Operations Research Program (1978).
[9] Bialas. W and Karwan. M, Two-level linear programming, J. Management Science, 30 (1984) 10041020.
[10] Calvete. H. I and Gale. C, Bilevel multiplicative problems: A penalty approach to optimality and a cutting plane based algorithm, J. of Computational and Applied Mathematics, 218 (2008) 259-269.
[11] Calvete. H. I and Gale. C, On the quasiconcave bilevel programming problem, J. of Optimization Theory and Applications, 98 (3) (1998) 613-622.
[12] Candler. W and Townsley. R, Alinear two-level programming problem, Comput, Oper. Res, 9 (1982) 59-76.
[13] Cochran. W. G, Sampling Techniques, second ed., Wiley, New York, (1963).
[14] Dahl. G, An Introduction To Convexity, University of Oslo publication, Oslo, (2004).
[15] Dempe. S, Discrete bi-level optimization problems, TUChemnizt (1995).
[16] Deng. X, Complexity issues in bilevel linear programming, In: Migdalas. A, Pardalos. P and Varbrand. P (Eds.): Multilevel Optimization: Algorithms and Applications, Kluwer Academic Publishers, Dordrecht et al., (1998) 149-164.
[17] Ehrgott. M, Multicriteria Optimization, University of Auckland publication, New Zealand, (2005).
[18] Grossmann. I. E and Floudas. C. A, Active constraint strategy for flexibility analysis in chemical processes, Comput. Chem. Eng., 11 (675) (1987).
[19] Gm. H and Floudas. A, Global optimization of mixed-integer bilevel programming problems, Computational Management Science, (2005) 181-212.
[20] Hansen. P, Jaumard. B and Savard. G, New branch-and-bound rules for linear bi-level programming, SIAMJ. Sci. Stat.Comput. 13 (1992) 1194-1217.
[21] Junger. M, Liebling. T, Naddef. D, Nemhauser. G, Pulleyblank. W, Reinelt. G, Rinaldi. G and Wolsey. L, 50 years of integer programming 1958-2008, Springer, (2010).
[22] Moore. J. T and Bard. J, VThe mixed integer linear bi-level programming problem, Oper. Res. 38 (5) (1990).
[23] Masoumzadeh. A and Moradmand Rad. N, Optimal Resource Allocation in DEA with Integer Variables, Int. J. of Mathematical Modelling Computations, 1(4) (2011) 251-256.
[24] Saharidis. G. K, Minoux. M and Ierapetritou. M, Accelerating Benders decomposition using covering cut bundles generation, submitted (2008).
[25] Saharidis. G. K and Ierapetritou. M. G, Resolution method for mixed integer bilevel linear problems based on decomposition technique, J Glob Optim, 44 (2009) 29-51.
[26] Shi. C, Lu. J and Zhang. G, An extended KuhnTucker approach for linear bi-level programming, Appl. Math. Comput, bf 162 (2005) 51-63.
[27] Shi. C, Zhang. G and Lu. J, On the definition of linear bilevel programming solution, Applied Mathematics and Computation, in press.
[28] Toloo. M and Khoshhal Nakhjiry. Z, Alternative Mixed Integer Programming for Finding Efficient BCC Unit, Int. J. of Mathematical Modelling Computations, 2 (1) (2012) 77-85.
[29] University of Cambridge. http://thesaurus.maths.org/dictionary/map/ word/10037, (2001).
[30] Wen. U. P and Yang. Y. H, Algorithms for solving the mixed integer two level linear programming problem, Comput. Op. Res, 17 (1990) 133-142.
[31] White. D and Anandalingam. G, A penalty function approach for solving bi-level linear programs, J. Global Optimization, 3 (1993) 397-419.


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