# The Definition of Optimal Solution and an Extended Kuhn-Tucker Approach for Fuzzy Linear Bilevel Programming

Guangquan Zhang and Jie Lu

Abstract— Bilevel decision techniques are mainly developed for solving decentralized management problems with decision makers in a hierarchical organization. Organizational bilevel decision-making, such as planning of land-use, transportation and water resource, all may involve uncertain factors. The parameters shown in a bileved programming model, either in the objective functions or constraints, are thus often imprecise, which is called fuzzy parameter bilevel programming (FPBLP) problem. Following our previous work [1, 2], this study first proposes a model of FPBLP. It then gives the definition of optimal solution for an FPBLP problem. Based on the definition and related theorems, this study develops a fuzzy number based Kuhn-Tucher approach to solve the proposed FPBLP problem. Finally, an example further illustrates the power of the fuzzy number based Kuhn-Tucher approach.

Index Terms— Linear bilevel programming, Kuhn-Tucker approach, Fuzzy set, Optimization.

## I. INTRODUCTION

THE execution of many decisions in businesses is sequential, from a higher level (leader) to a lower level (follower); each unit independently optimizes its own objective, but is affected by other unit's actions through externalities. This is called bilevel programming (BLP) problem (also called bilevel decision or bilevel optimization problems). BLP was first introduced by Von Stackelberg [3] in the context of unbalanced economic markets [4, 5]. In a BLP problem, each decision maker (leader or follower) tries to optimize his/her own objective function with partially or without considering the objective of the other level, but the decision of each level affects the objective optimization of the other level [6].

There have been nearly two dozen algorithms [5, 7-10] proposed for solving BLP problems since the field caught the attention of researchers in the mid-1970s [11-19]. Although BLP theory and technology have been applied with remarkable success in different domains [20-22], existing approaches mainly support the decision situation in which the objective functions and constraints are characterized with precise parameters. Therefore, the parameters are required to be fixed at some values in an experimental and/or subjective manner through the experts' understanding of the nature of the parameters in the problem-formulation process. It has been observed that, in most

Authors are with Faculty of Information Technology, University of Technology, Sydney, PO Box 123, Broadway, NSW 2007, Australia (e-mail: {jielu, zhangg}@it.uts.edu.au).

real-world situations, particularly in critical resource planning, such as planning of land-use, transportation and water resource, the possible values of these parameters are often only imprecisely or ambiguously known to these experts. It results in a difficulty to fix parameters in the objective functions or constraints of a bilevel programming model. With this observation, it would be certainly more appropriate to interpret the experts' understanding of parameters as fuzzy numerical data which can be represented by means of fuzzy sets theory [23]. A bilevel programming problem in which the parameters either in objective function or in constrains are described by fuzzy values is called a fuzzy parameter bilevel programming (FPBLP) problem.

The FPBLP problem was first explored by Sakawa et al. in 2000 [24]. Sakawa et al. formulates bilevel programming problems with fuzzy parameters from the perspective of experts' imprecision and proposes a fuzzy programming method for fuzzy bilevel programming problems. However, Sakawa's work is mainly based on the definition of solution for bilevel programming proposed by Bard [5, 15]. One deficiency of Bard's linear BLP theory is that it could not well solve a linear bilevel programming problem when the upper-level constraint functions are of arbitrary linear form. Our recent research work has extended Bard's theory of bilevel programming by proposing a new definition of optimal solution for linear bilevel programming which can overcome the arbitrary linear form problem indicated above [1]. We have then proposed an extended Kuhn-Tucher approach, based on our definition of optimal solution, for solving linear bilevel problems [2].

Following our previous research results shown in [1, 2], this study aims at solving a FPBLP problem by transferring it into a non-fuzzy bilevel programming problem. This paper first proposes a model of FPBLP problem, then gives a definition of the optimal solution for the FPBLP problem. Based on the definition and related theorems, this paper develops a fuzzy number based Kuhn-Tucher approach to solve the proposed FPBLP problem. As this paper only deals with linear bilevel problem, so bilevel programming means linear bilevel programming in this paper.

Following the introduction, Section 2 reviews related definitions, theorems and properties of fuzzy number, BLP solution and Kuhn-Tucher approach for solving an BLP problem. A definition of optimal solution and a fuzzy number based Kuhn-Tucher approach for solving FPBLP problems are presented in Section 3. A numeral example is shown in Section 4 for illustrating the proposed fuzzy number based Kuhn-Tucher approach. Conclusion and further study are discussed in Section 5.

#### II. PRELIMINARIES

## A. Fuzzy Numbers

In this section, we present some basic concepts, definitions and theorems that are to be used in the subsequent sections. The work presented in this section can also be found from our recent paper in [25].

Let R be the set of all real numbers,  $R^n$  be n-dimensional Euclidean space, and  $x = (x_1, x_2, ..., x_n)^T$ ,  $y = (y_1, y_2, ..., y_n)^T \in R^n$  be any two vectors, where  $x_i, y_i \in R$ , i = 1, 2, ..., n and T denotes the transpose of the vector. Then we denote the inner product of x and y by  $\langle x, y \rangle$ . For any two vectors  $x, y \in R^n$ , we write  $x \ge y$  iff  $x_i \ge y_i, \forall i = 1, 2, ..., n$ ;  $x \ge y$  iff  $x \ge y$  and  $x \ne y$ ; x > y iff  $x_i > y_i, \forall i = 1, 2, ..., n$ .

**Definition 2.1** A fuzzy number  $\tilde{a}$  is defined as a fuzzy set on R, whose membership function  $\mu_{\tilde{a}}$  satisfies the following conditions:

- 1.  $\mu_{\bar{a}}$  is a mapping from *R* to the closed interval [0, 1];
- 2. it is normal, i.e., there exists  $x \in R$  such that  $\mu_{\pi}(x) = 1$ ;
- 3. for any  $\lambda \in (0, 1]$ ,  $a_{\lambda} = \{x; \ \mu_{\widetilde{a}}(x) \ge \lambda\}$  is a closed interval, denoted by  $[a_{i}^{L}, a_{\lambda}^{R}]$ .

Let F(R) be the set of all fuzzy numbers. By the decomposition theorem of fuzzy set, we have

$$\widetilde{a} = \bigcup_{\lambda \in [0,1]} \lambda [a_{\lambda}^{L}, a_{\lambda}^{R}], \tag{2.1}$$

for every  $\tilde{a} \in F(R)$ .

Let  $F^*(R)$  be the set of all finite fuzzy numbers on R.

**Theorem 2.1** Let  $\tilde{a}$  be a fuzzy set on R, then  $\tilde{a} \in F(R)$  if and only if  $\mu_{\tilde{a}}$  satisfies

$$\mu_{\tilde{a}}(x) = \begin{cases} 1 & x \in [m, n] \\ L(x) & x < m \\ R(x) & x > n \end{cases}$$

where L(x) is the right-continuous monotone increasing function,  $0 \le L(x) < 1$  and  $\lim_{x \to \infty} L(x) = 0$ , R(x) is the left-continuous monotone decreasing function,  $0 \le R(x) < 1$  and  $\lim_{x \to \infty} R(x) = 0$ .

