Multi-time scale optimization of urban micro-grids considering high-penetration of PVs and heterogeneous energy storage systems

Yingcong Sun, *Student Member, IEEE*, Hongxun Hui, *Member, IEEE*, Taoyi Qi, *Student Member, IEEE*, Laijun Chen, *Member, IEEE*

***Abstract*—The increasing penetration of distributed photovoltaics(PV) brings volatility and uncertain power outputs to micro-grids. Larger local regulation capacity is needed for maintaining the system balance between power supply-side and demand-side. It is promising to utilize widely distributed demand-side resources to provide regulation services, such as battery energy storage system (BESS), heating, ventilation, and air conditioning (HVAC), et al. However, most heterogeneous demand-side resources are regulated without coordination, resulting in the insufficient utilization of the regulation potential. To address this issue, this paper establishes a multi-time scale optimization model for micro-grids considering large-scale heterogeneous BESS and HVAC. Firstly, elements inside the urban micro-grids are modelled, where the HVAC systems and buildings are modelled as building based energy storage systems(BBESS), providing short-term energy storage. Then, a day-ahead optimization is carried out with the participation of day-ahead electricity market and ancillary market. Next, an intra-day rolling optimization is carried out in the real-time market. Finally, the case study shows that lower operation cost of the urban micro-grid and higher self-consumption rate of PV can be achieved by applying the proposed method, and BBESS can replace the demand for energy storage construction to a large extent.**

***Index Terms*—Photovoltaic, urban micro-grids, HVAC, heterogeneous energy storage systems, multi-time scale**

NOMENCLATURE

Abbreviations

RES	Renewable energy sources
PV	Photovoltaics
HVAC	Heat, ventilation, and air conditioning
BESS	Battery energy storage systems
BBESS	Building based energy storage systems
MILP	Mixed integer linear programming
QP	Quadratic programming

This work is funded in part by the Science and Technology Development Fund, Macau SAR (File no. 001/2024/SKL, and File no. 0117/2022/A3), in part by the Start-up Research Grant of University of Macau (File no. SRG2023-00063-IOTSC), and in part by the Natural Science Foundation of Guangdong Province, China (Grant No. 2414050004006). The corresponding author is *Hongxun Hui*.

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Variables/Parameters

P_{buy}, P_{sell}	electricity bought from or sold to the grid
P_{dis}, P_{char}	charging power and discharging power of BESS
P_{load}	power consumption of fixed loads
P_{PV}	power generated from PV
P_{HVAC}	power consumption of HVAC systems
e_{PV}	relative error of prediction on PV generation
σ_{DA}	variance of the relative prediction error in day-ahead stage
σ_{RT}	the common difference for variance of the prediction error over time
$\sigma_{RT,0}$	the variance of the relative prediction error of the first prediction time period in the real-time stage
τ_{char}, τ_{dis}	charging and discharging state of BESS
S_{bat}	energy stored in the BESS
SoC	state of charge of BESS
η	efficiency of BESS
C_m	heat capacities of heat accumulating medium
C_i	heat capacities of indoor air / equivalent heat capacity in the *i*th room
R_{im}, R_{ia}	thermal resistance against heat transfer between indoor air and heat accumulation medium, and external air
T_i	temperature of indoor air (of the *i*th room)
T_a, T_m	temperature of environment and heat accumulating mediums
η_{COP}, η_{EER}	heating coefficient and cooling coefficient of HVAC systems
A	effective window area of the building
p	fraction of solar irradiance which directly affects T_m
ϕ_m	solar irradiance
C_{air}	specific heat capacity of air
ρ_{air}, V_i	density and volume of indoor air
S_i	energy stored in the *i*th BBESS
$P_{fix,i}$	equivalent fixed load of the *i*th HVAC systems
C^{DA}, C^{RT}	day-ahead and real-time electricity price
τ_{HVAC}	state of HVAC systems
C^{tr}	transmission fee
R_{PR}	unit revenue from peak regulation ancillary

	service
P_{PR}	power for peak regulation
τ_{PR}	state of peak regulation

Superscript

DA	value in the day-ahead stage
RT	value in the real-time stage
$pred$	predicted value
$real$	realistic value

Subscript/index

t	index of time slot
max	the upper bound of the value
min	the lower bound of the value

I. Introduction

WITH the concerns of environmental pollution and the crisis of fuel energy, the technologies of renewable energy resources (RES) are developing rapidly [1]. As the urban micro-grids have become the main body of energy consumption in modern power systems [2], they should take the responsibility of cutting carbon emissions and saving energy resources. Therefore, many renewable distributed generators, such as photovoltaics (PV) and wind turbines, are established in the urban micro-grids [3], and provide more power supply for the consumers [4]. However, PV output shows significant time and weather dependence [5] and is characterized by uncertainty and volatility [6]. Due to these identities of PV, larger local regulation capacity is needed for maintaining the system balance between power supply-side and demand-side.

With the development of the technologies of communication and internet of things [7], it is promising to utilize widely distributed demand-side resources in urban micro-grids to provide regulation services and accommodate RES, such as battery energy storage system (BESS), heating, ventilation, and air conditioning (HVAC), et al [8]. The technology of BESS has developed rapidly and is applied widely because of fast response and reliability [9]. Several studies have been conducted on the energy management of BESS to maximize profits or satisfy reliability requirements. In [10], an operational optimization model of BESS considering the degradation is proposed to determine the residential energy storage capacity, which improves the return on investment. In [11], several optimization models of BESS are reviewed and compared. These studies introduce typical application, sizing, and control methods of a single BESS, which is not economically efficient enough. In addition, due to the high cost of BESS and the limited space in urban areas [12], it is difficult to build a large capacity of BESS in urban micro-grids.

Since the existing power systems lack BESS [13], dispatching flexible loads or virtual energy storage systems (e.g., HVAC) becomes more and more popular in many researches [14], [15]. HVAC systems can play a similar role as BESS in some specific situations. In [16], Ghasem et al. propose a stochastic-robust strategy and find that the resiliency of the smart distribution grid can be improved by integrating flexible loads. In [17], Liu et al. propose an optimal dispatch strategy to allow HVAC systems to participate in frequency regulation. In urban micro-grids, the HVAC systems consume a large amount of energy, and therefore have great potential to participate in the regulation of micro-grids [18]. The buildings have the ability to store heat or cold temporarily, so they can be regarded as a kind of virtual energy storage systems, which is called building based energy storage systems (BBESS). in [19]. Modeling and dispatching the BBESS properly can relieve the pressure of insufficient capacity of BESS and reduce the requirement for energy storage configuration. In [20], Nagpal et al. propose a second-order model for the BBESS and controlled the energy consumption with local energy management systems, while it does not consider the interaction with other BESS. In [21], an accurate model for BBESS is established via EnergyPlus and is applied in the cost-optimal operation model of smart buildings, while the model is too complex to be applied in large-scale problems. Besides, few researches about HVAC systems' dispatch consider the participation of different markets.

The BESS and BBESS have different characteristics, especially in the perspectives of capacity scale and duration time for energy storage. Besides, short-term forecasts on PV or loads are more accurate than long-term forecasts. To take advantage of the characteristics of different energy storage systems and the accurate short-term forecast results, the method of multi stage optimization can be applied to dispatch BESS and BBESS coordinately. In [22], Cheng et al. establish a multi-time scale coordinated optimization framework of energy hub operation. The model consists of day-ahead optimization, intra-day optimization, and real-time optimization, whose targets are minimum operation cost, minimum market cost, and minimum total adjustment amount separately. In this model, the dramatic fluctuation of the electricity price in the real-time market is not considered. In [23], Watari et al. propose a multi-time scale energy management framework for PV system to schedule BESS operation and appliance usage, considering a coarse-grained time scale with 15min resolution and fine-grained time scale with 1s resolution. The mix of fast and slow system dynamics reduces electricity costs by 48.1%. In [24], Jani et al. propose a multi-objective two-stage optimization model for the operation planning of multi-micro-grids taking account into flexible loads and uncertain RES. The model can lower operating costs and reduce carbon emissions, while the load is modeled simply without consideration of the actual identity. In [25], a two-stage stochastic optimization model is proposed for the operation of virtual power plants (VPP), where BESS, thermal energy storage systems and flexible loads are included. The model considers the participation in the day-ahead and real-time market to maximize profit and guarantee the resiliency of the VPP. Overall, most of the current studies focused on the multi-time dispatch apply over-simplified flexible load models such as interruptible or shiftable loads, which cannot consider the characteristics of specific loads like HVAC.

Considering the shortcomings of the literature, the objective in this research is to develop a multi-time scale centralized optimization model considering BESS and BBESS in the PV-powered urban micro-grids. Firstly, the models of each element in the urban micro-grids are established and the features of BESS and BBESS are compared. After that, multi-time scale optimization is conducted. The first stage is day-ahead optimization. Based on the forecasts of the output of PV and the electricity price of day-ahead market, the micro-grids operator tries to minimize the operation cost by controlling the power consumption of BESS and the HVAC systems. Then the operator submits the power purchase and sale scheme to the main grid. After the peak-regulation ancillary service market opens, the operator will decide whether to participate in the market and how much to provide to maximize the profits. In the second stage, an intra-day rolling optimization model is applied to minimize the adjustment amount and the cost in the real-time market with a more accurate forecast result.

The main contributions of this research can be summarized below:

(1) A two-stage optimization model is proposed for the operation of the urban micro-grids considering multi-type energy storage systems. Different characteristics of BESS and BBESS are analyzed and considered in the model. They are dispatched in different time scales based on spot markets and peak regulation ancillary markets to minimize the operation cost. By dispatching them coordinately, a larger equivalent energy storage capacity can be achieved.

(2) In this two-stage optimization model, the day-ahead optimization model is a mixed-integer linear programming (MILP) problem, and the intra-day optimization model is a quadratic programming (QP) problem, which are both easy to solve with a commercial solver. The intra-day optimization model can track the dramatic fluctuation of the electricity price in the real-time market while taking into account the price of electricity throughout the day.

II. Models for the urban micro-grids

A. Framework of the urban micro-grids

A typical urban micro-grid is shown in Fig. 1. It is connected to the main grid, consisting of PV generators, BESS, HVAC systems considered as BBESS, and fixed loads. Due to the development of the technologies of Internet of Things, it is technically feasible for energy management systems (EMS) to obtain the data from the elements and control power generation and consumption. In the urban micro-grids, the PV can supply electricity to the consumers, and the BBESS will adjust the power supply and consumption together with the BESS. The urban micro-grid will purchase or sell electricity if there is a shortage or surplus of electricity.

B. System model

In the urban micro-grids, demand and supply balance must be achieved:

$$P_{buy,t}+P_{PV,t}+P_{dis,t} = P_{sell,t}+P_{HVAC,t}+P_{load,t}+P_{char,t} \quad (1)$$

where $P_{buy,t}$ and $P_{sell,t}$ are the power bought from or sold to the grid at t, respectively; $P_{PV,t}$ is the power generated from PV at t; $P_{HVAC,t}$ is the power consumption of all HVAC systems in the urban micro-grids; $P_{load,t}$ is the power consumption of

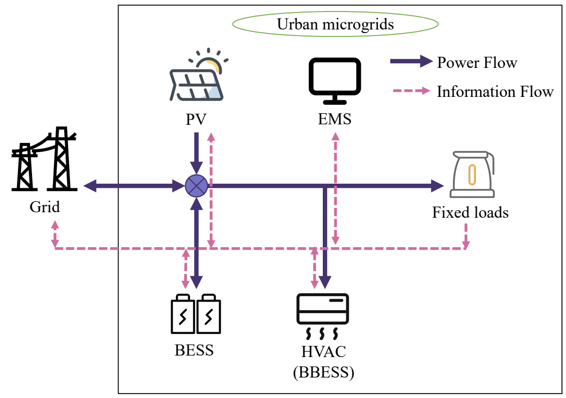

Figure 1. The scheme of typical urban micro-grids.

fixed loads at t; and $P_{char,t}$ and $P_{dis,t}$ denote the charging power and discharging power of BESS at t, respectively.

The urban micro-grids also need to satisfy the following restrictions:

$$P_{buy,t} \leq P_{buy,max} \quad (2)$$

$$P_{sell,t} \leq P_{sell,max} \quad (3)$$

where $P_{buy,max}$ is the maximum bound of power input from grid and $P_{sell,max}$ is the maximum bound of power output to the grid.

C. PV model

The power output of PV is predicted in advance. Denote $P_{PV,t}^{pred}$ as the predicted maximum power output of PV at t, and denote $P_{PV,t}$ as the scheduled power output during operation. The PV needs to satisfy the restriction:

$$P_{PV,t} \leq P_{PV,t}^{pred} \quad (4)$$

The PV output needs to be predicted in advance. Let $P_{PV,t}^{real}$ be the realistic PV output, and $e_{PV,t}^{pred}$ be the relative error of prediction. It is calculated by:

$$P_{PV,t}^{pred} = P_{PV,t}^{real}(1+e_{PV,t}^{pred}) \quad (5)$$

In day-ahead stage, the relative prediction error usually satisfies the Gaussian distribution.

$$e_{PV,t}^{DA,pred} \sim N(0,\sigma_{DA}^2) \quad (6)$$

where σ_{DA} is the variance of the relative prediction error in day-ahead stage.

In real-time stage, short-term prediction is executed, and the prediction error is larger if the time is far from when the prediction is made. The prediction error is modelled as a discrete time Markov chain, and is expressed in the following equation:

$$e_{PV,t+1}^{RT,pred} - e_{PV,t}^{RT,pred} \sim N(0,\sigma_{RT}^2) \quad (7)$$

$$e_{PV,1}^{RT,pred} \sim N(0,\sigma_{RT,0}^2) \quad (8)$$

where $\sigma_{RT,0}$ is the variance of the relative prediction error of the first prediction time period; σ_{RT} is the common difference for the variance of the prediction error over time.

D. BESS model

The BESS charges during the low electricity price period or the period that the micro-grids provide peak-regulation ancillary service. It switches to the discharging state when the price is high. During operation, the BESS needs to comply with the following restrictions:

$$P_{char,t} \leq \tau_{char,t} P_{char,max} \tag{9}$$

$$P_{dis,t} \leq \tau_{dis,t} P_{dis,max} \tag{10}$$

$$\tau_{char,t} + \tau_{dis,t} \leq 1 \tag{11}$$

$$S_{bat,t+1} = S_{bat,t} + \eta P_{char,t} \Delta t - P_{dis,t} \Delta t / \eta \tag{12}$$

$$SoC_t = S_{bat,t} / S_{bat,r} \tag{13}$$

$$SoC_t \leq SoC_{max} \tag{14}$$

$$SoC_t \geq SoC_{min} \tag{15}$$

Eqs. 9 and 10 imply the power bounds of charging and discharging, respectively; $P_{char,max}$ and $P_{dis,max}$ are the maximum power of charging and discharging of BESS, respectively; $\tau_{char,t}$ and $\tau_{dis,t}$ are binary variables and shows the state of BESS. Eqs. 11 shows that BESS cannot be charged and discharged at the same time. Eqs. 12 and 13 show the level of stored energy in the BESS; $S_{bat,t}$ means the energy stored in BESS at t; $S_{bat,r}$ is the maximum capacity of BESS; SoC_t is the state of charge (SoC) of BESS; η is the efficiency of BESS. Eqs. 14 and 15 imply the maximum and minimum SoC bounds of BESS, respectively. SoC_{min} and SoC_{max} are minimum SoC and maximum SoC of BESS, respectively.

E. BBESS model

Buildings can store heat or cold generated by HVAC systems and can be considered as BBESS. In [20], Nagpal et al. apply the following differential equations to describe the thermal dynamics of BBESS when HVAC systems work at the heating condition.

$$C_m \dot{T}_m = \frac{T_i - T_m}{R_{im}} + A \cdot p \cdot \phi_m \tag{16}$$

$$C_i \dot{T}_i = \frac{T_m - T_i}{R_{im}} + \frac{T_a - T_i}{R_{ia}} + \eta_{COP} P_{HVAC} + A \cdot (1-p) \cdot \phi_m \tag{17}$$

where C_i and C_m are the heat capacities of indoor air and heat accumulating medium such as furniture, respectively; T_i, T_m and T_a are the temperature of indoor air, heat accumulating medium and environment, respectively. R_{im} and R_{ia} are the thermal resistance against heat transfer between indoor air and heat accumulation medium, and external air, respectively; A is the effective window area of the building and p is the fraction of solar irradiance which directly affects T_m; ϕ_m is the solar irradiance; η_{COP} is the heating coefficient of HVAC systems; P_{HVAC} is the power consumption of HVAC systems.

Considering the relatively long time resolution (15min or 1h) in the study, the temperature of indoor air and heat accumulating medium is almost the same. Suppose the HVAC systems are working at cooling conditions, the model can be simplified and discretized as follows:

$$C_i(T_{i,t+1} - T_{i,t}) = (\frac{T_{a,t} - T_{i,t}}{R_{ia}} - \eta_{EER} P_{HVAC,i,t} + A_i \phi_{s,t}) \Delta t \tag{18}$$

where η_{EER} is the cooling coefficient of the HVAC systems; C_i is the equivalent heat capacities of the ith building and can be calculated with the following equation.

$$C_i = \gamma C_{air} \rho_{air} V_i \tag{19}$$

where C_{air} is the specific heat capacity of air; ρ_{air} and V_i are the density and volume of air in the room, respectively; γ is the coefficient to calculate the total capacity considering the heat accumulating mediums.

Besides, the HVAC systems need to comply with the following restrictions:

$$P_{HVAC,i,t} \leq \tau_{HVAC,i,t} P_{HVAC,max} \tag{20}$$

$$P_{HVAC,i,t} \geq \tau_{HVAC,i,t} P_{HVAC,min} \tag{21}$$

where $\tau_{HVAC,i,t}$ is the state of the ith HVAC at t as a 0-1 variable; $\tau_{HVAC,i,t} = 0$ means the HVAC system is shut down and $\tau_{HVAC,i,t} = 1$ means the HVAC system is working; $P_{HVAC,max}$ and $P_{HVAC,min}$ are the maximum and minimum power of HVAC systems in the operation mode, respectively.

The HVAC systems are supposed to maintain the indoor temperature within the comfortable range. The indoor temperature needs to comply with these restrictions:

$$T_{i,t} \leq T_{i,t,max} \tag{22}$$

$$T_{i,t} \geq T_{i,t,min} \tag{23}$$

where $T_{i,t,max}$ and $T_{i,t,min}$ are the maximum and minimum comfortable temperature in the ith building at t, respectively.

F. Comparisons between BESS model and BBESS model

The thermal dynamics of BBESS (Eq. 18) can be altered as follows:

$$S_{i,t+1} - S_{i,t} = P_{HVAC,i,t} \Delta t - \frac{1}{C_i R_{ia}} S_{i,t} \Delta t - P_{fix,i,t} \Delta t \tag{24}$$

where

$$S_{i,t} = -\frac{C_i}{\eta_{EER}} (T_{i,t} - T_{i,t,max}) \tag{25}$$

$$P_{fix,i} = \frac{A_i}{\eta_{EER}} \phi_{s,t} + \frac{T_a - T_{i,t,max}}{\eta_{EER} R_{ia}} \tag{26}$$

Suppose the comfortable temperature range is constant. Eq. 24 has a similar form as Eq. 12. Eq. 24 suggests that the buildings and HVAC systems can be considered and modelled as two parts: virtual energy storage systems and fixed loads. For the part of virtual energy storage system, parameter $S_{i,t}$ is the energy stored in the energy storage systems, which is only related to the indoor temperature according to Eq. 25; $\frac{1}{C_i R_{ia}} S_{i,t}$ is the power leakage, with a linear relationship with $S_{i,t}$. We define leakage time constant $\tau_i = C_i R_{ia}$ to show

Table I
COMPARISON OF CHARACTERISTICS BETWEEN BBESS AND BESS

Parameters	BESS	BBESS
Energy storage capacity	$S_{bat,r}$	$\frac{C_i}{\eta_{EER}}(T_{i,max} - T_{i,t})$
State of charge	SoC_t	$\frac{T_{i,max} - T_{i,t}}{T_{i,max} - T_{i,min}}$
Efficiency	η	1
Leakage time constant	∞	$C_i R_{ia}$

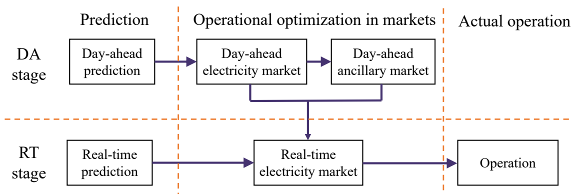

Figure 2. Block diagram of market participation and operation process.

the rate of energy leakage of BBESS. Parameter P_{fix} can be considered as fixed loads and is determined by environmental temperature and solar radiance only according to Eq. 26. Table I compares the characteristics between the kind of virtual energy storage systems, BBESS in other words, and BESS.

