A Bi-Level Programming Model for Energy and Flexiramp Procurement in Day-ahead Market and a Fuzzy Max-Min Approach for its Solution

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Abstract

In this paper, we focus on solving the integrated energy and flexiramp procurement problem in the day-ahead market. The problem of energy and ramp procurement could be perfectly analyzed through Stackelberg concept, because of its hierarchical nature of the decision-making process. Such a circumstance is modeled via a bi-level programming, in which suppliers act as leaders and the ISO appear as the follower. The ISO intends to minimize the energy and spinning reserve procurement cost, and the suppliers aim to maximize their profit. To solve the proposed model, a fuzzy max-min approach is applied to maximize the players' utilities. The objectives and suppliers' dynamic offers, determined regarding the market clearing prices, are reformulated through fuzzy utility functions. The proposed approach is an effective and simple alternative to the KKT method, especially for problems with non-convex lower-level.

Keywords: Integrated Energy and Flexiramp Market, Bi-level Programming, Fuzzy Max-Min, Dynamic Pricing.

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NOMENCLATURE

Indices

i: Index of the generating units, $i \in \{1,...,I\}$.

k: Index of the blocks of the balancing energy offers, k:{1,…,K}.

t: Index of the time periods, $t \in \{1,...,T\}$

p: Index of the parameters which are variable in other level.

Decision variables in upper level

$C_{t,i,k}$: Proposed price in k_{th} bid (the ramp of k_{th} block of the offer) by unit i at period t

$R_{i,t}^{up}$: Proposed ramp-up by unit i at period t

$R_{i,t}^{dn}$: Proposed ramp-down by unit i at period t

ϑ: Binary variable for linearization

Decision variables in lower level

$g_{t,i,k}$: The allocated energy in each offer at each period to each unit

TG_i^t: Total amount of allocated energy to generator i at period t

$\mu_{t,i}^{A}$: LM of unit i energy balance at period t

$\mu_{t,i}^{up}$: LM of unit i ramp-up constraint at period t

$\mu_{t,i}^{Down}$: LM of unit i ramp-down constraint at period t

$z_{t,i}^{\bullet}$: Binary variables for general non-linear form of the Heaviside function

Parameters

D^t: Demand at period t

p_i^{max}: Maximum capacity of unit i.

p_i^{min}: Minimum capacity of unit i

$SR_{t,i}^{max}$: Spinning reserve of unit i at period t

MSR: Minimum required spinning reserve

$MR_{t,i}^{up}$: Maximum ramp-up rate capability for unit i at period t

$MR_{t,i}^{down}$: Maximum ramp-down rate capability for unit i at period t

$L_{t,i,k}$: The length of k_{th} piece of generator i's offer at period t

$MC_{t,i}$: Marginal cost of generator i at period t

$g^{p}_{t,i,k}$: The allocated energy in each offer at each period to each unit, which determined in lower-level and is a fixed parameter in upper-level

$TG_{t,i}^{p}$: Total amount of allocated energy to generator i at period t, which determined in the lower-level and is a fixed parameter in the upper-level.

1. INTRODUCTION

1.1.Background and motivation

Efficient integration of the renewable generation into the conventional power systems requires advanced market structures and analysis methods [1]. By increased penetration of the unreliable generation, it has been recognized that the conventional operating reserves are insufficient for responding to the net load variations. Therefore, the establishment of the effective strategies for flexibility promoting is necessary [2-5]. Because of the inadequacy of the traditional reserves, California independent operator of the system (CAISO) declared the need for more ramp rate capability in the next decade [2]. For additional up and down ramping capability, the CAISO [6] and MISO [7] have proposed establishment of the markets for flexible ramping products.

Wind and hydro generators due to their high flexibility are prone to propose strategically. The strategic behavior of wind generators for ramp rate offering is because of the market abnormality that emanates from the regional pricing structure of the electricity market [8].

An aspect of the flexiramp providing through renewable power plants is the intentional curtailment of the variable generation by the system operator or market-based mechanisms [9]. However, such curtailments are not common and rationale for wind plants. In addition, even though power plants may have the technical capability for flexiramp providing, they usually propose a lower rate of the ramping capability to remain their output in a stable level [10]. This issue is examined in [8]. Through an effective optimization model, the optimum contribution share of each player according to its object is determined.

There are numerous researches which consider the bi-level programming for problem modeling [8, 11-19]. In this section, a number of these studies are reviewed.

Moiseeva et al. [8] developed a bi-level programming model to capture the behavior on the ramp rate offering. They considered a market operator who collects bids in form of marginal costs, quantities, and ramp rates; and run a ramp-constrained economic dispatch in the real-time market. Therefore, the lower-level problem was the ramp-constrained economic dispatch and the higher-level represented the profit maximization problems solved by strategic generators.

Riaz et al. [11] developed a Stackelberg game to capture the interaction between ISO and renewable energy sources aggregation (REA). In their game, the ISO attempted to minimize the generation cost, whereas REA maximized the revenue. Wu et al. [12] developed a day-ahead scheduling model through bi-level programming, in which the hourly demand response was considered to reduce the system operation cost and incremental changes in generation dispatch.

Tohidi et al. [17] developed a mathematical model to explore the transmission network switching from an economic perspective in the context of the market power. They developed a model to capture the game between strategic GenCos based on the Cournot game as the lower-level problem in bi-level model. Also, in upper-level, the TSO as a leader minimized the system dispatch cost using its transmission switching decisions.

Chen et al. [20] developed an inexact bi-level simulation-optimization model for conjunctive regional renewable energy planning and air pollution control for electric power systems. An improved interactive solution algorithm based on the satisfactory degree is introduced to make a tradeoff between meeting the constraints and attaining the optima for the objectives.

1.2. Gaps in the literature and our contribution

Despite the existence of several promotional strategies for the corporation of wind power plants in power markets, most attention has been concentrated on some strategies include investment subsidies, feed-in tariff schemes, fixed premium schemes, obligated quotas, and tendering and tradable green certificate systems. These instruments are discussed in more detail in the [21]. In this paper, we examine a dynamic price offering method, in which the wind units are allowed to propose the bids regarding the market clearing price in the previous period.

In this paper, we concentrate on solving an integrated energy and flexiramp procurement problem, where the partners intend to attain their objectives. Procurement planning and order allocation to the suppliers are modeled via a bi-level programming, in which the suppliers are the upper-level decision makers and the ISO, as the follower, act in accordance with the leader's decisions. The reason for the applying a bi-level programming model according to the Stackelberg game lies on the innate nature of the problem. Actually, the ISO chooses its actions after the action selection by suppliers. The suppliers' actions are their bids include proposed prices and the amounts of available energy and ramp. Also, the leaders (suppliers) know that the follower (ISO) selects its actions after observing the suppliers' actions (bids).

In our proposed model, using a centralized model or KKT optimality conditions transforming the bi-level programming into an equivalent single-level problem [18] wrongly eliminates the distributed nature of the problem and implies that information is fully revealed to the upper-level players [19]. To solve the bi-level model, a fuzzy max-min approach is applied to maximize the players' utilities. Fuzzy Max-Min approach is designed to obtain a satisfactory compromise between the objectives of the decision-makers [22].

For the case of a multiple-leader-multiple-follower equilibrium, Equilibrium Problem with Equilibrium Constraints (EPEC) optimization models are usually sufficient for representation of the interaction between the market participants. However, EPEC models are too hard to solve and very difficult to compute for large systems [23].

EPECs are a set of coupled MPECs, so they inherit the bad properties of MPECs. They are non-convex and non-linear and finding a global solution for them is challenging [23].

Shih et al [24] used the concepts of membership functions and multiple objective optimization to develop a fuzzy approach for solving the bi-level models. Their approach relies on changes of membership functions expressing satisfactory degrees of potential solutions for both upper and lower level decision makers. Such a satisfactory concept is more acceptable than optimality, because it is difficult to define a solid optimality in a multi-person game, and it is questionable by restricting the potential solutions at feasible region's corners. Potential satisfactory solutions are those in the non-dominated region. Thus, the fuzzy approach is more efficient and will not increase the complexities of the original problems [24].

Therefore, a simple reason of using the fuzzy approach is its convenience; but the more important reason is its capability for finding the satisfying solution for all partners through transactions during the decision-making process instead of an optimal solution [19].

2. STACKELBERG EQUILIBRIUM

Despite the simultaneous games, players in Stackelberg game choose their strategies sequentially in a known order and knowing the strategies chosen by the precedent players. Also, the leader/leaders (suppliers in our problem) know that the follower (ISO in our problem) observes their actions [21, 25]. Solution procedure for sequential games is backward, which means that we first solve the problem in the second level (follower's problem) and afterward the problem in the first level (leader's problem). The simple algorithm for the bi-level problem explains as follows [26]:

1) At 2nd level: Follower chooses his/her reaction given what leader has chosen.

- Outcome: follower's reaction function

2) At 1st level: Leader chooses its action taking follower's reaction function into account (optimize its objective function subject to the follower's reaction function)

- Outcome: Stackelberg strategy

In static games, if the two players' cost functions are $J_1(u_1,u_2)$, $J_2(u_1,u_2)$, and J_2 would be the leader and the J_1 would be the follower. Also, u_2 would be the leader's decision variable and u_1 would be the follower's decision variable. The Stackelberg strategy is obtained by minimizing the leader's objective (J_2) subject to the follower's reaction function ($\frac{\partial J_1}{\partial u_1}$=0) [26]. The general solution procedure is shown in figure 1.

Despite matrix games, the Stackelberg solution in static games need not always exist [25]. So, to find a near optimal solution several methods are defined. In this paper, we used the fuzzy max-min method, which presented by [27].

It should be noticed that the current auction-game finish in a period which each of the players draw back from the game, and a new game with a fewer player is started. But the principal player which his refusing is the end of the game surprisingly is the follower or ISO. The principal player is not the leader. To clear this issue, it is enough to remember the leader and follower definition. The leader is the player who determines its strategy at first and knows the other player (follower) observes its action. The proposed model is completely introduced in the next section.

3. THE BI-LEVEL PROGRAMMING MODEL

3.1. THE BI-LEVEL PROGRAMMING

The Bi-level Programming problem is a special case of the multilevel programming (MLP), which is categorized as a non-convex programming problem that is NP-hard [28]

A general formulation of bi-level programming problems is as follows:

$$\begin{aligned}
&\underset{x,y}{Max}\, F_1(x,y)\\
&s.t.\\
&G_1(x,y) \le 0\\
&y \in \arg \underset{\hat{y}}{Min}\, f_1(x,\hat{y})\\
&s.t.\\
&g_1(x,\hat{y}) \le 0
\end{aligned}$$

Bi-level programming problems are complicated optimization problems, some reasons are as follows: (1) they are intrinsically NP-hard; (2) their nested structure has inherent difficulties even with respect to the notion of a solution; (3) for many methods regularity conditions cannot be satisfied at any feasible point. These features of bi-level programming problems make them very difficult to globally solve. In recent years, considerable research has sought to address the solution strategies of bi-level programming problems [29].

There have been several methods to solve BLPP, like methods based on Kuhn–Tucker conditions [30], fuzzy approach [31], Metaheuristic algorithms like genetic [32], PSO [33], hybrid of GA and PSO [34], and evolutionary multi-agent system [35]. In [36] it is mentioned that in the hierarchical decision making no one can gain his individual optimum decision while his existing competitor has conflicting objectives, and thus, a satisfactory decision is rational for all players trying to maximize their individual objectives as much as possible.

3.2. THE PROPOSED BI-LEVEL PROGRAMMING

In this section, we explain our proposed mathematical model. Set $S_{i1}:\left\{C_{i,k}^{t}, R_{i,t}^{up}, R_{i,t}^{dn}\right\}$ is the set of variables which are controlled by each of suppliers independently in the upper level and sent to the lower level as fixed parameters, also Set $S_2:\left\{TG_{t,i}, \mu_{t,i}^{A}, \mu_{t,i}^{up}, \mu_{t,i}^{Down}, OBJ_L\right\}$ is the set of variables which are controlled by the ISO on the lower level and sent to the upper level as fixed parameters. Despite [37], the dispatched quantity of the wind power producer and their proposed price in their second and third offer is dependent on market prices through a dynamic approach. For simplicity, the grid constraints are not considered in this model, but the inclusion of grid constraints is straightforward.

Upper level model is a multi-objective programming, which intends to maximize the energy and ramp revenue, minimize the ramp penalty and fuel cost for conventional generating units. The proposed model is as follows:

$$\begin{aligned}
&\underset{S_{i1}}{Max}\left(\sum_{t,i,k} {g^{p}}_{t,i,k} \times C_{t,i,k}\right)\\
&\underset{S_{i1}}{Max}\left(\left(R_{i,t}^{up} \times \mu_{t,i}^{up}\right) + \left(R_{i,t}^{dn} \times \mu_{t,i}^{Down}\right)\right)\\
&\underset{S_{i1}}{Min}\left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right)\\
&\underset{S_{i1}}{Min}\left(\sum_{t,i} \alpha_{t,i} + (TG_{t,i}^{p} \times \beta_i) + ((TG_{t,i}^{p})^2 \times \gamma_i)\right)
\end{aligned} \tag{1}$$

$$\begin{aligned}
&R_{t,i}^{up} \le MR_{t,i}^{up}\\
&R_{t,i}^{dn} \le MR_{t,i}^{down}
\end{aligned} \tag{2}$$

Equations 1 and 2 are the upper-level problem, and the lower-level problem acts as constraints for upper-level problem. Also, the objectives in both levels transformed to the utility functions. According to the Max-Min method [38], we must use the min operator to aggregate the satisfactory levels, then maximize the aggregated utility. Therefore, the upper-level problem is not a separable problem.

In the lower level, ISO as a follower solve a Multi-period economic dispatch problem. The ISO's objective is minimization of the procurement cost of energy and reserve.

$$\mathrm{Min}\left(\sum_{t,i,k} g_{t,i,k} \times C_{t,i,k}\right) + \left(SR_{t,i} \times \mu^{reserve}_{t-1,i}\right) \tag{3}$$

$$\begin{aligned} & L_{t,i} \times z^1_{t,i} \le g_{t,i,1} \le L_{t,i} \\ & L_{t,i} \times z^2_{t,i} \le g_{t,i,2} \le L_{t,i} \times z^1_{t,i} \\ & 0 \le g_{t,i,3} \le L_{t,i} \times z^2_{t,i} \end{aligned} \tag{4}$$

The above equations are considered for general nonlinear format, and $L_{t,i}$ is the length of each piece of Heaviside function. But if the ramp of proposed Heaviside function is in an incremental order for minimization problem, we can use the linear form.

The other lower level's constraints are as follows:

$$\begin{aligned} & \sum_k g_{tik} = TG_{t,i} \\ & \sum_i TG_{t,i} = D^t \end{aligned} \tag{5}$$

$$\begin{aligned} & TG_{t,i} \ge p^{min}_{t,i} \\ & TG_{t,i} \le p^{max}_{t,i} \end{aligned} \tag{6}$$

$$\begin{aligned} & TG_{t,i} - TG_{(t-1),i} \le R^{up}_{t,i} \Leftrightarrow \mu^{up}_{t,i} \\ & TG_{(t-1),i} - TG_{t,i} \le R^{dn}_{t,i} \Leftrightarrow \mu^{down}_{t,i} \end{aligned} \tag{7}$$

The spinning reserve constraint is as follows:

$$SR_{t,i} \le \mathrm{Min}\left\{SR^{max}_i, p^{max}_{t,i} - TG_{t-1,i}\right\} \tag{8}$$

The above constraint rewrite as follows:

$$y = \mathrm{Min}\left\{SR^{max}_i, p^{max}_{i,t} - TG_{i,t-1}\right\} \tag{9}$$

$$\begin{aligned} & \text{if} \quad SR^{max}_i \le p^{max}_{i,t} - TG_{i,t-1} \quad \rightarrow y = SR^{max}_i \\ & \text{if} \quad SR^{max}_i \ge p^{max}_{i,t} - TG_{i,t-1} \quad \rightarrow y = p^{max}_{i,t} - TG_{i,t-1} \end{aligned} \tag{10}$$

The linearize constraints are as follows:

$$\begin{aligned} & SR^{max}_i \le (p^{max}_{i,t} - TG_{i,t-1}) + M\vartheta \\ & (p^{max}_{i,t} - TG_{i,t-1}) \le SR^{max}_i + M(1-\vartheta) \\ & y = SR^{max}_i + M\vartheta \\ & y = (p^{max}_{i,t} - TG_{i,t-1}) + M(1-\vartheta) \end{aligned} \tag{11}$$

4. Model reformulating and Solution procedure

4.1. Fuzzy solution procedure for bi-level models

Many heuristics and metaheuristics methods are applied to solve the bi-level problems. The first step of many methods like fuzzy method is solving the problem at each level separately with existing methods like CPLEX. If the optimal solution for the lower-level problem is also feasible for the upper level, and vice versa, this pair of the solution is the optimal one for the BLP [39]. However, this solution is usually unfeasible.

In fuzzy Max-Min method, several linear or nonlinear utility functions must be considered for objectives and upper-level variables. Some simple principles of the fuzzy method for bi-level problems are presented in the next section. According to the Max-Min method [38], we must use the min operator to aggregate the satisfactory levels, then maximize the aggregated utility. The general form of utility function for maximizing and minimizing objective functions is shown in figure 2.

Furthermore, the general flowchart of the fuzzy Max-Min method is shown in figure 3. To fully understand the fuzzy approach for bi-level model, we refer to the [40].

It should be mentioned that the dimension of various parts of the objective function are different; therefore, we must have applied multi-objective solution procedures like allocating weights to each objective or using utility functions and normalized it. We introduced separate objective and associated normalized utility functions. This is an acceptable method to deal with the multi-objective problems.

4.1.1. Fuzzy utility functions for day-ahead market

In this section, some simple linear utility functions for objectives are introduced. According to the Max-Min method [27], initially, the min operator must be used to aggregate the satisfactory levels, then maximize the aggregated utility. Furthermore, the general form of the utility function for maximizing and minimizing objective functions is shown in figure 2. To fully understand the fuzzy approach for bi-level models, we refer to the [22].

Some simple utility functions for lower-level and upper-level objectives are introduced as follows:

1. An objective is the energy and ramp revenue maximization. Therefore, utility functions with respect to the energy revenue and ramp revenue are defined in equations 12 and 13 (figure 4).

According to the fuzzy max-min method [28], the value of the λ must be maximized subject to the constraints 14 and 15.

2. The other objective is the minimization of the ramp cost for thermal units. Therefore, its utility function is defined in equation 16 (figure 5), and the value of the λ must be maximized subject to the constraint 17.
3. The other objective is the minimization of the fuel cost. Its utility function is defined in equation 18 (figure 6), and the value of the λ must be maximized subject to the constraint 19.

$$\mu_{\left(E\_REV=\sum_{t,i,k} g^{P}_{t,i,k}\times C_{t,i,k}\right)} = \begin{cases} 1 & \text{if} \quad (E\_REV) > \left(\sum_{t,i,k} p^{max}_{t,i}\times(3MC_{t,i}+\mu^{A}_{t,i})\right) \\ \dfrac{(E\_REV)-OBJ^{P}_{L}}{\left(\sum_{t,i,k} p^{max}_{t,i}\times(3MC_{t,i}+\mu^{A}_{t,i})\right)-OBJ^{P}_{L}} & \text{if} \quad OBJ^{P}_{L}\le(E\_REV)\le\left(\sum_{t,i,k} p^{max}_{t,i}\times(3MC_{t,i}+\mu^{A}_{t,i})\right) \\ 0 & \text{if} \quad (E\_REV)<OBJ^{P}_{L} \end{cases} \tag{12}$$

$$\mu_{\left(R\_REV=\sum_{t,i}(R^{up}_{t,i}\times\mu^{up}_{t,i})+(R^{down}_{t,i}\times\mu^{Down}_{t,i})\right)} = \begin{cases} 1 & \text{if} \quad (R\_REV) > \left(\sum_{t,i,k} p^{max}_{t,i}\times(3MC_{t,i}+\mu^{A}_{t,i})\right) \\ \dfrac{(R\_REV)-0}{\left(\sum_{t,i,k}(MR^{up}_{t,i}+MR^{down}_{t,i})\times(3MC_{t,i}+\mu^{A}_{t,i})\right)-0} & \text{if} \quad 0\le(R\_REV)\le\left(\sum_{t,i,k} p^{max}_{t,i}\times(3MC_{t,i}+\mu^{A}_{t,i})\right) \end{cases} \tag{13}$$

$$\frac{\left(\sum_{t,i,k} g^{p}{}_{t,i,k} \times C_{t,i,k}\right) - OBJ_{L}^{P}}{\left(\sum_{t,i,k} p_{t,i}^{max} \times (3MC_{t,i} + \mu_{t,i}^{A})\right) - OBJ_{L}^{P}} \geq \lambda \tag{14}$$

$$\frac{\left(\sum_{t,i} (R_{t,i}^{up} \times \mu_{t,i}^{up}) + (R_{t,i}^{down} \times \mu_{t,i}^{Down})\right) - 0}{\left(\sum_{t,i,k} (MR_{t,i}^{up} + MR_{t,i}^{down}) \times (3MC_{t,i} + \mu_{t,i}^{A})\right) - 0} \geq \lambda \tag{15}$$

$$\mu_{\left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right)} = \begin{cases} 0 & \text{if} \quad \left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right) > \left(\sum_{t,i} (MR_{t,i}^{up} + MR_{t,i}^{dn}) \times RPN_i\right) \\ \dfrac{\left(\sum_{t,i} (MR_{t,i}^{up} + MR_{t,i}^{dn}) \times RPN_i\right) - \left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right)}{\left(\sum_{t,i} (MR_{t,i}^{up} + MR_{t,i}^{dn}) \times RPN_i\right) - OBJ_{U}^{P}} & \text{if} \quad OBJ_{U}^{P} \leq \left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right) \leq \left(\sum_{t,i} (MR_{t,i}^{up} + MR_{t,i}^{dn}) \times RPN_i\right) \\ 1 & \text{if} \quad \left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right) \leq OBJ_{U}^{P} \end{cases} \tag{16}$$

$$\frac{\left(\sum_{t,i} (MR_{t,i}^{up} + MR_{t,i}^{dn}) \times RPN_i\right) - \left(\sum_{t,i} (R_{t,i}^{up} + R_{t,i}^{dn}) \times RPN_i\right)}{\left(\sum_{t,i} (MR_{t,i}^{up} + MR_{t,i}^{dn}) \times RPN_i\right) - OBJ_{U}^{P}} \geq \lambda \tag{17}$$

$$\mu_{\left(C_i^{fuel}\right)} = \begin{cases} 0 & \text{if} \quad C_i^{fuel} > \left(\sum_{t,i} \alpha_{t,i} + (p_{t,i}^{max} \times \beta_i) + ((p_{t,i}^{max})^2 \times \gamma_i)\right) \\ \dfrac{\left(\sum_{t,i} \alpha_{t,i} + (p_{t,i}^{max} \times \beta_i) + ((p_{t,i}^{max})^2 \times \gamma_i)\right) - \left(C_i^{fuel}\right)}{\left(C_i^{fuel}\right) - OBJ_{help2}^{P}} & \text{if} \quad OBJ_{help}^{P} \leq C_i^{fuel} \leq \left(\sum_{t,i} \alpha_{t,i} + (p_{t,i}^{max} \times \beta_i) + ((p_{t,i}^{max})^2 \times \gamma_i)\right) \\ 1 & \text{if} \quad C_i^{fuel} \leq OBJ_{help}^{P} \end{cases} \tag{18}$$

$$\frac{\left(\sum_{t,i} \alpha_{t,i} + (p_{t,i}^{max} \times \beta_i) + ((p_{t,i}^{max})^2 \times \gamma_i)\right) - \left(\sum_{t,i} \alpha_{t,i} + (TG_{t,i}^{p} \times \beta_i) + ((TG^{p}_{t,i})^2 \times \gamma_i)\right)}{\left(\sum_{t,i} \alpha_{t,i} + (p_{t,i}^{max} \times \beta_i) + ((p_{t,i}^{max})^2 \times \gamma_i)\right) - OBJ_{help2}^{P}} \geq \lambda \tag{19}$$

4. If the market is cleared pay as bid, suppliers will be interested in approaching their proposed prices to the market balancing price, to increase their revenue meanwhile increase the chance of winning their bids. So the objective could be as follows:

$$\operatorname{Min} \sum_{t,k} \left| \mu_{i,t}^{A} - C_{i,t,k} \right| \tag{20}$$

$$k = \{1, ..K\}$$

This objective through goal programming could be rewritten as follows:

$$\operatorname{Min}(d1_{t,i,k}^{+} - d1_{t,i,k}^{-}) \tag{21}$$

$$(C_{t,i,k} - \mu_{t,i}^{A}) - o = d1_{t,i,k}^{+} - d1_{t,i,k}^{-}$$

Nevertheless, suppliers do not tend to confine their proposed prices with the value of the $\mu_{t,i}^{A}$ which is an upper-level's parameter. Therefore, the fuzzy programming is much more appropriate to model this objective. The price bidding is dynamic and related to the market clearing prices, also, suppliers tend to propose prices at least equal to their marginal cost. Two types of utility functions (a, b) associated with suppliers' price proposing approach are as follows.

The utility function associated with the first, second, and third blocks of proposed cost function are brought in equations 22-24. So, According to the fuzzy max-min method, the value of the λ must be maximized subject to the constraint 25.

Finally, the lower-level utility function is in equation 26, its associated constraint is brought in equation 27.

$$\mu_{C_{t,i,'1'}} = \begin{cases} \dfrac{C_{t,i,'1'} - (MC_{t,i})}{\mu^{A}_{t,i}} & \text{if} \quad MC \le c_{t,i,'1'} \le MC + \mu^{A}_{t,i} \\ 0 & \text{O.W.} \end{cases} \tag{22}$$

$$\mu_{C_{t,i,'2'}} = \begin{cases} \dfrac{C_{t,i,'2'} - (MC_{t,i} + \mu^{A}_{t,i})}{\mu^{A}_{t,i}} & \text{if} \quad MC_{t,i} + \mu^{A}_{t,i} \le c_{t,i,'2'} \le MC_{t,i} + 2\mu^{A}_{t,i} \\ 0 & \text{O.W.} \end{cases} \tag{23}$$

$$\mu_{C_{t,i,'3'}} = \begin{cases} \dfrac{C_{t,i,'3'} - (MC_{t,i} + 2\mu^{A}_{t,i})}{\mu^{A}_{t,i}} & \text{if} \quad MC_{t,i} + 2\mu^{A}_{t,i} \le c_{t,i,'3'} \le MC_{t,i} + 3\mu^{A}_{t,i} \\ 0 & \text{O.W.} \end{cases} \tag{24}$$

$$\begin{aligned} &\frac{C_{t,i,'1'} - (MC_{t,i})}{\mu^{A}_{t,i}} \ge \lambda \\ &\frac{C_{t,i,'2'} - (MC_{t,i} + \mu^{A}_{t,i})}{\mu^{A}_{t,i}} \ge \lambda \\ &\frac{C_{t,i,'3'} - (MC_{t,i} + 2\mu^{A}_{t,i})}{\mu^{A}_{t,i}} \ge \lambda \end{aligned} \tag{25}$$

$$\mu_{(ISO\_EnergyCost)} = \begin{cases} 0 & \text{if} \quad \left(\left(\sum_{t,i,k} g_{t,i,k} \times C_{t,i,k}\right) + \left(\sum_{t,i} SR_{t,i} \times \mu^{reserve}_{t-1,i}\right)\right) > \left(OBJ^{P}_{MAX\,Cost}\right) \\ \dfrac{\left(OBJ^{P}_{MAX\,Cost}\right) - \left(\left(\sum_{t,i,k} g_{t,i,k} \times C_{t,i,k}\right) + \left(\sum_{t,i} SR_{t,i} \times \mu^{reserve}_{t-1,i}\right)\right)}{\left(OBJ^{P}_{MAX\,Cost}\right) - \left(OBJ^{P}_{MIN\,Cost}\right)} & \text{if} \quad \left(OBJ^{P}_{MIN\,Cost}\right) \le \left(\left(\sum_{t,i,k} g_{t,i,k} \times C_{t,i,k}\right) + \left(\sum_{t,i} SR_{t,i} \times \mu^{reserve}_{t-1,i}\right)\right) \le \left(OBJ^{P}_{MAX\,Cost}\right) \\ 1 & \text{if} \quad \left(\left(\sum_{t,i,k} g_{t,i,k} \times C_{t,i,k}\right) + \left(\sum_{t,i} SR_{t,i} \times \mu^{reserve}_{t-1,i}\right)\right) \le \left(OBJ^{P}_{MIN\,Cost}\right) \end{cases} \tag{26}$$

$$\frac{\left(OBJ^{P}_{MAX\,Cost}\right) - \left(\left(\sum_{t,i,k} g_{t,i,k} \times C_{t,i,k}\right) + \left(\sum_{t,i} SR_{t,i} \times \mu^{reserve}_{t-1,i}\right)\right)}{\left(OBJ^{P}_{MAX\,Cost}\right) - \left(OBJ^{P}_{MIN\,Cost}\right)} \ge \lambda \tag{27}$$

The flowchart of the auction based bi-level programming is brought in figure 7.

The computational analyses are illustrated in the next section.

5. COMPUTATIONAL ANALYSES

In this section, we illuminate the validity of our approach by solving the proposed model for a simple example. The model is implemented on GAMS platform 24.7.4 and solved through BARON (Branch and Reduce Optimization Navigator) Solver. The GAMS code runs on 4 GHz Intel Processor core i7 and 16 GB of RAM. The problem parameters are shown in table 1, 2, and 3. The market clearing prices in each period in the 10_{th} iteration of the game are shown in table 4. Table 5 illustrates the units' proposed prices for each proposed intervals in the 10th iteration of the game. Table 6 illuminates the units' ramp up in the 10_{th} iteration of the game. Table 7 demonstrates the units' ramp down in the 10th iteration of the game. Table 8 elucidates the allocated energy in each offer at each period in the 10th iteration of the game.

We compare the results of the Fuzzy method with those of the EPEC reformulation method in term of ISO's cost. The ISO's cost calculated through fuzzy max-min method is shown in figure 8. According to figure 8 and in comparison with the ISO's cost through EPEC method (694328.739 $), the ISO's cost through fuzzy method is decreased during the game iterations and converge to a value less than the ISO's cost through the EPEC method.

The proposed approach decreases the ISO's cost without decreasing the units' revenues through introducing multiple utility functions and considering the ramp penalties for conventional units.

The ramp prices (Lagrange multipliers $\mu_{t,i}^{up}$ and $\mu_{t,i}^{down}$) in all iterations of the game are equal zero, which imply the flexiramp price in the day-ahead market is equal to zero. According to the results, we should not rely only on the day-ahead market analyzing to study the ramp procurement. Therefore, the price of flexiramp is determined regarding the possible contingencies in the real-time market.

6. CONCLUSION AND FURTHER RESEARCH

In this paper, a bi-level programming model based on the Stackelberg game for integrated energy and ramp procurement problem in the day-ahead market is developed. In addition, to solve the proposed bi-level programming model, a fuzzy max-min approach is applied to maximize the players' utilities. The proposed approach is an effective and simple alternative instead of KKT method for problems with numerous constraints in its lower-level or problems with non-convex lower-level, also it simulates the iterative hierarchical game.

According to the results of the Fuzzy and the EPEC methods, the ISO's cost through fuzzy method is decreased during the game iterations and converge to a value less than the ISO's cost through the EPEC method. The proposed fuzzy method is so simple and do not have the EPEC's complexities.

According to the calculated ramp prices equal zero, we conclude, we should not only rely on the day-ahead market analyzing to study the ramp procurement. Actually, the price of flexiramp is determined regarding the possible contingencies in the real-time market and considering the accepted bids and commitments in the day-ahead market into account.

We aim to improve this paper from several aspects. The most important aspect is the improvement of the utility functions, such as more complex and nonlinear utility functions.

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Table 1. Demand in each period

Periods (hours)	Demand	Periods (hours)	Demand
1	700	13	860
2	700	14	860
3	700	15	900
4	700	16	900
5	700	17	900
6	700	18	900
7	800	19	970
8	830	20	990
9	830	21	990
10	830	22	990
11	830	23	950
12	830	24	800

Table 2. The type of each generating unit types, fuel cost coefficient, and the capacity limits

Unit	Type	α	β	γ	p_i^{min}	p_i^{max}
1	Thermal	240	7	0.007	50	500
2	Hydro	0	0	0	0	140
3	Hydro	0	0	0	0	400
4	Wind	0	0	0	0	300
5	Wind	0	0	0	0	200
6	Thermal	190	12	0.0075	50	500

Table 3. The units' maximum spinning reserve, ramp up, and ramp down

Unit	SR_i^{max}	$MR_{t,i}^{up}$	$MR_{t,i}^{down}$
1	80	100	100
2	40	70	70
3	80	200	200
4	80	300	300
5	80	200	200
6	80	100	100

Table 4. The market clearing price in each period in 10_{th} iteration of the game (with price proposing scheme 1)

Periods	Energy price	Periods	Energy price	Periods	Energy price	Periods	Energy price
1	35	**7**	112.195	**13**	143.443	**19**	193.911
2	35	**8**	143.117	**14**	144.210	**20**	199.493
3	36.934	**9**	115.977	**15**	185.505	**21**	214.282
4	36.151	**10**	142.909	**16**	190.265	**22**	221.359
5	35.907	**11**	133.404	**17**	191.031	**23**	210.595
6	35	**12**	158.706	**18**	175.269	**24**	181.034

Table 5. The units' proposed prices for each proposed intervals in 10_{th} iteration of the game

periods	units	proposed prices for each proposed intervals			periods	units	proposed prices for each proposed intervals		
		1	2	3			1	2	3
1	1	31.712	66.712	101.712	**13**	1	26.861	170.303	313.746
	2	33.751	68.751	103.751		2	37.706	181.149	324.592
	3	30.401	65.401	100.401		3	28.285	171.728	315.170
	4	-	35.000	70.000		4	-	143.443	286.886
	5	-	35.000	70.000		5	-	143.443	286.886
	6	33.077	68.077	103.077		6	31.612	175.055	318.498
2	1	29.155	64.155	99.155	**14**	1	27.052	171.262	315.472
	2	18.816	53.816	88.816		2	32.580	176.790	321.000

periods	units	proposed prices for each proposed intervals			periods	units	proposed prices for each proposed intervals		
		1	**2**	**3**			**1**	**2**	**3**
	3	20.704	55.704	90.704		3	42.477	186.687	330.896
	4	-	35.000	70.000		4	-	144.210	288.420
	5	-	35.000	70.000		5	-	144.210	288.420
	6	32.665	67.665	102.665		6	45.104	189.314	333.524
	1	32.817	69.751	106.686		1	35.793	221.299	406.804
	2	29.627	66.561	103.495		2	37.835	223.341	408.846
3	3	31.044	67.978	104.912	**15**	3	42.565	228.070	413.576
	4	-	36.934	73.868		4	-	185.505	371.011
	5	-	36.934	73.868		5	-	185.505	371.011
	6	36.934	73.868	110.803		6	43.170	228.676	414.181
	1	20.452	56.603	92.754		1	39.422	229.686	419.951
	2	24.373	60.524	96.675		2	42.024	232.289	422.553
4	3	33.197	69.348	105.500	**16**	3	43.361	233.625	423.890
	4	-	36.151	72.302		4	-	190.265	380.529
	5	-	36.151	72.302		5	-	190.265	380.529
	6	36.151	72.302	108.453		6	44.454	234.718	424.983
	1	34.988	70.894	106.801		1	38.362	229.393	420.424
	2	34.899	70.805	106.712		2	42.308	233.339	424.370
5	3	26.808	62.714	98.621	**17**	3	47.338	238.369	429.400
	4	-	35.907	71.813		4	-	191.031	382.062
	5	-	35.907	71.813		5	-	191.031	382.062
	6	35.907	71.813	107.720		6	44.117	235.148	426.180
	1	29.755	64.755	99.755		1	25.299	200.568	375.837
	2	20.860	55.860	90.860		2	34.817	210.087	385.356
6	3	28.180	63.180	98.180	**18**	3	41.463	216.733	392.002
	4	-	35.000	70.000		4	-	175.269	350.539
	5	-	35.000	70.000		5	-	175.269	350.539
	6	27.011	62.011	97.011		6	47.005	222.275	397.544
	1	19.049	131.244	243.439		1	36.482	230.393	424.304
	2	19.609	131.804	243.999		2	41.907	235.818	429.728
7	3	26.168	138.364	250.559	**19**	3	48.842	242.753	436.664
	4	-	112.195	224.390		4	-	193.911	387.821
	5	-	112.195	224.390		5	-	193.911	387.821
	6	32.509	144.704	256.899		6	40.476	234.387	428.297
	1	33.256	176.372	319.489		1	38.145	237.637	437.130
	2	38.559	181.676	324.793		2	44.353	243.846	443.339
8	3	31.230	174.347	317.464	**20**	3	47.309	246.802	446.295
	4	-	143.117	286.233		4	-	199.493	398.986
	5	-	143.117	286.233		5	-	199.493	398.986
	6	26.779	169.896	313.013		6	41.783	241.276	440.768
	1	38.887	154.864	270.841		1	44.011	258.294	472.576
	2	36.231	152.208	268.186		2	46.180	260.463	474.745
9	3	30.016	145.994	261.971	**21**	3	46.617	260.899	475.181
	4	-	115.977	231.955		4	-	214.282	428.565
	5	-	115.977	231.955		5	-	214.282	428.565
	6	19.994	135.972	251.949		6	44.757	259.039	473.322
	1	29.894	172.803	315.712		1	44.193	265.552	486.911
	2	31.787	174.696	317.605		2	45.203	266.561	487.920
10	3	35.112	178.021	320.931	**22**	3	47.055	268.414	489.773
	4	-	142.909	285.819		4	-	221.359	442.718
	5	-	142.909	285.819		5	-	221.359	442.718
	6	26.727	169.637	312.546		6	48.008	269.367	490.726
	1	28.548	161.953	295.357		1	39.918	250.512	461.107
	2	38.020	171.424	304.828		2	40.864	251.459	462.053
11	3	24.351	157.755	291.160	**23**	3	44.892	255.487	466.081
	4	-	133.404	266.808		4	-	210.595	421.189
	5	-	133.404	266.808		5	-	210.595	421.189
	6	32.646	166.051	299.455		6	46.100	256.695	467.289
	1	30.676	189.382	348.087		1	37.359	218.393	399.427
	2	37.690	196.396	355.101		2	35.618	216.652	397.686
12	3	35.652	194.357	353.063	**24**	3	38.097	219.131	400.164
	4	-	158.706	317.411		4	-	181.034	362.068
	5	-	158.706	317.411		5	-	181.034	362.068
	6	37.058	195.763	354.469		6	36.345	217.379	398.412

Table 6. The units' ramp up in 10_{th} iteration of the game

Periods	Scheme 1 Units 1	2	3	4	5	6
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	20	0
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	0	20
7	80	0	0	0	20	0
8	0	0	0	0	0	100
9	0	0	0	0	0	0
10	0	0	0	0	0	0
11	110	0	0	0	0	0
12	100	0	0	0	0	0
13	30	0	0	0	0	0
14	0	0	0	0	0	0
15	0	0	0	100	80	0
16	0	0	0	0	0	0
17	0	0	0	20	0	0
18	100	0	0	0	0	0
19	0	0	0	120	80	0
20	20	0	0	0	0	0
21	0	0	0	0	0	0
22	0	0	0	0	0	0
23	0	0	0	0	0	0
24	0	0	0	0	0	0

Table 7. The units' ramp down in 10_{th} iteration of the game

Periods	Scheme 1 Units 1	2	3	4	5	6
1	0	0	0	0	0	0
2	0	0	0	0	0	0
3	0	0	0	0	0	20
4	0	0	0	0	0	0
5	0	0	0	0	0	0
6	0	0	0	0	20	0
7	0	0	0	0	20	0
8	80	0	0	0	0	0
9	0	0	0	0	0	0
10	0	0	0	0	0	0
11	0	0	0	0	0	100
12	0	0	100	0	0	0
13	0	0	0	0	0	0
14	0	0	0	0	0	0
15	100	0	0	0	0	0
16	0	0	0	0	0	0
17	0	0	0	0	20	0
18	0	0	0	120	60	0
19	100	0	0	0	0	0
20	0	0	0	0	0	0
21	0	0	0	0	0	0
22	0	0	0	0	0	0
23	40	0	0	0	0	0
24	30	0	0	120	0	0

Table 8. The allocated energy in each offer at each period in 10_{th} iteration of the game

periods	The allocated energy to each unit					
	1	2	3	4	5	6
1	130	50	120	180	100	120
2	130	50	120	180	100	120
3	130	50	120	180	120	100
4	130	50	120	180	120	100
5	130	50	120	180	100	120
6	130	50	120	160	120	120
7	210	50	120	180	120	120
8	130	50	120	180	120	230
9	130	50	120	180	120	230
10	130	50	120	180	120	230
11	130	50	230	180	120	120
12	240	50	120	180	120	120
13	270	50	120	180	120	120
14	270	50	120	180	120	120
15	310	50	120	180	120	120
16	310	50	120	180	120	120
17	310	50	120	180	120	120
18	310	50	120	180	120	120
19	310	50	120	180	120	190
20	310	50	120	180	120	210
21	310	50	120	180	120	210
22	310	100	160	180	120	120
23	310	100	120	180	120	120
24	130	100	120	180	120	150

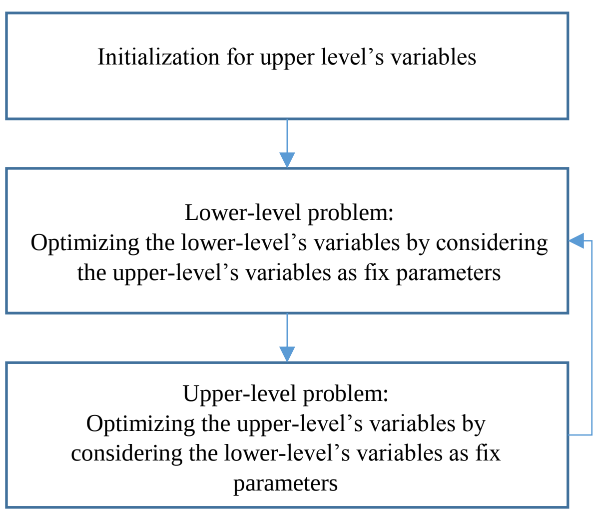
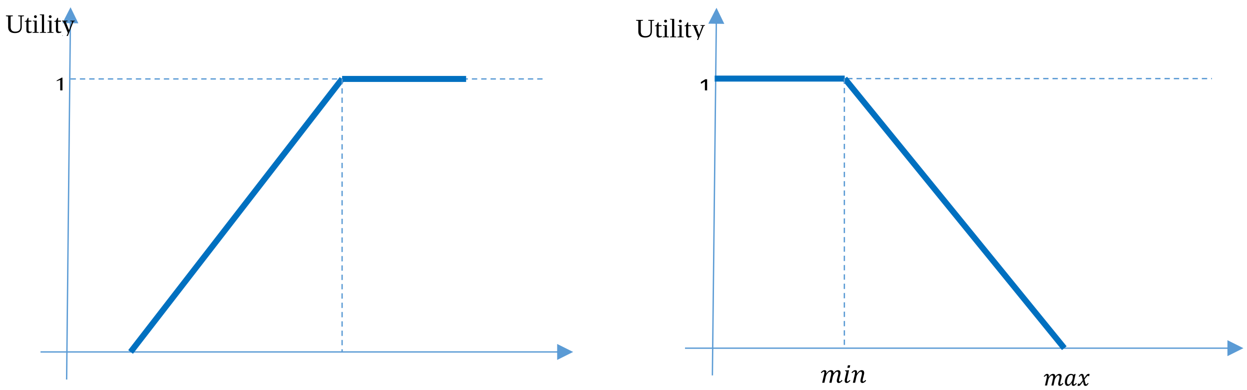


Figure 1. A simple solution process of Stackelberg game in bi-level form



$$u_i(y_i)=\begin{cases} 1 & \text{if} \quad y_i \ge g_{i,max} \\ \dfrac{y_i - g_{i,min}}{g_{i,max} - g_{i,min}} & \text{if} \quad g_{i,min} \le y_i \le g_{i,max} \\ 0 & \text{if} \quad y_i \le g_{i,min} \end{cases}$$

$$u_i(y_i)=\begin{cases} 1 & \text{if} \quad y_i \le g_{i,min} \\ \dfrac{g_{i,max} - y_i}{g_{i,max} - g_{i,min}} & \text{if} \quad g_{i,min} \le y_i \le g_{i,max} \\ 0 & \text{if} \quad y_i \ge g_{i,max} \end{cases}$$

(a) maximizing objective functions (b) minimizing objective functions

Figure 2. the general form of defining the utility function for maximization and minimization objective function

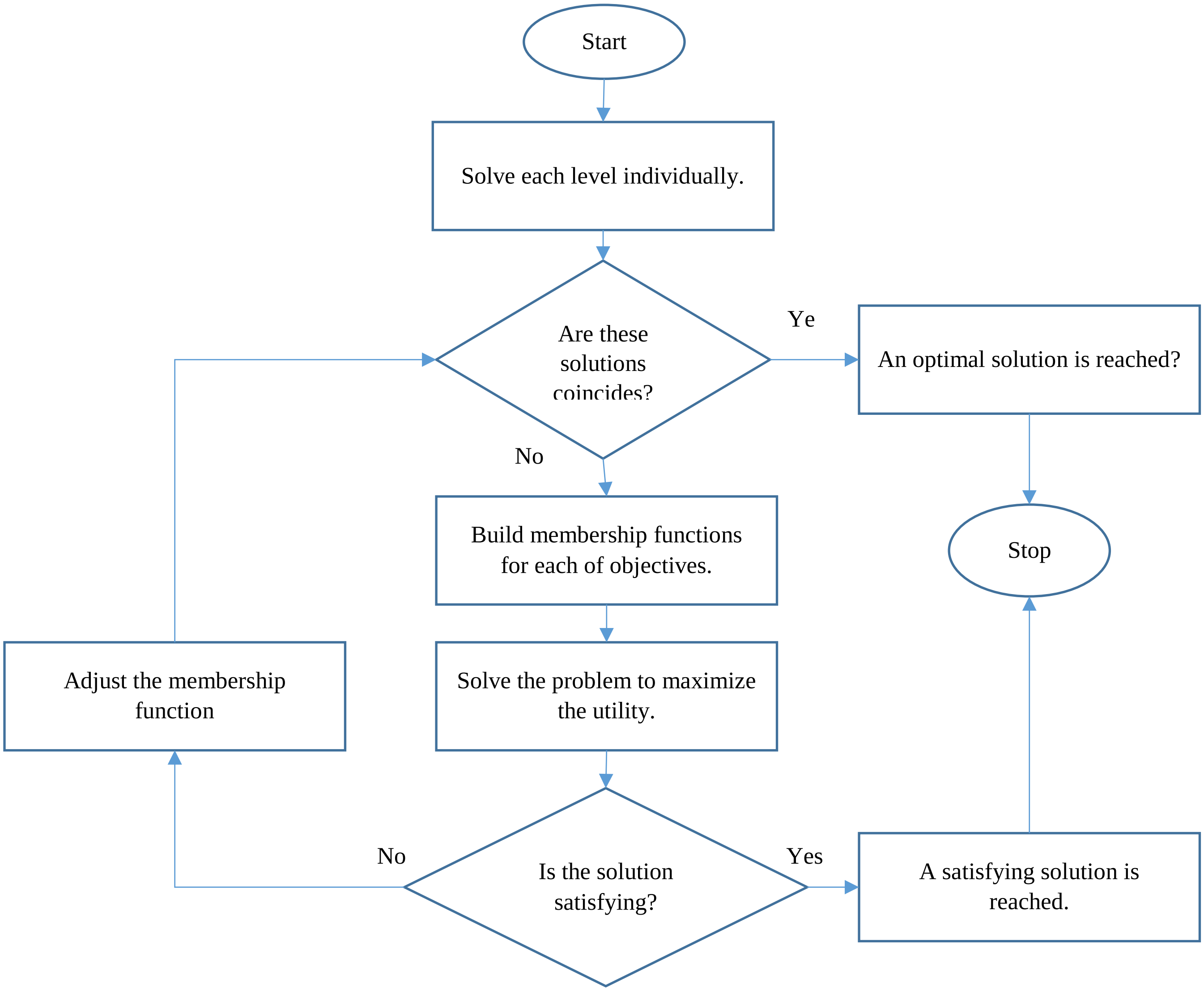


Figure 3. A simple solution process of the Stackelberg game in bi-level form

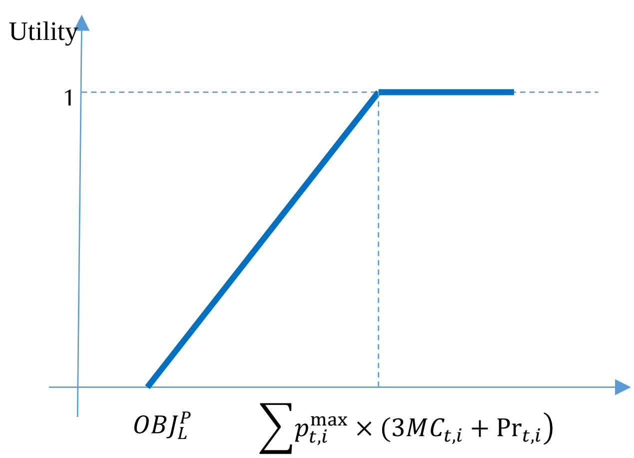


Figure 4. Utility function for each supplier's revenue

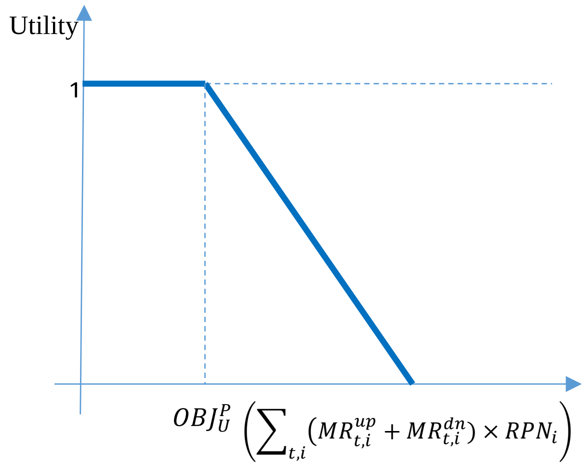


Figure 5. Utility function for ramping cost

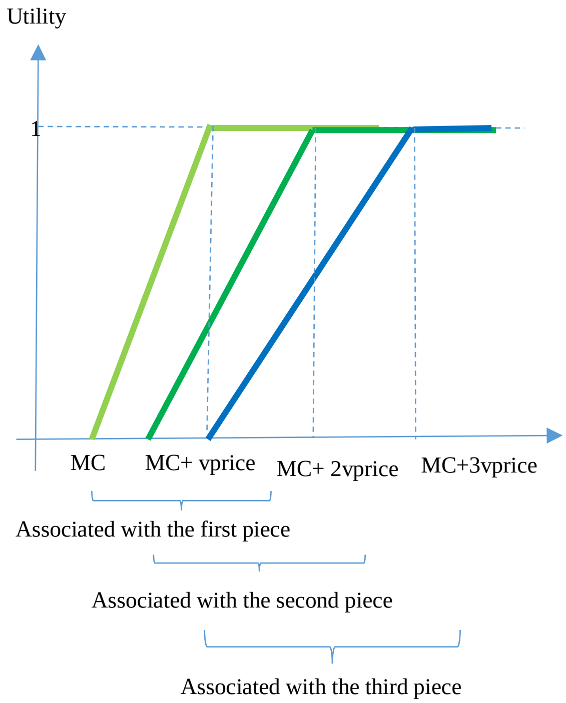


Figure 6. Utility function for proposed price

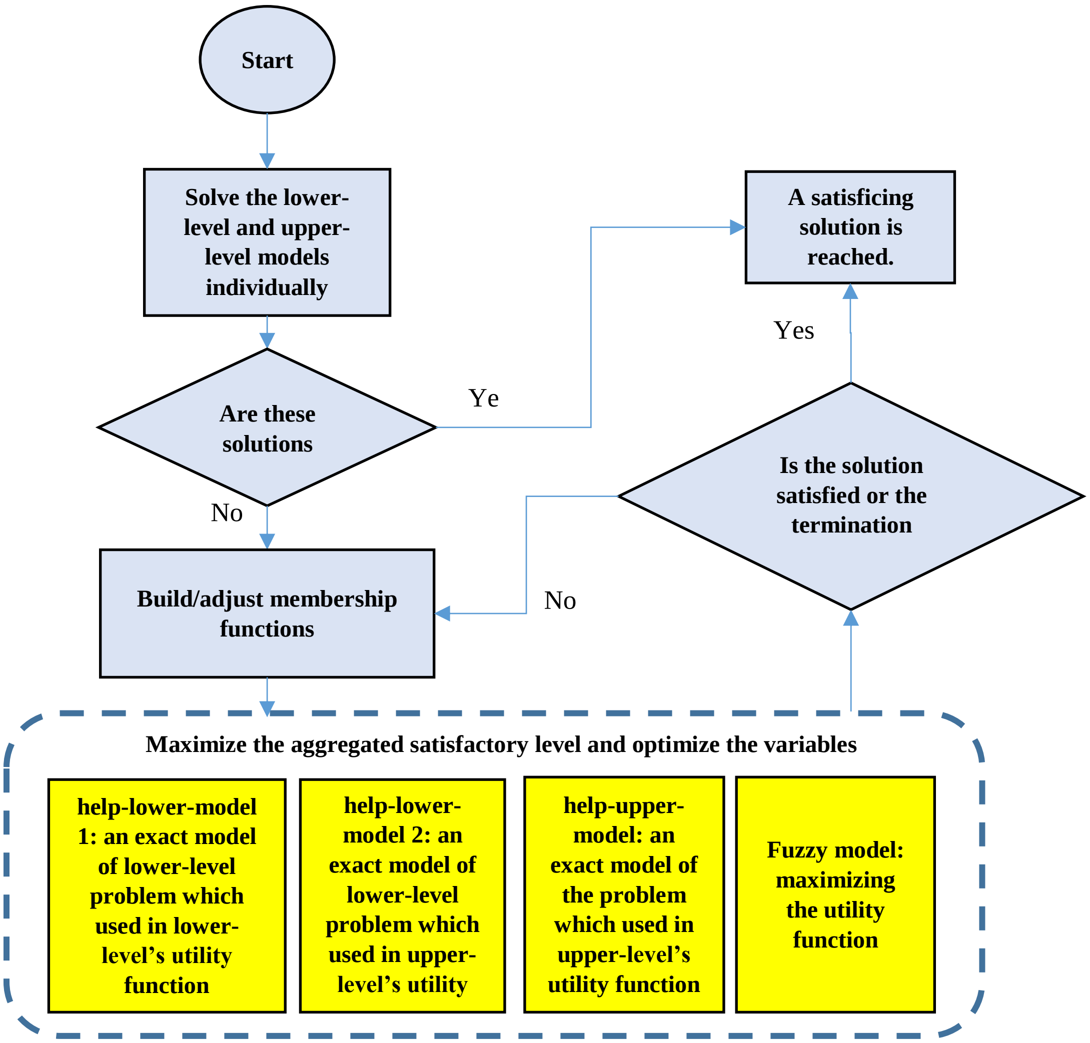


Figure 7. Flowchart of the auction-based bi-level programming

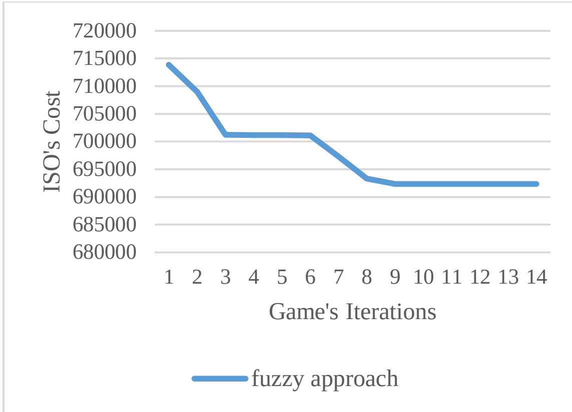


Figure 8. The ISO's cost through fuzzy method

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