A Bilevel Model for Optimal Bidding and Offering of Flexible Load Aggregator in Day-Ahead Energy and Reserve Markets

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ABSTRACT With the development of smart grid and active distribution network, the flexible load recourse would play a key role in the electricity market. In this paper, we proposed a framework that the distributed storage energy systems, electric vehicles, and temperature control loads are aggregated in the flexible load aggregator, trading in day-ahead energy and reserve markets. The framework is modeled as a bilevel optimization model. In the propose model, the operation problem of the FLA is modeled in upper-level problem, which is to maximize the profit of the aggregator. The biding and offering strategic of Gencos and flexible load aggregator in the independent system operator are presented in lower-level problem, which aim at improving the social benefits. Karush–Kuhn–Tucker and dual theory are used to transform the nonlinear bilevel problem to a mixed-integer linear programming of single-level model. Finally, the numerical studies based on modifying PJM-5bus power system, showing the effectiveness of the proposed framework and bilevel model.

INDEX TERMS Bilevel optimization model, flexible load aggregator, day-ahead energy and reserve markets, offering and biding strategic.

NOMENCLATURE

A. ACRONYMS

FLA	Flexible load aggregator
DES	Distributed energy storage
DESA	Distributed energy storage aggregator
TCL	Temperature control load
TCLA	Temperature control load aggregator
EV	Electric vehicle
EVA	Electric vehicle aggregator
Genco	Generation company
KKT	Karush-Kuhn-Tucker
ISO	Independent System Operator
MILP	Mixed-integer linear programming
MINLP	Mixed-integer non-linear programming
dn	Down
VPP	virtual power plant

B. SETS AND INDICES

n	Index(set) of Genco
m	Index(set) of load
t	Time interval

C. PARAMETERS

$\bar{E}_t^D$	Maximum energy stored of DESA (MWh)
E_t^D	Minimum energy stored of DESA (MWh)
$E_t^{D,ini}$	Initial energy storage capacity of DESA (MWh)
$\bar{P}_t^{D,ch}$	Maximum charging power of DESA (MW)
$P_t^{D,ch}$	Minimum charging power of DESA (MW)
$\bar{P}_t^{D,dis}$	Maximum discharging power of DESA (MW)
$P_t^{D,dis}$	Minimum discharging power of DESA (MW)
$\bar{P}_t^E$	Maximum charging power of EVA (MW)
P_t^E	Minimum charging power of EVA (MW)
$\bar{P}_t^T$	Maximum power of TCLA curtailment (MW)
P_t^T	Minimum power of TCLA curtailment (MW)
$\bar{P}_{t,n}^G$	Maximum power generation of Genco n (MW)
$P_{t,n}^G$	Minimum power generation of Genco n (MW)
$P_t^{E,before}$	Power demand for random charging of EVA (MW)
$\bar{P}_t^{FLA,in}$	Maximum purchased power by FLA (MW)
$P_t^{FLA,in}$	Minimum purchased power by FLA (MW)
$\bar{P}_t^{FLA,out}$	Maximum sold power by FLA (MW)

$P_t^{FLA,out}$	Minimum sold power by FLA (MW)
$R_t^{FLA,up/dn}$	Maximum up/down-reserve provided by FLA (MW)
$R_t^{D,up/dn}$	Maximum up/down-reserve provided by DESA (MW)
$R_{t,n}^{G,up/dn}$	Maximum up/down–reserve provided by Genco (MW)
$R_t^{up/dn}$	Up/down-reserve requirement in reserve market (MW)
$C_{t,n}^{G}$	Offer price of Genco n ($/MWh)
$C_{t,m}^{L}$	Offer price of load m ($/MWh)
$C_{t,n}^{r,up}$	Offer price of Genco n provide up-reserve ($/MWh)
$C_{t,n}^{r,dn}$	Offer price of Genco n provide down-reserve ($/MWh)
P_t^{L}	Power demand of Load (MW)

D. DECISION VARIABLES

$P_t^{FLA,in}$	Power purchased by FLA (MW)
$P_t^{FLA,out}$	Power sold by FLA (MW)
$r_t^{FLA,dn}$	Down-reserve commitment of FLA (MW)
$r_t^{FLA,up}$	Up-reserve commitment of FLA (MW)
$P_t^{D,ch}$	Charging power of DESA (MW)
$P_t^{D,dis}$	Discharging power of DESA (MW)
$r_t^{D,up}$	Up-reserve commitment of DESA (MW)
$r_t^{D,dn}$	Down-reserve commitment of DESA (MW)
e_t^{D}	Energy storage capacity of DESA
P_t^{E}	Charging power of EVA (MW)
P_t^{T}	Power curtailment of TCLA (MW)
$P_{t,n}^{G}$	Power generation of Genco (MW)
$r_{t,n}^{G,up}$	Up-reserve commitment of Genco (MW)
$r_{t,n}^{G,dn}$	Down-reserve commitment of Genco (MW)
$\sigma_t^{r,up}$	Up-reserve price in reserve market ($/MWh)
$\sigma_t^{r,dn}$	Down-reserve price in reserve market ($/MWh)
σ_t^{DA}	Day-ahead market price ($/MWh)
$\lambda_t^{F,da}$	Price offer by FLA in day-ahead energy market ($/MWh)
$\lambda_t^{F,res,up}$	Up-reserve price bid/offer by FLA ($/MWh)
$\lambda_t^{F,res,dn}$	Down-reserve price bid/offer by FLA ($/MWh)

I. INTRODUCTION

With the increasing proportion of EVs, DESs, TCLs and other fragmented flexible loads connected to the smart grid, the flexible load recourse would play a key role in power system and electricity market [1], [2]. Along on advanced information network architecture and communication control technology, FLA aggregates a large of flexible load resource, forming large-capacity and high-power schedulable and transaction resource pool. There are many ancillary services provided by FLA [3], such as frequency regulation [4], peak shaving [5], spinning reserve [6] and renewable energy accommodation [7] in the power system. In addition, the resource pool is composed of DESs and EVs with the bidirectional charging and discharging battery. It would purchase/sell energy from wholesale energy market and provide commitment reserve in the reserve market. The TCL is curtailment load, which gets compensation in response to dispatching signals of power system. FLA consists of various types of flexible loads. Therefore, it is a need for studying the optimal co-operation and biding/offering strategies of FLA participation in the energy and ancillary service markets [8].

