

Stochastic and Distributed Optimal Energy Management of Active Distribution Networks Within Integrated Office Buildings

Zening Li, Su Su, Xiaolong Jin, *Member, IEEE*, Mingchao Xia, *Senior Member, IEEE*, Qifang Chen, *Member, IEEE*, and Koji Yamashita, *Member, IEEE*

Abstract—This paper proposes a stochastic and distributed optimal energy management approach for active distribution networks (ADNs) within office buildings. The proposed approach aims at scheduling office buildings fitted with heating ventilation and air conditioning (HVAC) systems, and electric vehicle (EV) charging piles, to participate in the ADN optimization. First, an energy management approach for the ADN with aggregated office buildings is proposed. And the ADN optimization model is formulated considering the detailed building thermal dynamics and the mobile behaviors of workers. Then, to consider uncertainties of photovoltaic (PV) power, scenario-based stochastic programming is integrated into the ADN optimization model. To further realize the stochastic energy management of the ADN within office buildings in a distributed manner, the alternating direction method of multipliers (ADMM) is used to solve the ADN optimization model. The original ADN optimization problem is divided into the network-side and the building-side sub-problems to effectively protect the privacy of the ADN and the office buildings. Finally, the ADN optimization model incorporating office buildings is validated in the winter by numerical studies. In addition, the impacts of comfort temperature range and expected state of charge (SOC) at departure are analyzed.

Index Terms—ADN, EV, HVAC system, Office building, Stochastic and distributed energy management.

NOMENCLATURE

A. Sets

- h EV index.
- k Working zone index.
- n Node index.
- t Time slot index.
- w Scenario index.

B. Parameters

- $A_{\text{wall},ij}$ Wall area (m^2).
- $A_{\text{win},ij}$ Window area (m^2).
- c_p Specific heat capacity of air [$\text{J}/(\text{kg}\cdot^\circ\text{C})$].
- C_{cop} Coefficient of performance.
- $C_{\text{wall},ij}$ Wall heat capacity (J/K).
- $C_{\text{room},k}$ Room heat capacity (J/K).
- d_h Daily driving distance of the EV (km).
- E_B EV battery capacity ($\text{kW}\cdot\text{h}$).
- $I_{mn,\max}$ Maximum current (p.u.).
- l Child node of n th node.
- $m_{\text{room},k,t}$ Mass air flow (kg/s).
- N_n Number of nodes connected to office buildings.
- N_w Number of scenarios.
- N_h Number of EVs.
- N_t Number of scheduling periods.
- N_k Number of working zones.
- p_w Probability of scenario w .
- P_{static} Static pressure difference (Pa).
- $P_{\text{max}}^c, P_{\text{min}}^c$ Maximum and minimum values for charging power (kW).
- $P_{\text{max}}^d, P_{\text{min}}^d$ Maximum and minimum values for discharging power (kW).
- $P_{\text{pv},w,n,t}$ Distributed PV power of node n (kW).
- $P_{\text{el},t}$ Power consumption of other electric equipment (kW).
- $P_{\text{load},n,t}$ Active power of node n (kW).
- $P_{mn,w,t}$ Active power of the node m side (kW).
- $Q_{\text{load},n,t}$ Reactive power of node n (kvar).
- $Q_{mn,w,t}$ Reactive power of node m side (kvar).
- $Q_{\text{int},k,t}$ Internal heat gain (W).
- $Q_{\text{rad},k,t}$ Radiant heat flow density on the window (W/m^2).
- $Q_{\text{rad},ij,t}$ Radiant heat flow density on the wall (W/m^2).
- q_{ij} Sunlit wall identifier.
- r_{mn} Resistance (Ω).
- $R_{\text{wall},ij}$ Wall thermal resistance (K/W).
- $R_{\text{win},ij}$ Window thermal resistance (K/W).
- $\text{SOC}_{\min}$ Upper limits of the SOC.
- $\text{SOC}_{\max}$ Lower limits of the SOC.
- $\text{SOC}_{h,\text{home}}$ Expected SOC for EVs when leaving home.

Manuscript received June 16, 2021; revised August 09, 2021; accepted August 24, 2021. Date of online publication May 06, 2022, date of current version March 15, 2024. This work was supported in part by the Fundamental Research Funds for the Central Universities (2021YJS148) and the National Natural Science Foundation of China (Grant No. 51677004).

Z. N. Li (corresponding author, email: zeningli@bjtu.edu.cn), S. Su, M. C. Xia and Q. F. Chen are with the National Active Distribution Network Technology Research Center, Beijing Jiaotong University, Beijing 100044, China.

X. L. Jin is with the Key Laboratory of Smart Grid of Ministry of Education, Tianjin University, Tianjin 300072, China.

K. Yamashita is with Electrical and Computer Engineering, University of California Riverside, CA, 92521, USA.

DOI: 10.17775/CSEEJPES.2021.04510

$SOC_{h,dep}$	Expected SOC for EVs at the departure.
Δt	Scheduling interval.
$T_{room,max}$	Upper limits of indoor setpoint temperature ($^{\circ}C$).
$T_{room,min}$	Lower limits of indoor setpoint temperature ($^{\circ}C$).
$T_{supply,max}$	Maximum airflow temperature ($^{\circ}C$).
$T_{supply,min}$	Minimum airflow temperature ($^{\circ}C$).
$\delta T_{supply,max}$	Maximum change rate for airflow temperature ($^{\circ}C/h$).
$\delta T_{supply,min}$	Lower limits of change rate for airflow temperature ($^{\circ}C/h$).
$t_{h,arr}, t_{h,dep}$	Scheduled start/end time.
v	Wind speed (m/s).
$V_{m,max}$	Maximum voltage of the node (p.u.).
$V_{m,min}$	Minimum voltage of the node (p.u.).
v_{ij}	Absorption coefficient of the wall.
W	Energy consumption per kilometer (kWh·km $^{-1}$).
w_{ij}	Window transmittance coefficient.
x_{mn}	Reactance (Ω).
η_{fan}	Fan coefficient of airflow device.
η_{motor}	Motor coefficient of airflow device.
η^c, η^d	Charging/Discharging efficiency of the EV.
ρ	Penalty parameters.
τ	Self-loss coefficient.
μ_m, σ_m	Position/Scale parameters.
$\varepsilon_{pri}, \varepsilon_{dual}$	Terminating thresholds.
π_{ij}	Sunlit window identifier.

C. Variables

$i_{mn,w,t}$	Square of line current amplitude (p.u.).
$P_{bld,n,t}$	Power consumption of office buildings of node n at period t (kW).
$P_{thermal,t}$	Heating power (kW).
$P_{fan,t}$	Fan power (kW).
$P_{HVAC,t}$	Power consumption of HVAC system (kW).
$P_{EV,t}$	EV power consumption (kW).
$P_{w,n,t}$	Injected active power of node n (kW).
$P_{ex,w,n,t}$	Power exchange with external grid of node n (kW).
$P_{loss,t}$	Losses of distribution network (kW).
$P_{h,t}^c$	EV charging power (kW).
$P_{h,t}^d$	EV discharging power (kW).
$p_{w,n,t}$	Dummy variable of $P_{w,n,t}$ (kW).
$Q_{w,n,t}$	Injected reactive power of node n (kvar).
$Q_{ex,w,n,t}$	Reactive power exchange with external grid of node n (kvar).
$q_{w,n,t}$	Dummy variable of $Q_{w,n,t}$ (kvar).
r_w^k	Primal residuals at scenario w .
s_w^k	Dual residuals at scenario w .
$SOC_{h,arr}$	SOC when arriving working zone.
$SOC_{h,t}$	SOC of the EV.
$T_{j,t}$	temperature of j th node ($^{\circ}C$).
$T_{room,k,t}$	Indoor temperature ($^{\circ}C$).
$T_{supply,k,t}$	Airflow temperature ($^{\circ}C$).
$T_{wall,ij,t}$	Wall temperature ($^{\circ}C$).
$v_{m,w,t}$	Square of node voltage amplitude (p.u.).

$x_{net,w,n,t}$	Local variables of network-side in node n .
$x_{bld,w,n,t}$	Local variables of building-side in node n .
$z_{net,w,n,t}$	Global variables of network-side in node n .
$z_{bld,w,n,t}$	Global variables of building-side in node n .
$\alpha_{h,t}^c, \alpha_{h,t}^d$	Boolean variables about the EV.

I. INTRODUCTION

WITH the rapid development of global urbanization, the proportion of building energy consumption within total energy consumption has steadily increased [1]. Therefore, energy management methods, aiming at energy consumption decreases and energy efficiency increases in buildings, have gained the attention of power engineers. The active distribution network (ADN) can integrate a large number of buildings and enable them to take part in the optimal dispatch of the ADN. In this context, the ADN can provide efficient energy management solutions for buildings. However, the large-scale access of buildings also brings a challenge for the optimal ADN operation [2]. Therefore, the optimal energy management methods for the ADN within integrated buildings are of great significance.

Based on the building thermal dynamics, and the vehicle-to-grid and vehicle-to-building technologies, significant progress has been made in flexible energy management of buildings fitted with heating ventilation and air conditioning (HVAC) systems and electric vehicle (EV) charging piles. A linearized and economic model predictive controller according to the feedback linearization technique was provided to minimize the HVAC energy consumption in buildings [3]. A real-time algorithm according to the Lyapunov optimization framework was proposed [4]. The total cost of HVAC systems could be reduced, dynamically adjusting the average fluctuation value of interior temperatures. An energy management method for buildings incorporating HVAC systems was proposed to improve the load factor of aggregated buildings by pre-heating during the off-peak energy consumption periods [5]. To reduce the annual electricity bill, a co-optimization method for the HVAC system and the battery energy storage system was proposed without causing thermal discomfort to the residents [6]. In [3]–[6], based on building thermal dynamics, the energy consumption of HVAC systems was reduced by flexibly adjusting the indoor temperature. In addition, the EV charging piles distributed in buildings and their charging load were studied [7], [8]. A hierarchic energy management approach to office buildings was proposed using vehicle-to-grid and vehicle-to-building technologies [7]. The power exchange at the point of the common coupling was smoothed by combined scheduling HVAC systems and EVs. A four-stage intelligent smart optimal control algorithm for the bidirectional EV charging station integrated with a commercial building was proposed [8]. The algorithm reduced operational costs and provided a higher tolerance for uncertainties.

In the above research, the buildings equipped with HVAC systems and EV charging piles have great demand response potential as flexible resources, positively impacting the ADN. However, the interaction between buildings and ADN was not thoroughly studied in [3]–[8]. Moreover, the ADN's operations

were ignored or only treated as constraints, rather than optimized as objectives in the studies mentioned above, e.g., the maximum network loss and maximum voltage deviations were limited to a particular range. Consequently, the optimal ADN's operation cannot be ensured. To further investigate the impact of building demand response potential on the ADN, in-depth explorations were conducted in [9]–[13]. A hierarchic scheduling strategy for ADN was developed, considering building thermal dynamics [9]. First, the building power consumption decreases. Then, the action number of the on-load tap changer can be reduced. A novel building-to-grid framework was proposed to achieved the load penetration increment, improving the load factor in the distribution system [10]. An energy management method for the ADN integrated with wind power and HVAC systems was developed within the customers' comfort temperature ranges [11]. The integrated ADN model with non-convex constraints was reformulated as a convex model to guarantee the feasibility of the solution. A Stackelberg game approach aimed at solving the mismatch between the renewable power generation and demand was proposed utilizing scenario-based stochastic programming [12]. A stochastic energy management strategy for a load-serving entity with HVAC systems and energy storage was proposed based on bi-level and stochastic programming [13].

Although the above studies have made outstanding contributions, centralized optimization requires collecting the private data of all entities, and it is challenging to protect each entity's privacy. Therefore, a distributed optimization strategy is needed to deal with the ADN optimal scheduling problem. The ADN optimal power flow model was established to reduce the photovoltaic (PV) power curtailment of customers and the loss in the distribution network [14]. The alternating direction method of multipliers (ADMMs) was also utilized to realize the distributed optimization of different interests between customers and the distribution network. A distributed economic dispatch model of the ADN with integrated distributed generations was established to reduce the losses by utilizing the second-order cone relaxation, based on the framework of multi-district coordination optimization [15]. A self-governing optimization model for the ADN integrated with multi-microgrids based on the analytical objective cascade theory was proposed to improve their operation and economic benefits [16]. The distributed energy management method of the ADN was studied in [14]–[16]. However, as a large and common collection of flexible resources, the flexibility of buildings was not integrated into the ADN. Furthermore, the impact of the distributed renewable resource's uncertainty on the ADN's optimal scheduling should also be considered. An adaptive stochastic approach was proposed to obtain the optimal multi-energy microgrid's operation decisions, utilizing distinct energy properties [17]. The proposed approach can ensure system security with minimal operating costs and risks. A flexible management method was proposed based on the information-gap decision-making theory for an ADN with integrated distributed energy resources, considering the reserve uncertainty [18]. A stochastic optimal operation problem of the ADN according to active management strategies was presented, considering the uncertainties associated with dis-

tributed generation output and load fluctuation [19]. In [17]–[19], the uncertainties of renewable energy were fully considered, and the demand response potential of multiple distributed resources in the ADN was further explored. However, as mentioned above, the flexibility of buildings was not integrated into the ADN as a large and common collection of flexible resources. To further investigate the interaction of buildings and the ADN under uncertainties, a risk-averse approach to heterogenous energy storage arrangement in residential multi-energy microgrids was proposed to increase the multi-energy systems' holistic energy utilization efficiency [20]. Ref. [20] capitalized on the building demand response potential in the ADN under uncertainties. However, each entity's privacy cannot be protected because a centralized energy management method rather than a distributed method was used. Table I curates the differences of studies between the existing literature and this paper.

TABLE I
OVERVIEW OF TECHNICAL STATUS

References	Building Thermal Dynamics	Vehicle-to-Building	Interaction between buildings and ADN	Uncertainty considered	Privacy protected
[3]	✓				
[4]	✓			✓	
[5]	✓				
[6]					
[7]	✓	✓			
[8]		✓		✓	
[9]	✓		✓		
[10]	✓		✓		
[11]	✓		✓		
[12]	✓			✓	
[13]	✓			✓	
[14]			✓	✓	✓
[15]			✓		✓
[16]			✓		✓
[17]			✓	✓	
[18]			✓	✓	
[19]			✓	✓	
[20]			✓	✓	
This paper	✓	✓	✓	✓	✓

In view of the above, an ADMM-based distributed optimal energy management approach for the ADN with aggregated office buildings considering PV power uncertainties, is proposed. The main contributions are as follows:

1) An energy management framework for the ADN with aggregated office buildings equipped with HVAC systems and EV charging piles is proposed. The interaction between buildings and the ADN, detailed building thermal dynamics, and the mobile behaviors of workers are considered in this framework. The proposed energy management approach can provide benefits to both the ADN and office buildings.

2) The aggregated office buildings equipped with HVAC systems and EV charging piles are leveraged as flexible resources for optimal energy management of the ADN. The proposed energy management approach can sufficiently capitalize on the demand response capacity of office buildings, and further realize the flexible operation of ADNs while ensuring the comfort temperature and travel demands of workers.

3) To further protect the privacy of the ADN and the office

buildings in the ADN energy management, the ADMM is exploited to solve the ADN optimization model in a distributed manner. The original ADN optimization problem is divided into the network-side and building-side sub-problems, which can not only respect all the operational constraints of the ADN and office buildings, but also enable intelligent dispatch of HVAC systems and EVs.

The remainder of this paper is organized as follows: Section II presents the framework and mathematical model for the ADN with aggregated office buildings. In Section III, a scenario-based stochastic energy management system is formulated. Section IV further elaborates on an ADMM-based distributed optimization solution for the stochastic energy management model. In Section V, case studies are showcased to corroborate the proposed approach. Section VI concludes this paper.

II. SYSTEM MODELS

A. Energy Management Framework

This section presents a framework for ADN energy management system considering buildings, as shown in Fig. 1. This framework considers incentive-based demand response, and the distribution system pays the response subsidy to the staff in one payment [21].

Buildings link flexible resources to the ADN to meet the customer's electricity demand, and to interact with the ADN. By responding to the excitation signals of the distribution system operator (DSO) and uploading the feedback signals, the building energy management systems (BEMSs) distribute the dispatching signals to the flexible resources (i.e., HVACs and EVs) in buildings. Then, the flexible resources are dispatched by BEMS to locally accommodate the PV power. On the other hand, the DSO sends the excitation signal to the buildings and receives the feedback signal uploaded by BEMSs under the condition of the system's secure operation. The purpose is to decrease network losses and improve the ADN's economic operations.

It can be seen that BEMSs and DSO are different entities with different dispatch objectives. The electric power over tie-lines couple the BEMSs and DSO, enabling the interaction between BEMSs and the DSO in energy management. Based

on the above framework, the global energy coordination management of the ADN with buildings can be realized. Detailed dynamic scheduling models of the building and network sides are given below.

B. Building-side Model

1) Thermal Dynamic Model of Working Zones in Office Buildings

A thermal dynamic model of working zones in office buildings is developed to capitalize on the HVAC system's flexible power according to the resistor-capacity network model.

The resistor-capacity network model of a working zone has five nodes, four wall nodes and one room node. There is one window in the working zone. The model transfers heat through the thermal resistance and stores heat through the thermal capacity. The heating requirements of the staff in the work zone are provided by HVAC systems of the office buildings. The parameters are the same for all work zones in the office building. Therefore, the total heating loads of the aggregated building can be obtained by summing up the heating loads of each working zone. According to our previous study [9], the mathematical model of the work zone with the HVAC system is described as follows:

$$C_{\text{wall},ij}(T_{\text{wall},ij,t+1} - T_{\text{wall},ij,t}) = \Delta t \left(\sum_{j \in N_{\text{wall}}} \frac{T_{j,t} - T_{\text{wall},ij,t}}{R_{\text{wall},ij}} + q_{ij} v_{ij} A_{\text{wall},ij} Q_{\text{rad},ij,t} \right) \quad (1)$$

$$C_{\text{room},k}(T_{\text{room},k,t+1} - T_{\text{room},k,t}) = \Delta t \left[\sum_{j \in N_{\text{room}}} \frac{T_{\text{wall},ij,t} - T_{\text{room},k,t}}{R_{\text{wall},ij}} + Q_{\text{int},k,t} + \pi_{ij} \sum_{j \in N_{\text{room}}} \frac{T_{j,t} - T_{\text{room},k,t}}{R_{\text{win},ij}} + \pi_{ij} w_{ij} A_{\text{win},ij} Q_{\text{rad},k,t} + m_{\text{room},k,t} c_p (T_{\text{supply},k,t} - T_{\text{room},k,t}) \right] \quad (2)$$

Using the example of a single working zone in the diagram above, (1) and (2) can be translated into the following form:

$$C_{\text{wall},12}(T_{\text{wall},12,t+1} - T_{\text{wall},12,t})$$

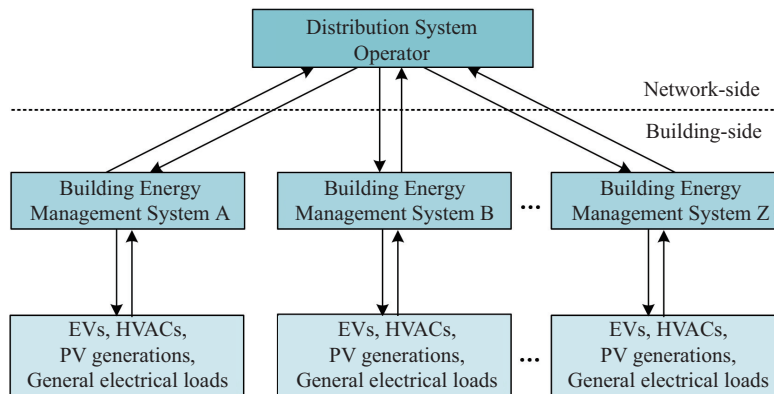


Fig. 1. Diagrammatic sketch of the ADN considering buildings.

$$\begin{aligned}
&= \Delta t \left(\frac{T_{\text{room},1,t} - T_{\text{wall},12,t}}{R_{\text{wall},12}} + \frac{T_{2,t} - T_{\text{wall},12,t}}{R_{\text{wall},12}} \right. \\
&\quad \left. + q_{12}v_{12}A_{\text{wall},12}Q_{\text{rad},12,t} \right) \\
&C_{\text{wall},13}(T_{\text{wall},13,t+1} - T_{\text{wall},13,t}) \\
&= \Delta t \left(\frac{T_{\text{room},1,t} - T_{\text{wall},13,t}}{R_{\text{wall},13}} + \frac{T_{3,t} - T_{\text{wall},13,t}}{R_{\text{wall},13}} \right. \\
&\quad \left. + q_{13}v_{13}A_{\text{wall},13}Q_{\text{rad},13,t} \right) \\
&C_{\text{wall},14}(T_{\text{wall},14,t+1} - T_{\text{wall},14,t}) \\
&= \Delta t \left(\frac{T_{\text{room},1,t} - T_{\text{wall},14,t}}{R_{\text{wall},14}} + \frac{T_{4,t} - T_{\text{wall},14,t}}{R_{\text{wall},14}} \right. \\
&\quad \left. + q_{14}v_{14}A_{\text{wall},14}Q_{\text{rad},14,t} \right) \\
&C_{\text{wall},15}(T_{\text{wall},15,t+1} - T_{\text{wall},15,t}) \\
&= \Delta t \left(\frac{T_{\text{room},1,t} - T_{\text{wall},15,t}}{R_{\text{wall},15}} + \frac{T_{5,t} - T_{\text{wall},15,t}}{R_{\text{wall},15}} \right. \\
&\quad \left. + q_{15}v_{15}A_{\text{wall},15}Q_{\text{rad},15,t} \right) \\
&C_{\text{room},1}(T_{\text{room},1,t+1} - T_{\text{room},1,t}) \\
&= \Delta t \left[\sum_{j=1}^4 \frac{T_{\text{wall},1j,t} - T_{\text{room},1,t}}{R_{\text{wall},1j}} + \frac{T_{5,t} - T_{\text{room},1,t}}{R_{\text{win},15}} \right. \\
&\quad \left. + w_{15}A_{\text{win},15}Q_{\text{rad},1,t} + Q_{\text{int},1,t} \right. \\
&\quad \left. + m_{\text{room},1,t}c_p(T_{\text{supply},1,t} - T_{\text{room},1,t}) \right]
\end{aligned} \tag{3}$$

According to the thermal dynamic model of a single working zone shown above, the HVAC system's heating power in the working zone can be determined.

2) EV Model

In the bi-directional vehicle-to-grid context, the ADN can enable the bi-directional energy transmission between EVs and the grid. EVs can be used as temporary and mobile fast-acting generators/loads. Proper management makes this bidirectional exchange suitable for the peaker replacement or ancillary services in the grid [22]. In this paper, the parking lot of office buildings is fitted with charging piles to satisfy the travel demand of EV commuters. The EV charging/discharging model is established to capitalize on the flexible charging/discharging capability of EV batteries used in the parking lot. The linearized EV model can be expressed as follows [23]:

$$\text{SOC}_{h,t} - (1 - \kappa)\text{SOC}_{h,t-1} = \left(\eta^c \cdot P_{h,t}^c - \frac{P_{h,t}^d}{\eta^d} \right) \frac{\Delta t}{E_B} \tag{8}$$

$$0 \leq P_{h,t}^c \leq P_{\text{max}}^c \cdot \alpha_{h,t}^c \tag{9}$$

$$0 \leq P_{h,t}^d \leq P_{\text{max}}^d \cdot \alpha_{h,t}^d \tag{10}$$

$$\alpha_{h,t}^c + \alpha_{h,t}^d \leq 1 \tag{11}$$

Each EV should reach the required state of charge (SOC) value when it departs. On arrival at the parking lot of the office building, the EV is charged/discharged for proper management. According to the U.S. Department of Transportation's travel survey, the daily total distance distribution of EVs is

expressed as follows [24]:

$$f(d_h) = \frac{1}{\sqrt{2\pi}\sigma_m d_h} \exp \left(-\frac{(\ln d_h - \mu_m)^2}{2\sigma_m^2} \right) \mu_m = 2.98, \tag{12}$$

$$\sigma_m = 1.14$$

According to the information provided by EV battery properties and mobile behaviors, the total daily driving distance of each EV is generated by the Monte-Carlo simulation method. Suppose that the driving distance of each EV from home to the office building is half of the driving distance for the whole day [25]. When each worker arrives at the office building, the SOC value of each EV can be obtained from the following equation:

$$\text{SOC}_{h,\text{arr}} = \text{SOC}_{h,\text{home}} - (0.5d_h \cdot W)/E_B \tag{13}$$

3) Office Buildings Model

The office building's energy consumption is determined by the external power network and distributed PVs under multiple stochastic scenarios, as follows:

$$P_{\text{bld},n,t} = P_{\text{ex},w,n,t} + P_{\text{pv},w,n,t}, \quad n \in N_k \tag{14}$$

When the staff reaches the building (or departs from the building), the HVAC system is switched on (or off), and the EV is parked at the parking lot for charging/discharging management. Therefore, the total building's power consumption consists of electric energy to meet the daily heating and travel demands for workers, as well as the general electrical loads (such as lightings and electrical appliances). The energy consumption at the office buildings is described as follows:

$$P_{\text{bld},n,t} = P_{\text{HVAC},t} + P_{\text{EV},t} + P_{\text{el},t} \tag{15}$$

For the non-working time, the EV does not participate in the energy scheduling of the office building, and the HVAC system is the same, illustrated as follows:

$$P_{\text{EV},h,t} = 0, \quad t \notin [t_{h,\text{arr}}, t_{h,\text{dep}}] \tag{16}$$

$$P_{\text{HVAC},k,t} = 0, \quad t \notin [t_{h,\text{arr}}, t_{h,\text{dep}}] \tag{17}$$

C. Network-side Model

The network-side model is constructed according to the branch flow model (BFM) [26], and the mathematical model under multiple stochastic scenarios is demonstrated as follows:

$$v_{m,w,t} - v_{n,w,t} = 2(r_{mn}P_{mn,w,t} + x_{mn}Q_{mn,w,t}) - (r_{mn}^2 + x_{mn}^2)i_{mn,w,t} \tag{18}$$

$$P_{w,n,t} = \sum_{l:n \rightarrow l} P_{nl,w,t} - (P_{mn,w,t} - i_{mn,w,t}r_{mn}) \tag{19}$$

$$Q_{w,n,t} = \sum_{l:n \rightarrow l} Q_{nl,w,t} - (Q_{mn,w,t} - i_{mn,w,t}x_{mn}) \tag{20}$$

$$i_{mn,w,t}v_{m,w,t} = P_{mn,w,t}^2 + Q_{mn,w,t}^2 \tag{21}$$

Since (21) contains non-convex and nonlinear terms, it is converted through second-order cone relaxation (SOCR) into the following form:

$$\begin{aligned} &\| [2P_{mn,w,t} \quad 2Q_{mn,w,t} \quad i_{mn,w,t} - v_{m,w,t}]^T \|_2 \\ &\leq i_{mn,w,t} + v_{m,w,t} \end{aligned} \tag{22}$$

Reference [27] has demonstrated that the BFM after SOCR can meet all the constraints of the original problem and ensure the correctness of the result.

III. STOCHASTIC ENERGY MANAGEMENT METHOD

Since uncertainties of the PV power will impact the ADN, the Monte-Carlo simulation is leveraged to produce an appropriate number of scenarios that can simulate these uncertainties of the PVs. It is necessary to utilize scenario reduction to reduce the computational burden for the numerous scenarios. In this paper, the SCENRED toolbox in the GAMS is employed for scenario reduction. Before reduction, the probabilities of all scenarios are considered to be equivalent, and the sum is equivalent to 1. Note that, a day-ahead single-stage stochastic optimization approach is used in this study [28]. The two-stage stochastic optimization method will be studied in the future. According to the above mathematical model, the stochastic energy management approach for the ADN considering office buildings is formulated.

A. Objective function

The objective function is provided as shown in (23).

$$\min \sum_w p_w \sum_t \left(\sum_n |P_{\text{bld},n,t} - P_{\text{pv},w,n,t}| + P_{\text{loss},w,t} \right) \quad (23)$$

The former is the tracking item of the difference between the office building energy consumption and the PV power. The second term is the power loss in the ADN. The energy consumption at the office building is shown in (15); where the HVAC system's energy consumption is as follows:

$$P_{\text{HVAC},t} = \sum_{k \in N_k} (P_{\text{thermal},k,t} + P_{\text{fan},k,t}) \quad (24)$$

The heating and fan power consumptions of the HVAC system is calculated as follows:

$$P_{\text{thermal},k,t} = [m_{\text{room},k,t} \cdot c_p (T_{\text{supply},k,t} - T_{\text{room},k,t})] / C_{\text{cop}} \quad (25)$$

$$P_{\text{fan},k,t} = \left[m_{\text{room},k,t} \left(P_{\text{static}} + \rho \frac{v^2}{2} \right) \right] / (\eta_{\text{fan}} \cdot \eta_{\text{motor}}) \quad (26)$$

The power of the EV charging/discharging is expressed as follows:

$$P_{\text{EV},t} = \sum_{h \in N_h} (P_{h,t}^c - P_{h,t}^d) \quad (27)$$

where N_h is the dispatchable EV number.

The ADN's power loss is defined as follows:

$$P_{\text{loss},w,t} = \sum_{mn \in E} i_{mn,w,t} r_{mn} \quad (28)$$

B. Constraints

1) Office Building Constraints

Building-side constraints include the thermal balance con-

straints, the office worker demand constraints, and the HVAC system and EV battery operational constraints.

Thermal balance constraints of the office buildings have already been presented in (1) and (2).

Constraints of the comfortable temperature demand and travel demand for workers are expressed as follows:

$$T_{\text{room},\min} \leq T_{\text{room},k,t} \leq T_{\text{room},\max} \quad (29)$$

$$\text{SOC}_{h,t} \geq \text{SOC}_{h,\text{dep}}, \quad t = t_{h,\text{dep}} \quad (30)$$

Operational constraints of HVAC systems are expressed as follows:

$$T_{\text{supply},\min} \leq T_{\text{supply},k,t} \leq T_{\text{supply},\max} \quad (31)$$

$$\delta T_{\text{supply},\min} \leq T_{\text{supply},k,t+1} - T_{\text{supply},k,t} \leq \delta T_{\text{supply},\max} \quad (32)$$

Charging/discharging limits and SOC limits of EV batteries are expressed as follows:

$$\text{SOC}_{\min} \leq \text{SOC}_{h,t} \leq \text{SOC}_{\max} \quad (33)$$

2) Network Distribution Constraints

Network-side constraints consist of power flow and secure operational constraints.

The ADN's power flow constraints are shown in (18)–(20), and (22).

The ADN's secure operational constraints are expressed as follows:

$$(V_{m,\min})^2 \leq v_{m,w,t} \leq (V_{m,\max})^2 \quad (34)$$

$$0 \leq i_{mn,w,t} \leq (I_{mn,\max})^2 \quad (35)$$

In summary, the stochastic energy management approach to the ADN with office buildings is depicted as follows:

$$\begin{aligned} \min \sum_w p_w \sum_t \left(\sum_n |P_{\text{bld},n,t} - P_{\text{pv},w,n,t}| + P_{\text{loss},w,t} \right) \\ \text{s.t.} \quad (1), (2), (8)–(20), (22), (29)–(35) \end{aligned} \quad (36)$$

Based on the integrated modeling of the building and ADN, the ADN optimization problem with integrated aggregated office buildings can be developed as a mixed-integer second-order cone programming (MISOCP) problem.

IV. THE ADMM-BASED DISTRIBUTED SOLUTION

Since the ADN system with buildings generally has multiple entities, the privacy of all entities and the different interests of the building and network sides cannot be fully guaranteed in the centralized optimization. To this end, the ADN optimization problem with office buildings is decomposed into sub-problems on the network-side and building-side, according to the ADMM [29]. The ADMM-based distributed energy management approach to the ADN with integrated office buildings in light of PV power uncertainties is then presented in this section.

The injection power to the node n connected to the building is taken as the coupling variable to establish the coupling constraint to achieve the distributed optimization. Use scenario w , as an example, relative to the node injection power $P_{w,n,t}$,

$Q_{w,n,t}$ to the network, a set of dummy variables $p_{w,n,t}$, $q_{w,n,t}$, indicating the nodal injection power to the building is added at node n connected to the buildings.

The nodal injection power to the network is shown in (19) and (20). The dummy variables for the nodal injection power to the building are shown as follows:

$$p_{w,n,t} = P_{ex,w,n,t} - P_{load,n,t} \quad (37)$$

$$q_{w,n,t} = Q_{ex,w,n,t} - Q_{load,n,t} \quad (38)$$

Coupling constraints between the network and building are given as follows:

$$P_{w,n,t} = p_{w,n,t}, \quad Q_{w,n,t} = q_{w,n,t}, \quad n \in N_k \quad (39)$$

The ADN model with office buildings can be decoupled with the decomposition mechanism illustrated in Fig. 2. The centralized optimal model of the ADN is transformed into a decentralized optimization model that consists of the network and the building sides. The injection power, $P_{w,n,t}$ and $Q_{w,n,t}$, to node n connecting the buildings are solved using the network-side model, while the corresponding dummy injection power, $p_{w,n,t}$ and $q_{w,n,t}$, are solved using the building-side model. After solving both optimization models, the boundary information $P_{w,n,t}$, $Q_{w,n,t}$, $p_{w,n,t}$, and $q_{w,n,t}$, is transferred to each other as parameters to enter the next optimization.

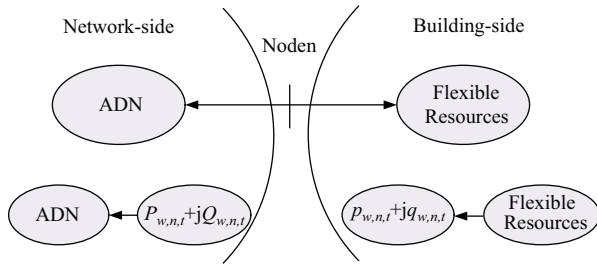


Fig. 2. Decoupling mechanism of the network-side and building-side.

From the above, in the ADMM-based distributed energy management approach to the ADN with office buildings in consideration of PV power uncertainties, local and global variables for the network and building are expressed respectively, as follows:

$$x_{net,w,n,t} = \{P_{w,n,t}, Q_{w,n,t}\}, \quad x_{bld,w,n,t} = \{p_{w,n,t}, q_{w,n,t}\} \quad (40)$$

$$z_{net,w,n,t} = z_{bld,w,n,t} = \left\{ \frac{(P_{w,n,t} + p_{w,n,t})}{2}, \frac{(Q_{w,n,t} + q_{w,n,t})}{2} \right\} \quad (41)$$

It is obvious that (36) is able to be decomposed into optimization sub-problems solved separately at the building and network sides. ADMM is used to solve (36) in a distributed manner. The coordination between the injection power to the network and building is reflected, adding the Lagrange penalty function into the objective function.

1) Building-side Sub-problem

The building-side sub-optimization model is able to be

transformed into a mixed-integer linear programming (MILP) problem that can be efficiently solved, as follows:

$$\begin{aligned} \min \sum_w p_w \sum_{t=1}^{N_t} \left[\sum_{n \in N_k} |P_{bld,n,t} - P_{pv,w,n,t}| \right. \\ \left. + \sum_{n \in N_k} (\lambda_{bld,w,n,t})^T (x_{bld,w,n,t} - \tilde{z}_{bld,w,n,t}) \right. \\ \left. + \sum_{n \in N_k} (\rho/2) \|x_{bld,w,n,t} - \tilde{z}_{bld,w,n,t}\|_2^2 \right] \\ \text{s.t. (1), (2), (8)–(17), (29)–(33), (37), (38)} \end{aligned} \quad (42)$$

2) Network-side Sub-problem

The network-side sub-optimization model is able to be transformed into a second-order cone programming (SOCP) problem that can also be efficiently solved, as follows:

$$\begin{aligned} \min \sum_w p_w \sum_{t=1}^{N_t} \left[P_{loss,w,t} + \sum_{n \in N_k} (\lambda_{net,w,n,t})^T \right. \\ \left. \cdot (x_{net,w,n,t} - \tilde{z}_{net,w,n,t}) \right. \\ \left. + \sum_{n \in N_k} (\rho/2) \|x_{net,w,n,t} - \tilde{z}_{net,w,n,t}\|_2^2 \right] \\ \text{s.t. (18)–(20), (22), (34), (35)} \end{aligned} \quad (43)$$

The aforementioned two sub-optimization models are solved separately, and the boundary information of each side is exchanged.

3) Update of Local/Global Variables and Lagrangian Multipliers

Constraints (44)–(48) are the alternate iteration process of ADMM variables on building and network sides. The local variables are updated as follows:

$$\begin{aligned} x_{bld,w,n,t}^{k+1} \\ = \arg \min_x \left\{ \sum_w p_w \sum_{t=1}^{N_t} \left[\sum_{n \in N_k} |P_{bld,n,t} - P_{pv,w,n,t}| \right. \right. \\ \left. \left. + \sum_{n \in N_k} (\lambda_{bld,w,n,t})^T (x_{bld,w,n,t} - \tilde{z}_{bld,w,n,t}) \right. \right. \\ \left. \left. + \sum_{n \in N_k} (\rho/2) \|x_{bld,w,n,t} - \tilde{z}_{bld,w,n,t}\|_2^2 \right] \right\} \end{aligned} \quad (44)$$

$$\begin{aligned} x_{net,w,n,t}^{k+1} = \arg \min_x \left\{ \sum_w p_w \sum_{t=1}^{N_t} \left[P_{loss,w,t} \right. \right. \\ \left. \left. + \sum_{n \in N_k} (\lambda_{net,w,n,t})^T (x_{net,w,n,t} - \tilde{z}_{net,w,n,t}) \right. \right. \\ \left. \left. + \sum_{n \in N_k} (\rho/2) \|x_{net,w,n,t} - \tilde{z}_{net,w,n,t}\|_2^2 \right] \right\} \end{aligned} \quad (45)$$

where k is the iteration number.

The global variables are updated as follows:

$$z_{bld,w,n,t}^{k+1} = z_{net,w,n,t}^{k+1} = \frac{x_{bld,w,n,t}^{k+1} + x_{net,w,n,t}^{k+1}}{2} \quad (46)$$

The Lagrangian multipliers are updated as follows:

$$\lambda_{bld,w,n,t}^{k+1} = \lambda_{bld,w,n,t}^k + \rho(x_{bld,w,n,t}^{k+1} - z_{bld,w,n,t}^{k+1}) \quad (47)$$

$$\lambda_{net,w,n,t}^{k+1} = \lambda_{net,w,n,t}^k + \rho(x_{net,w,n,t}^{k+1} - z_{net,w,n,t}^{k+1}) \quad (48)$$

4) Convergence Criteria

Constraints (49) and (50) are the termination condition of iterations:

$$\|p^{k+1}\|_2^2 = \max(\|x_{\text{bld},1,n,t}^{k+1} - z_{\text{net},1,n,t}^{k+1}\|_2^2, \|x_{\text{bld},2,n,t}^{k+1} - z_{\text{net},2,n,t}^{k+1}\|_2^2, \dots, \|x_{\text{bld},w,n,t}^{k+1} - z_{\text{net},w,n,t}^{k+1}\|_2^2) \leq \varepsilon_{\text{pri}} \quad (49)$$

$$\|s^{k+1}\|_2^2 = \max(\|(-\rho)(z_{\text{net},1,n,t}^{k+1} - z_{\text{net},1,n,t}^k)\|_2^2, \|(-\rho)(z_{\text{net},2,n,t}^{k+1} - z_{\text{net},2,n,t}^k)\|_2^2, \dots, \|(-\rho)(z_{\text{net},w,n,t}^{k+1} - z_{\text{net},w,n,t}^k)\|_2^2) \leq \varepsilon_{\text{dual}} \quad (50)$$

If the primal and dual residuals are less than the threshold, the iteration ceases, and scheduling results are output; other-

wise, the local/global variables and Lagrangian multipliers of ADMM are updated until the ADMM converges.

Based on the stochastic and distributed energy management approach to the ADN with integrated aggregated office buildings, the solution flow is given, as shown in Fig. 3.

Step 1: Establish the thermal dynamic model and EV model, considering the demands of office workers for heating and traveling.

Step 2: Construct an office building model with HVACs and EV charging piles, integrating the thermal dynamic model and EV model.

Step 3: Build a stochastic ADN optimization model with office buildings and PV generations, considering the aggre-

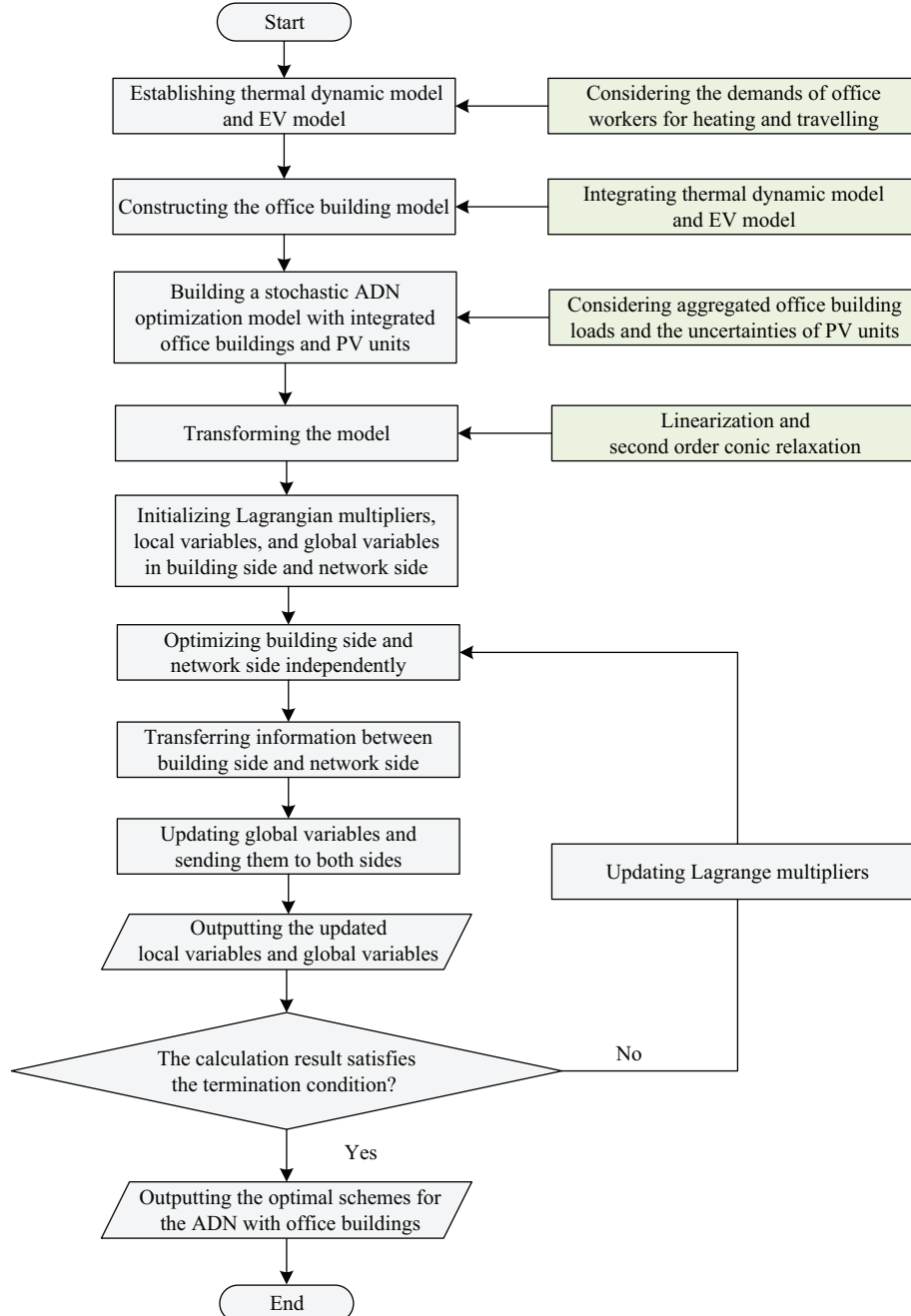


Fig. 3. Flowchart of stochastic and distributed energy management method for ADN with integrated office buildings.

gated office building loads and the PV output uncertainties. Also, the ADN optimization model is converted according to the linearization and SOCR.

Step 4: Initialize the Lagrangian multipliers, local variables, and global variables in the building and network sides.

Step 5: Update global variables to exchange messages between both sides after building and network sides are separately optimized.

Step 6: Stop the iteration process if the primal and dual residuals are smaller than a threshold; otherwise, update Lagrange multipliers and skip to step 5 until the ADMM converges.

Step 7: Export the optimal results according to the stochastic and distributed energy management approach to the ADN with integrated office buildings.

V. CASE STUDIES

This section examines a stochastic and distributed optimal energy management approach to the ADN with integrated office buildings. All sub-problems are solved by GUROBI in the MATLAB on a PC with Intel® Core™ i7 2.60 GHz CPU and 8 GB RAM. The calculation time of this optimization model is around 1438 seconds.

The PV output prediction errors are presented as the normal distribution function [30]. 1000 uncertain scenarios for PV power are produced utilizing the Monte-Carlo simulation and reduced to 5 through GAMS using the SCENRED toolbox. The geographic locations of the connected PVs are considered to be relatively close. Therefore, the power outputs of the PVs are almost the same and the interdependency of PVs is not considered in this paper. The predicted PV outputs are derived from the PJM history information in December 2020, as illustrated in Fig. 4.

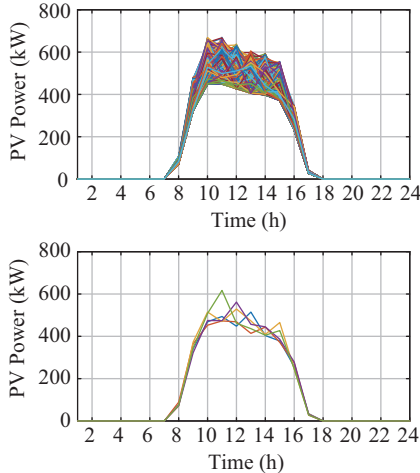


Fig. 4. Original and reduced scenarios of PV power.

Slow thermal dynamic characteristics of buildings means that it often takes a certain amount of time for the building temperature to rise or fall when the building is heated or cooled. Therefore, the slow thermal dynamics of buildings causes them to be at thermal inertia [31]. The room temperatures are able to be regulated within a specific scope

while maintaining the consumers' comfort levels. The analysis is performed for a 24-hour scheduling horizon with a one-hour time resolution because of the slow building thermal dynamics [11]. The iteration step is set to be one. The convergence threshold of residuals is set to be 10^{-3} . The working hours of the buildings are between 08:00 to 19:00. The thermal comfort degree for people is decided by multiple environmental elements, such as temperature, metabolic rate, etc. [32]. Therefore, the acceptable comfort temperature range for human habitation in buildings can vary depending on the situation. For humans, the thermoneutral temperature scope is from 17°C to 33°C [33]. Thus, the comfortable temperature in this work environment is able to be set differently. The comfort indoor temperature range for office workers is set as 20°C–26°C. The expected SOC for EVs at departure is set as 0.8. Table II summarizes the parameters of office buildings, HVAC systems, and EVs [9], [34]. The solar radiation intensity of different directions, the outdoor temperature, the general power load (not including HVACs and EVs) of an office building, and the building interior heat are displayed in Fig. 5 [11], [35].

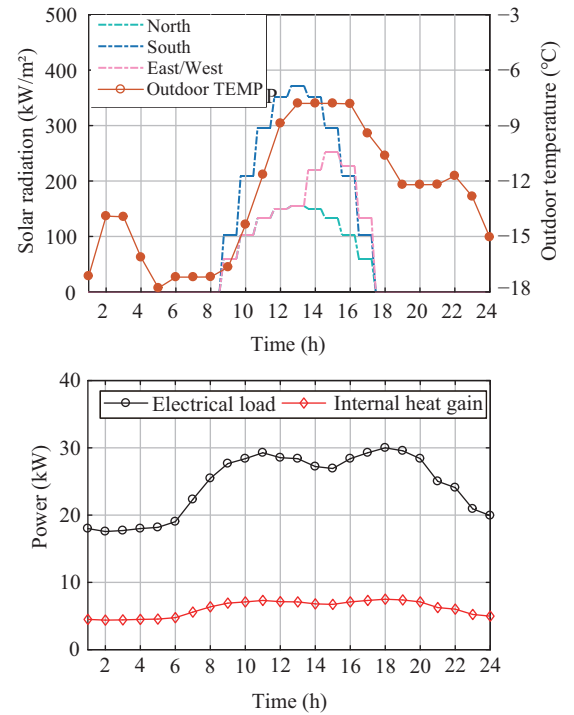


Fig. 5. Solar irradiance, outside temperature, power load, and interior heat in an office building.

Nodes 6, 18, 25, and 33 in the IEEE-33 system connect the collection of PV units and office buildings, respectively, and the schematic diagram of the ADN is illustrated in Fig. 6. