# Optimal Bidding Strategy for Microgrids Considering Renewable Energy and Building Thermal Dynamics

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Abstract-In this paper, we study an optimal day-ahead pricebased power scheduling problem for a community-scale microgrid (MG). The proposed optimization framework aims to balance between maximizing the expected benefit of the MG in the deregulated electricity market and minimizing the MG operation cost considering users' thermal comfort requirements and other system constraints. The power scheduling and bidding problem is formulated as a two-stage stochastic program where various system uncertainties are captured by using the Monte Carlo simulation approach. Our formulation is novel in that it can exploit the thermal dynamic characteristics of buildings to compensate for the variable and intermittent nature of renewable energy resources and enables us to achieve desirable tradeoffs for different conflicting design objectives. Extensive numerical results are presented to demonstrate the great benefits in exploiting the building thermal dynamics and the flexibility of the proposed scheduling method in achieving different practical design tradeoffs. We also investigate the impacts of different design and system parameters on the curtailment of renewable energy resources and the optimal expected profit of the MG.

*Index Terms*—Building thermal dynamics, climate comfort requirement, day-ahead market, optimal biding strategy.

#### NOMENCLATURE

$\Delta T$	Duration of time slot (h).
$\delta_{j,t}$	Maximum allowable temperature deviation (°C).
$\eta_j$	Coefficient of performance of HVAC system in building $j$ .
$\eta_p$	Conversion coefficient of solar unit $p$ (%).
$\eta_k^c,\eta_k^d$	Charging/discharging efficiency of battery $k$ .
$\Phi^s_t$	Solar irradiance $(kW/m^2)$ .
$\pi_{j,t}$	Cost of temperature deviation ( $^{\circ}C$ ).
$\psi_t$	Cost of bid deviation (\$/kWh).
$\rho_s$	Probability of scenario s.
$\sigma_i$	"1" for cooling, " $-1$ " for heating.

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$b_{k,t}^{s,c}, b_{k,t}^{s,d}$	Binary variable, "1" if charging/ discharging.	
$C_i(.)$	Production cost of unit $i$ (\$).	
$C_k^{deg}$	Cost for battery degradation (\$/kWh).	
$CD_{i,t}, CU_{i,t}$	Shutdown/startup offer cost of unit $i$ (\$).	
$DR_i, UR_i$	Ramping-down/up rate limit of unit $i$ (kW).	
$DT_i, UT_i$	Minimum down/up time of unit $i$ (h).	
$E^{cap}_{k}$	Capacity of battery $k$ (kWh).	
$E_k^{\min}, E_k^{\max}$	Minimum/maximum energy stored in battery $k$ (kWh).	
$e_t^{s,DA}, e_t^{s,RT}$	Day-ahead and real-time prices (\$/kWh).	
$E^s_{k,t}$	Energy stored in battery $k$ (kWh).	
i, w, p, j, k, t, s	Indices of conventional unit, wind unit, solar unit, building, battery, time slot, and scenario.	
$I_{i,t}$	Commitment status of unit $i$ at time $t\{0, 1\}$ .	
$L_t^s$	Total non-HVAC load (kW).	
$LOL_t^{\max}$	Maximum loss of load percentage at time $t$ .	
$LS^s_t, LS^{\max}_t$	Realized and maximum load shedding (kW).	
$m, N_i$	Index of segment and number of segments of piecewise linear cost function of unit $i$ .	
NB, NS, NH	Number of buildings/scenarios/time slots.	
NG, NK	Number of conventional/battery units.	
NW, NP	Number of wind/solar units.	
$P_i^{\min}, P_i^{\max}$	Minimum/maximum power generation of unit $i$ (kW).	
$P_i^{hvac,max}$	Rated power of HVAC system $j$ (kW).	
$P_t, P_t^s$	Scheduled day-ahead bid and actual real-time power delivery (kW).	
$P_w^{r}$	Rated power of wind unit $w$ (kW).	
$P^s_{i,t}$	Power generation of unit <i>i</i> (kW).	
$P^s_{i,t}(m)$	Power generation of unit $i$ from the $m$ -th segment at time $t$ in scenario $s$ (kW).	
$P^{s,hvac,o}_{j,t}$	Output power of HVAC system $j$ (kW).	

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$P^{s,hvac}_{j,t}$	Input power supplied to HVAC system $j$ (kW).
$P^{s,c}_{k,t},P^{s,d}_{k,t}$	Charging/discharging power of battery $k$ (kW).
$P_k^{\rm c,max},P_k^{\rm d,max}$	Maximum charging/discharging power (kW).
$P^{s,\mathrm{ws}}_{w,t},P^{s,\mathrm{pvs}}_{p,t}$	Wind/solar power curtailment (kW).
$P^s_{w,t}, P^s_{p,t}$	Wind/solar available output power (kW).
$S_p$	Array area of solar unit $p$ (m <sup>2</sup> ).
$SD_{i,t}, SU_{i,t}$	Shutdown/startup cost of unit $i$ (\$).
$T^d_{j,t}$	Desired indoor temperature of building $j$ (°C).
$T^{s,\mathrm{in}}_{j,t},T^{s,\mathrm{a}}_t$	Indoor temperature of building j and outdoor temperature at time t in scenario $s$ (°C).
$V_{RES}$	Cost of renewable energy curtailment (\$/kWh).
$v_t^s$	Wind speed at time $t$ in scenario $s$ (m/s).
$V^{\sf W}_t, V^{\sf PV}_t, V^{\sf LL}_t$	Cost of wind/solar/load curtailment (\$/kWh).
$v_w^{\rm r}, v_w^{\rm ci}, v_w^{\rm co}$	Rated, cut-in, and cut-out wind speed (m/s).
$y_{i,t}, z_{i,t}$	Startup and shutdown indicators $\{0,1\}$ .
LSF	Load scaling factor.
USF	Uncertainty scaling factor.

# I. INTRODUCTION

• HE intermittent and volatile nature of renewable energy generation imposes a significant challenge to integrate these resources into power systems. Various methods have been proposed to tackle the intermittency and volatility of renewable energy resources. In [1]–[4], the authors proposed to use pumped-storage hydro units coordinated with wind sources to maximize the profits of generation companies (GENCOs), or to minimize the operating costs for power system operators. The optimal battery sizing problem was studied in [5], [6] to cope with the uncertainties in renewable energy generation. The potential of using charging/discharging capability of electric vehicles (EVs) to support renewable energy was investigated in [7], [8]. Other technologies such as compressed air storage [9], fast-response units (e.g., gas-fired units) [10] can also be used to mitigate the fluctuation of renewable energy generation. However, these solutions have some drawbacks, e.g., pumped-storage hydro systems are geographically dependent and it takes a long time to build a pumped-storage facility with a high capital cost.