**Corollary 2.1** For every  $\tilde{a} \in F(R)$  and  $\lambda_1, \lambda_2 \in [0, 1]$ , if  $\lambda_1 \leq \lambda_2$ , then  $a_{\lambda_1} \subset a_{\lambda_1}$ .

**Definition 2.2** For any  $\tilde{a}, \tilde{b} \in F(R)$  and  $0 \le \lambda \in R$ , the sum of  $\tilde{a}$  and  $\tilde{b}$  and the scalar product of  $\lambda$  and  $\tilde{a}$  are defined by the membership functions

$$\mu_{\tilde{a}+\tilde{b}}(t) = \sup \min\{\mu_{\tilde{a}}(u), \mu_{\tilde{b}}(v)\}, \tag{2.2}$$

$$\mu_{\bar{a}-\bar{b}}(t) = \sup \min_{t=u-v} \{\mu_{\bar{a}}(u), \mu_{\bar{b}}(v)\}, \tag{2.2}$$

$$\mu_{\tilde{\lambda}\tilde{a}}(t) = \sup_{t = \lambda u} \mu_{\tilde{a}}(u). \tag{2.3}$$

**Theorem 2.2** For any  $\tilde{a}, \tilde{b} \in F(R)$  and  $0 < \alpha \in R$ ,

$$\begin{split} \widetilde{a} + \widetilde{b} &= \bigcup_{\lambda \in [0,1]} \lambda [a_{\lambda}^{L} + b_{\lambda}^{L}, a_{\lambda}^{R} + b_{\lambda}^{R}], \\ \widetilde{a} - \widetilde{b} &= \widetilde{a} + \left( -\widetilde{b} \right) = \bigcup_{\lambda \in [0,1]} \lambda [a_{\lambda}^{L} - b_{\lambda}^{R}, a_{\lambda}^{R} - b_{\lambda}^{L}], \\ \alpha \widetilde{a} &= \bigcup_{\lambda \in [0,1]} \lambda [\alpha a_{\lambda}^{L}, \alpha a_{\lambda}^{R}]. \end{split}$$

**Definition 2.3** Let  $\widetilde{a}_i \in F(R), i = 1, 2, \dots, n$ . We define  $\widetilde{a} = (\widetilde{a}_1, \widetilde{a}_2, \dots, \widetilde{a}_n)$ 

$$\mu_{\tilde{a}}: R^n \to [0,1]$$

$$x \mapsto \bigwedge_{i=1}^n \mu_{\tilde{a}_i}(x_i),$$

where  $x = (x_1, x_2, ..., x_n)^T \in R^n$ , and  $\widetilde{a}$  is called an *n*-dimensional fuzzy number on  $R^n$ . If  $\widetilde{a}_i \in F^*(R), i = 1, 2, ..., n$ ,  $\widetilde{a}$  is called an *n*-dimensional finite fuzzy number on  $R^n$ .

Let  $F(R^n)$  and  $F^*(R^n)$  be the set of all *n*-dimensional fuzzy numbers and the set of all *n*-dimensional finite fuzzy numbers on  $R^n$  respectively.

**Proposition 2.1** For every  $\tilde{a} \in F(\mathbb{R}^n)$ ,  $\tilde{a}$  is normal.

**Proposition 2.2** For every  $\tilde{a} \in F(R^n)$ , the  $\lambda$ -section of  $\tilde{a}$  is an n-dimensional closed rectangular region for any  $\lambda \in [0,1]$ .

**Proposition 2.3** For every  $\tilde{a} \in F(\mathbb{R}^n)$  and  $\lambda_1$ ,  $\lambda_2 \in [0,1]$ , if  $\lambda_1 \leq \lambda_2$  then  $a_{\lambda_2} \subset a_{\lambda_1}$ .

**Definition 2.4** For any n-dimensional fuzzy numbers  $\tilde{a}, \tilde{b} \in F(\mathbb{R}^n)$ , we define

- 1.  $\widetilde{a} \succ \widetilde{b}$  iff  $a_{i\lambda}^L > b_{i\lambda}^L$  and  $a_{i\lambda}^R > b_{i\lambda}^R$ ,  $i = 1, 2, \dots, n, \lambda \in (0,1]$ ;
- 2.  $\widetilde{a} \succeq \widetilde{b}$  iff  $a_{i,i}^L \geq b_{i,i}^L$  and  $a_{i,i}^R \geq b_{i,i}^R$ ,  $i = 1, 2, \dots, n, \lambda \in (0,1]$ ;
- 3.  $\widetilde{a} \succ \widetilde{b}$  iff  $a_{i\lambda}^L > b_{i\lambda}^L$  and  $a_{i\lambda}^R > b_{i\lambda}^R$ ,  $i = 1, 2, \dots, n, \lambda \in (0,1]$ .

We call the binary relations  $\succeq$ ,  $\succeq$  and  $\succ$  a fuzzy max order, a strict fuzzy max order and a strong fuzzy max order, respectively.

B. The Extended Kuhn-Tucker Approach for Linear Bilevel Programming

Let write a linear programming (LP) as follows.

$$\min f(x) = cx$$
subject to  $Ax \le b$ 

$$x \ge 0,$$

where C is an n-dimensional row vector, b an m-dimensional column vector, A an  $m \times n$  matrix with  $m \le n$ , and  $x \in R^n$ .

Let  $\lambda \in R^m$  and  $\mu \in R^n$  be the dual variables associated with constraints  $Ax \ge b$  and  $x \ge 0$ , respectively. Bard [5] gave the following proposition.

**Proposition 2.4** [5] A necessary and sufficient condition that  $(x^*)$  solves above LP is that there exist (row) vectors  $\lambda^*$ ,  $\mu^*$  such that  $(x^*, \lambda^*, \mu^*)$  solves:

$$\lambda A - \mu = -c$$

$$Ax - b \ge 0$$

$$\lambda (Ax - b) = 0$$

$$\mu x = 0$$

$$x \ge 0, \lambda \ge 0, \mu \ge 0$$

For  $x \in X \subset \mathbb{R}^n$ ,  $y \in Y \subset \mathbb{R}^m$ ,  $F: X \times Y \to \mathbb{R}^1$ , and  $f: X \times Y \to \mathbb{R}^1$ , a linear BLP problem is given by Bard [4]:

$$\min_{x \in X} F(x, y) = c_1 x + d_1 y \tag{2.5a}$$

subject to 
$$A_1x + B_1y \le b_1$$
 (2.5b)

$$\min_{x} f(x, y) = c_2 x + d_2 y \tag{2.5c}$$

subject to 
$$A_1x + B_2y < b_1$$
 (2.5d)

where  $c_1$ ,  $c_2 \in R^n$ ,  $d_1$ ,  $d_2 \in R^m$ ,  $b_1 \in R^p$ ,  $b_2 \in R^q$ ,  $A_1 \in R^{p \times n}$ ,  $B_1 \in R^{p \times m}$ ,  $A_2 \in R^{q \times n}$ ,  $B_2 \in R^{q \times m}$ .

# **Definition 2.5** [1]

(a)Constraint region of the linear BLP problem:

$$S = \{(x, y) : x \in X, y \in Y, A_1x + B_1y \le b_1, A_2x + B_2y \le b_2\}$$

(b) Feasible set for the follower for each fixed  $x \in X$ :

$$S(X) = \{x \in X : \exists y \in Y, A_1 x + B_1 y \le b_1, A_2 x + B_2 y \le b_2\}$$

(c)Projection of S onto the leader's decision space:

$$S(X) = \{x \in X : \exists y \in Y, A_1 x + B_1 y \le b_1, A_2 x + B_2 y \le b_2\}$$

(d) Follower's rational reaction set for  $x \in S(X)$ :

$$P(x) = \{ y \in Y : y \in \arg\min[f(x, \hat{y}) : \hat{y} \in S(x)] \}$$

where

$$\arg\min[f(x,\hat{y}): \hat{y} \in S(x)] = \{y \in S(x): f(x,y) \le f(x,\hat{y}), \hat{y} \in S(x)\}$$

(e)Inducible region:

$$IR = \{(x, y) : (x, y) \in S, y \in P(x)\}$$

**Definition 2.6** [1]  $(x^*, y^*)$  is said to be a complete optimal solution, if and only if there exists  $(x^*, y^*) \in S$  such that  $F(x^*, y^*) \le F(x, y)$  and  $f(x^*, y^*) \le f(x, y)$  for all  $(x, y) \in S$ .

However, in general, such a complete optimal solution that simultaneously minimizes both the leader' and follower's objective functions does not always exist. Instead of a complete optimal solution, a new solution concept, called Pareto optimality, is introduced in linear BLP.

**Definition 2.7** [1]  $(x^*, y^*)$  is said to be a Pareto optimal solution, if and only if there does not exist  $(x, y) \in S$  such that  $F(x, y) \leq F(x^*, y^*)$ ,  $f(x, y) \leq f(x^*, y^*)$  and  $F(x, y) \neq F(x^*, y^*)$  or  $f(x, y) \neq f(x^*, y^*)$ .

**Definition 2.8** A topological space is compact if every open cover of the entire space has a finite subcover. For example, [a,b] is compact in R (the Heine-Borel theorem) [26].

To ensure that (2.5) has a Pareto optimal solution, Bard gave the following assumption.

### **Assumption 2.1**

- (a) S is nonempty and compact.
- (b) For decisions taken by the leader, the follower has some rooms to respond; i.e,  $P(x) \neq \phi$ .
- (c) P(x) is a point-to-point map.

To ensure that (2.5) is well posed we assume that S is nonempty and compact, and that P(x) is a point-to-point map. The rational reaction set P(x) defines the response while the inducible region IR represents the set over which the leader may optimize his objective. Thus in terms of the above notations, the linear BLP problem can be written as

$$\min\{F(x,y):(x,y)\in IR\}\tag{2.6}$$

We also present the following theorem to characterize the condition under which there is a Pareto optimal solution for a linear BLP problem.

**Theorem 2.3** [1] If S is nonempty and compact, there exists a Pareto optimal solution for a linear BLP problem

**Theorem 2.4** [2] [Extended Kuhn-Tucher Theorem] A necessary and sufficient condition that  $(x^*, y^*)$  solves the linear

BLP problem (2.5) is that there exist (row) vectors  $u^*$ ,  $v^*$  and  $w^*$  such that  $(x^*, y^*, u^*, v^*, w^*)$  solves:

$$\min F(x, y) = c_1 x + d_1 y$$
 (2.7a)

subject to 
$$A_1x + B_1y \le b_1$$
 (2.7b)

$$A_2 x + B_2 y \le b_2 \tag{2.7c}$$

$$uB_1 + vB_2 - w = -d_2 (2.7d)$$

$$u(b_1 - A_1x - B_1y) + v(b_2 - A_2x - B_2y) + wy = 0$$
 (2.7e)

$$x \ge 0, y \ge 0, u \ge 0, v \ge 0, w \ge 0$$
 (2.7f)

# III. FUZZY PARAMETER LINEAR BILEVEL PROGRAMMING PROBLEM

Consider the following fuzzy parameter linear bilevel programming (FPBLP) problem:

For  $x \in X \subset R^n$ ,  $y \in Y \subset R^m$ ,  $F: X \times Y \to F^*(R)$ , and  $f: X \times Y \to F^*(R)$ ,

$$\min_{\mathbf{y}} F(\mathbf{x}, \mathbf{y}) = \tilde{c}_1 \mathbf{x} + \tilde{d}_1 \mathbf{y} \tag{3.1a}$$

subject to 
$$\tilde{A}_{,x} + \tilde{B}_{,y} \prec \tilde{b}_{,y}$$
 (3.1b)

$$\min_{x} f(x, y) = \tilde{c}_2 x + \tilde{d}_2 y \tag{3.1c}$$

subject to 
$$\widetilde{A}_{,x} + \widetilde{B}_{,y} \prec \widetilde{b}_{,y}$$
 (3.5d)

where 
$$\widetilde{c}_1, \widetilde{c}_2 \in F^*(R^n)$$
,  $\widetilde{d}_1, \widetilde{d}_2 \in F^*(R^m)$ ,  $\widetilde{b}_1 \in F^*(R^p)$ ,  $\widetilde{b}_2 \in F^*(R^q)$ ,  $\widetilde{d}_1 = \left(\widetilde{a}_{ij}\right)_{p \times n}$ ,  $\widetilde{d}_3 \in F^*(R)$ ,  $\widetilde{d}_4 = \left(\widetilde{b}_{ij}\right)_{p \times m}$ ,  $\widetilde{b}_{ij} \in F^*(R)$ ,  $\widetilde{d}_5 = \left(\widetilde{b}_{ij}\right)_{q \times m}$ ,  $\widetilde{b}_{ij} \in F^*(R)$ ,  $\widetilde{d}_7 = \left(\widetilde{b}_{ij}\right)_{q \times m}$ ,  $\widetilde{b}_{ij} \in F^*(R)$ ,  $\widetilde{d}_8 = \left(\widetilde{b}_{ij}\right)_{q \times m}$ ,  $\widetilde{b}_{ij} \in F^*(R)$ .

Associated with the FPBLP problem, we now consider the following linear multi-objective multi-follower bilevel programming (LMMBLP) problem:

For  $x \in X \subset R^n$ ,  $y \in Y \subset R^m$ ,  $F: X \times Y \to F^*(R)$ , and  $f: X \times Y \to F^*(R)$ ,

$$\min_{x \in X} \left( F(x, y) \right)_{\lambda}^{L} = c_{1\lambda}^{L} x + d_{1\lambda}^{L} y, \quad \lambda \in [0, 1]$$
(3.2a)

 $\min (F(x, y))^{R} = c_{1}^{R} x + d_{1}^{R} y, \quad \lambda \in [0, 1]$ 

subject to 
$$A_{1,2}^{L}x + B_{1,2}^{L}y < b_{1,2}^{L}, A_{1,2}^{R}x + B_{1,2}^{R}y < b_{1,2}^{R}, \lambda \in [0,1]$$
 (3.2b)

$$\min_{y \in Y} (f(x, y))_{\lambda}^{L} = c_{2\lambda}^{L} x + d_{2\lambda}^{L} y, \quad \lambda \in [0, 1]$$
(3.2c)

$$\min(f(x, y))^{R} = c_{x}^{R} x + d_{x}^{R} y, \quad \lambda \in [0, 1]$$

subject to 
$$A_{2,1}^{L}x + B_{2,1}^{L}y < b_{2,1}^{L}, A_{2,1}^{R}x + B_{2,1}^{R}y < b_{2,1}^{R}, \lambda \in [0, 1]$$
 (3.5d)

where 
$$c_{1\lambda}^{L}, c_{1\lambda}^{R}$$
,  $c_{2\lambda}^{L}, c_{2\lambda}^{R} \in R^{n}$ ,  $d_{1\lambda}^{L}, d_{1\lambda}^{R}$ ,  $d_{2\lambda}^{L}, d_{2\lambda}^{R} \in R^{m}$ ,  $b_{1\lambda}^{L}, b_{1\lambda}^{R} \in R^{p}$ ,  $b_{2\lambda}^{L}, b_{2\lambda}^{R} \in R^{q}$ ,  $A_{1\lambda}^{L} = (a_{ij\lambda}^{L}), A_{1\lambda}^{R} = (a_{ij\lambda}^{R}) \in R^{p\times n},$   $B_{1\lambda}^{L} = (b_{ii\lambda}^{L}), B_{1\lambda}^{R} = (b_{ii\lambda}^{R}), B_{1\lambda}^{R} = (b_{ii\lambda}^{R}), B_{2\lambda}^{R} = (s_{ii\lambda}^{R}), B_{2\lambda}^{R} = (s_{$ 

**Theorem 3.1** Let  $(x^*, y^*)$  be the solution of the LMMBLP

problem (3.2). Then it is also a solution of the FPBLP problem defined by (3.1).

Proof. The proof is obvious from Definition 2.4.

**Lemma 3.1** If there is  $(x^*, y^*)$  such that  $cx + dy > cx^* + dy^*$ ,  $c_0^L x + d_0^L y > c_0^L x^* + d_0^L y^*$  and  $c_0^R x + d_0^R y > c_0^R x^* + d_0^R y^*$ , for any (x, y) and isosceles triangle fuzzy numbers  $\tilde{c}$  and  $\tilde{d}$ , then

$$c_{\lambda}^{L}x + d_{\lambda}^{L}y \ge c_{\lambda}^{L}x^{*} + d_{\lambda}^{L}y^{*},$$
  
$$c_{\lambda}^{R}x + d_{\lambda}^{R}y > c_{\lambda}^{R}x^{*} + d_{\lambda}^{R}y^{*},$$

for any  $\lambda \in (0,1)$ , where c and d are the centre of  $\tilde{c}$  and  $\tilde{d}$ respectively.

Proof. As  $\lambda$ -section of isosceles triangle fuzzy numbers  $\tilde{c}$  and  $\tilde{d}$  are

$$c_{\lambda}^{L} = c_{0}^{L}(1-\lambda) + c\lambda$$
 and  $c_{\lambda}^{R} = c_{0}^{R}(1-\lambda) + c\lambda$   
 $d_{\lambda}^{L} = d_{0}^{L}(1-\lambda) + d\lambda$  and  $d_{\lambda}^{R} = d_{0}^{R}(1-\lambda) + d\lambda$ .

Therefore, we have

$$c_{\lambda}^{L}x + d_{\lambda}^{L}y = c_{0}^{L}(1-\lambda)x + c\lambda x + d_{0}^{L}(1-\lambda)y + d\lambda y$$

$$= (c_{0}^{L}x + d_{0}^{L}y)(1-\lambda) + (cx + dy)\lambda$$

$$\geq (c_{0}^{L}x^{*} + d_{0}^{L}y^{*})(1-\lambda) + (cx^{*} + dy^{*})\lambda$$

$$= c_{1}^{L}x^{*} + d_{0}^{L}y^{*},$$

from  $cx + dy > cx^* + dy^*$  and  $c_0^L x + d_0^L y > c_0^L x^* + d_0^L y^*$ , we can prove  $c_{\lambda}^{R}x + d_{\lambda}^{R}y \ge c_{\lambda}^{R}x^{*} + d_{\lambda}^{R}y^{*}$  from similar reason.

**Theorem 3.2** For  $x \in X \subset R^n$ ,  $y \in Y \subset R^m$ , If all the fuzzy coefficients  $\tilde{a}_{ii}, \tilde{b}_{ii}, \tilde{e}_{ii}, \tilde{s}_{ii}, \tilde{c}_{i}$  and  $\tilde{d}_{ii}$  have triangle membership functions of the FPBLP problem (3.1).

$$\mu_{z}(t) = \begin{cases} 0 & t < z_{0}^{L} \\ \frac{t - z_{0}^{L}}{z - z_{0}^{L}} & z_{0}^{L} \leq t < z \\ \frac{-t + z_{0}^{R}}{z_{0}^{R} - z} & z \leq t < z_{0}^{R} \\ 0 & z_{0}^{R} \leq t \end{cases}$$
(3.3)

where  $\tilde{z}$  denotes  $\tilde{a}_{u}, \tilde{b}_{u}, \tilde{e}_{u}, \tilde{s}_{u}, \tilde{c}_{z}$  and  $\tilde{d}_{z}$  and z are the centre of  $\tilde{z}$  respectively. Then, it is the solution of the problem (3.1) that  $(x^*, y^*) \in R^n \times R^m$  satisfying

$$\min_{x \in X} (F(x, y))_{c} = c_{1}x + d_{1}y, 
\min_{x \in X} (F(x, y))_{0}^{L} = c_{10}^{L}x + d_{10}^{L}y, 
\min_{x \in X} (F(x, y))_{0}^{R} = c_{10}^{R}x + d_{10}^{R}y,$$
(3.4a)

subject to  $A_1x + B_1y \le b_1$ ,

$$A_{1_0}^L x + B_{1_0}^L y \le b_{1_0}^L,$$

$$A_{1_0}^R x + B_{1_0}^R y \le b_{1_0}^R,$$
(3.4b)

$$\min_{\mathbf{y} \in Y} (f(\mathbf{x}, \mathbf{y}))_{c} = c_{2}\mathbf{x} + d_{2}\mathbf{y},$$

$$\min_{y \in Y} (f(x, y))_0^L = c_{2_0}^L x + d_{2_0}^L y, \tag{3.4c}$$

$$\min_{y \in Y} (f(x, y))_{\lambda}^{R} = c_{20}^{R} x + d_{20}^{R} y,$$

subject to 
$$A_{2}x + B_{2}y \le b_{2}$$
,  

$$A_{20}^{L}x + B_{20}^{L}y \le b_{20}^{L},$$

$$A_{20}^{R}x + B_{20}^{R}y \le b_{20}^{R}.$$
(3.4d)

Proof. From Lemma 3.1, if  $(x^*, y^*)$  satisfies (3.4a) and (3.4c),

then it satisfies (3.2a) and (3.2c). Then we need only prove,  $if_{(x^*, y^*)}$  satisfies (3.4b) and (3.4d), then it satisfies (3.2b) and (3.2d). In fact, for any  $\lambda \in (0,1)$ .

$$a_{ij}^{L} = a_{ij}\lambda + a_{ij}^{L}(1-\lambda),$$
  
 $b_{ij}^{L} = b_{ij}\lambda + b_{ij}^{L}(1-\lambda)$  and  $b_{ij}^{L} = b_{i}\lambda + b_{i0}^{L}(1-\lambda),$ 

we have

$$A_{1\lambda}^{L}x^{*} + B_{1\lambda}^{L}y^{*} = (a_{ij}^{L})x^{*} + (b_{ij}^{L})y^{*}$$

$$= (a_{ij}\lambda + a_{ij}^{L}(1-\lambda))x^{*} + (b_{ij}\lambda + b_{ij}^{L}(1-\lambda))y^{*}$$

$$= (a_{ij})x^{*}\lambda + (a_{ij}^{L})x^{*}(1-\lambda) + (b_{ij})y^{*}\lambda + (b_{ij}^{L})y^{*}(1-\lambda)$$

$$= ((a_{ij})x^{*} + (b_{ij})y^{*})\lambda + ((a_{ij}^{L})x^{*} + (b_{ij}^{L})y^{*})(1-\lambda)$$

$$= (A_{1}x^{*} + B_{1}y^{*})\lambda + (A_{10}^{L}x^{*} + B_{10}^{L}y^{*})(1-\lambda)$$

$$\leq b_{1}\lambda + b_{10}^{L}(1-\lambda) = b_{1\lambda}^{L},$$

from (3.4b). Similarly, we can prove

$$\begin{aligned} &A_{1\lambda}^{R}x^{*}+B_{1\lambda}^{R}y^{*} \leq b_{1\lambda}^{R}, \\ &A_{2\lambda}^{L}x^{*}+B_{2\lambda}^{L}y^{*} \leq b_{2\lambda}^{L}, \\ &A_{2\lambda}^{R}x^{*}+B_{2\lambda}^{R}y^{*} \leq b_{2\lambda}^{R}, \end{aligned}$$

for any  $\lambda \in (0, 1)$  from (3.4b) and (3.4d). The proof is complete.

**Theorem 3.3** [Extended Kuhn-Tucher Theorem] A necessary and sufficient condition that  $(x^*, y^*)$  solves the FPBLP problem (3.1) with triangle fuzzy numbers is that there exist (row) vectors  $u^*$ ,  $v^*$  and  $w^*$  such that  $(x^*, y^*, u^*, v^*, w^*)$  solves:

$$\min_{x \in Y} (F(x, y)) = (c_1 x + d_1 y) + (c_{10}^L x + d_{10}^L y) + (c_{10}^R x + d_{10}^R y)$$
(3.5a)

subject to  $A_1x + B_1y < b_1$ ,

$$A_{10}^{L}x + B_{10}^{L}y \leq b_{10}^{L},$$

$$A_{10}^{R}x + B_{10}^{R}y < b_{10}^{R},$$
(3.5b)

$$D_{10} \times D_{10} Y \stackrel{>}{=} D_{10}$$

$$A_2 x + B_2 y \le b_2,$$

$$A_{2_0}^{L}x + B_{2_0}^{L}y \le b_{2_0}^{L},$$
 (3.5c)

$$A_{20}^{L}x + B_{20}^{L}y < b_{20}^{L}$$

$$u_1B_1 + u_2B_{10}^L + u_3B_{10}^R + v_1B_2 + v_2B_{20}^L + v_3B_{20}^R - w$$

$$= -\left(d_2 + d_{20}^L + d_{20}^L\right)$$
(3.5d)

$$u_1(b_1 - A_1x - B_1y) + u_2(b_{10}^L - A_{10}^Lx - B_{10}^Ly) + u_3(b_{10}^R - A_{10}^Rx - B_{10}^Ry) + v_1(b_2 - A_2x - B_2y) +$$
(3.5e)

$$v_2(b_{20}^L - A_{20}^L x - B_{20}^L y) + v_3(b_{20}^R - A_{20}^R x - B_{20}^R y) + wy = 0$$
  
  $x \ge 0, y \ge 0, u \ge 0, v \ge 0, w \ge 0$  (3.5f)

Proof: (1) From Theorem 3.2, we know that we need only to

solve the problem (3.4). In fact, to solve the problem (3.4), we can use the method of weighting [27] to this problem, such that it is the following problem:

$$\min_{x \in X} \left( F(x, y) \right) = \left( c_1 x + d_1 y \right) + \left( c_{10}^L x + d_{10}^L y \right) + \left( c_{10}^R x + d_{10}^R y \right)$$
 (3.6a)

subject to  $A_1x + B_1y < b_1$ ,

$$A_{1_0}^L x + B_{1_0}^L y \le b_{1_0}^L, \tag{3.6b}$$

$$A_{10}^{R}x + B_{10}^{R}y \leq b_{10}^{R}$$
,

$$\min_{y \in Y} (f(x, y)) = c_2 x + d_2 y + c_{20}^{L} x + d_{20}^{L} y + c_{20}^{R} x + d_{20}^{R} y$$
 (3.6c)

subject to 
$$A_2x + B_2y \le b_2$$
,  
 $A_{20}^L x + B_{20}^L y \le b_{20}^L$ , (3.6d)  
 $A_{20}^R x + B_{20}^R y \le b_{20}^R$ .

Therefore, the linear BLP problem can be written as

$$\min\{F(x, y) : (x, y) \in IR\}$$
 (3.7)

Let us get an explicit expression of (3.7) and rewrite (3.7) as follows:

 $\min F(x, y)$ subject to  $(x, y) \in IR$ .

We have

 $\min F(x, y)$ 

subject to  $(x, y) \in S$ 

 $y \in P(x)$ 

by Definition 2.5(e). Then, we have

 $\min F(x, y)$ 

subject to  $(x, y) \in S$ 

 $y \in \arg\min[f(x, \hat{y}) : \hat{y} \in S(x)]$ 

by Definition 2.5(d). We rewrite it as:

 $\min F(x, y)$ 

subject to  $(x, y) \in S$ 

 $\min f(x, y)$ 

subject to  $y \in S(x)$ .

We have

 $\min F(x, y)$ 

subject to  $(x, y) \in S$ 

 $\min_{y \in V} f(x, y)$ 

subject to  $(x, y) \in S$ ,

by Definition 2.5(c). Consequently, we can have

$$\min_{\mathbf{y}} \left( F(\mathbf{x}, \mathbf{y}) \right) = \left( c_1 \mathbf{x} + d_1 \mathbf{y} \right) + \left( c_{10}^L \mathbf{x} + d_{10}^L \mathbf{y} \right) + \left( c_{10}^R \mathbf{x} + d_{10}^R \mathbf{y} \right) \tag{3.8a}$$

subject to  $A_1x + B_1y < b_1$ ,

$$A_{10}^{L}x + B_{10}^{L}y \le b_{10}^{L}$$

$$A_{10}^{R} x + B_{10}^{R} y < b_{10}^{R},$$
 (3.8b)

 $A_2 x + B_2 y < b_2$ 

 $A_{20}^{L}x + B_{20}^{L}y < b_{20}^{L}$ 

 $A_{20}^{R}x + B_{20}^{R}y < b_{20}^{R}$ .

$$\min_{y \in Y} (f(x, y)) = c_2 x + d_2 y + c_{20}^{L} x + (3.8c)$$

 $d_{20}^{L}y + c_{20}^{R}x + d_{20}^{R}y$ 

subject to  $A_1x + B_1y \le b_1$ ,

$$A_{10}^{L}x + B_{10}^{L}y \leq b_{10}^{L},$$

$$A_{10}^{R}x + B_{10}^{R}y < b_{10}^{R}$$
, (3.8d)

 $A_2 x + B_2 y \le b_2,$ 

 $A_{20}^{L}x + B_{20}^{L}y < b_{20}^{L}$ 

 $A_{20}^{R}x + B_{20}^{R}y \le b_{20}^{R}$ .

by Definition 2.5(a).

This simple transformation has shown that solving the fuzzy linear BLP (3.1) is equivalent to solving (3.8).

(2) Necessity is obvious from (3.8).

(3) Sufficiency. If  $(x^*, y^*)$  is the optimal solution of (3.6), we need to show that there exist (row) vectors  $u_1^*, u_2^*, u_3^*, v_1^*, v_2^*, v_3^*$  and  $w^*$  such that  $(x^*, y^*, u_1^*, u_2^*, u_3^*, v_1^*, v_2^*, v_3^*, w^*)$  to solve (3.5). Going one step farther, we only need to prove that there exist (row) vectors  $u_1^*, u_2^*, u_3^*, v_1^*, v_2^*, v_3^*$  and  $w^*$  such that  $(x^*, y^*, u_3^*, u_3^*, u_3^*, v_3^*, v_3^*, v_3^*, v_3^*)$  satisfy the follows

$$u_{1}B_{1} + u_{2}B_{10}^{L} + u_{3}B_{10}^{R} + v_{1}B_{2} + v_{2}B_{20}^{L} + v_{3}B_{20}^{R} - w$$
 (3.9a)

 $= -(d_2 + d_{20}^L + d_{20}^R)$ 

$$u_1(b_1 - A_1x - B_1y) = 0$$
 (3.9b)

$$u_{2}(b_{10}^{L} - A_{10}^{L}x - B_{10}^{L}y) = 0 (3.9c)$$

$$u_3(b_{10}^R - A_{10}^R x - B_{10}^R y) = 0 (3.9d)$$

$$v_1(b_2 - A_1x - B_2y) = 0$$
 (3.9e)

$$v_2(b_{20}^L - A_{20}^L x - B_{20}^L y) = 0$$
 (3.9f)

$$v_3(b_{20}^R - A_{20}^R x - B_{20}^R y) = 0 ag{3.9g}$$

$$wv = 0, (3.9h)$$

where  $u_1, u_2, u_3 \in R^p$ ,  $v_1, v_2, v_3 \in R^q$ ,  $w \in R^m$  and they are not negative variables.

Because  $(x^*, y^*)$  is the optimal solution of (3.6), we have

$$(x^*, y^*) \in IR$$
,

by (3.7). Thus we have

$$y^* \in P(x^*)$$
,

by Definition 2.5(e).  $y^*$  is the optimal solution to the following problem

$$\min(f(x^*, y) : y \in S(x^*)), \tag{3.10}$$

by Definition 2.5(d). Rewrite (10) as follows

 $\min f(x, y)$ 

subject to  $y \in S(x)$ 

$$x = x^*$$
.

From Definition 3.2(b), we have

$$\min_{y} (f(x, y)) = c_2 x + d_2 y + c_{20}^{L} x + d_{20}^{L} y + c_{20}^{R} x + d_{20}^{R} y$$
 (3.11a)

subject to 
$$A_1 x + B_1 y < b_1$$
, (3.11b)

$$A_{10}^{L}x + B_{10}^{L}y < b_{10}^{L}, (3.11c)$$

$$A_{10}^{R}x + B_{10}^{R}y < b_{10}^{R},$$
 (3.11d)

$$A_2 x + B_2 y < b_2,$$
 (3.11e)

$$A_{20}^{L}x + B_{20}^{L}y \le b_{20}^{L}, (3.11f)$$

$$A_{2_0}^R x + B_{2_0}^R y \le b_{2_0}^R. \tag{3.11g}$$

$$x = x^* \tag{3.11h}$$

$$y > 0$$
 (3.11i)

To simplify (3.11), we can have

$$\min g(y) = (d_2 + d_{20}^L + d_{20}^R)y \tag{3.12a}$$

subject to 
$$-B_1 y \ge -(b_1 - A_1 x^*)$$
, (3.12b)

$$-B_{10}^{L}y > -(b_{10}^{L} - A_{10}^{L}x^{*}), (3.11c)$$

$$-B_{10}^{R}y > -(b_{10}^{R} - A_{10}^{R}x^{*}), (3.12d)$$

$$-B_2 y > -(b_2 - A_2 x^*), \tag{3.12e}$$

$$-B_{20}^{R}y \ge -(b_{20}^{R} - A_{20}^{R}x^{*}), (3.12g)$$

$$y > 0. (3.12h)$$

Let we note

$$B = \begin{pmatrix} B_{1} \\ B_{10}^{L} \\ B_{10}^{R} \\ B_{2} \\ B_{20}^{L} \\ B_{20}^{R} \end{pmatrix}, \quad A = \begin{pmatrix} A_{1} \\ A_{10}^{L} \\ A_{10}^{R} \\ A_{20} \\ A_{20}^{R} \end{pmatrix}, \quad \text{and} \quad b = \begin{pmatrix} b_{1} \\ b_{10}^{L} \\ b_{10}^{R} \\ b_{2} \\ b_{20}^{L} \\ b_{20}^{L} \\ b_{20}^{R} \end{pmatrix}.$$
(3.13)

We rewrite (3.12) by using (3.13) and we get

$$\min g(y) = (d_2 + d_{20}^L + d_{20}^R)y \tag{3.14a}$$

subject to 
$$-By \ge -(b - Ax^*)$$
 (3.14b)

$$y \ge 0. \tag{3.14c}$$

Now we see that  $y^*$  is the optimal solution of (3.14) which is a LP problem. By Proposition 2, there exists vector  $\chi^*, \mu^*$ , such that  $(y^*, \lambda^*, \mu^*)$  satisfy a system below

$$\lambda B - \mu = -(d_2 + d_{20}^{L} + d_{20}^{R})$$
 (3.15a)

$$-By + (b - Ax^*) \ge 0 (3.15b)$$

$$\lambda(-By + (b - Ax^*)) = 0 (3.15c)$$

$$\mu y = 0, \qquad (3.15d)$$

where  $\lambda \in R^{3p+3q}$  and  $\mu \in R^m$ .

Let 
$$u_1, u_2, u_3 \in R^p$$
,  $v_1, v_2, v_3 \in R^q$  and  $w \in R^m$  and define  $\lambda = (u_1, u_2, u_3, v_1, v_2, v_3)$   
 $w = \mu$ .

Thus we have  $(x^*, y^*, u_1^*, u_2^*, u_3^*, v_1^*, v_2^*, v_3^*, w^*)$  that satisfy (3.9). Our proof is completed.

Theorem 3.3 means that the most direct approach to solving (3.1) is to solve the equivalent mathematical program given in (3.5). One advantage that it offers is that it allows for a more robust model to be solved without introducing any new computational difficulties

# IV. AN ILLUSTRATIVE EXAMPLE

Example 1 Consider the following FPBLP problem with  $x \in R^1$ ,  $y \in R^1$ , and  $X = \{x \ge 0\}$ ,  $Y = \{y \ge 0\}$ ,

$$\min_{x \in \mathcal{X}} F(x, y) = \tilde{1}x - \tilde{2}y \tag{4.1a}$$

subject to 
$$-\widetilde{1}x + \widetilde{3}y \stackrel{\sim}{=} 4$$
 (4.1b)
$$\min_{y \in Y} f_1(x, y) = \widetilde{1}x + \widetilde{1}y$$
 (4.1c)

$$\min_{\mathbf{y} \in Y} f_1(x, y) = \tilde{1}x + \tilde{1}y \tag{4.1c}$$

subject to 
$$\tilde{1}_{x} - \tilde{1}_{y} \prec \tilde{0}$$
 (4.1d)

$$= -\tilde{1}x - \tilde{1}y \prec \tilde{0}$$
 (4.1e)

where

$$\mu_{\bar{1}}(t) = \begin{cases} 0 & t < 0 \\ t & 0 \le t < 1 \\ 2 - t & 1 \le t < 2 \\ 0 & 2 \le t \end{cases}$$

$$\mu_{\bar{2}}(t) = \begin{cases} 0 & t < 1 \\ t - 1 & 1 \le t < 2 \\ 3 - t & 2 \le t < 3 \\ 0 & 3 \le t \end{cases}$$

$$\mu_{\tilde{3}}(t) = \begin{cases} 0 & t < 2 \\ t - 2 & 2 \le t < 3 \\ 4 - t & 3 \le t < 4 \end{cases}$$

$$0 & 4 \le t$$

$$0 & 4 \le t \end{cases}$$

$$\mu_{\tilde{4}}(t) = \begin{cases} 0 & t < 3 \\ t - 3 & 3 \le t < 4 \\ 5 - t & 4 \le t < 5 \end{cases}$$

$$0 & 5 \le t$$

$$\mu_{\tilde{0}}(t) = \begin{cases} 0 & t < -1 \\ t + 1 & -1 \le t < 0 \\ 1 - t & 0 \le t < 1 \\ 0 & 1 \le t \end{cases}$$

<u>Step 1</u> The problem is transferred to the following LMMBLP problem by using Theorem 3.2

$$\min_{x \in X} (F(x, y))_{c}^{L} = 1x - 2y$$

$$\min_{x \in X} (F(x, y))_{0}^{L} = 0x - 3y$$

$$\min_{x \in X} (F(x, y))_{0}^{R} = 2x - 1y$$
subject to  $-1x + 3y \le 4$ 

$$-2x + 2y \le 3$$

$$0x + 4y \le 5$$

$$\min_{y \in Y} (f(x, y))_{c}^{L} = 1x + 1y$$

$$\min_{y \in Y} (f(x, y))_{0}^{L} = 0x + 0y$$

$$\min_{y \in Y} (f(x, y))_{0}^{R} = 2x + 2y$$
subject to  $1x - 1y \le 0$ 

$$0x - 2y \le -1$$

$$2x - 0y \le 1$$

$$-1x - 1y \le 0$$

$$0x - 0y \le 0$$

$$-2x - 2y \le -1$$

Step 2. The problem is transferred to the following linear BLP problem by using method of weighting [27].

$$\min_{x \in X} F(x, y) = 3x - 6y$$
subject to  $-1x + 3y \le 4$ 
 $-2x + 2y \le 3$ 
 $0x + 4y \le 5$ 
 $\min_{y \in Y} f(x, y) = 3x + 3y$ 
subject to  $1x - 1y \le 0$ 
 $0x - 2y \le -1$ 
 $2x - 0y \le 1$ 
 $-1x - 1y \le 0$ 
 $-2x - 2y \le -1$ 
 $0x - 0y \le 1$ 

Step 3 Solve this linear BLP problem

$$\min_{x \in X} F(x, y) = 3x - 6y$$
subject to  $-1x + 3y \le 4$ 

$$-2x + 2y \le 3$$

$$0x + 4y \le 5$$

$$1x - 1y \le 0$$

$$0x - 2y \le -1$$

$$2x - 0y \le 1$$

$$-1x - 1y \le 0$$

$$-2x - 2y \le -1.$$

$$0x - 0y \le 1$$

$$3u_1 + 2u_2 + 4u_3 - u_4 - 2u_5 - 0u_6 - u_7 - 2u_8 - 0u_9 - u_{10} = -3$$

$$u_1(4 + 1x - 3y) + u_2(3 + 2x - 2y) + u_3(5 - 4y) +$$

$$u_4(-x + y) + u_5(-1 + 2y) + u_6(1 - 2x) +$$

$$u_7(x + y) + u_8(-1 + 2x + 2y) + u_9 + u_{10}y = 0$$

$$x \ge 0, y \ge 0, u_1 \ge 0, \dots, u_{10} \ge 0.$$
Step 4
The result is
$$\min_{x \in X} (F(x, y))_c = 1x - 2y = -1$$

Step 4 The result is  $\min_{x \in X} (F(x, y))_{c} = 1x - 2y = -1$   $\min_{x \in X} (F(x, y))_{0}^{L} = 0x - 3y = -1.5$   $\min_{x \in X} (F(x, y))_{0}^{R} = 2x - 1y = -0.5$ 

and

$$\min_{y \in Y} (f(x, y))_{c} = 0.5$$

$$\min_{y \in Y} (f(x, y))_{0}^{L} = 0$$

$$\min_{y \in Y} (f(x, y))_{0}^{R} = 1$$

$$x = 0, y = 0.5$$

Consequently, we have the solution of the problem (4.1)

$$\min_{x \in X} F(x, y) = \tilde{1}x - \tilde{2}y = \tilde{c}$$

$$\min_{y \in Y} f_1(x, y) = \tilde{1}x + \tilde{1}y = \tilde{d}$$

and

$$x = 0, y = 0.5$$

where

$$\mu_{\tilde{e}}(t) = \begin{cases} 0 & t < -1.5 \\ \frac{t+1.5}{0.5} & -1.5 \le t < -1 \\ \frac{-0.5-t}{0.5} & -1 \le t < -0.5 \\ 0 & -0.5 \le t \end{cases}, \quad \mu_{\tilde{d}}(t) = \begin{cases} 0 & t < 0 \\ \frac{t}{0.5} & 0 \le t < 0.5 \\ \frac{1-t}{0.5} & 0.5 \le t < 1 \\ 0 & 1 \le t \end{cases}$$

# V. CONCLUSION

Many organizational decision problems can be formulated by bilevel programming models. Following our previous research [1, 2], this paper proposes the definition of optimal solution and related theorems for fuzzy parameter based linear bilevel programming. By using the proposed definition and theorems, this study develops a fuzzy number based Kuhn-Tucher approach to solve proposed FPBLP problem. A numeral example illustrates the power and details of the proposed approach. Further study includes the development of the model and related solving approaches for fuzzy parameter based multi-follower bilevel programming problems.

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## REFERENCES

[1] C. Shi, G. Zhang, and J. Lu, "On the definition of linear bilevel programming solution", Applied Mathematics and Computation, vol. 160, 169-176, 2005.

- [2] C. Shi, J. Lu, and G. Zhang, "An extended Kuhn-Tucker approach for linear bilevel programming", Applied Mathematics and Computation, vol. In press, 2004.
- [3] H. Stackelberg, The Theory of the Market Economy. New York, Oxford: Oxford University Press, 1952.
- [4] G. Anandalingam and T. Friesz, "Hierarchical optimization: An introduction", Annals of Operations Research, vol. 34, pp. 1-11, 1992.
- [5] J. Bard, Practical Bilevel Optimization: Algorithms and Applications.: Kluwer Academic Publishers, 1998.
- [6] Y. J. Lai, "Hierarchical optimization: A satisfactory solution", Fuzzy Sets and Systems, vol. 77, pp. 321-335, 1996.
- [7] J. Bracken and J. McGill, "Mathematical programs with optimization problems in the constraints", Operations Research, vol. 21, pp. 37-44, 1973.
- [8] E. Aiyoshi and K. Shimizu, "Hierarchical decentralized systems and its new solution by a barrier method", IEEE Transactions on Systems, Man, and Cybernetics, vol. 11, pp. 444-449, 1981.
- [9] W. Bialas and M. Karwan, "Multilevel linear programming. Technical Report 78-1," State University of New York, Buffalo, Operations Research Program 1978.
- [10] W. Candler and R. Townsley, "A linear twolevel programming problem", Computers and Operations Research, vol. 9, pp. 59-76, 1982.
- [11] W. Bialas and M. Karwan, "Two level linear programming", Management Science, vol. 30, pp. 1004-1020, 1984.
- [12] Y. Chen, M. Florian, and S. Wu, "A descent dual approach for linear bilevel programs. Technical Report CRT866," Centre de Recherche sur les Transports 1992.
- [13] S. Dempe, "A simple algorithm for the linear bilevel programming problem." Optimization, vol. 18, pp. 373-385, 1987.
- [14] G. Papavassilopoulos, "Algorithms for static Stackelberg games with linear costs and polyhedral constraints", presented at the 21st IEEE Conference on Decisions and Control, 1982.
- [15] J. Bard and J. Falk, "An explicit solution to the programming problem", Computers and Operations Research, vol. 8, pp. 77-100, 1982.
- [16] J. F. Amat and B. McCarl, "A representation and economic interpretation of a twolevel programming problem", Journal of the Operational Research Society, vol. 32, pp. 783-792, 1981.
- [17] P. Hansen, B. Jaumard, and G. Savard, "New branchandbound rules for linear bilevel programming", SIAM Journal on Scientific and Statistical Computing, vol. 13, pp. 1194-1217, 1992.
- [18] W. Bialas, M. Karwan, and J. Shaw, "A parametric complementary pivot approach for twolevel linear programming. Technical Report 802," State University of New York at Buffalo, Operations Research Program 1980.
- [19] D. White and G. Anandalingam, "A penalty function approach for solving bilevel linear programs", Journal of Global Optimization, vol. 3, pp. 397-419, 1993.
- [20] L. Leblanc and D. Boyce, "A bilevel programming algorithm for exact solution of the network design problem with useroptimal flows", Transportation Research, vol. 20, pp. 259-265, 1986.
- [21] P. Marcotte, "Network optimization with continuous control parameters", Transportation Science, vol. 17, pp. 181-197, 1983.
- [22] T. Miller, T. Friesz, and R. Tobin, "Heuristic algorithms for delivered price spatially competitive network facility location problems", Annals of Operations Research, vol. 34, pp. 177-202, 1992.
- [23] L. A. Zadeh, "Fuzzy sets", Inform & Control, vol. 8, pp. 338-353, 1965.
- [24] M. Sakawa, I. Nishizaki, and Y. Uemura, "Interactive fuzzy programming for multilevel linear programming problems with fuzzy parameters", Fuzzy Sets and Systems, vol. 109, pp. 3-19, 2000.
- [25] G. Zhang, Y. Wu, M. Remia, and J. Lu, "Formulation of fuzzy linear programming problems as four-objective constrained problems", Applied Mathematics and Computation, vol. 139, pp. 383-399, 2003.
- [26] University of Cambridge http://thesaurus.maths.org/dictionary/map/word/10037, 2001.
- [27] M. Sakawa, "Interactive multiobjective linear programming with fuzzy parameters", in Fuzzy sets and interactive mulitobjective optimization. New York: Plenum Press, 1993.