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Exploiting Flexibility of Renewable Energy Integrated Buildings for Optimal Day-ahead and Real-time Power Bidding Considering Batteries and EVs as Demand Response Resources

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Abstract—This study examines the flexibility potential of energy demand resources in buildings. The building flexible demand resources considered are electric vehicles (EVs) and energy storage batteries. The paper investigates the combined optimization of EVs and batteries with the objective of maximizing the total profit of building microgrids in day-ahead and regulation (real-time) electricity markets. The major contribution of the paper is the exploitation of the energy flexibility of buildings using EVs as dynamic energy storage device and batteries as manageable demand facility with possibilities of advancing or delaying their consumptions. The proposed optimization objective takes into account EV driving patterns, penalties for renewable energy curtailment, involuntary load shedding and bid imbalance in an explicit optimization setup. The proposed optimization problem is formulated as a dual-step mixed-integer linear programming (MILP) problem, and solved using the CPLEX solver. A number of simulation results are provided to demonstrate the effectiveness of the proposed optimization framework using real data of building electricity consumption and local renewable energy production in the Otaniemi area of Espoo, Finland. We reveal that the devised optimization solution achieves considerable saving in electricity bills, increase profit, reduce renewable energy curtailment, and smoothen peak electricity consumption, compared to a non-optimized operation.

Keywords—Building microgrid, energy flexibility, electricity market, optimization, demand response, battery, EV, renewable energy.

I. INTRODUCTION

Deep participation of the demand side into the energy management and trading ventures and efficient mixing of flexible loads (FLs), prosumers and renewable energy sources (RESs) into the energy system are major goals in planning the future smart grid. Actually, RESs have numerous benefits over the conventional energy generation sources because they are the clean energy suppliers with very little operation and maintenance (O&M) cost and zero emission cost. Moreover, RESs are available everywhere, easy to install, require smaller space, noncomplex structures, and contain smaller number of components. Nevertheless, the integration of RESs causes several challenges to grid operators and aggregators primarily due to their uncertain and intermittent behaviors. Predominantly, the stochasticity and instability of RESs can be overwhelmed through accurate forecasting and effective storage and utilization. A number of solutions for renewable generation forecasting have been proposed in the literature such as the hybrid of wavelet transform, particle swarm optimization and support vector machines [1], integration of particle swarm optimization and neural networks [2], hybrid of genetic algorithm and neuro-fuzzy systems [3] and others. Similarly, several solutions for renewable generation storage have been devised in the literature, for example using vanadium redox flow battery (VRB) [4],

pumped storage hydro units [5], multiple energy storage units [6], or compressed-air energy storage [7] to smooth the instability of renewable generation.

Flexible load (FL) is another important element in the forthcoming smart grid. FL is a load whose consumption can be managed to delay, advance, increase or decrease without sacrificing its basic function or comfort. Generally, FLs are based on customer needs and production capability. FLs can constitute thermostatically controlled appliances (TCAs) comprising refrigerator, electric water heater, and heating, ventilation, and air conditioning (HVAC) devices. They can also include electric vehicles (EVs) and energy storage devices such as batteries. Research and development (R&D) on optimal control of TCAs has been a hot issue in the previous few years. References [8] and [9] devised optimal control configurations to reduce the electricity bills for HVAC systems taking into account customer thermal comfort requirements. Because of the economic and ecological benefits of EVs over the conventional fuel-fired cars, it is estimated that EVs will revolutionize the transportation system we have today. The effect of a high EV penetration on a residential distribution network was examined in [10]. Reference [11] investigated a joint optimization of EVs and home energy scheduling taking into account customer thermal comfort needs. However, RESs were not included in this joint optimization problem. The flexibility in the joint operation of EVs and HVACs can be improved to lodge the uncertainties in RES generations. Reference [12] devised an optimization model to exploit the profit of a fleet of EVs in a multi-clearance electricity price market with the help of energy storage devices. Nevertheless, RESs were not included in this model, and the devised model was not stochastic. The flexibility in the EV charging/discharging practice can be enhanced to handle the stochasticity of RESs. References [13], [14] analyzed the influences of EVs on the dispatching and operations of energy systems with RESs and fuel-fired generators.

Unlike these works which intended to reduce the running cost of large-scale energy systems, [15] proposed an optimization framework to exploit the advantages of coordinating EVs and RESs in a building microgrid setup with the target of maximizing the microgrid income in the electricity market while at the same time minimizing the microgrid running cost (fuel cost of fuel-fired generators). Similarly, [16] devised an optimization strategy for optimal bidding of a community-scale microgrid to explore the benefits of coordinating HVACs and RESs with the objective of minimizing the microgrid running costs taking into account customers' thermal comfort preferences while simultaneously maximizing the revenue of the microgrid in the electricity market.

Unlike those works where the authors focused to formulate the joint optimization of HVACs with EVs, HVACs with RESs or EVs with RESs, for the exploiting the benefits of the flexibility of flexible

loads in decentralized energy systems (buildings or microgrids), this work proposes to formulate the joint optimization of batteries and EVs with RESs. We study the benefits of coordinating the major flexible loads, energy storage batteries and EVs, with RESs in a building microgrid. The proposed objective is to maximize the revenue of the building microgrid in the day-ahead and real-time (regulation) electricity market while at the same time minimizing the operating cost of the microgrid.

The major contributions of this study are outlined below:

- We devise an extensive optimization model to exploit the flexibility of batteries and EVs with RESs in a building microgrid (BMG) through the development of an optimal day-ahead/real-time bidding and day-ahead scheduling approach in a two-clearance electricity market, which is the common energy market model in the Nordic [17].
- We demonstrate an optimal and coordinated EV charging/discharging approach can achieve considerable profit enhancement for the BMG compared an uncontrolled EV charging approach. We also show the optimal EV charging/discharging approach can assist to decrease the renewable generation curtailment which is important to alleviate the bid mismatch penalties.

The remaining sections of the paper are organized as follows. The system model and solution methodology are presented in Section II. The detail optimization problem description is provided in Section III. The case study and simulation results are given in Section IV and the conclusions are drawn in Section V.

II. SYSTEM MODEL

A. System Configuration

We consider a BMG operating in grid-connected mode which contains the components below: RES (PV), energy storage batteries, various buildings with plenty of houses (apartments, flats, classrooms, offices or large rooms) and their associated loads (flexible and nonflexible), and EV charging/discharging station (EV CDS). The BMG aggregate load demand is modeled using a bottom-up approach where the load demand of each house is formulated first and summed up to form the total load demand of the BMG then. The flexible and nonflexible loads of each house are formulated independently. The optimization horizon is one-day with one-hour resolution. The BMG is supposed to involve in two-clearance energy market where the BMG has to submit its hourly bids to the day-ahead (DA) market a few hours ahead of the real-time (RT) power transfer [5]. The bid can be to provide bid for selling power to the market or to request bid for buying power from the market. Any deviation between the RT power transfer and the DA schedule is fined. The deviation is corrected by trading power in the RT regulation market. The MG is assumed as a price-taker because of its smaller size to affect the electricity price compared to the main grid [5]. The grid operator is liable for computing the clearing energy price that is employed to calculate the BMG income and operating cost. It shall be remarked that the DA electricity price is cleared to the BMG when it submits the day-ahead bids to the energy market [5], [17].

The stochasticities of the renewable generation, load demand and electricity price make the bidding optimization process of the BMG a complex task. To circumvent an excess penalty on bid mismatch, it is occasionally desirable to cut generated power of RESs to maintain the RT power transfer as close as possible to the DA schedule. Nevertheless, curtailment of renewable generation is unnecessary or it is not the better option. Thus, we apply a high penalty charge to limit the quantity of renewable generation curtailment. Load shedding is the other solution to avoid the excess penalty due to the power bid deviation. However, load shedding is not recommended in microgrids if it is involuntary without the permission of the customer. Therefore, we impose a high penalty charge payable to the customer to limit the involuntary load curtailment. The batteries and EVs are the major demand response sources in the proposed optimization framework.

In this study, the flexibility in the battery and EV charging/discharging mechanisms are explored to assist the operation of the renewable generations. Generally, EVs are charged instantaneously with the maximum power when they reach at charging stations/points. We call this as *uncontrolled charging approach*. Nevertheless, by regulating the charging/discharging plan for EVs smartly taking into both the fluctuation in the energy prices and renewable generations, we can improve the profit of the BMG and decrease the quantity of renewable energy curtailment. Besides, when the energy price is at its peak and/or when there is shortage of power in the BMG to supply the local load demands, batteries and EVs can be discharged to deliver power to the local demands. The customers in the building microgrid submit their hourly desired EVs travel plans to the building energy aggregator before the operating day.

B. Solution Approach

In this study, we take into account the stochasticities of renewables, load demands and electricity prices. Improved forecasts can be used to manage these uncertainties. We employ the approach we used in our previous work [1] to model and forecast the PV power generation. We use the method we employed in our present work [18] to model and forecast the BMG aggregate local load demand. Similarly, the technique in [19] can be utilized to model and predict the real-time electricity prices. Normally, day-ahead electricity prices are cleared before several hours of the operating day [20] (i.e., before we run the optimization and submit the day-ahead bids) and thus no forecast is used for day-ahead prices. The devised optimization problem is described as a dual-step stochastic program. The first-step decisions are performed before any stochastic values (i.e., forecasted values) are disclosed assuming that the realization (regulating compensation) of the stochasticities when the second-step decisions are executed following the disclosure of the stochasticities, and they rely on the first-step decisions [5].

III. OPTIMIZATION PROBLEM FORMULATION

The proposed dual-step stochastic optimization problem is described here. The first-step decision consists of the hourly power bids submitted to the day-ahead electricity market. The second-step decisions contain the curtailment of involuntary demands and renewable generation, the battery charging/discharging decisions, the EV charging/discharging decisions, and the real-time power transfer between the BMG and the main utility grid. We present the objective function, and all the capacity and technical constraints in the next subsequent subsections.

A. System Configuration

We devise to maximize the objective function formulated below:

$$\max \sum_{t=1}^N \Delta T \left\{ P_t^{DA} e_t^{DA} + (P_t^{RT} - P_t^{DA}) e_t^{RT} - \varphi_t |P_t^{RT} - P_t^{DA}| \right. \quad (1) \\ \left. - c_{curt,t}^{PV} \sum_{p=1}^{N_{PV}} P_{p,t}^{PV,curt} - \sum_{b=1}^B \sum_{h=1}^H \beta_{h,b,t} L_{h,b,t}^{S_{h,b,t}^{invol}} \right\}$$

where, the P_t^{DA} is the day-ahead hourly bid, and $P_t^{RT} - P_t^{DA}$ is the power trading in the real-time regulation market. The sign agreement here is that if the power is exported to the utility grid, it will assign a positive value, and vice versa.

The objective function in fact apprehends the costs of energy trading in the day-ahead and real-time markets, the penalty costs for bid mismatch, renewable generation curtailment, and involuntary load shedding. It has to be remarked that a positive value of $P_t^{DA} e_t^{DA} + (P_t^{RT} - P_t^{DA}) e_t^{RT}$ indicates the BMG is making profits by exporting power to the utility grid.

B. Power Balance

The sum of available local generation (RESs), the quantities of involuntary load curtailments and the discharging powers from the batteries and EVs should be equal to the sum of the real-time power transfer, the BMG aggregate nonflexible local load and the charging powers of batteries and EVs, at each operating time slot of the optimization horizon.

$$\sum_{p=1}^{N_{PV}} (P_{p,t}^{PV} - P_{p,t}^{PV,curt}) + \sum_{b=1}^B \sum_{h=1}^H \left(LS_{h,b,t}^{invol} + \sum_{v=1}^V (P_{v,h,b,t}^{EV,d} - P_{v,h,b,t}^{EV,c}) \right) + \sum_{u=1}^U (P_{u,t}^{Bat,d} - P_{u,t}^{Bat,c}) = P_t^{RT} + P_t^{NFL}, \forall t. \quad (2)$$

C. Power Exchange with the Main/Utility Grid

The day-ahead hourly bids and the real-time power transfers are limited by the line and transformer capacities between the BMG and the utility grid.

$$-P_t^{grid,max} \leq P_t^{DA}, P_t^{RT} \leq P_t^{grid,max}, \forall t \quad (3)$$

D. EV Constraints

The EV behaviors and the traveling patterns shall also be precisely modeled. The important parameters while modeling the EV charging/discharging characteristics are the EV battery capacity (kWh), the travel efficiency (kWh/km) and the charging type (fast, slow, DC or AC). These characteristics can be obtained from the manufacturer's datasheet or website. The traveling pattern of the EVs can be formulated by the quantity of travels per day, the departure and returning times, and the trip distance of each travel. A trip is described as the period between the times when the EV departs from and returns back to the charging/discharging station of the BMG. This is associated with the customer travel plan, which can be sent by the customer to the BMG aggregator a few hours ahead of the operating day.

1) Power Constraints

We suppose the EVs are only charged/discharged when they are parked at the BMG CDS. Furthermore, EVs are plugged to the piles immediately they reach at the CDS. Thus, the charging/discharging power constraints are used only during the times when the EV is parked at the CDS as:

$$0 \leq P_{v,h,b,t}^{EV,c} \leq b_{v,h,b,t}^{EV,c} P_{v,h,b,t}^{EV,c,max} \quad (4)$$

$$0 \leq P_{v,h,b,t}^{EV,d} \leq b_{v,h,b,t}^{EV,d} P_{v,h,b,t}^{EV,d,max} \quad (5)$$

$$b_{v,h,b,t}^{EV,c} + b_{v,h,b,t}^{EV,d} = 1, b_{v,h,b,t}^{EV,c}, b_{v,h,b,t}^{EV,d} \in \{0, 1\} \quad (6)$$

where, $b_{v,h,b,t}^{EV,c}$ denotes the availability of EV v of house h of building b at the CDS for charging at time t , $b_{v,h,b,t}^{EV,d}$ denotes the availability of EV v of house h of building b at the CDS for discharging at time t , $P_{v,h,b,t}^{EV,c,max}$ and $P_{v,h,b,t}^{EV,d,max}$ represent the peak charging/discharging bounds, respectively. The EV charging/discharging powers are zero if the EV is not at the CDS (i.e., since $b_{v,h,b,t}^{EV,c} = b_{v,h,b,t}^{EV,d} = 0$). Moreover, (6) ensures that an EV cannot charge and discharge at the same time.

2) SOC Dynamics and Constraints

We suppose the EVs can make a number of travels during the optimization horizon (for example, one day). Let $t_{v,h,b,tr}^{dep}$ and $t_{v,h,b,tr}^{arr}$ be the time slots when EV v of house h in building b departs and arrives the BMG CDS or home for trip tr , respectively. Then, the objective function must abide the constraints below:

$$SOC_{v,h,b,t+1}^{EV} = SOC_{v,h,b,t}^{EV} + \Delta T \left(\frac{\eta_{v,h,b}^{EV,c} P_{v,h,b,t}^{EV,c}}{C_{v,h,b}^{EV}} - \frac{P_{v,h,b,t}^{EV,d}}{\eta_{v,h,b}^{EV,d} C_{v,h,b}^{EV}} \right) \quad (7)$$

$$\text{if } t \notin [t_{v,h,b,tr}^{dep}, t_{v,h,b,tr}^{arr}], \forall t, v, h, b, tr$$

$$SOC_{v,h,b,t+\sigma_{v,h,b,tr}}^{EV} = SOC_{v,h,b,t}^{EV} - \frac{l_{v,h,b,tr}^{EV} q_{v,h,b}^{EV}}{C_{v,h,b}^{EV}} \quad (8)$$

$$\text{if } t = t_{v,h,b,tr}^{dep}, \forall t, v, h, b, tr$$

$$SOC_{v,h,b,t_{v,h,b,tr}^{arr}}^{EV} \leq SOC_{v,h,b,t}^{EV} \leq SOC_{v,h,b,t_{v,h,b,tr}^{dep}}^{EV} = SOC_{v,h,b}^{EV,max} \quad (9)$$

$$\text{if } t \in [t_{v,h,b,tr}^{dep}, t_{v,h,b,tr}^{arr}], \forall t, v, h, b, tr$$

$$SOC_{v,h,b}^{EV,min} \leq SOC_{v,h,b,t}^{EV} \leq SOC_{v,h,b}^{EV,max}, \forall t, v, h, b \quad (10)$$

The SOC of EV v of house h in building b varies based on the charging/discharging powers when the EV parks at the CDS (7) and the deviation of the SOC at departing and arriving times corresponds to the energy consumption while driving the EV (8). Equation (9) guarantees that the SOC decreases when the EV travels. Equation (10) ensures the EV battery can keep long lifetime, following the SOC range recommended by the manufacturer [21].

E. Energy Storage Battery Constraints

The constraints below denote the charging/discharging bounds for battery u (11 and 12), SOC bounds (13), charging/discharging status restrictions where battery u is not permitted to charge and discharge at the same time (14). The battery SOC dynamics is formulated in (15).

$$0 \leq P_{u,t}^{Bat,c} \leq b_{u,t}^{Bat,c} P_{u,t}^{Bat,c,max} \quad (11)$$

$$0 \leq P_{u,t}^{Bat,d} \leq b_{u,t}^{Bat,d} P_{u,t}^{Bat,d,max} \quad (12)$$

$$SOC_u^{Bat,min} \leq SOC_{u,t}^{Bat} \leq SOC_u^{Bat,max} \quad (13)$$

$$b_{u,t}^{Bat,c} + b_{u,t}^{Bat,d} = 1, b_{u,t}^{Bat,c}, b_{u,t}^{Bat,d} \in \{0, 1\} \quad (14)$$

$$SOC_{u,t+1}^{Bat} = SOC_{u,t}^{Bat} + \Delta T \left(\frac{\eta_u^{Bat,c} P_{u,t}^{Bat,c}}{C_u^{Bat}} - \frac{P_{u,t}^{Bat,d}}{\eta_u^{Bat,d} C_u^{Bat}} \right), \forall t, u \quad (15)$$

F. Renewable Energy Curtailment

The quantity of renewable generation curtailment is restricted by the peak available renewable generation:

$$0 \leq P_{p,t}^{PV,curt} \leq P_{p,t}^{PV}, \forall t, p \quad (16)$$

G. Involuntary Load Curtailment

The involuntary load shedding should be less than the peak permissible involuntary shedding and the maximum nonflexible demand:

$$0 \leq LS_{h,b,t}^{invol} \leq LS_{h,b}^{invol,max}, \forall t, h, b \quad (17)$$

$$0 \leq LS_{h,b}^{invol} \leq P_{h,b}^{NFL,max}, \forall t, h, b \quad (18)$$

To summarize, we have described the proposed optimization problem as a mixed integer linear program (MILP) which can be solved by the CPLEX solver of the GAMS software environment [22].

IV. CASE STUDY AND SIMULATION RESULTS

In this paper, we consider a building microgrid (BMG) that contains one PV solar system, one energy storage battery and one educational building with several classrooms, laboratories and offices with their associated loads. The BMG also contains one large EV charging/discharging station with several charging/discharging piles

to accommodate many EVs at a time. For the purpose of computational simplicity and clarity of illustrations, we consider the aggregate nonflexible load of the building. That means, the aggregate electricity demand is the sum of the individual demands of all the classrooms, laboratories and offices in the building. Thus, to achieve numerical results for the aggregate building scenario, we simply set $B = H = 1$ in all the associated objective function, constraints and values. We consider ten EVs ($V = 10$) in the BMG.

The electricity demand data is collected from an actual building with a suitable scaling factor. Data for the PV system is collected from real (operational) rooftop PV plant with a suitable scaling factor. The PV is indeed located on the rooftop of the case study building. Improved forecasts for the PV power production and nonflexible aggregate load are obtained using the approaches in [1] and [18], respectively. We take the historical data for the energy prices [20] as their predicted values. The forecasts for the aggregate nonflexible base load and PV power are shown in Fig. 1. The historical day-ahead and real-time electricity prices are also shown in Fig. 2.

Fig. 1. Forecasted nonflexible base load and PV power production

Fig. 2. Day-ahead and real-time electricity prices

We suppose all the EVs are Nissan Leaf ('Acenta' model) with a battery storage capacity of 40kWh [23] and maximum charging/discharging power of 6kW [24]. In fact, this Nissan Leaf model can be charged/discharged at a maximum power of 50kW but with a fast charging mode which is not considered in this work. We also suppose the BMG charging/discharging station is furnished with Level 2 EV charging/discharging piles with a power ratings of 7.2kW. The EVs are assumed to make a single trip in the optimization period (one-day). The minimum and maximum SOC of the EVs are 0.2 and 0.9, respectively. A charging/discharging efficiency of 90% is assumed for the EVs. The initial SOC of the EVs are supposed to be evenly distributed in the range [0.2, 0.9]. The returning and leaving times of the EVs are represented by normal distributions with the averages of 8:00 and 17:00, respectively, and standard deviations of 2 hours for both. The expected SOC of the EVs when they depart the CDS is supposed to be the maximum SOC. The travel efficiencies of the EVs are taken as 16.5kWh/100km [25]. The driving distance of the EVs is assumed to be 50km, which is the average daily travel distance in Finland [26]. This is a typical driving pattern in Finland,

which is employed to achieve the numerical results in the various scenarios in this study.

We illustrate a summer scenario in this paper; but, results for scenarios from the other seasons (winter, spring and autumn) can be demonstrated likewise. We assume a 24h optimization horizon with one hour time resolution/slot.

Penalty fees for involuntary load shedding ($\beta_{h,b,t} = \beta, \forall t, b, h$), PV power curtailment ($c_{curt,t}^{PV} = c_{curt,vt}^{PV}$) and bid mismatch ($\varphi_t = \varphi, \forall t$) are 1 \$/kWh, 0.02 \$/kWh and 0.08 \$/kWh, respectively. The peak aggregate involuntary load shedding ($LS_{h,b}^{invol,max} = LS_{h,b}^{invol,max}$) at each time slot is set as 10% of the aggregate nonflexible load of the BMG at the same time slot. The energy storage battery capacity is 100kWh. Its minimum and maximum SOC are 0.2 and 0.9, respectively. The peak charging/discharging power is 25kW and the charging/discharging efficiency is assumed to be 90%. The utility grid, constraint (3), is not considered. However, when the maximum power trading in the day-ahead market is not limited, we have to assign φ_t a suitably large value to guarantee the bid mismatch is not very big and the real-time power transfer is near to the submitted day-ahead bid.

We describe a Load Scaling Factor (LSF) as the ratio of the aggregate nonflexible load forecast to the aggregate renewable generation forecast over the optimization horizon. For instance, the LSF in Fig. 1 is 0.6, which is selected as the *benchmark or base scenario*. For all the results shown in this section, only the system data clearly shown in the results are varied, the other data remain similar as in the benchmark scenario.

Figs. 3(a), 3(b) show the benefits of the devised optimal EV charging/discharging strategy over the uncontrolled one. In the uncontrolled EV charging/discharging strategy, EVs are charged instantly with the maximum power when they reach at the BMG CDS, and the charging terminates when the EVs reach their desired SOC. As shown, the optimal EV charging/discharging strategy provides a higher profit (optimal objective value) and a smaller PV power curtailment compared to the uncontrolled strategy.

(a) Profit

(b) PV curtailment

Fig. 3. Comparison between optimally controlled and uncontrolled EV charging/discharging strategies by varying c_{curt}^{PV}

Besides, the BMG profit and the amount of PV power curtailment decrease as the penalty for renewable energy curtailment (c_{curt}^{PV}) increases, and they finally become saturated since c_{curt}^{PV} is suitably high.

V. CONCLUSION

An optimal power bidding and scheduling problem for a BMG with battery, EVs and RES is considered in this paper. The battery and EVs are the major demand response resources of the BMG and the bidding takes place in both the day-ahead and real-time electricity markets. We describe the problem as a dual-step optimization process considering uncertainties of RES, electricity demand and prices. The battery as a static energy storage and the EVs as dynamic energy storage capabilities are used to balance the variability of the demands, prices and RESs. Simulation findings demonstrate that by optimally coordinating the battery and EV charging/discharging with renewable generation, the profit of the BMG participating in two-settlement electricity market is considerably enhanced compared to a non-optimized operation. Moreover, the obtained optimization solution decrease the BMG operating expense and reduce the quantity of renewable energy curtailment.

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NOMENCLATURE

N	Optimization horizon or scheduling period
t	Time slot index
ΔT	Length of time slot (h)
p_t^{DA}	Day-ahead power bid (kW)
e_t^{DA}	Day-ahead electricity price (\$/kWh)
p_t^{RT}	Real-time power bid (kW)
e_t^{RT}	Real-time electricity price (\$/kWh)
φ_t	Bid mismatch penalty (\$/kWh)
p	PV system index
N_{PV}	Number of PV systems
$P_{p,t}^{PV}$	PV system output power (kW)
$P_{p,t}^{PV,curt}$	Amount of PV power curtailment (kW)
u	Battery index
U	Number of batteries
$P_{u,t}^{Bat,d}$	Battery discharging power (kW)
$\eta_{u,t}^{Bat,d}$	Battery discharging efficiency (%)
$P_{u,t}^{Bat,c}$	Battery charging power (kW)
$\eta_{u,t}^{Bat,c}$	Battery charging efficiency (%)
$b_{u,t}^{Bat,c}$	Binary variable for battery charging
$b_{u,t}^{Bat,d}$	Binary variable for battery discharging
$P_{u,t}^{Bat,c,max}$	Battery maximum charging power (kW)
$P_{u,t}^{Bat,d,max}$	Battery maximum discharging power (kW)
$SOC_{u,t}^{Bat}$	State of charge of battery (%)
$SOC_u^{Bat,min}$	Battery minimum state of charge (%)

$SOC_u^{Bat,max}$	Battery maximum state of charge (%)
b	Building index
B	Number of buildings
h	House index
H	Number of houses
v	EV index
V	Number of EVs
$p_{u,t}^{EV,d}$	EV discharging power (kW)
$\eta_{u,t}^{EV,d}$	EV discharging efficiency (%)
$p_{u,t}^{EV,c}$	EV charging power (kW)
$\eta_{u,t}^{EV,c}$	EV charging efficiency (%)
$b_{v,h,b,t}^{EV,c}$	Binary variable for EV charging
$b_{v,h,b,t}^{EV,d}$	Binary variable for EV discharging
$p_{v,h,b,t}^{EV,c,max}$	EV maximum charging power (kW)
$p_{v,h,b,t}^{EV,d,max}$	EV maximum discharging power (kW)
tr	EV trip index
$\sigma_{v,h,b,tr}$	Length/duration of trip tr (h)
$t_{v,h,b,tr}^{dep}$	EV departure time for trip tr (h)
$t_{v,h,b,tr}^{arr}$	EV arrival time for trip tr (h)
$l_{v,h,b,tr}^{EV}$	Distance of trip tr (km)
$q_{v,h,b}^{EV}$	Travel efficiency of EV (kWh/km)
$SOC_{v,h,b,t}^{EV}$	State of charge of EV (%)
$SOC_{v,h,b}^{EV,min}$	Minimum state of charge of EV (%)
$SOC_{v,h,b}^{EV,max}$	Maximum state of charge of EV (%)
$C_{v,h,b}^{EV}$	Storage capacity of EV (kWh)
$c_{curt,t}^{PV}$	PV power curtailment penalty (\$/kWh)
$\beta_{h,b,t}$	Involuntary load curtailment penalty (\$/kWh)
$LS_{h,b,t}^{invol}$	Amount of involuntary load curtailment (kW)
$LS_{h,b}^{invol,max}$	Maximum involuntary load curtailment (kW)
p_t^{NFL}	Aggregate nonflexible load (kW)
$p_{h,b}^{NFL,max}$	Maximum nonflexible load (kW)
$p_t^{grid,max}$	Maximum power exchange with main grid (kW)