Another important issue in future smart grids is intelligent demand side management (DSM) by taking advantages of time-varying electricity prices. In this paper, we consider the smart DSM of the heating, ventilation, and air-conditioning (HVAC) system. There have been several proposed optimal

control schemes for HVAC systems to minimize their operation costs considering different temperature comfort criteria [11]-[15]. Users typically desire to maintain the indoor temperature at their preferred setpoint, which depends on users' preferences and building occupancy status [12]. In general, users can tolerate a small deviation of the indoor temperature from the desired setpoint. Obviously, users would feel more comfortable when the indoor temperature is closer to the preferred setpoint. If the desirable temperature and the maximum allowable temperature deviation are given then the indoor temperature should be maintained to be in the temperature comfort range. Then, the HVAC power consumption can be scheduled intelligently to achieve electricity cost saving without violating users' comfort requirements. In particular, the HVAC system can consume more power during low-priced hours to precool (preheat) buildings in the summer (winter) while it can reduce the power consumption during high-priced hours while still maintaining indoor temperature in the comfort zone thanks to the building thermal inertia.

In this paper, we not only consider electricity price variation in scheduling HVAC power consumption, but we also propose to exploit the thermal dynamic characteristics of buildings (e.g., campus, residential or office buildings) to accommodate the uncertainties in renewable energy generation. In the U.S., buildings contribute for a significant fraction of the overall power consumption; moreover, thermal load accounts for about 50% of the total load in buildings [16]. Therefore, the high thermal storage capacity of buildings could make the HVAC system a great candidate in solving the renewable energy integration problem. The idea is that HVAC power consumption can be scheduled according to the renewable energy generation profile. e.g., when the renewable power is higher than expected, HVAC systems may consume more power to precool/preheat buildings, and vice versa. The potential of the thermal storage capability of buildings is assessed in a MG setting where the considered MG participates in a deregulated electricity market with the objective of maximizing its expected profit (i.e., revenue minus operation cost).

Optimal bidding strategies for participants in power markets have been extensively studied in the literature. The majority of existing works has focused on optimizing the operation of generators in the supply side to maximize the profits of GENCOs [1]–[4], [17]–[23]. In addition to GENCOs, there are other important entities such as distribution companies (DISCOs), retail companies (RETAILCOS), aggregators [23] that can participate in the deregulated electricity market where these entities can be considered belonging to the demand side (e.g., buying electricity from the wholesale market to serve customers). In [24]–[28], different operation frameworks for DISCOs, RETAILERs, and larger customers in the competitive electricity market have been proposed. In [29], [30], the authors studied the optimal energy trading problem for an aggregator that controls the operation of a number of EVs.

In this work, we consider a particular market entity which is a MG aggregator. In general, a MG can be defined as a cluster of distributed energy resources (DERs) and associated loads, and it can be operated in grid-connected mode or islanded mode [31]. A MG can be of different sizes ranging from a building, a university campus, to the community scale (e.g., a village). Capacities of DERs in a MG can be relatively small to allow them participate directly in the power market. Therefore, local electricity generation and demand in the MG can be aggregated and controlled by a MG aggregator which serves as the representative of the MG in the market. Moreover, the MG can be considered as a "prosumer" which not only consumes but also produces electricity [32]. Particularly, when the local generation is higher than the local demand, the MG acts as a producer selling its surplus energy to the main grid. In contrast, when the local generation is not sufficient to meet the local demand, the MG plays the role of a consumer who buys electricity from the market to serve its local demand. In this work, we assume that the MG is allowed to participate in the electricity market and the market operator treats the MG the same manner as other market entities (e.g., GENCOs and DISCOs). From the market operator's perspective, the MG can act either as a supplier or a customer depending on the direction of power flow between the MG and the main grid.

There is an important difference between MGs and GENCOs in that the supply-demand balancing constraint does not exist in the power scheduling problem for GENCOs. On the other hand, supply-demand balance is a critical requirement in the power scheduling and bidding problem for MGs. Moreover, the demand response can be integrated in the power scheduling optimization for MGs, which can potentially reduce considerably the operating cost for MGs and compensate for the fluctuation of RESs. Optimal energy trading for MGs has been considered in several studies [31], [33]-[44] where the typical objectives of these works are to maximize the revenue for the MG in the power market and to minimize the MG operation cost. Our current work belongs to this line of research, which, however, has several distinct modeling aspects. To best of our knowledge, there is no existing work considering a detailed model for building thermal dynamics and the potential of using HVAC systems and the associated thermal load to cope with the uncertainties of RESs and maximize the profit for MGs in the electricity market. Our work fills this important gap in the literature where its main contributions can be summarized as follows:

- We propose a comprehensive model based on which we develop an optimal day-ahead scheduling strategy for a MG in a two-settlement electricity market, which is the common practice in the U.S. [3], [22], [23]. The proposed model aims to balance between maximizing the revenue for the MG and minimizing the load and renewable curtailment as well as bid deviation while maintaining users' comfort requirements and other system constraints. The proposed model is novel in that it enables us to exploit the building thermal dynamics properties to compensate for the variability of renewable energy generation, which can significantly improve the MG profit. Specifically, HVAC load is used as a demand response source and integrated into the optimal bidding strategy of the MG aggregator in the electricity market.
- The optimization model is formulated as a two-stage stochastic programming problem where uncertainties are captured by using the Monte Carlo simulation method. Firststage and second-stage variables are appropriately defined for efficient operations of the power systems integrating different renewable energy sources.

 We present extensive simulation results to demonstrate the advantages in coordinating the operations of the HVAC systems and renewable energy resources compared to the uncoordinated case where HVAC systems and other components of the MG aim to optimize their power consumption/generation independently. The performance of the proposed scheme is also compared with that under the strict climate comfort requirement where no temperature deviation is allowed. Finally, the sensitivity analysis is performed to assess the impacts of different system and design parameters on the optimal solution.

The remaining of this paper is organized as follows. The system model and modeling approach are presented in Section II. Detailed problem formulation is described in Section III. The case studies and numerical results are provided in Section V followed by conclusion in Section VI.

# II. SYSTEM MODEL AND MODELING APPROACH

# A. System Model

1) MG Components: We consider a large-scale MG that consists of several renewable generating units, conventional units, a number of buildings with associated loads, and an optional battery storage facility. The renewable generating units include solar panels and wind turbines. In this study, conventional generating units refer to non-renewable generating units such as microturbines, fuel cells, diesel generators.<sup>1</sup> The MG loads are divided into two separate types, namely HVAC and non-HVAC loads. In reality, this kind of MG is very popular (e.g., *energy cooperative* model [45]).

In general, the MG aggregator desires to maximize the utilization of renewable energy generation. The shortened and excess amount of energy required to balance the local load can be accommodated by trading with the main grid through the Point of Common Coupling (PCC) [31] or by running conventional units. The MG aggregator will make decisions on purchasing electricity from the market or running local conventional units depending on various factors such as electricity price, the states of conventional units, and the marginal cost of operating conventional units. We consider the energy scheduling and bidding problem for MG in discrete time slots, denoted by t in our model, over a scheduling period of NH time slots.

2) HVAC Operation: HVAC systems are typically controlled by the thermostats to maintain indoor temperature at preferred setpoints. Users can choose desirable temperature setpoints for different occupancy statuses (e.g., being at home, away, and slipping). As discused in Section I, users would feel the most comfortable if the indoor temperature is at the preferred setpoint. However, they can tolerate a certain small deviation of the indoor temperature from the setpoint. The larger the deviation is, the less comfortable users would feel. In this work, we assume that the indoor temperature must be maintained to be in the comfort range (e.g., [21 °C, 25 °C]).

Moreover, indoor temperature in a particular time slot depends on the amount of scheduled power and the temperature in the previous time slot due to building thermal inertia. Therefore, it would be beneficial if the HVAC system consumes more energy when the electricity price is low or when the amount

<sup>1</sup>In reality, conventional units are often refereed to as thermal generators.

of generated renewable energy is high to precool or preheat buildings (for the summer and winter, respectively) and reduce the power consumption in opposite cases. Thus, the HVAC power consumption should be scheduled economically while maintaining the indoor temperature within the required comfort range. By allowing the MG aggregator to control the operation of HVAC systems in their buildings, significant cost saving may be achieved based on which users of the MG could receive some saving in their electricity bills.

3) Market Model: The MG is assumed to be a price-taker in the electricity market. During the time slots where the local power generation is surplus, the MG would sell its power to the main grid. In contrast, if the local generation is not enough to meet its local load, the MG would need to buy electricity from the main grid. Everyday the MG has to submit its hourly bids to the day-ahead market several hours before physical power delivery [2]. The MG bids include both selling and buying electricity bids. Also, the MG can participate in the real-time electricity market to supplement for any power deviation from the day-ahead schedule. It is the common practice that the MG offers selling bids at a very low price (e.g., normally set to 0 \$/MWh [2], [3], [46]) and buying bids at high prices to ensure that its submitted bids are always accepted in the market. The market operator is responsible for calculating the market clearing prices after collecting all offer bids and demand bids from all competitive entities in the market [23], [46]. The payment made between the MG and the market operator is calculated based on the market clearing prices.

Finding an optimal hourly bidding strategy for the MG is a challenging task due to various uncertainties in the system, which may cause a significant deviation between the scheduled power delivery and the real-time power delivery. If the MG cannot follow the day-ahead scheduled power, a penalty will be applied to the bid deviation [1]-[4], [22]. When the available renewable output power is higher than scheduled, it is sometimes preferable to curtail the surplus renewable power to avoid a high penalty cost on the bid deviation. The thermal storage capability of buildings can help mitigate the affects of renewable energy uncertainties by increasing HVAC power consumption when renewable energy generation is higher than scheduled, and vice versa. By exploiting this aspect in HVAC power scheduling, it is, therefore, expected that the real-time power delivery will be closer to the day-ahead schedule, and the renewable energy curtailment is reduced.

# B. Stochastic-Based Optimization Approach

There are various sources of uncertainties in our proposed model, which arise from the renewable energy generation, the total non-HVAC load, the ambient temperature, and the day-ahead and real-time electricity prices. The Monte Carlo simulation is used to generate scenarios that represent these uncertain parameters based on the corresponding distribution functions [1]–[4], [6]–[8], [47]–[49]. In general, the larger the number of scenarios we generate, the more accurate the optimal solution can be achieved. However, there is a trade-off between the number of simulated scenarios and the computational burden of the scenario-based optimization method. For a large-scale problem, suitable scenario reduction techniques can be employed to reduce the number of scenarios, consequently, reduce the computational burden [47], [50].

# **III. PROBLEM FORMULATION**

The power scheduling and bidding problem is formulated as a two-stage stochastic program. The inputs to the underlying problem include Monte Carlo scenarios which represent the uncertainties in renewable output power (wind and solar), total non-HVAC load of all buildings, ambient temperature, and electricity price information. The outputs of the optimization problem consist of the sets of first-stage decisions and the second-stage decisions. The decisions taken at the first stage must be made before uncertainties are disclosed considering possible realizations of uncertain parameters at the second stage. The recourse decisions at the second-stage are made after the uncertainties are unveiled, and they depend on the first-stage decisions.

In this paper, the first-stage decisions include the commitment statuses of all conventional units and the hourly bid quantities submitted to the day-ahead market. The second-stage decisions include the power dispatch of all generating units, the amount of involuntary load curtailment, the real-time power delivery between the MG and the main grid, and the battery charging/discharging decisions. In the following, all the second-stage decision variables are denoted with a superscript *s* representing scenario *s*. The stochastic problem in the joint optimization case is described as follows.

# A. Objective Function

Our design goal is to maximize the following objective function.

$$\max -\sum_{i=1}^{NG} \sum_{t=1}^{NH} (SU_{i,t} + SD_{i,t}) - \sum_{s=1}^{NS} \rho_s \sum_{i=1}^{NG} \sum_{t=1}^{NH} C(P_{i,t}^s) -\sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NH} \pi_{j,t} \sum_{j=1}^{NB} |T_{j,t+1}^s - T_{j,t+1}^d| + \sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NH} \Delta T \Big\{ P_t e_t^{s,\mathsf{DA}} + (P_t^s - P_t) e_t^{s,\mathsf{RT}} - \psi_t | P_t^s - P_t| - C_k^{\mathsf{deg}} \sum_{k=1}^{NK} \left( \frac{P_{k,t}^{s,\mathsf{d}}}{\eta_k^d} + \eta_k^c P_{k,t}^{s,\mathsf{c}} \right) - V_t^{LL} LS_t^s - V_t^{\mathsf{W}} \cdot \sum_{w=1}^{NW} P_{w,t}^{s,\mathsf{ws}} - V_t^{\mathsf{PV}} \cdot \sum_{p=1}^{NP} P_{p,t}^{s,\mathsf{pvs}} \Big\}$$
(1)

where  $P_t$  is the hourly bid that the MG submits to the day-ahead market,  $P_t^s$  is the real-time power delivery. The mismatch between the scheduled day-ahead power and the actual power delivery  $|P_t^s - P_t|$  is indeed the amount of power that the MG trades in the real-time market. A positive value of  $P_t$  means that the power is exported from the MG to the main grid and vice versa. The same convention is applied to  $P_t^s$  and  $P_t^s - P_t$ .

The proposed objective function represents the *expected profit* of the MG which is equal to the expected revenue attained by trading in both day-ahead and balancing markets minus the MG operating cost. The expected revenue of the MG is

$$\sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NH} \Delta T \left[ P_t e_t^{s, \mathsf{DA}} + (P_t^s - P_t) e_t^{s, \mathsf{RT}} - \psi_t \left| P_t^s - P_t \right| \right].$$
(2)

In fact, if  $P_t$  is positive (negative) then the term  $\Delta T P_t e_t^{s,\text{DA}}$  represents the revenue (cost) of the MG by selling (buying) electricity in the day-ahead market in time t. Similarly, if  $(P_t^s - P_t)$  is positive (negative) then the term  $\Delta T (P_t^s - P_t) e_t^{s,\text{RT}}$  describes the revenue (cost) of the MG by selling (buying) electricity in the real-time market in time slot t and scenario s. The term  $\psi_t \Delta T |P_t^s - P_t|$  presents the penalty imposed on the MG aggregator in time slot t and scenario s when the actual real-time power delivery is different from the scheduled day-ahead value [22].

The MG operating cost consists of the startup cost, the shutdown cost, the operating cost of conventional units, and other costs including users' temperature discomfort cost, battery degradation cost, penalties due to wind/solar energy curtailment, and involuntary load curtailment. In particular, the total startup cost and the shutdown cost for conventional units over the scheduling horizon is expressed in the first term in (1) while the second term in (1) presents the operating cost of conventional units.

The third term in (1) represents the penalty due to temperature deviations in buildings. Specifically,  $\pi_{j,t}|T_{j,t+1}^s - T_{j,t+1}^d|$  describes the temperature discomfort cost for residents of building j in time slot t and scenario s. The parameter  $\pi_{j,t}$  represents the willingness of residents of building j to trade their climate comfort for cost saving in time slot t. The larger  $\pi_{j,t}$  is, the less willing the residents in building j are, which results in less flexibility in scheduling power consumption of the HVAC system of building j. Here,  $\pi_{j,t}|T_{j,t+1}^s - T_{j,t+1}^d|$  can be interpreted as the payment that the MG aggregator pays the residents of building j in time slot t and scenario s for their participation in the underlying control scheme.

The term  $C_k^{\text{deg}}((P_{k,t}^{s,d}/\eta_k^d) + \eta_k^c P_{k,t}^{s,c})$  captures the degradation cost for battery k in time slot t and scenario s due to charging/discharging activities [7], [17], [51], [52]. In addition, the penalty for curtailment of involuntary load is proportional to the amount of load shedding. To ensure a high quality of service for users, involuntary load curtailment needs to be avoided, hence  $V_t^{LL}$  should be set to a very high value. Finally, the last two terms in (1) represent the penalty for wind and solar energy curtailment, respectively. Renewable energy curtailment penalty is employed to account for the benefits associated with renewable energy that have not been included explicitly in the existing model (e.g., subsides from government to encourage increasing renewable energy penetration, carbon emissions reduction, and Renewable Energy Certificate (REC) policy) [49], [53]. We propose to include the renewable energy curtailment penalty in the objective function to increase the flexibility of the proposed model, which provides the MG aggregator the mechanism to efficiently control the amount of curtailment<sup>2</sup>. In general, the higher values of weighting factors  $V_t^{\mathsf{W}}$  and/or  $V_t^{\mathsf{PV}}$  results in a lower amount of renewable energy

curtailment. Other constraints of the optimization problem are described in the following.

# B. Power Balance

For each scenario s, the sum of the total power generation from all local generating units, the amount of involuntary load curtailment, and the charging/discharging power of battery units must be equal to the sum of the real-time power delivery, HVAC and non-HVAC loads. Note that  $P_{w,t}^{s}$  and  $P_{w,t}^{s,\text{WS}}$  are the maximum available wind power and the amount of wind power curtailment at time t in scenario s, respectively. The difference between them is the actual wind power generation at time t in scenario s. Similar explanation is applied to solar power generation. The power balance equation for each time t and scenario sis given as follows:

$$\sum_{i=1}^{NG} P_{i,t}^{s} + \sum_{w=1}^{NW} \left( P_{w,t}^{s} - P_{w,t}^{s,\text{ws}} \right) + \sum_{p=1}^{NP} \left( P_{p,t}^{s} - P_{p,t}^{s,\text{pvs}} \right) + LS_{t}^{s} + \sum_{k=1}^{NK} \left( P_{k,t}^{s,\text{d}} - P_{k,t}^{s,\text{c}} \right) = P_{t}^{s} + \sum_{j=1}^{NB} P_{j,t}^{s,\text{hvac}} + L_{t}^{s}, \,\forall s, t. \quad (3)$$

# C. Power Exchange With Main Grid

We can impose a limit on the quantity of power submitted to the day-ahead market as well as the amount of real-time power delivery. Let  $P_t^{g,max}$  be the maximum allowable power exchange between the MG and the main grid then we have

$$-P_t^{\mathsf{g},\mathsf{max}} \le P_t^s \le P_t^{\mathsf{g},\mathsf{max}}; \quad -P_t^{\mathsf{g},\mathsf{max}} \le P_t \le P_t^{\mathsf{g},\mathsf{max}}.$$
(4)

# D. Constraints for Conventional Units

The operating cost of conventional unit *i* can be modeled approximately by a piecewise linear function as follows [49], [54]:

$$C\left(P_{i,t}^{s}\right) = a_{i}I_{i,t} + \Delta T\sum_{m=1}^{N_{i}}\lambda_{i,t}(m)P_{i,t}^{s}(m), \ \forall i,t,s \quad (5)$$

$$0 \le P_{i,t}^s(m) \le P_{i,t}^{\max}(m), \quad \forall i, t, s \tag{6}$$

$$P_{i,t}^{s} = P_{i}^{\min} I_{i,t} + \sum_{m=1}^{m} P_{i,t}^{s}(m), \quad \forall i, t, s$$
(7)

where  $N_i$  is number of segments of energy production curve for unit *i* and  $\lambda_{i,t}(m)$  is the marginal cost of the segment *m* offered by unit *i* in time slot *t* (\$/kWh) [49].  $a_i$  is the cost of running unit *i* at its minimum power generation [54]. The following constraints represent the output power generation limits (8), ramping down/up rate limits (9), (10), minimum ON/OFF time limits (11), and the relationship between the start-up and shutdown indicators ( $y_{i,t}$  and  $z_{i,t}$ ) (12) of the conventional generating unit *i* [6], [47]–[49], [54]

$$P_i^{\min} I_{i,t} \le P_{i,t}^s \le P_i^{\max} I_{i,t}$$
(8)

$$P_{i,t}^{s} - P_{i,t-1}^{s} \le UR_{i}(1 - y_{i,t}) + P_{i}^{\min}y_{i,t}$$
(9)

$$P_{i,t-1}^{s} - P_{i,t}^{s} \le DR_{i}(1 - z_{i,t}) + P_{i}^{\min}z_{i,t}$$

$$t + UT_{i-1} \qquad t + DT_{i-1}$$

$$(10)$$

$$\sum_{h=t}^{n} I_{i,t} \ge UT_i y_{i,t}; \quad \sum_{h=t}^{n} (1-I_{i,t}) \ge DT_k z_{i,t} \quad (11)$$

$$y_{i,t} - z_{i,t} = I_{i,t} - I_{i,t-1}; \quad y_{i,t} + z_{i,t} \le 1.$$
 (12)

<sup>&</sup>lt;sup>2</sup>In many cases, penalty for renewable energy curtailment (or, also the discomfort cost) might not have actual economic values (e.g., there is no subside policies for renewable energy, no REC policy, etc or users do not receive the exact amount of discomfort cost as modeled in (1)), we might still want to put the terms representing those penalties in the objective function with the purpose of allowing the MG aggregator more flexibly in controlling the amount of renewable energy curtailment, and users discomfort. However, the cost for those penalties will not be included in the real cost (or profit) value for the MG aggregator.

Start-up cost and shut down cost constraints are given as follows [6], [7], [49], [54]:

$$SU_{i,t} \ge CU_{i,t}(I_{i,t} - I_{i,t-1}); \quad SU_{i,t} \ge 0$$
 (13)

$$SD_{i,t} \ge CD_{i,t}(I_{i,t-1} - I_{i,t}); \quad SD_{i,t} \ge 0.$$
 (14)

Interested readers can find more details about modeling conventional units in [54].

### E. Thermal Dynamic Model

A third-order state-space model, which is widely used in literature [11]–[13], [15], is employed to describe the thermal dynamic model for buildings. This model captures the impacts of ambient temperature and solar irradiance on the indoor temperature [12], [13], [15].

$$T_{j,t+1}^{s} = A_{j}T_{j,t}^{s} + B_{j}U_{j,t}^{s}, \quad \forall j, t, s$$
(15)

$$T_{j,t}^{s,\text{in}} = CT_{j,t}^s, \quad \forall j, t, s \tag{16}$$

where  $T_{j,t}^s = [T_{j,t}^{s,\text{in}}, T_{j,t}^{s,\text{om}}, T_{j,t}^{s,\text{om}}]'$  is the state vector.  $T_{j,t}^{s,\text{im}}$  is the temperature of the thermal accumulating layer in the inner walls and floor in building j in time slot t and scenario  $s(^{\circ}C)$ .  $T_{j,t}^{s,\text{om}}$  is the temperature of the envelope of the of building j in time slot t and scenario  $s(^{\circ}C)$ .  $U_{j,t}^{s} = [T^{s,a}, \Phi_t^s, \sigma_j P_j^{s,\text{hvac,o}}]'$  is the input control vector with  $P_j^{s,\text{hvac,o}} = \eta_j P_j^{s,\text{hvac,o}}$ . The coefficients of matrices  $A_j$  and  $B_j$  of building j can be calculated based on the effective window area, the fraction of solar irradiation entering the inner walls and floor, and the thermal capacitance, thermal resistance parameters of the building and C = [1, 0, 0]. Due to the space limitation, interested readers can find more details about this building thermal dynamic model in [11], [12]. The constraints on the indoor temperature and HVAC power consumption are represented as follows:

$$T_{j,t}^{d} - \delta_{j,t} \le T_{j,t}^{s, \text{in}} \le T_{j,t}^{d} + \delta_{j,t}$$
(17)

$$0 \le P_{j,t}^{s,\mathsf{hvac}} \le P_j^{\mathsf{hvac},\mathsf{max}}.$$
 (18)

#### F. Battery Constraints

The constraints (19), (20) capture the limits on the charging and discharging power as well as the level of energy stored in a battery unit k. Here, the level of battery storage at the end of the scheduling horizon is equal to its initial energy level. Constraints (21) are imposed to ensure the battery cannot be charged and discharged simultaneously in any time slot. The energy dynamic model for battery k is captured in (22).

$$0 \le P_{k,t}^{s,c} \le b_{k,t}^{s,c} P_k^{c,\max}; 0 \le P_{k,t}^{s,d} \le b_{k,t}^{s,d} P_k^{d,\max}, \ \forall k,t,s \quad (19)$$

$$E_{k}^{\min} \le E_{k,t}^{s} \le E_{k}^{\max}; E_{k,NH}^{s} = E_{k,1}^{s}, \,\forall k, t, s$$
(20)

$$b_{k,t}^{s,c} + b_{k,t}^{s,d} = 1; \ b_{k,t}^{s,c}, b_{k,t}^{s,d} \in \{0,1\}, \ \forall k, t, s$$
(21)

$$E_{k,t+1}^{s} = E_{k,t}^{s} + \left(\eta_{k}^{c} P_{k,t}^{s,c} \Delta T - \frac{P_{k,t}^{s,u} \Delta T}{\eta_{k}^{d}}\right), \ \forall k, t, s.$$
(22)

# G. Involuntary Load Curtailment

Constraints (23) limit the amount of involuntary load curtailment at time t. The expected amount of involuntary load curtailment at time t is  $\sum_{s=1}^{NS} \rho_s LS_t^s$ , while the expected total non-HVAC load at time t is  $\sum_{s=1}^{NS} \rho_s L_t^s$ . In this study, we force the expected involuntary load curtailment is smaller than a certain percentage of the expected non-HVAC load for every time slot as described in (24). Constraints (24) can be considered as a reliability criterion for the operation of the MG.

$$\leq LS_t^s \leq LS_t^{\max}, \quad \forall t, s \tag{23}$$

$$\frac{\sum_{s=1}^{NS} \rho_s LS_s^s}{\sum_{s=1}^{NS} \rho_s L_t^s} \le LOL_t^{\max}, \quad \forall t.$$
(24)

## H. Renewable Energy Curtailment

0

The available output power of solar unit p at maximum power point (MPP) in time slot t and scenario s can be calculated based on the solar irradiance and ambient temperature as follows [5]:

$$P_{p,t}^{s} = \eta_p S_p \Phi_t^{s} \left( 1 - 0.005 \left( T_t^{s,a} - 25 \right) \right).$$
 (25)

The output power of wind generator w in time slot t and scenario s is given as follows [5]:

$$P_{w,t}^{s} = \begin{cases} 0, & \text{if } v_{t}^{s} \leq v_{w}^{\text{ci}} \text{ or } v_{t}^{s} \geq v_{w}^{\text{co}}, \\ P_{w}^{r} \frac{v_{t}^{s} - v_{w}^{\text{ci}}}{v_{w}^{t} - v_{w}^{\text{ci}}}, & \text{if } v_{w}^{\text{ci}} \leq v_{t}^{s} \leq v_{w}^{r}, \\ P_{w}^{r}, & \text{otherwise.} \end{cases}$$
(26)

In each time slot, the amount of wind/solar power curtailment must obviously be smaller than the available wind/solar output power. Hence, we must have

$$0 \le P_{w,t}^{s,\mathsf{ws}} \le P_{w,t}^s, \quad \forall w, t, s.$$

$$(27)$$

$$0 \le P_{p,t}^{s, \mathsf{pvs}} \le P_{p,t}^s, \quad \forall p, t, s.$$
(28)

Note that spinning reserve and voluntary demand response load are not considered in our model; however, their integration into the model is straightforward.

## IV. SOLUTION APPROACH AND COMPUTATION TIME

The power scheduling and bidding problem for joint optimization of HVAC systems and distributed resources in the MG described in the previous section is a mixed integer linear program (MILP), which can be solved effectively by using available commercial solvers such as CPLEX [55]. The absolute terms in the objective function (1) can be easily transformed into equivalent linear functions by introducing some auxiliary variables [56].

Suppose that the forecasts for uncertain parameters in the considered system model are available. Available forecasting techniques (e.g., time series, artificial neural networks, support vector machines) for wind speed, electricity prices, temperature, solar radiation and load [23], [57]–[61] can be used to attain this. In practice, the MG aggregator can obtain forecast data from a local forecasting center. For simplicity, wind speed, non-HVAC load, solar irradiance, ambient temperature, day-ahead and real-time electricity prices are assumed to follow normal distributions where the means are set equal to the forecast values and the standard deviations are 10%, 3%, 10%, 5%, 5%, and 15% of the mean values, respectively. Furthermore, we assume that the system uncertainties are independent [53]. Modeling the correlation among the uncertain parameters [63]–[65] is beyond the scope of this paper.

Based on the distributions of uncertainty parameters, the Monte Carlo method and Latin Hypercube Sampling technique are employed to generate 3000 scenarios with even probability

Gen #	Туре	a (\$)	$\lambda(\$/kWh)$	$\mathbf{P}^{\min}(kW)$	$\mathbf{P}^{max}(kW)$
1	МТ	30	0.13	100	2000
2	MT	50	0.35	100	1000
3	FC	80	0.5	100	1000
Gen #	CU (\$)	CD (\$)	UT (hrs)	DT (hrs)	IC (hrs)
1	150	15	2	2	-2
2	30	3	0	0	-1
3	30	3	0	0	-1

TABLE I Conventional Unit Data

(1/3000) where each scenario contains the information of the hourly load, the hourly wind speed, hourly ambient temperature, hourly solar irradiance, and the DA and RT electricity prices over the operating day. The fast-forward reduction algorithm is utilized to reduce the original 3000 scenarios to 15 scenarios [50]. In particular, we used GAMS/SCENRED software to run the scenario reduction process [62]. In general, a larger number of scenarios results in higher computation time while a small number of scenarios may reduce the accuracy of the results. Considering the tradeoff between computational complexity and modeling accuracy, we decided to choose 15 as the reasonable number of reduced scenarios. Some sensitivity analysis has been conducted, which confirms that the variation of the objective function is sufficiently small if larger number of reduced scenarios is chosen. For brevity, these detailed sensitivity studies are not presented in this paper.

All the test cases presented in Section V are implemented on a desktop computer with 3.5 GHz Intel Core i7-3370 CPU and 16 GB RAM. The computational time needed to run scenario reduction from 3000 scenarios to 15 scenarios using GAMS/ SCENRED is recorded to be about 120 seconds. The calculation time (using CPLEX 12.4) for the proposed model with the 15 reduced scenarios is about 1 second, which is pretty small.

# V. NUMERICAL RESULTS

We consider a MG whose portfolio consists of three conventional generating units, one wind turbine, one solar source, 100 buildings with their associated loads, and an optional battery facility. The parameters of three conventional units including two microturbines (MT) and one fuel cell (FC) are taken from [5], which are summarized in Table I. For simplicity, the operating cost of each unit *i* is modeled by a single curve segment (m = 1) [5], [49]. The shutdown cost is assumed to be 10% of the start-up cost. The parameter IC in Table I presents the number of hours that a unit is ON (positive) or OFF (negative) at the beginning of the scheduling horizon.

We take the building thermal data from [11] and use the approach in our previous work [12] to model the diversity of thermal characteristics of buildings. We consider a summer case in this study; however, results for the winter case can be obtained similarly. We consider a 24-hour scheduling period where one time slot is one hour. Unless stated otherwise, we will set  $\delta_{j,t} = \delta_T$ ,  $\forall j, t$ ;  $\pi_{j,t} = \pi$ ,  $\forall j, t$ ;  $V_t^{PV} = V_t^W = V_t^{RES}$ ,  $\forall t$ ; and  $\psi_t = \psi$ ,  $\forall t$ .

The forecasts for uncertain parameters in the system model are assumed to be available. To run the simulation, we use the historical data for wind speed [66], non-HVAC load [48], solar irradiance [67], ambient temperature [68], day-ahead and real-time electricity prices [46] with appropriate scaling coefficients as in the forecasts. Figs. 1(a), (b), (c) show the hourly forecasts for the uncertain parameters in the considered model. Wind output power and solar output power can be calculated from the wind speed, solar irradiance, and ambient temperature by using (25) and (26), respectively. The parameters of the wind and solar sources are retrieved from [5] as follows:

- For wind source:  $P^{r} = 1000 \text{ kW}$ ,  $v^{ci} = 3 \text{ m/s}$ ,  $v^{r} = 12 \text{ m/s}$ ,  $v^{co} = 30 \text{ m/s}$ .
- For solar source:  $\eta = 15.7\%$  and  $S = 7000 \text{ m}^2$ . Under standard condition test (SCT) with ambient temperature of 25 °C, solar irradiance of 1000 W/m<sup>2</sup>, and at the maximum power point (MPP) [69], the rated PV power is 1100 kW.

System parameters for *the base case* are set as follows. The value of lost load  $V_t^{LL}$  is set to 1000 \$/MWh, the bid deviation penalty cost  $\psi_t$  is set to 80 \$/MWh, and no penalty cost for renewable power generation curtailment and indoor temperature deviation. The maximum involuntary load curtailment is set equal to 5% of the expected non-HVAC load in each time slot and no battery storage unit is included. Also, we do not consider the maximum power exchange constraints (4). Note that when we do not set a limit on the amount of power submitted to the day-ahead market, we need to set  $\psi_t$  sufficiently high to ensure the bid deviation is not too large and the actual power delivery is close the the day-ahead schedule.

We define the Load Scaling Factor (LSF) as the ratio between the total forecasted non-HVAC load and the total forecasted renewable energy generation over the scheduling period. For example, the LSF in Fig. 1(a) is equal to 0.5, which is chosen in the base case. For simplicity, we assume that all buildings are always occupied over the scheduling period. The desired temperature is set to 23 °C and the maximum allowable temperature deviation is set to 2 °C for all buildings in any time slots. The initial indoor temperatures of all buildings are assumed to be equal to the desired indoor temperature 23 °C. HVAC rated power in all buildings is set to 10 kW. The data defining *the base case* is given in Table II. For all figures presented in this section, only the system parameters explicitly presented in the figures are varied, other parameters are the same as in the base case.

Three control schemes are studied in this section as follows: **Scheme 1**: In this scheme, we apply to the proposed optimal scheme to the considered MG.

Scheme 2: In this scheme, we still apply the proposed optimal control scheme to the MG; however, the indoor temperatures of buildings are always maintained at the setpoint. In other word, no temperature deviation is allowed  $(\delta_T = 0)$ .

Scheme 3 (uncoordinated optimal scheme): In this scheme, HVAC systems and the rest of the MG optimize their power profiles separately (Problems 1 and 2 described below). Here, the objective of HVAC scheduling is set to minimize the operation cost of HVAC systems. HVAC systems submit their aggregated demand bids to the day-ahead



Fig. 1. Wind power, solar power, non-HVAC load, ambient temperature, and price forecasts. (a) Wind, solar and non-HVAC load forecasts; (b) Hourly forecasted day-ahead and real-time electricity prices; (c) Hourly forecasted ambient temperature.

TABLE II System Parameters in the Base Case

$V_t^{LL}$ (\$/MWh)	$\psi$ (\$/MWh)	$V^{RES}$ (\$/MWh)	π (S/°C)
1000	80	0	0
$\delta_T (^oC)$	LSF	$P_j^{hvac,max}$ (kW)	Battery
2	0.5	10	No

market and face the same penalty scheme for bid deviation charge as we described above. The technical constraints for HVAC system, thermal constraints for buildings, and others remain the same. The only the difference is that the power balancing equation (29) does not have the HVAC-related terms.

$$\begin{split} \min \quad & \sum_{s=1}^{NS} \rho_s \sum_{t=1}^{NH} \Delta T \left\{ P_t^{\text{hvac}} e_t^{s,\text{DA}} + \left( P_t^{s,\text{hvac}} - P_t^{\text{hvac}} \right) e_t^{s,\text{RT}} \right. \\ & + \pi_{j,t} \sum_{j=1}^{NB} \left| T_{j,t+1}^s - T_{j,t+1}^d \right| \\ & + \psi_t \left| P_t^{s,\text{hvac}} - P_t^{\text{hvac}} \right| \right\} \\ \text{s.t.} \quad & P_t^{s,\text{hvac}} = \sum_{j=1}^{NB} P_{j,t}^{s,\text{hvac}} \end{split}$$

and other constraints for HVAC system and thermal comfort requirement (15), (16), (17), and (18). Here,  $P_t^{\text{hvac}}$  and  $P_t^{s,\text{hvac}}$  are positive numbers which denote the imported power for HVAC systems.

*Problem 2:* For this problem, the expected profit for the MG is maximized. The objective function remains the same as (1) but the discomfort cost term is not included. The power balance equation now becomes

$$\sum_{i=1}^{NG} P_{i,t}^{s} + \sum_{w=1}^{NW} \left( P_{w,t}^{s} - P_{w,t}^{s,\text{ws}} \right) + \sum_{p=1}^{NP} \left( P_{p,t}^{s} - P_{p,t}^{s,\text{pvs}} \right) \\ + \sum_{k=1}^{NK} \left( P_{k,t}^{s,\text{d}} - P_{k,t}^{s,\text{c}} \right) + LS_{t}^{s} = P_{t}^{s} + L_{t}^{s}$$

and other constraints for the components in the MG are unchanged as described in the problem formulation.

#### A. Comparison Between Scheme 1 and Scheme 2

Fig. 2(a), 2(b) illustrate the advantages of the proposed optimal scheme, which exploits the flexibility offered by building thermal storage capacity, and the flexible comfort requirements (Scheme 1) compared to the case where no temperature deviation is allowed (Scheme 2 with  $\delta_T = 0$ ). As discussed in Section I, the curtailment of renewable energy generation is required in some cases to avoid the high penalty charge on bid deviation and to ensure that the real time power delivery is sufficiently close to the day-ahead schedule. Due to their flexibility, the HVAC systems could increase their power consumption by absorbing more energy from renewable sources to help the MG reduce the amount of renewable energy curtailment.

Fig. 2(a) confirms that the amount of renewable energy curtailment is reduced as  $\delta_T$  increases. Furthermore, the increase in discomfort penalty cost  $\pi$  results in more curtailed renewable energy. Fig. 2(b) shows the expected profit (i.e., the value of the objective function) for different values of  $\delta_T > 0$  and  $\pi$ . As evident, as  $\delta_T$  increases, the MG expected profit increases. Also, as the cost of temperature deviation  $\pi$  increases, the MG expected profit decreases. In fact, larger values of  $\delta_T$  (and/or smaller values of  $\pi$ ) enables more flexible scheduling of the HVAC power consumption, which results in larger performance gain in terms of both MG profit and renewable energy curtailment reduction.

## B. Comparison Between Scheme 1 and Scheme 3

Fig. 3(a), 3(b), and 3(c) show the advantages of the coordinated optimal scheme compared to the uncoordinated scheme versus the curtailment parameter  $V^{RES}$ . We compare the two



Fig. 2. Impacts of  $\delta_T$  and  $\pi$  on the optimal solution. (a) Renewable energy curtailment; (b) Expected profit.

schemes in two cases with and without battery. For the case with battery, one battery unit with capacity of 200 kWh is chosen where the charging/discharging power ratings are set equal to 100 kW. The minimum and maximum energy stored in the battery are 40 kWh and 180 kWh, respectively. Table III summarizes the parameters of the considered battery unit. We can see that the total amount of renewable energy curtailment is much smaller in the coordinated scheme compared with that of the uncoordinated one. This is because in the uncoordinated scheme, we do not exploit the flexibility offered by HVAC systems to absorb the fluctuation of renewable energy generation.

To mitigate the high penalty due to the bid deviation charge, some surplus renewable energy needs to be curtailed to ensure that the real-time power delivery is close to the day-ahead schedule. However, in the coordinated scheme, HVAC systems can increase their power consumption when the renewable energy sources produce surplus energy, which helps reduce the amount of renewable energy curtailment. Additionally, it can be observed that the amount of renewable energy curtailment decreases as  $V^{RES}$  increases and it tends to zeros as  $V^{RES}$  becomes larger. Fig. 3(b) shows that the bid deviation charges for the uncoordinated scheme is much higher than that in the coordinated scheme. This is because when the renewable energy generation is smaller than expected, in the coordinated scheme, we can reduce the power consumption of HVAC systems to reduce the charge due to the shortage of delivered power to the market as being scheduled in advance. Finally, the expected profit for the MG is also higher in the coordinated scheme than the one in the uncoordinated scheme as shown in Fig. 3(c).



Fig. 3. Comparison between coordinated and uncoordinated schemes. (a) Renewable energy curtailment; (b) Expected bid deviation charge; (c) Expected profit.

TABLE III BATTERY PARAMETERS

$E^{cap}$ (kWh)	E <sup>min</sup> (kWh)	$E^{\max}(\mathbf{kW})$	
200	40	180	
P <sup>c,max</sup> (kW)	$\mathbf{P}^{d,max}(kW)$	$C^{\text{wear}}(8/kWh)$	
100	100	0.00027 [17]	

# C. Sensitivity Analysis

We now investigate the impacts of various design and system parameters on the optimal solution.

Fig. 4(a) and 4(b) illustrate the impacts of temperature deviation penalty  $\cot \pi$  on the optimal solution. Specifically, Fig. 4(a)



Fig. 4. Impact of temperature deviation penalty  $(\pi)$  on the optimal solution. (a) Renewable energy curtailment; (b) Expected profit.

confirms that the energy curtailment tends to increase as  $\pi$  increases. This is due to the fact that as  $\pi$  increases, the indoor temperature is forced to be closer to the desired value  $(T^d)$  to reduce the climate discomfort cost, which means we have the less flexibility in controlling the HVAC power consumption. Moreover, the amount of renewable energy curtailment becomes saturated at certain values of  $\pi$  where the indoor temperature of all buildings becomes very close to the desired temperature. Also, we can see that the expected profit of the MG decreases and becomes flattened as  $\pi$  is sufficiently large as shown in Fig. 4(b).

In addition, as parameter  $\psi$  increases, we expect that the bid deviation becomes smaller to avoid the high bid deviation penalty cost, which results in less flexibility in controlling the operation of the MG. Therefore, the expected profit for the MG decreases and the amount of renewable energy curtailment increases as  $\psi$  increases, which is confirmed by the results in Figs. 4(a), 4(b), 5(a), and 5(b).

Fig. 6(a), 6(b) illustrate the variation of the amount of total renewable energy curtailment and the MG expected profit versus the HVAC rated power. This figure shows that lower amount of renewable energy curtailment and higher MG expected profit can be achieved as the HVAC rated power increases, which indeed offers more flexibility in controlling the HVAC power consumption. However, with each value of battery capacity, the quantities are saturated at certain values of HVAC rated power, which can be interpreted as follows. The HVAC power consumption can only be varied within a certain range to meet the indoor temperature comfort requirement. Here, the minimum and maximum energy levels stored in the battery are set equal to 20% and 90% of the battery capacity. The maximum charging/ discharging rate of battery is set equal to 100 kW.



Fig. 5. Impacts of  $\psi$  and  $V^{RES}$  on the optimal solution. (a) Renewable energy curtailment; (b) Expected profit.



Fig. 6. Impacts of  $\psi$  and  $V^{RES}$  on the optimal solution. (a) Renewable energy curtailment; (b) Expected profit.

The impact of the maximum allowable power exchange between the MG and the main grid  $(P^{g,max})$  on the optimal

4500





Fig. 7. Impact of  $P^{g,max}$  on the optimal solution. (a) Renewable energy curtailment; (b) Expected profit.

solution is presented in Fig. 7(a) and 7(b). In particular, Fig. 7(a) shows that the amount of renewable energy curtailment increases for decreasing  $P^{g,max}$ . This can be interpreted as follows. If  $P^{g,max}$  is small and the amount of available renewable energy is large, then the HVAC systems may not be able to absorb all the surplus renewable energy due to the temperature comfort constraint, and  $P^{g,max}$  directly affects the ability of exchange power between the MG and the main grid. Therefore, more power curtailment is expected as  $P^{g,max}$  is small. Also, the  $P^{g,max}$  parameter has a direct impact on the ability of the MG in offering bid to the power market; therefore, the expected profit of the MG increases before getting saturated as  $P^{g,max}$  increases as being shown in Fig. 7(b).

The variations in expected profit of the MG with different values of the LSF and P<sup>g,max</sup> are presented in Fig. 8(a). Here, the negative value of expected profit corresponds to the case where the MG needs to purchase additional energy from the main grid on average; in other words, the MG has to pay the main grid operator for its operation. This is the case when the local load consumes more energy than what can be generated by the local renewable energy sources. The deficit amount of energy must, therefore, be compensated by importing energy from the main grid. Note also that as the LSF is sufficiently high, the MG may need to operate its local conventional generation units due to the constraints on the maximum amount of imported power. The conventional units in the considered model are only needed for backup purposes because their operation cost is relatively high, which implies that importing energy from the grid might be more cost-efficient than running conventional units to serve the local demand. The optimal bid quantities submitted to the day-ahead market for different values of the LSF are shown in Fig. 8(b). Here, if the power bid is negative, the MG imports power from the main grid.



Fig. 8. Impacts of  $P^{g,max}$  and LSF on the optimal solution. (a) Expected profit; (b) Day-ahead hourly bids.



Fig. 9. Impact of uncertainty level on the expected optimal profit.

To investigate the impact of the uncertainty level on the optimal solution, we utilize the *uncertainty scaling factor* (USF) where *the base case* described in Section IV has USF = 1. Also, we scale the standard deviations of uncertain parameters in the base case by the factor of USF to obtain the result presented in Fig. 9. It can be observed that the MG expected profit decreases as USF increases (i.e., the uncertainty level increases).

Finally, we show the impact of battery operation cost (degradation) parameter  $C^{deg}$  on the gain as battery storage is utilized. The presented gain captures the difference between the expected profit when using the battery and when not using the battery. It can be observed from Fig. 10 that the gain due to utilizing battery storage facility decreases and becomes saturated as  $C^{deg}$  increases. This can be interpreted as follows. If  $C^{deg}$  is sufficiently high, the cost saving due to energy storage can be neutralized by the battery degradation (wear) cost. In general, if  $C^{deg}$  is small then utilization of battery storage can result in positive performance gain.



Fig. 10. Impacts of battery charging and discharging (degradation) cost.

# VI. CONCLUSION

In this paper, we have proposed an optimal power scheduling framework for a MG with renewable energy considering users thermal comfort requirements and other system constraints. Extensive numerical results have been presented to illustrate the great benefits of our design in reducing the renewable energy curtailment, mitigating the high penalty due to energy imbalance, and increasing the expected profit for the MG by exploiting the building thermal dynamics. Based on these numerical studies, the following conclusions are in order.

- 1) Coordination of HVAC load (or in general flexible loads) and RESs through a unified energy management framework is important. Integrating flexible HVAC load scheduling into energy management decisions of the MG aggregator can increase significantly its expected profit and reduce the amount of renewable energy curtailment, which also helps avoid the high energy imbalance charge caused by bid deviation.
- 2) The benefits of the proposed coordinated scheme depend on the flexibility offered by the HVAC system. Specifically, the expected profit of the MG aggregator increases and the amount of renewable energy curtailment decreases as the maximum allowable temperature deviation  $(\delta_T)$  increases, the cost of temperature deviation decreases, and the rated power of HVAC systems increases. However, the performance gain becomes saturated at certain values of  $\delta_T$ ,  $\pi$ , and the HVAC rated power.
- 3) Cost of bid deviation ( $\psi$ ) and cost of renewable energy curtailment  $(V^{\mathsf{RES}})$  have significant impacts on the optimal solution. In particular, the MG expected profit decreases and the amount of renewable energy curtailment increases as  $\psi$  increases and/or  $V^{\text{RES}}$  increases.
- 4) Battery storage can help the MG aggregator reduce the amount of renewable energy curtailment and increase the expected profit. The expected profit of the MG aggregator increases and the amount renewable energy curtailment decreases as the maximum power exchange limit between the MG aggregator and the main grid  $(P^{g,max})$  increases. However, it is saturated as  $P^{g,max}$  becomes sufficiently large. Finally, the uncertainty level has significant impacts on the optimal solution.

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