III. OPTIMIZATION MODEL IN MARKETS

A. Operation process and market model

The profile of the market participation and the operation process of the studied micro-grids is shown in Fig. 2. On the day before the operation, the day-ahead predictions of the output of PV, power consumption of loads, temperature et al. are conducted. Then, the urban micro-girds participate in the day-ahead electricity market as price takers. Based on the information of the prediction and electricity prices, the day-ahead optimization is carried out to minimize the cost in the market. After that, the urban micro-grids provide peak-regulation ancillary service in the day-ahead ancillary market with flexible resources to get profits. In the day-ahead stage, the urban micro-grids declare a plan of power purchase and sale, and get the baseline of power generation and consumption of each element. In the real-time stage, more accurate predictions are conducted first. Based on the prediction and the baseline from the day-ahead stage, the urban micro-grids participate in the real-time electricity market as a price taker to balance the load and supply. Besides, the main grid charges transmission fee for electricity bought by the micro-grid.

The model for the peak regulation ancillary service market is described as follows:

Denote a tuple $R_i = (t_{start,i}, t_{end,i}, P_{PR,i}, R_{PR,i})$ to represent the ith peak regulation ancillary service. The ancillary service market is open between $t_{start,i}$ and $t_{end,i}$, and the urban micro-grids need to claim the peak regulation amount $P_{PR,i}$. To satisfy the amount, the micro-grids have to increase the consumption or decrease power generation by $P_{PR,i}$ during

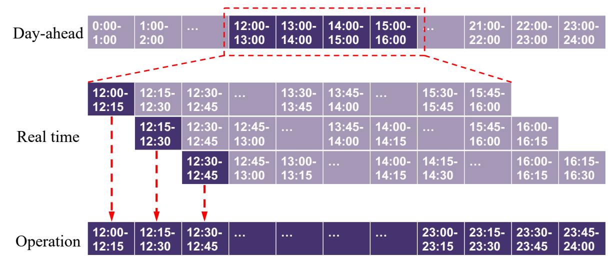

Figure 3. Optimization and operation process of urban micro-grids.

$(t_{start,i}, t_{end,i})$, and earn revenue of $R_{PR,i}P_{PR,i}(t_{end,i} - t_{start,i} + 1)\Delta t$.

The optimization and operation process are shown in Fig. 3. In the day-ahead stage, the power generation and consumption of each element are optimized within 24 hours with a resolution of 1h. Firstly, an optimization with electricity market participation only is conducted, and a baseline of energy generation and consumption is claimed. Then, another optimization with ancillary service market is executed based on the baseline. Finally, in the real-time stage, a rolling optimization is conducted every 15min with a resolution of 15min. In each optimization process, the operation of 4h is optimized based on the prediction and market price, and only the result of the first 15min is executed.

B. Day-ahead optimization

1) Participate in the electricity market only: The objective of the optimization in the day-ahead electricity market is to minimize the total cost. The objective function can be described as follows:

$$\begin{aligned} min\ f = \sum_t C_t^{DA}(P_{buy,t}^{DA,a} - P_{sell,t}^{DA,a}) + \sum_t C^{tr} P_{buy,t}^{DA,a} \\ + \beta \sum_{t,i} |\tau_{HVAC,i,t+1}^{DA,a} - \tau_{HVAC,i,t}^{DA,a}| \end{aligned} \tag{27}$$

where C_t^{DA} is the electricity price at t in the day-ahead electricity market; $P_{buy,t}^{DA,a}$ and $P_{sell,t}^{DA,a}$ are the power bought from or sold to the grid in this step, respectively; C^{tr} is the transmission fee charged by the grid; β is the punishment coefficient of switching on or off the HVAC.

In this stage, time resolution $\Delta t = 1h$ and the time period $T = 24$. Constrains include Eqs. 1, 2, 3, 4, 9, 10, 11, 12, 13, 14, 15, 18, 20, 21, 22, 23. Besides, the SoC of BESS need to comply the restriction to guarantee the operation after the day studied:

$$SoC_0 = SoC_T \tag{28}$$

This optimization is an MILP problem, and can be easily solved by commercial solvers such as Gurobi.

2) Participate in the ancillary market: The objective of the optimization in this step is to get revenue from providing peak regulation ancillary service and minimize the operation cost. The objective function is:

$$\begin{aligned} min\ f = &\sum_t C_t^{DA}(P_{buy,t}^{DA} - P_{sell,t}^{DA}) + \sum_t C^{tr} P_{buy,t}^{DA} \\ &+\beta \sum_{t,i} |\tau_{HVAC,i,t+1}^{DA} - \tau_{HVAC,i,t}^{DA}| \\ &- \sum_i R_{PR,i} P_{PR,i}(t_{end,i} - t_{start,i} + 1)\Delta t \end{aligned} \tag{29}$$

where $P_{buy,t}^{DA}$ and $P_{sell,t}^{DA}$ are the power bought from or sold to grid in this step, respectively.

Constrains include Eqs. 1, 2, 3, 4, 9, 10, 11, 12, 13, 14, 15, 18, 20, 21, 22, 23, 28. Besides, the following constrains about peak-regulation service should also be complied:

$$\begin{aligned} &P_{buy,t}^{DA} - P_{sell,t}^{DA} \geq (P_{buy,t}^{DA,a} - P_{sell,t}^{DA,a} + P_{PR,i}) \\ &-(1-\tau_{PR,i})P_{large}, \quad \forall t \in [t_{start,i}, \leq t_{end,i}] \end{aligned} \tag{30}$$

$$\tau_{PR,i} P_{PR,i,min} \leq P_{PR,i} \leq \tau_{PR,i} P_{PR,i,max} \tag{31}$$

where $\tau_{PR,i}$ is a binary variable representing whether the urban micro-grids provide the peak regulation ancillary service. If $\tau_{PR,i} = 1$, the urban micro-grids choose to provide ancillary service to the grid, and vice versa. Parameter P_{large} is a constant big number to ensure Eq. 30 always satisfies if $\tau_{PR,i} = 0$. Eq. 31 imply the power bounds of the ancillary service. Parameters $P_{PR,i,min}$ and $P_{PR,i,max}$ are the minimum and maximum power the urban micro-grids can provide ancillary service of, respectively.

This optimization problem in the ancillary market is an MILP problem, and can also be easily solved by commercial solvers.

C. Intra-day rolling optimization

In real-time stage, intra-day rolling optimization is carried out with time resolution $\Delta t = 0.25$ and the time period $T = 16$ in each optimization. The objective of each optimization is to minimize the operation cost in the real-time market, while minimizing the amount of adjustment to follow the result from day-ahead stage. The objective function is proposed as follows:

$$\begin{aligned} min\ g = &\sum_t C_t^{RT}((P_{buy,t}^{RT} - P_{buy,t}^{DA}) - (P_{sell,t}^{RT} - P_{sell,t}^{DA})) \\ &+ C^{tr} \sum_t (P_{buy,t}^{RT} - P_{buy,t}^{DA}) \\ &+ a_1 \sum_t (P_{char,t}^{RT} - P_{char,t}^{DA})^2 \\ &+ a_2 \sum_t (P_{dis,t}^{RT} - P_{dis,t}^{DA})^2 \\ &+ a_3 \sum_{i,t} (P_{HVAC,i,t}^{RT} - P_{HVAC,i,t}^{DA})^2 \\ &+ a_4 \sum_t (S_{bat,t}^{RT} - S_{bat,t}^{DA})^2 \\ &+ a_5 \sum_{i,t} (T_{i,t}^{RT} - T_{i,t}^{DA})^2 \end{aligned} \tag{32}$$

Table II
PARAMETER CONFIGURATION OF THE ELEMENTS IN THE URBAN MICRO-GRIDS

Facility	Parameters/units	Values
BESS	$P_{char,max}/kW$	300
	$P_{dis,max}/kW$	300
	$S_{bat,r}/kWh$	600
	SoC_{max}	0.9
	SoC_{min}	0.1
	η	90%
HVAC systems in resident rooms	$C_r/kJ \cdot K^{-1}$	100*20
	$R_{ra}/K \cdot kW^{-1}$	3.5
	$\eta_{EER,r}$	3.3
	$P_{HVAC,r,max}/kW$	2.0
	$P_{HVAC,r,min}/kW$	0.1
	$T_{r,max}/^\circ C$	24
	$T_{r,min}/^\circ C$	21.5
	n_r	600
	A_r/m^2	1
HVAC systems in offices	$C_w/kJ \cdot K^{-1}$	100*20
	$R_{wa}/K \cdot kW^{-1}$	3.5
	$\eta_{EER,w}$	3.3
	$P_{HVAC,w,max}/kW$	2.0
	$P_{HVAC,w,min}/kW$	0.1
	$T_{w,max}/^\circ C$	23
	$T_{w,min}/^\circ C$	21.5
	n_w	400
	A_w/m^2	1

where C_t^{RT} is the electricity price at t in the real-time electricity market. The urban micro-grids need to buy electricity when there is more demand than that in the day-ahead markets, and can sell electricity when there is extra supply. Parameters a_1, a_2, a_3, a_4, a_5 are the punishment coefficients of the deviation. These coefficients can be obtained through typical methods of hyperparameter optimization. Grid search method is applied in the article. The state of HVAC $\tau_{HVAC,i,t}$ in the real-time stage remains the same as the result in the day-ahead optimization.

Constrains include Eqs. 1, 2, 3, 4, 9, 10, 11, 12, 13, 14, 15, 18, 20, 21, 22, 23, and

$$\begin{aligned} P_{buy,t}^{RT} - P_{sell,t}^{RT} \geq &(P_{buy,t}^{DA} - P_{sell,t}^{DA}) \\ &-(1-\tau_{PR,i})P_{large} \end{aligned} \tag{33}$$

Eq. 33 is to guarantee the ancillary service providing. If $\tau_{PR,i} = 0$, the equation always satisfies. The intra-day rolling optimization can be converted to a QP problem.

IV. CASE STUDY

A. Input data

The urban micro-grids in the case study consist of PV, BESS, fixed loads, 600 HVAC systems in resident rooms, and 400 HVAC systems in working offices. Table II shows the parameters of these elements. The parameters related to HVAC in resident rooms are described with subscript r, and the parameters related to HVAC in offices are described with subscript w. Each room is set at an area of about $40m^2$ with $\gamma = 20$ [26]. The transmission fee is $C^{tr} = 0.01USD/kWh$. The peak regulation service market can be provided during 11:00-14:00. The day-ahead prediction error of PV is $\sigma_{DA} = 12\%$, and

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content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2024.3354803

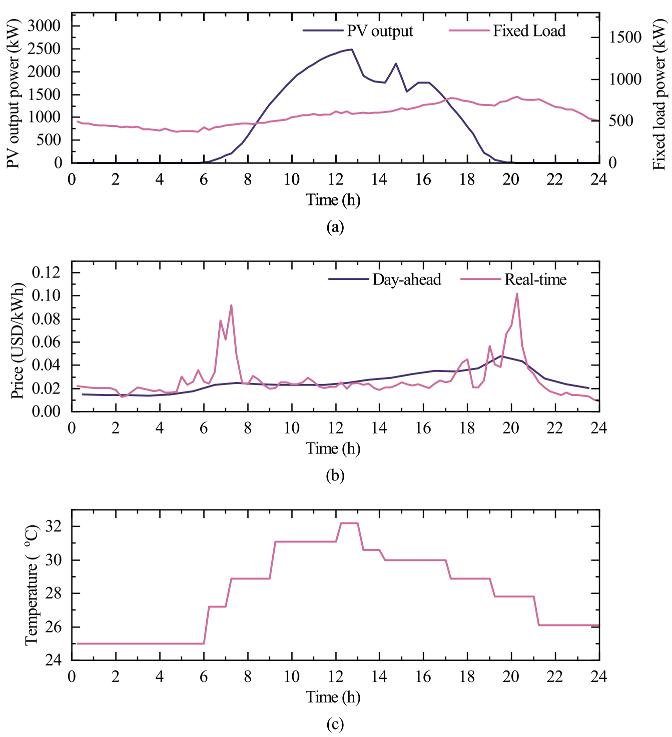

Figure 4. Time-variable parameters. (a) PV output power and power of fixed load within a typical summer day. (b) Electricity price in day-ahead market and real-time market. (c) Temperature in a typical summer day.

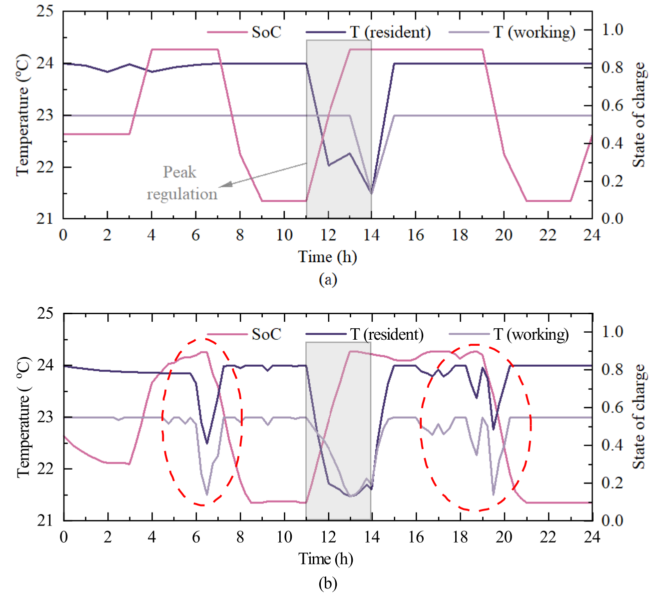

Figure 5. SoC of BESS and indoor temperature of buildings. (a) Results in day-ahead stage. (b) Results in real-time stage.

the parameters for the prediction error of real-time stage is $\sigma_{RT} = \sigma_{RT,0} = 0.5\%$. The hyperparameters of the model are $a_1 = a_2 = 2 \times 10^{-5}, a_3 = 4 \times 10^{-3}, a_4 = 4 \times 10^{-6}, a_5 = 1 \times 10^{-3}$.

Fig. 4 shows the time-variable parameters of the case study, including the maximum power output of PV, power consumption of fixed loads, day-ahead and real-time electricity market price and the environmental temperature of a typical summer day. The data of electricity prices comes from the operation data in the PJM market [27], [28].

In the case study, two typical scenarios with several cases are carried out.

Scenario 1: In the case study, the power bought from or sold to the grid never exceeds the system limitation, due to the sufficient infrastructure of substations, transmission lines, and so on. $P_{buy,max}$ and $P_{sell,max}$ are set at a large value. Four cases are carried out to analyse the effect of regulating BESS and BBESS.

Scenario 2: Due to the limitation of the substation, stability, and so on, the power output of the micro-grids is forbidden, but the power input is guaranteed to ensure power supply. In this scenario, light curtailment occurs when necessary because the exceeding PV output cannot be sold. $P_{sell,max} = 0$, and $P_{buy,max}$ are set at a large amount. Four cases are carried out the same as scenario 1.

Case 1: Regulate with BESS and BBESS. In this case, the power generation and consumption of each element is controlled with the strategies proposed in this paper. The BESS and BBESS will provide regulation services coordinately.

Case 2: Regulate with BESS only. In this case, the HVAC systems will try to maintain the indoor temperature at the upper bound of the comfortable temperature range, which can be considered as fixed loads. The BESS provide regulation services individually.

Case 3: Regulate with BBESS only. In this case, there is no charge and discharge in the BESS, and the HVAC systems are controlled with the strategies proposed in this paper. Only BBESS provide regulation services.

Case 4: Without regulation resources. In this case, the HVAC systems will try to maintain the indoor temperature, and the BESS doesn't work. There is no regulation in the micro-grids.

The above models and methods are implemented using Matlab R2022a with Gurobi Optimizer version 9.5.2, on a 2GHz Intel Core i5 CPU with 16GB RAM. The computation time of the optimization in the day-ahead stage is less than 2 seconds. The total computation time of the real-time stage is less than 60 seconds in each case.

B. Result analysis in Scenario 1

1) Results of the operation cost

Table III compares the operational cost and revenue of 30 days in each market in the four cases. Comparing the results of Case 1 and Case 4, we can find that the coordinated regulation of BBESS and BESS can reduce the total operational cost of urban micro-grids by about 20%, the amount of which is 1740 USD. If only BESS is applied as regulation capacity, the cost can be decreased by 854 USD, while the amount for only HVAC participation is 769 USD. Therefore, the combination of BESS and BBESS can reduce the cost by about 8% more than regulating BESS and BBESS separately. Besides, we can also find that BESS can reduce day-ahead costs and real-time electricity costs significantly. BESS can track the day-

Table III
OPERATION COSTS OF THE URBAN MICRO-GRIDS IN SCENARIO 1

	Day-ahead electricity cost (USD/month)	Revenue from ancillary service (USD/month)	Real-time electricity cost (USD/month)	Total cost (USD/month)	Real-time electricity cost without optimization (USD/month)
Case 1: With BBESS and BESS	8785	551	-1184	7050	305
Case 2: With BESS only	8821	360	-525	7936	185
Case 3: With BBESS only	9122	405	-696	8021	377
Case 4: Without BBESS and BESS	8869	0	-79	8790	-79

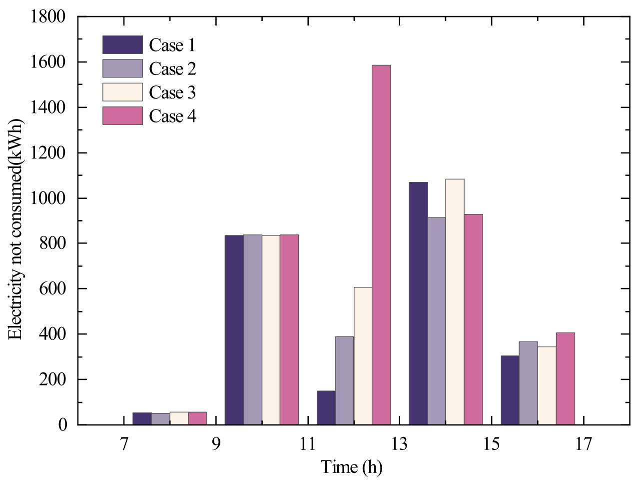

Figure 6. Comparison of PV not consumed locally in different cases.

ahead electricity price, store energy at low prices, discharge at high prices to reduce day-ahead electricity costs, and provide ancillary services to earn revenue. Also, it can track the real-time electricity price. BBESS mainly reduce the real-time electricity cost because buildings can only store energy for a short time. The power consumption of HVAC can only respond to the fast fluctuation of electricity prices in the real-time market.

Table III also compares the real-time electricity cost under optimized and non-optimized conditions to examine the performance of the proposed rolling optimization method. In the non-optimized condition, the real-time control strategy will maintain the SoC of BESS and the indoor temperature of buildings the same as the results optimized in the day-ahead stage. It can be found that the real-time electricity cost decreases a lot in case 1,2 and 3. In case 1, the cost is reduced by about 1500 USD/month, which shows the efficiency of the proposed rolling optimization method.

2) Results of the dispatch of BESS and BBESS

Fig. 5 shows the SoC of BESS and the indoor temperature of the two kinds of buildings in the day-ahead stage and real-time stage. In the day-ahead stage, the following statements can be drawn from the figure. The BESS charges at low prices and discharges at relatively high prices to earn revenue from the price gap. The BESS also discharges before the peak regulation period, and charges to provide peak regulation ancillary service in order to get profits. HVAC systems mainly increase the power consumption during the period to provide peak regulation ancillary service. During the period, the indoor temperature decreases, which can be regarded as the BBESS charge. After the period, the temperature increases during one hour. It can be regarded as the BBESS discharge and energy leaks during the hour. As for the perspective of coordination control, the BESS charges first, and then BBESS charge to provide as much ancillary service as possible. The reason for the phenomenon can be explained as follows: BESS can store energy for a long time without much leakage, but if BBESS store energy for a long time, there is too much energy leakage. So BESS charges first and HVAC systems increase power consumption to avoid more energy waste.

In real-time stage, the SoC curve is similar to that in the day-ahead stage, but the indoor temperature curves fluctuate more frequently and violently. The electricity prices in the real-time market change frequently, and BBESS can track the frequent alteration, storing cold when the price decreases and release the energy stored when the price increases. The BESS need to track the electricity price change in the whole day, so the SoC curve of BESS is supposed to change little from the result of the day-ahead stage. Therefore, scheduling BBESS in the real-time stage can decrease real-time electricity costs significantly.

The effectiveness of the proposed model in promoting renewable energy self-consumption levels is shown in fig. 6. All electricity generated by PV before 7:00 and after 17:00 is self-consumed. It can be seen from fig. 6 that the electricity not consumed during 11:00-13:00 can be reduced substantially by the coordinated regulation of BESS and BBESS. Without any coordination, about 1585 kWh electricity cannot be consumed during the period and is sold to the grid, putting huge peak pressure to the grid. With the regulation of BESS or BBESS, the amount of electricity not consumed can be reduced to 391 kWh and 607 kWh, respectively. And with the coordination regulation, the amount can be reduced to 149 kWh. The midday peak pressure on the grid can be relieved significantly. In total, the coordination control can increase the self-consumption rate of PV from 79% to 87%.

3) Sensitivity analysis

Fig. 7 illustrates the effects of BESS capacity on the optimization results in scenario 1. The monthly operation costs of the urban micro-grids are negatively correlated with the BESS capacity. The costs decrease by 150 USD/month for every 100kWh increase in BESS capacity. This figure also shows the effect of BBESS controlling: In case 2 (without regulation of BBESS), the capacity of BESS is required to increase by about 75% to achieve the same monthly cost as

This article has been accepted for publication in IEEE Internet of Things Journal. This is the author's version which has not been fully edited and content may change prior to final publication. Citation information: DOI 10.1109/JIOT.2024.3354803

Table IV
OPERATION COSTS AND PV CURTAILMENT RATE OF THE URBAN MICRO-GRIDS IN SCENARIO 2

	Day-ahead electricity cost (USD/month)	Revenue from ancillary service (USD/month)	Real-time electricity cost (USD/month)	Total cost (USD/month)	PV curtailment rate
Case 1: With BBESS and BESS	10530	0	-895	9635	13.65%
Case 2: With BESS only	10877	0	-342	10535	17.83%
Case 3: With BBESS only	11374	0	-462	10912	16.76%
Case 4: Without BBESS and BESS	11561	0	235	11796	20.28%

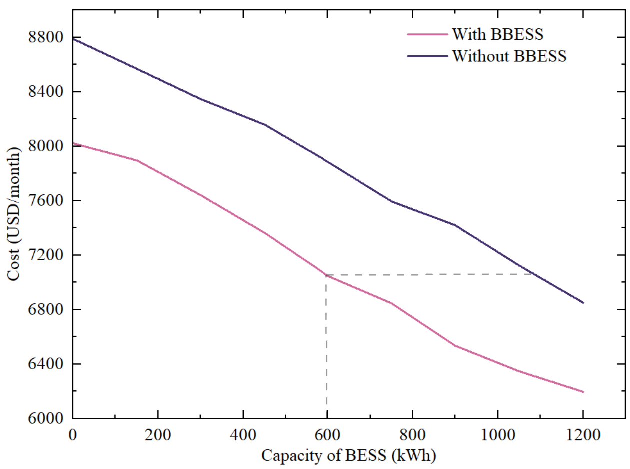

Figure 7. Effects of BESS capacity on operation cost in scenario 1.

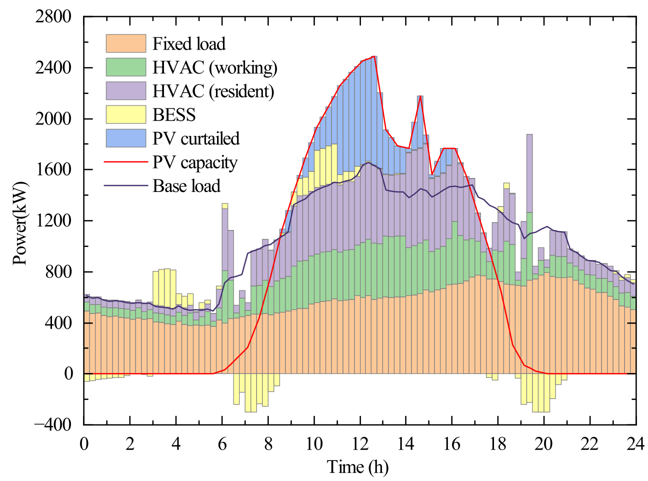

Figure 8. Power profile of different devices with consideration of BESS and BBESS in scenario 2.

that in case 1. Coordination control of BESS and BBESS can reduce the need for energy storage configuration, and thus saves space in the urban.

C. Result analysis in Scenario 2

1) Results of the operation and dispatch

In scenario 2, extra PV generation need to be curtailed. Table. IV compares the operation cost and PV curtailment rate of the four cases. Due to the limitation of PV output to the main-grid, it is not economic for the micro-grid to provide peak regulation ancillary service. Therefore, the revenue from ancillary market is zero in the four cases. The same conclusion as scenario 1 can be drawn in this scenario: coordination control of BESS and BBESS can maximize the cost reduction. BESS reduce day-ahead cost and real-time cost while BBESS mainly reduce real-time electricity cost. In the perspective of PV curtailment, it can be found that BESS can reduce the PV curtailment rate by 2.45%, and BBESS can reduce PV curtailment rate by 3.52%. Coordination control of BESS and BBESS can reduce it by 6.63%.

Fig. 8 shows the power consumption of each elements in case 1 in this scenario. The purple line 'base load' is the power consumed by fixed loads and HVAC loads in case 4. When PV capacity is larger than the loads, BESS charges first to consume extra PV, and then BBESS charges during the period when PV output is larger than load and there is a decreasing trend of PV output. When PV capacity is less than the loads, BBESS discharges first to to satisfy the load demand, and then BESS discharges. The reasons can be explained as follows. It is mentioned in section II-F that the leakage time constant of BBESS (in the case, the value is 1.94h) is shorter than that of BESS (considered ∞). BBESS is tend to store energy for a short time to avoid too much energy leakage. Therefore, BBESS charges later and discharges at first. The coordination control of BESS and BBESS can consume extra PV to promote PV consumption rate, and reduce the amount of electricity bought to cut the cost. Also, BESS and BBESS regulate with the change of electricity price. They charges at low prices and discharges at high prices to reduce electricity cost.

2) Sensitivity analysis

Fig. 9 illustrates the effect of BESS capacity on the operation cost and PV curtailment rate in scenario 2. The costs decrease by about 180 USD/month, and the PV curtailment rate decrease by 0.5% in average for every 100kWh increase in BESS capacity. Without regulation of BBESS, the capacity of BESS is required to increase 900 kWh to achieve the same PV curtailment rate as that with the regulation of BBESS. This shows the huge potential of BBESS to promote PV consumption. In other words, regulation of BBESS can replace BESS to some extent.

V. CONCLUSIONS

The paper proposes a multi-time scale optimization model for urban micro-grids to schedule large-scale heterogeneous BESS and BBESS. In this model, the different characteristics

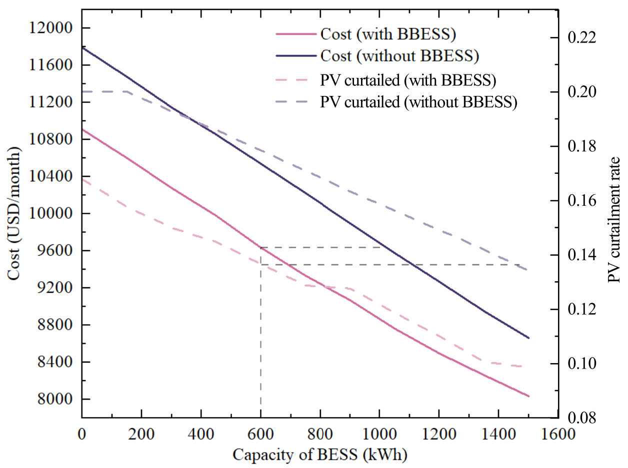

Figure 9. Effects of BESS capacity on optimization results in scenario 2

of heterogeneous energy storage systems are considered and analyzed. On the basis of the present results, several conclusions can be drawn as follows.

HVAC systems and buildings can be modelled and regarded as BBESS, which has different characteristics from BESS. BESS can provide a relatively long time of energy storage. They can track electricity price alteration in the day-ahead and real-time electricity market to reduce cost, and provide peak-regulation ancillary service by turning into charging state to earn revenue. BBESS can provide a short time energy storage. They can track the fast electricity price changes in the real-time electricity market to reduce cost, and provide ancillary service by increasing power consumption to earn revenue.

Lower operation cost of urban micro-grid and higher self-consumption rate of PV can be achieved by scheduling BESS and BBESS coordinately using the method proposed by the paper, and BBESS shows great potential to replace the demand for BESS in urban micro-grids. In the case study, the operation cost can be reduced by about 20% and the self-consumption rate can increase by about 8%. The dispatch of BBESS is equivalent to a 75% increase of BESS in urban micro-grids. Thus, the effectiveness of this model can be proved.

REFERENCES

[1] A. Pena-Bello, D. Parra, M. Herberz, V. Tiefenbeck, M. K. Patel, and U. J. J. Hahnel. Integration of prosumer peer-to-peer trading decisions into energy community modelling. *Nature Energy*, 7(1):74–82, 2022.

[2] H. Hui, Y. Chen, S. Yang, H. Zhang, and T. Jiang. Coordination control of distributed generators and load resources for frequency restoration in isolated urban microgrids. *Applied Energy*, 327:120116, 2022.

[3] B. Wang, C. Zhang, C. Li, G. Yang, and Z. Dong. Transactive energy sharing in a microgrid via an enhanced distributed adaptive robust optimization approach. *IEEE Transactions on Smart Grid*, 13(3):2279–2293, 2022.

[4] P. A. Østergaard, Y. Noorollahi N. Duic, and S. Kalogirou. Renewable energy for sustainable development. *Renewable Energy*, 199:1145–1152, 2022.

[5] J. Koskela, A. Rautiainen, and P. Järventausta. Using electrical energy storage in residential buildings–sizing of battery and photovoltaic panels based on electricity cost optimization. *Applied Energy*, 239:1175–1189, 2019.

[6] Q. Wang, X. Zhang, C. Yi, Z. Li, and D. Xu. A novel shared energy storage planning method considering the correlation of renewable uncertainties on the supply side. *IEEE Transactions on Sustainable Energy*, 13(4):2051–2063, 2022.

[7] X. Zhang, M. Pipattanasomporn, T. Chen, and S. Rahman. An iot-based thermal model learning framework for smart buildings. *IEEE Internet of Things Journal*, 7(1):518–527, 2020.

[8] D. Li, K. Shi, X. Zhou, Y. Wu, L. Yao, and S. Liao. Optimal dispatch of integrated energy system considering source-load-storage interaction. In *2021 3rd Asia Energy and Electrical Engineering Symposium (AEEES)*, pages 1165–1169. IEEE, 2021.

[9] S. Koohi-Fayegh and M. A. Rosen. A review of energy storage types, applications and recent developments. *Journal of Energy Storage*, 27:101047, 2020.

[10] U. G. K. Mulleriyawage and W. X. Shen. Optimally sizing of battery energy storage capacity by operational optimization of residential pv-battery systems: An australian household case study. *Renewable Energy*, 160:852–864, 2020.

[11] M. A. Hannana, S. B. Wali, P. J. Ker, M. S. A. Rahman, M. Mansor, V. K. Ramachandaramurthy, K. M. Muttaqi, T. M. I. Mahlia, and Z. Y. Dong. Battery energy-storage system: A review of technologies, optimization objectives, constraints, approaches, and outstanding issues. *Journal of Energy Storage*, 42:103023, 2021.

[12] R. Dai, R. Esmaeilbeigi, and H. Charkhgard. The utilization of shared energy storage in energy systems: A comprehensive review. *IEEE Transactions on Smart Grid*, 12(4):3163–3174, 2021.

[13] A. G. Olabi, C. Onumaegbu, T. Wilberforce, M. Ramadan, M. A. Abdelkareem, and A. H. Al-Alami. Critical review of energy storage systems. *Energy*, 214:118987, 2021.

[14] C. P. Barala, P. Mathuria, and R. Bhakar. Virtual energy storage systems: Challenges and opportunities. In *2021 9th IEEE International Conference on Power Systems (ICPS)*, pages 1–6. IEEE, 2021.

[15] F. H. Aghdam, M. W. Mudiyanselage, B. Mohammadi-Ivatloo, and M. Marzband. Optimal scheduling of multi-energy type virtual energy storage system in reconfigurable distribution networks for congestion management. *Applied Energy*, 333:120569, 2023.

[16] G. Piltan, S. Pirouzi, A. Azarhooshang, A. R. Jordehi, A. Paeizi, and M. Ghadamyari. Storage-integrated virtual power plants for resiliency enhancement of smart distribution systems. *Journal of Energy Storage*, 55:105563, 2022.

[17] H. Liu, H. Xie, H. Luo, J. Qi, H. H. Goh, and S. Rahman. Optimal strategy for participation of commercial hvac systems in frequency regulation. *IEEE Internet of Things Journal*, 8(23):17100–17110, 2021.

[18] J. Hong, H. Hui, H. Zhang, N. Dai, and Y. Song. Distributed control of large-scale inverter air conditioners for providing operating reserve based on consensus with nonlinear protocol. *IEEE Internet of Things Journal*, 9(17):15847–15857, 2022.

[19] W. Kang, M. Chen, Y. Guan, L. Tang, and J. M. Guerrero. Distributed event-triggered optimal control method for heterogeneous energy storage systems in smart grid. *IEEE Transactions on Sustainable Energy*, 13(4):1944–1956, 2022.

[20] H. Nagpal, I. Avramidis, F. Capitanescu, and A. G. Madureira. Local energy communities in service of sustainability and grid flexibility provision: Hierarchical management of shared energy storage. *IEEE Transactions on Sustainable Energy*, 13(3):1523–1535, 2022.

[21] G. Bianchini, M. Casini, D. Pepe, A. Vicino, and G. G. Zanvettor. An integrated model predictive control approach for optimal hvac and energy storage operation in large-scale buildings. *Applied Energy*, 240:327–340, 2019.

[22] S. Cheng, R. Wang, J. Xu, and Z. Wei. Multi-time scale coordinated optimization of an energy hub in the integrated energy system with multi-type energy storage systems. *Sustainable Energy Technologies and Assessments*, 47:101327, 2021.

[23] D. Watari, I. Taniguchi, H. Goverde, P. Manganiello, E. Shirazi, F. Catthoor, and T. Onoye. Multi-time scale energy management framework for smart pv systems mixing fast and slow dynamics. *Applied Energy*, 289:116671, 2021.

[24] A. Jani, H. Karimi, and S. Jadid. Multi-time scale energy management of multi-microgrid systems considering energy storage systems: A multi-objective two-stage optimization framework. *Journal of Energy Storage*, 51:104554, 2022.

[25] A. R. Jordehi. A stochastic model for participation of virtual power plants in futures markets, pool markets and contracts with withdrawal penalty. *Journal of Energy Storage*, 50:104334, 2022.

[26] K. A. Antonopoulos and E. Koronaki. Envelope and indoor thermal capacitance of buildings. *Applied Thermal Engineering*, 19(7):743–756, 1999.

[27] PJM. Day-ahead hourly LMPs. 2023. [Online]. Available: http://dataminer2.pjm.com/feed/da_hrl_lmps.
[28] PJM. Real-Time Five Minute LMPs. 2023. [Online]. Available: http://dataminer2.pjm.com/feed/rt_fivemin_hrl_lmps.