The role of FLA in the electricity market has changed and FLA behaves as a price-maker. Moreover, DESs are fast respond resources that enable FLA to participate in the reserve market. The main purpose of this paper is to model the optimal bidding and offering strategies of FLA participates in day-ahead energy and reserve market.

The operation problem of various aggregators participate in the energy and reserve markets, which are investigated in these literatures. These aggregators are considered as price-taker. In [9], the mathematical model, evaluation method and control strategic of heterogeneous TCLA are presented. The dispatch potential of TCLA, which aggregates regulation capacities and ramping rates, providing load-following services. In [4], distributed control framework of multiple load aggregators is proposed, providing frequency regulation services. In [10], the benefit relationship of DESA and storage units are described with using Nash Bargaining theory. DESA as a profit-seeking entity participates in the wholesale electricity market. In [11], the charging dispatch strategic of EVA in the retail electricity market is studied, which increases system efficiency and stability. A hierarchical control framework of various flexible load is presented in [12], which aims at studying collaborative scheduling method of flexible loads in the electricity market. In [13], the optimal scheduling strategy of micro-grid in day-ahead market is present, considering the uncertainty in renewable energy production. In [14], the optimization framework for demand response aggregator in the wholesale electricity market is proposed, which focus on modeling strategies of energy market and operation behaviors of load curtailment, load shifting and load interruption. In [15] and [16], the stochastic optimal bidding strategy for distributed energy resources aggregator in day-ahead market is present, which considers economic and environmental aspects.

Over the past few years, the offering and biding strategic of various entities trades in the energy and markets, which have been proposed in [17]–[27]. These strategies of trading entities transform the model into bilevel optimization model with using Stackelberg Game theory [17]. The trading entities are considered as a price-maker. In [19]–[21], the EVs and energy storage system are treated as a trading entity, participating in the energy and reserve markets. The entity seeks to maximize its profits, modeling in the upper-level problem. The markets clear the marginal price in the lower-level

problem, seeking minimization of operating costs or maximization of social benefits. The strategic behavior of a distribution company in wholesale energy and reserve markets is modeled in [21], a bilevel method for solving the proposed model. In [23]–[25], the offering strategic of demand respond aggregator in the day-ahead market and real-time market. The demand respond aggregator trades energy and reserves with distributed energy source, distributed generators and load entity in its network. A comprehensive study is described for virtual power plant to minimize the purchased energy from the market and optimal schedule strategic for each entity considering uncertainties in [26].

In the above research literature, it mainly focuses on the operation strategy of individual aggregator and the bidding and offering strategy of individual entities such as demand resources, VPP and distribution company. However, it was not been deeply studied in the bidding and offering strategy of various flexible loads co-operation, participating in the energy and reserve markets.

In this paper, FLA participates in day-ahead market. The day-ahead market is a forward market, include of energy and reserve market. Its day-ahead electricity hourly price is determined by the Genco offers, load demand bids, FLA bids/offers and scheduling strategy in the next day, and its reserve price is calculated as same as electricity price [28]. The contribution of the paper is categorized as follow: i) We propose a bilevel optimization model of the FLA as a price-maker, participateing in day-ahead energy and reserve markets. The operation problem of Genco and FLA are modeled in the lower-level and upper-level, respectively. ii) The framework model is a MILNP bilevel model, which is transformed into a non-linear single-level model using KKT condition. iii) The final model is a single-level MILP. It is transformed through dual theory.

The rest of the paper is organized as follows: The modeling framework is proposed in Section II, and Section III describes the bilevel optimal mathematical modeling of the proposed approach. Section IV provides a description of the test case and an analysis of simulation results. Finally, conclusions on the application of the integrated approach and future work are shown in Section V.

II. THE MODELING FRAMEWORK

In this paper, we propose a bilevel optimization model. In bilevel optimization problems, a hierarchical structure arises with an optimization problem on the upper-level and another optimization problem on the lower-level. The hierarchical structure is described in Figure.1. The Gencos, loads and FLA together participate biding and offering in day-ahead energy and reserve markets. The FLA includes DESA, EVA and TCLA, which are three different types of flexible loads. The offering decisions of FLA include purchasing energy bids and selling energy offer prices. FLA has also the capability to provide reserve in the reserve market. Since the charging behavior of EVA needs to consider the electricity price and user behavior, we assumed that it participates in
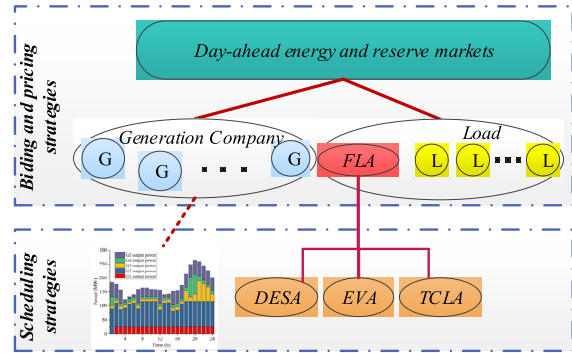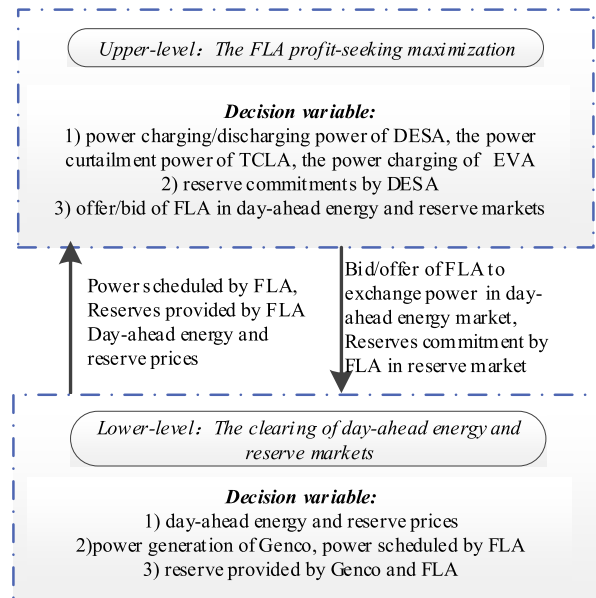

FIGURE 1. The hierarchical structure of FLA.

FIGURE. 2. The framework of FLA participating in day-ahead energy and reserve markets

FIGURE 2. The framework of FLA participating in day-ahead energy and reserve markets.

the day-ahead energy market. The DESA has the features of bidirectional flexible charge and discharge, which trades in energy and reserve markets. The TCLA can interrupt the controlled TCLs according to the control instruction.

Figure.2. shows the structure, decision variables and the role of partners in the bilevel optimization model. The operational strategy of FLA is modeled in the upper-level problem, which is leader. The lower-level problem consists of day-ahead energy and reserve markets where aim of the ISO is clearing the markets, maximizing social welfare, which is follower. In each level, the leader and follower variables which link the upper- and lower-level optimization model. The bilevel programming problem describes a hierarchical system, which is composed of two levels of decision makers. The upper-level decision maker, known as leader, while the lower-level decision maker, known as follower. They sequential and cooperation isn't allowed. Each decision maker optimizes its own objective without considering the objective

function of the other party, but the decision made by each party affects the objective space of the other party as well as the decision space. A subset of variables at the upper-level optimization problem is constrained to be the optimal solution of the lower-level optimization problem parameterized by the remaining variables. The decision variables of upper-level problem are: power selling/purchasing of FLA, reserves commitments by FLA, charging/discharging power of DESA, the power curtailment power of TCLA, the power charging of EVA, reserve commitments by DESA, biding/offering of FLA in day-ahead energy and reserve markets. The decision variables of lower-level problem: day-ahead energy and reserve prices, reserve provided by Gencos and FLA, energy generation of Gencos and power scheduled by FLA. In this paper, FLA is considered as a price-marker. The bid/offer behaviors of FLA participating in day-ahead market, would affect the energy and reserve prices to maximize its profit.

III. MATHEMATICAL MODELING

A. UPPER-LEVEL PROBLEM: THE FLA PROFIT-SEEKING MAXIMIZATION PROFIT

In this paper, the optimization offering strategy of the FLA is modeled in energy and reserve market. The bilevel optimization model is composed of the optimal operation of the FLA is modeled in the upper-level problem and bidding/offering strategy of the day-ahead energy and reserve markets in the lower-level problem. In the upper-level problem, the FLA is a price-taker and seeks to maximize the expected profit from day-ahead energy and reserve markets, and formulated below by (1)-(15). Decision variables: $X^{UL} = \{P_t^{D,ch}, P_t^{D,dis}, P_t^E, P_t^T, r_t^{D,up}, r_t^{D,dn}, \sigma_t^{DA}, \sigma_t^{r,dn}, \sigma_t^{r,up}\}$. The external decision variables $\{\sigma_t^{DA}, \sigma_t^{r,dn}, \sigma_t^{r,up}\}$ are determined and passed on to the lower-level optimization model, where they are parameters as $\{\lambda_t^{F,da}, \lambda_t^{F,res,dn}, \lambda_t^{F,res,up}\}$.

The objective function of the FLA is:

$$\underset{X^{UL}}{Maximize} \sum_t [(\sigma_t^{DA} P_t^{FLA,out} - \sigma_t^{DA} P_t^{FLA,in})$$

$$+ (r_t^{FLA,dn} \sigma_t^{r,dn} + r_t^{FLA,up} \sigma_t^{r,up})] \quad (1)$$

Subject to: $P_t^{FLA,in} = P_t^{D,ch} + P_t^E + P_t^T \quad (2)$

$$P_t^{FLA,out} = P_t^{D,dis} \quad (3)$$

$$r_t^{FLA,dn} = r_t^{D,dn} \quad (4)$$

$$r_t^{FLA,up} = r_t^{D,up} \quad (5)$$

$$\underline{P}_t^{D,ch} \leq P_t^{D,ch} \leq \bar{P}_t^{D,ch} \quad (6)$$

$$\underline{P}_t^{D,dis} \leq P_t^{D,dis} \leq \bar{P}_t^{D,dis} \quad (7)$$

$$0 \leq r_t^{D,up} \leq R_t^{D,up} \quad (8)$$

$$0 \leq r_t^{D,dn} \leq R_t^{D,dn} \quad (9)$$

$$\underline{P}_t^{D,ch} \leq P_t^{D,ch} + r_t^{D,dn} \leq \bar{P}_t^{D,ch} \quad (10)$$

$$\underline{P}_t^{D,dis} \leq P_t^{D,dis} + r_t^{D,up} \leq \bar{P}_t^{D,dis} \quad (11)$$

$$0 \leq P_t^E \leq \bar{P}_t^E \quad (12)$$

$$\underline{P}_t^T \leq P_t^T \leq \bar{P}_t^T \quad (13)$$

$$e_t^D = e_{t-1}^D + P_t^{D,ch} - P_t^{D,dis} \quad (14)$$

$$E_t^D \leq e_t^D \leq \bar{E}_t^D \quad (15)$$

The objective function (1) stands for the maximization of the FLA's profit from day-ahead energy trade and reserve commitment markets. The first term of the objective function expresses the cost of purchasing energy and the revenue from energy sold of FLA in the day-ahead energy market. The second term expresses the profit of upward and downward committing reserves from FLA.

The equation (2)-(5) represent energy and reserve balance constraints of the FLA. The commitment reserve provided by the FLA in the reserve market, which is supplied by DESA. The charging and discharging power of DESA are expressed in (6) and (7). The up/down-reserve commitment of DESA are described in (8)-(9). The sum of the energy and reserve provided by DESA is limited in its charging power model as described in (10). Constraints (11) is similar to (10) but in discharging power mode of DESA. The operational model constraints of EVA and TCLA are shown in (12) and (13). The energy storage balance of the DESA is expressed in (14). In this equation, when t=1, the initial energy capacity stored $e_{init}^D = e_{t-1}^D$. The minimum and maximum limits of energy storage capacity of DESA are modeled in equation (15).

Note that upper-level model (1)-(15) is constrained by lower-level problem (16)-(28) representing the clearing of day-ahead energy and reserve markets. All offering and bidding decisions of the FLA are variables in the upper-level problem, which treated as parameters in the lower-level problem. This enables the FLA to gain insight into the market-clearing outcomes as a function of its offering and bidding decisions, and then adjust them in the upper-level problem pursuing expected profit maximization.

B. LOWER-LEVEL PROBLEM: CLEARING OF DAY-AHEAD ENERGY AND RESERVE MARKETS

In the lower-level problem, the FLA participates in day-ahead energy and reserve markets. The market is operated by ISO, which consists of Gencos, FLA and loads. The Gencos and FLA participate in reserve market to guarantee system stability, and FLA is a price-maker. The optimization lower-level model of bilevel optimization model is given by (16)-(28) below. All dual variables are given in constraints after a colon. Decision variable:

$$X^{LL} = \{P_{t,n}^G, P_t^{FLA,in}, P_t^{FLA,out}, r_t^{FLA,up}, r_t^{FLA,dn}, r_{t,n}^{G,up}, r_{t,n}^{G,dn}\}$$

Dual variable:

$$X_{Dual}^{LL,DA}$$
$$= \{x_t^{da}, x_t^{up}, x_t^{dn}, x_t^G, \bar{x}_t^G, x_t^{G,r,up}, \bar{x}_t^{G,r,up},$$
$$x_t^{G,r,down}, \bar{x}_t^{G,r,down}, x_t^{FLA,in}, \bar{x}_t^{FLA,in}, x_t^{FLA,out}, \bar{x}_t^{FLA,out},$$
$$x_t^{FLA,r,up}, \bar{x}_t^{FLA,r,up}, x_t^{FLA,r,dn}, \bar{x}_t^{FLA,r,dn}\}$$

The objective function of day-ahead market is:

$$\underset{X^{LL}}{Maximize} \sum_{n,m} \sum_t [(C_{t,m}^L P_t^L - C_{t,n}^G P_{t,n}^G)$$

$$+ (P_t^{FLA,in}\lambda_t^{F,da} - P_t^{FLA,out}\lambda_t^{F,da})$$
$$- (\lambda_t^{F,res,dn}r_t^{FLA,dn} + \lambda_t^{F,res,up}r_t^{FLA,up})$$
$$- (C_{t,n}^{r,up}r_{t,n}^{G,up} + C_{t,n}^{r,dn}r_{t,n}^{G,dn})] \tag{16}$$

$$\text{Subject to: } P_{t,n}^G = P_t^{FLA,in} - P_t^{FLA,out} + P_t^L : x_t^{da} \tag{17}$$

$$r_{t,n}^{G,up} + r_t^{FLA,up} = R_t^{up} : x_t^{up} \tag{18}$$

$$r_{t,n}^{G,dn} + r_t^{FLA,dn} = R_t^{dn} : x_t^{dn} \tag{19}$$

$$\underline{P}_{t,n}^G \leq P_{t,n}^G \leq \bar{P}_{t,n}^G : \underline{x}_t^G, \bar{x}_t^G \tag{20}$$

$$0 \leq r_{t,n}^{G,up} \leq R_{t,n}^{G,up} : \underline{x}_t^{G,r,up}, \bar{x}_t^{G,r,up} \tag{21}$$

$$0 \leq r_{t,n}^{G,dn} \leq R_{t,n}^{G,dn} : \underline{x}_t^{G,r,dn}, \bar{x}_t^{G,r,dn} \tag{22}$$

$$P_{t,n}^G + r_{t,n}^{G,up} \leq \bar{P}_{t,n}^G : x_t^{G,r,up} \tag{23}$$

$$\underline{P}_{t,n}^G \leq P_{t,n}^G - r_{t,n}^{G,dn} : x_t^{G,r,dn} \tag{24}$$

$$\underline{P}_t^{FLA,in} \leq P_t^{FLA,in} \leq \bar{P}_t^{FLA,in} : \underline{x}_t^{FLA,in}, \bar{x}_t^{FLA,in} \tag{25}$$

$$\underline{P}_t^{FLA,out} \leq P_t^{FLA,out} \leq \bar{P}_t^{FLA,out} : \underline{x}_t^{FLA,out}, \bar{x}_t^{FLA,out} \tag{26}$$

$$0 \leq r_t^{FLA,up} \leq R_t^{FLA,up} : \underline{x}_t^{FLA,r,up}, \bar{x}_t^{FLA,r,up} \tag{27}$$

$$0 \leq r_t^{FLA,dn} \leq R_t^{FLA,dn} : \underline{x}_t^{FLA,r,dn}, \bar{x}_t^{FLA,r,dn} \tag{28}$$

The objective function of (16) maximizes the revenue in the day-ahead market including wholesale energy market and reserve commitments. This equation consists of four terms. The first term expresses that Genco offer energy and load bids their demand in the wholesale energy market. The profit of FLA in the day-ahead energy market, which is modeled in the second term. The third and fourth term express that the reserve requirement of reserve market provided by Genco and FLA. Constraint (17)-(19) represent the energy and reserve balance of the day-ahead market, respectively. The up-reserve commitment provided by Genco and FLA. The down-reserve constraint (18) is similar to (19). The minimum and maximum limits of power generation, reserve commitment of Genco are described in (20)-(22). The sum of power generation and up-reserve of Genco are limited in maximum power generation. The Genco supplies power and provides reserves are lower than their maximum power output is modeled in (23). The power output and down-reserve of Genco is higher than minimum power output is expressed in (24). The operational constraints of FLA are modeled in (25)-(28). The up/down-reserve provided by FLA are modeled in (27) and (28), respectively. In this model, we ignore that the transmission network constraint and the ramping of generators constraints.

C. SOLUTION METHODOLOGY (KKT CONDITIONS AND DUAL THEROY)

There are many approaches to solve the bilevel model [17]. The exact solution is to replace the constraints of follower problems with KKT conditions [17]. In the bilevel model, the decision variables of upper-level problem are considered
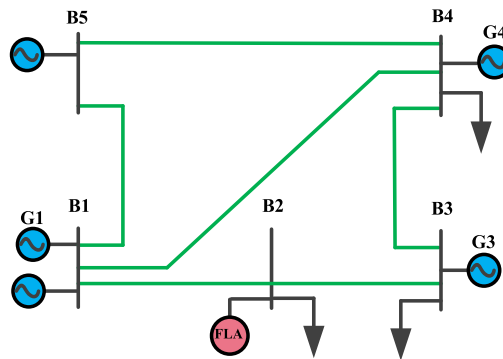

FIGURE 3. Modified PJM-5bus power system.

as parameters in the lower-level problem. The lower-level problem is replaced with its KKT conditions, describing in Appendix A. Equation (31)-(37) of Appendix A are stationarity constraints which are obtained from the first order derivatives of the Lagrangian function with respect to the decision variables of the lower-model. The equation (38)-(53) of Appendix A are complementary slackness constraints, which are described in (29) with using Big-M approach [29]. Then the nonlinear expression in the model is replaced with linear expressions using the dual theory, presenting in the Appendix B.

$$0 \leq \alpha \perp \beta \geq 0 \Rightarrow \begin{cases} \alpha \geq 0 \\ \beta \geq 0 \\ \alpha \leq M_1 U \\ \beta \leq M_2(1-U) \end{cases} \tag{29}$$

Where M1 and M2 are large enough values and U is a binary variable. If M is a too big value, it would not hold the constraint condition. If M is a too small value, it may result in numerical ill-condition. In this paper, we assume that the value of M is 10^7, and then solve the model.

Therefore, the bilevel problem is transformed into a single-level mathematical program with equilibrium constraints (MPEC) [2]. Through KKT conditions and dual theory, the bilevel optimization model is expressed as a MILP model as follow:

$$\underset{X^{UL}}{Maximize} \sum_{t,m,n} [(C_{t,m}^L - x_t^{da})P_t^L - C_{t,n}^G P_{t,n}^G + R_t^{up} x_t^{up}$$
$$+ R_t^{dn} x_t^{dn} + x_t^{da} P_{t,n}^G - x_t^{up} r_{t,n}^{G,up} - x_t^{dn} r_{t,n}^{G,dn})] \tag{30}$$

IV. NUMERICAL SIMULATION

In order to examine the effectiveness of the proposed bilevel optimization model, an illustrative example is analyzed in the section. We solve the bilevel model that using MOSEK solver under MATLAB on a 2.60 GHz Intel Core i7 CPU personal computer with 16GB of RAM.

A. TEST SYSTEM

This section provides a simulation test to demonstrate the effectiveness of bilevel model for the FLA. In the test sys-
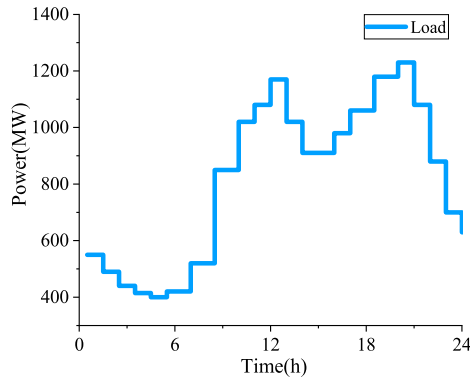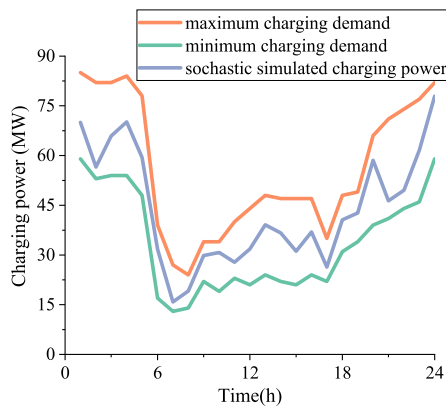
FIGURE 4. The demand of load.

FIGURE 5. The operational data of EVA.

TABLE 1. The technical and economic data of Gencos.

Genco	$\overline{P}^G$	C^G	$C_{t,n}^{r,up/dn}$	$R_{t,n}^{G,up/dn}$
G1	110	80	40	22
G2	100	40	22	20
G3	520	50	26	104
G4	200	60	32	40
G5	600	30	18	120

tem, we consider the modified PJM-5bus system, as shown in Figure 3. There is a FLA that include DESA, EVA and TCLA at 2 bus in the system. The DESA consists of DESs. The maximum charge and discharge power of DES is 100kW and the energy storage capacity is 500kWh. In this paper, we assume that EVA consists of 200 EVs, and does not distinguish type of EVs. The maximum/minimum charging power demand and stochastic simulated charging curve of EVA at each hour are shown in the Figure 5. The TCLA contains 1000 air conditioning loads with maximum power range of [14kW, 26kW]. The energy offers, reserve commitment and maximum energy provided of Gencos data are given in Table 1. The load forecast demand in day-ahead is shown in Figure 4. We assume that the hourly maximum reserve capacity of demand is considered to be 10% of its load demand. Loads bids their energy demands, during the whole
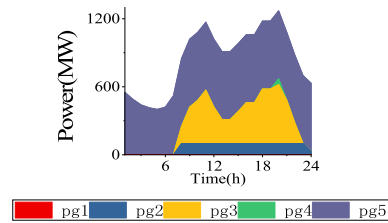

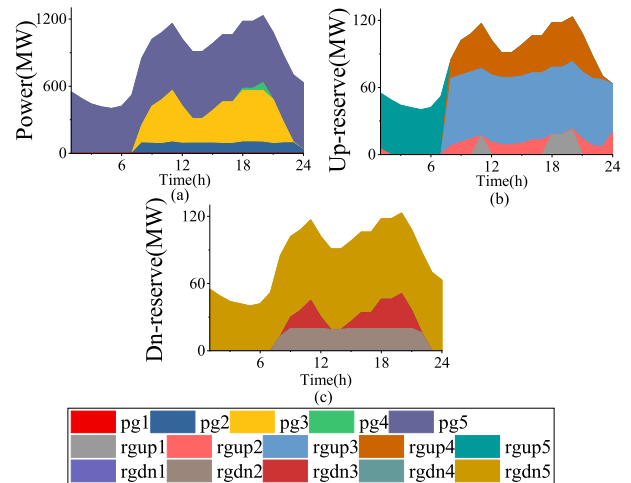**FIGURE 6.** Day-ahead energy market schedules in Case 1.

FIGURE 7. Day-ahead energy and reserve markets schedule in Case 2. (a) energy market. (b) Up-reserve market. (c) down-reserve market.

time horizon at an identical price $80/MWh. The scheduling period is 24h and each scheduling period is 1h. In this paper, we assume that the transmission line isn't congestion active power capacity.

We designed four progressive cases to compare and study, demonstrating the effectiveness and economics of FLA participation in the day-ahead energy and reserve markets.

Case 1: Clearing day-ahead energy market. The load demand is met by Gencos.
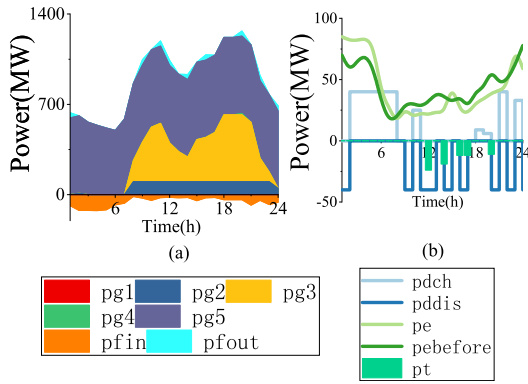
Case 2: Clearing both day-ahead energy and reserve markets. The requirement of energy and reserve are provided by Gencos.

Case 3: FLA only participates in day-ahead energy market. The profit of FLA is energy arbitrage during this period.
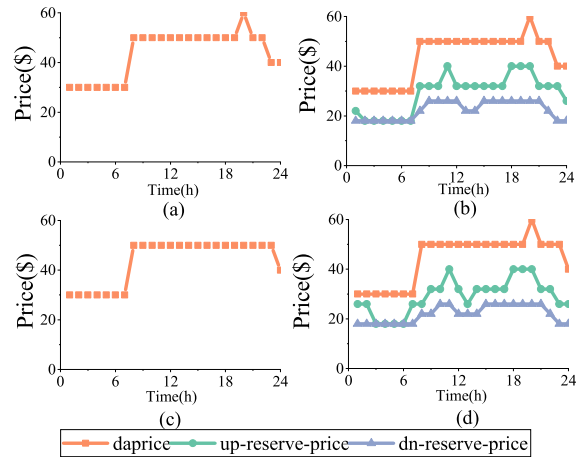
Case 4: FLA participates in day-ahead energy and reserve markets. FLA makes a profit through energy trading, compensating of load curtailment, saving cost of EVs charging.

B. NUMERICAL RESULTS
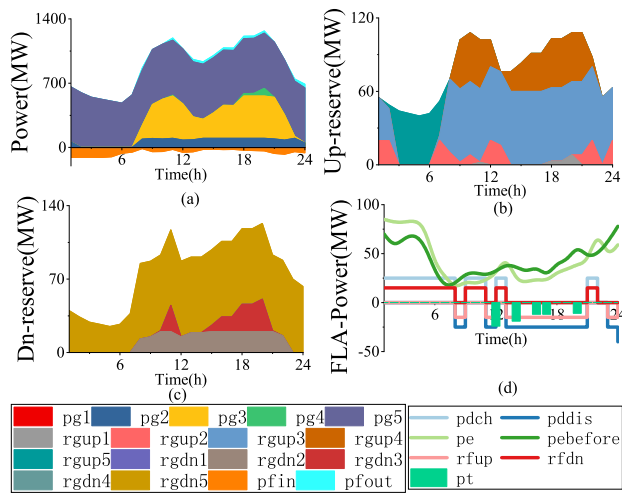Day-ahead energy market scheduled by Gencos are shown Figure 6. Day-ahead energy and reserve markets schedule are shown in Figure 7. The schedule plan of day-ahead energy market and FLA that include DESA, EVA and TCLA are shown in Figure 8. Day-ahead energy and reserve markets and FLA schedule are shown in Figure 9. Day-ahead energy and reserve prices in each case are shown in Figure 10.

FIGURE 8. Day-ahead energy market and FLA schedule in Case 3 (a) energy market (b) FLA

FIGURE 9. Day-ahead energy and reserve market and FLA schedule in Case 4. (a) energy market. (b) Up-reserve. (c) Down-reserve. (d) FLA

FIGURE 10. Day-ahead energy and reserve price in each case. (a) Case 1. (b) Case 2. (c) Case 3. (d) Case 4.

the output of G5 is close to the upper limit. G5 would provide down-reserve and no longer provide up-reserve. In the down-reserve market, the reserve requirement is provided by the Gencos with low reserve offer price, participating in the energy market at the same time. In the up-reserve market, due to the upper limit of Gencos. During the time period of 11:00 and 18:00-20:00, G5 with highest reserve offer price is started up to provide up-reserve. Therefore, the price of up-reserve market is raised to $40/MWh.

Case 3: FLA participates in the energy market, making a profit through energy arbitrage. DESA starts charging during the low-demand and low-price hour and discharging during the high-demand and high-pirce EVA changes the charging behavior according to the changed energy price. The curtailment load of TCLA is responded in12:00, 14:00, 16:00, 17:00 and 20:00. FLA and Gencos participate in the energy market as a price-maker, pursuing the maximization of their benefits, respectively. During 20:00, FLA sells some energy to meet demand of energy market, which makes G4 shut down. Therefore, the price of energy market in 20:00 is lower than Case 1. The selling energy capacity of FLA in the 20:00, which composed of TCLA interrupts power 12MW, EVA reduces the charging demand 10.7MW and DESA starts discharging 40MW. FLA purchases a portion of the energy in 23:00, causing the G2 to start up. Compared with Case 1, FLA acts as a strategic consumer, where the purchase energy has an impact on energy price. Thus, the price of energy market in 23:00 is higher than Case 1. The purchasing energy capacity of FLA in 23:00, which is caused by the increased charging demand for DESA and EVA. The energy price is reduced, due to FLA participation in the day-ahead energy market.

Case 4: FLA trades in day-ahead energy and reserve markets. In this way, FLA gets more opportunities to make a profit. Compared with Case 3, FLA needs to bid reserve-price and provide capacity in the reserve market. Therefore, in order to meet demand, G4 is restarted in 20:00. Compared

Case 1: The load demand in the day-ahead energy market is met by Gencos other than G1. It is reasonable that the offer price of G1 in the wholesale energy market higher than other Gencos. In 1:00-7:00, the schedule requirement of clearing wholesale energy market is provided by G5. Therefore, during this period, the energy price is the lowest, which is equal to the offer price of G5 in the wholesale energy market. In 8:00-19:00 and 21:00-22:00, the demand is met by G2, G3 and G5, as these Gencos have lower offer price. Therefore, the price of energy market is $50/MWh. In 20:00, the load demand is met by G2, G3 G4 and G5. Therefore, the price of energy market is $60/MWh, which is the offer price of G4.

Case 2: Compared with Case 1, Gencos would meet the requirement of energy and reserve market, respectively. Therefore, the output of Gencos are reduced in the energy market, so that they can provide more reserve requirement in the reserve market. In 11:00, the demand is met by G2, G3, G4 and G5. Thus, the energy price is $60/MWh, which is higher than the price in the Case 1. In reserve market, the up/down-reserve is provided by G5 in 1:00-7:00. In the time period after 7:00, the reserve requirement increases and

TABLE 2. The Profit of each case.

Type	The cost of ISO ($)	The profit of FLA ($)
Case 1	72385	/
Case 2	81841	/
Case 3	71153	8050
Case 4	79113	16475

with Case 2 in terms of the offering price of reserve market, in 1:00-8:00, 13:00 and 23:00, the price of up-reserve is lower than Case 2. In 8:00 and 11:00, the price of down-reserve is lower than Case 2. It is reasonable that FLA acts as a marginal player and decrease the reserve price in these hours. In other hours, the reserve prices are determined due to the offers of Gencos and load demand. During the low-demand and low-price period, DESA charges in the energy market and provides reserve in the reserve market. DESA discharges in the high-demand and high-price time. EVA changes charging behavior that increase the amount of charge during low energy price hours. The curtailment load of TCLA is responded at 12:00, 14:00, 16:00, 17:00 and 20:00. These hours are high-energy price and high-demand. The energy and reserve price of Case 4 is generally lower than that of Case2. Indicating that FLA participates in day-ahead energy and reserve market, which helps to improve the social benefits and reduce electricity price.

The profit of each case is presented in Table 2. The results obtained for the case study show that FLA play a strategic price-maker. FLA make a profit through energy arbitrage, which include DESA charging in the low-price hour and discharging in the high-price, saving profit of EVA plans charging behavior and response compensation of TCLA in the Case 3. In the Case 4, in addition to participating in the energy market, FLA also provides reserve capacity in the reserve market. This is why that FLA gains more profit in Case 4 than Case 3.

V. CONCLUSION

In this paper, the FLA is treated as price-maker. The operation strategies of FLA, which include that DESA, EVA and TCLA, in the day-ahead energy and reserve markets are modeled. For this purpose, a bilevel optimization model is proposed. The upper model is the leader in which maximum profit of FLA seeks in the day-ahead energy and reserve markets. The lower model is the follower in which the biding and offering of the Gencos and FLA. KKT and dual theory are used to transform the non-linear bilevel model to linear single-level model. The results of the study show that: 1) The bilevel structure has important impact on the profit of FLA. The profit of FLA is increased in Case 4 compared with Case 3. FLA has the ability to earn more revenue in the reserve market. 2) FLA can collaboratively schedules various types of aggregators, which earn revenues in the day-ahead energy and reserve markets, respectively. 3) The energy price in Case 3 is lower than Case 1 when FLA participates in day-ahead energy market. The reserve price in Case 4 is low,

compared with Case 2 when FLA participates in day-ahead energy and reserve markets. FLA can effectively reduce the energy and reserve prices.

APPENDIX A

Transformation of the non-linear bilevel optimization problem to the non-linear single-level one is done using KKT conditions. The appendix A includes the KKT conditions of lower-level day-ahead market and real-time market. As follow:

Day-ahead market of lower-level:

$$-C_{t,n}^G - x_t^{da} - x_t^G + \bar{x}_t^G + x_t^{G,r,up} - x_t^{G,r,dn} = 0 \tag{31}$$

$$\lambda_t^{F,da} + x_t^{da} - x_t^{FLA,in} + \bar{x}_t^{FLA,in} = 0 \tag{32}$$

$$-\lambda_t^{F,da} + x_t^{da} - x_t^{FLA,out} + \bar{x}_t^{FLA,out} = 0 \tag{33}$$

$$-\lambda_t^{F,res,dn} - x_t^{dn} - x_t^{FLA,r,dn} + \bar{x}_t^{FLA,r,dn} = 0 \tag{34}$$

$$-\lambda_t^{F,res,up} - x_t^{up} - x_t^{FLA,r,up} + \bar{x}_t^{FLA,r,up} = 0 \tag{35}$$

$$-C_{t,n}^{r,up} - x_t^{up} - x_t^{G,r,up} + \bar{x}_t^{G,r,up} + x_t^{G,r,up} = 0 \tag{36}$$

$$-C_{t,n}^{r,dn} - x_t^{dn} - x_t^{G,r,dn} + \bar{x}_t^{G,r,dn} + x_t^{G,r,dn} = 0 \tag{37}$$

$$0 \le (P_{t,n}^G - \underline{P}_{t,n}^G) \perp x_t^G \ge 0 \tag{38}$$

$$0 \le (\bar{P}_{t,n}^G - P_{t,n}^G) \perp \bar{x}_t^G \ge 0 \tag{39}$$

$$0 \le r_{t,n}^{G,up} \perp x_t^{G,r,up} \ge 0 \tag{40}$$

$$0 \le (R_{t,n}^{G,up} - r_{t,n}^{G,up}) \perp \bar{x}_t^{G,r,up} \ge 0 \tag{41}$$

$$0 \le r_{t,n}^{G,dn} \perp x_t^{G,r,dn} \ge 0 \tag{42}$$

$$0 \le (R_{t,n}^{G,dn} - r_{t,n}^{G,dn}) \perp \bar{x}_t^{G,r,dn} \ge 0 \tag{43}$$

$$0 \le (P_t^{FLA,in} - \underline{P}_t^{FLA,in}) \perp x_t^{FLA,in} \ge 0 \tag{44}$$

$$0 \le (\bar{P}_t^{FLA,in} - P_t^{FLA,in}) \perp \bar{x}_t^{FLA,in} \ge 0 \tag{45}$$

$$0 \le (P_t^{FLA,out} - \underline{P}_t^{FLA,out}) \perp x_t^{FLA,out} \ge 0 \tag{46}$$

$$0 \le (\bar{P}_t^{FLA,out} - P_t^{FLA,out}) \perp \bar{x}_t^{FLA,out} \ge 0 \tag{47}$$

$$0 \le r_t^{FLA,up} \perp x_t^{FLA,r,up} \ge 0 \tag{48}$$

$$0 \le (R_t^{FLA,up} - r_t^{FLA,up}) \perp \bar{x}_t^{FLA,r,up} \ge 0 \tag{49}$$

$$0 \le r_t^{FLA,dn} \perp x_t^{FLA,r,dn} \ge 0 \tag{50}$$

$$0 \le (R_t^{FLA,dn} - r_t^{FLA,dn}) \perp \bar{x}_t^{FLA,r,dn} \ge 0 \tag{51}$$

$$0 \le (\bar{P}_{t,n}^G - r_{t,n}^{G,up} - P_{t,n}^G) \perp x_t^{G,r,up} \ge 0 \tag{52}$$

$$0 \le (P_{t,n}^G - r_{t,n}^{G,dn} - \underline{P}_{t,n}^G) \perp x_t^{G,r,dn} \ge 0 \tag{53}$$

APPENDIX B

Appendix B used the strong duality equality of day-market of lower-level. Then, the nonlinear expression in the model is replaced with MILP linear expressions within the upper-level objective function (30).

Day-ahead market of lower-level:

From equation (31)-(53) of appendix A, obtained as follow:

$$P_{t,n}^G x_t^G = \underline{P}_{t,n}^G \underline{x}_t^G \tag{54}$$

$$\bar{P}_{t,n}^G \bar{x}_t^G = P_{t,n}^G \bar{x}_t^G \tag{55}$$

$$R_{t,n}^{G,up} \bar{x}_t^{G,r,up} = r_{t,n}^{G,up} \bar{x}_t^{G,r,up} \tag{56}$$

$$R_{t,n}^{G,dn} \bar{x}_t^{G,r,dn} = r_{t,n}^{G,dn} \bar{x}_t^{G,r,dn} \tag{57}$$

$$P_t^{FLA,in} \underline{x}_t^{FLA,in} = \underline{P}_t^{FLA,in} \underline{x}_t^{FLA,in} \quad (58)$$

$$\bar{P}_t^{FLA,in} \bar{x}_t^{FLA,in} = P_t^{FLA,in} \bar{x}_t^{FLA,in} \quad (59)$$

$$P_t^{FLA,out} \underline{x}_t^{FLA,out} = \underline{P}_t^{FLA,out} \underline{x}_t^{FLA,out} \quad (60)$$

$$\bar{P}_t^{FLA,out} \bar{x}_t^{FLA,out} = P_t^{FLA,out} \bar{x}_t^{FLA,out} \quad (61)$$

$$R_t^{FLA,up} \bar{x}_t^{FLA,r,up} = r_t^{FLA,up} \bar{x}_t^{FLA,r,up} \quad (62)$$

$$R_t^{FLA,dn} \bar{x}_t^{FLA,r,dn} = r_t^{FLA,dn} \bar{x}_t^{FLA,r,dn} \quad (63)$$

$$\bar{P}_{t,n}^{G} x_t^{G,r,up} = r_{t,n}^{G,up} x_t^{G,r,up} + P_{t,n}^{G} x_t^{G,r,up} \quad (64)$$

$$P_{t,n}^{G} x_t^{G,r,dn} - r_{t,n}^{G,dn} x_t^{G,r,dn} = \underline{P}_{t,n}^{G} x_t^{G,r,dn} \quad (65)$$

Using equation (54)-(65) to simplify equation (66):

$$
\begin{aligned}
(C_{t,m}^{L} P_t^{L} &- C_{t,n}^{G} P_{t,n}^{G}) + (P_t^{FLA,in} \lambda_t^{F,da} - P_t^{FLA,out} \lambda_t^{F,da}) \\
&- (\lambda_t^{F,res,dn} r_t^{FLA,dn} + \lambda_t^{F,res,up} r_t^{FLA,up}) \\
&- (C_{t,n}^{r,up} r_{t,n}^{G,up} + C_{t,n}^{r,dn} r_{t,n}^{G,dn}) \\
&= P_t^{L} x_t^{da} + R_t^{up} x_t^{up} + R_t^{dn} x_t^{dn} \\
&+ \underline{P}_{t,n}^{G} \underline{x}_t^{G} - \bar{P}_{t,n}^{G} \bar{x}_t^{G} - R_{t,n}^{G,up} \bar{x}_t^{G,r,up} \\
&- R_{t,n}^{G,dn} \bar{x}_t^{G,r,dn} - \bar{P}_{t,n}^{G} x_t^{G,r,up} \\
&+ \underline{P}_{t,n}^{G} x_t^{G,r,dn} + \underline{P}_t^{FLA,in} \underline{x}_t^{FLA,in} \\
&- \bar{P}_t^{FLA,in} \bar{x}_t^{FLA,in} + \underline{P}_t^{FLA,out} \underline{x}_t^{FLA,out} \\
&- \bar{P}_t^{FLA,out} \bar{x}_t^{FLA,out} - R_t^{FLA,up} \bar{x}_t^{FLA,r,up} \\
&- R_t^{FLA,dn} \bar{x}_t^{FLA,r,dn} \quad (66)
\end{aligned}
$$

The dual equation (67) of day-ahead market:

$$
\begin{aligned}
F(X^{da}) &= (P_t^{FLA,in} x_t^{da} - P_t^{FLA,out} x_t^{da}) \\
&+ (x_t^{dn} r_t^{FLA,dn} + x_t^{up} r_t^{FLA,up}) \\
&= (C_{t,m}^{L} - x_t^{da}) P_t^{L} - C_{t,n}^{G} P_{t,n}^{G} + R_t^{up} x_t^{up} + R_t^{dn} x_t^{dn} \\
&+ x_t^{da} P_{t,n}^{G} - x_t^{up} r_{t,n}^{G,up} - x_t^{dn} r_{t,n}^{G,dn} \quad (67)
\end{aligned}
$$

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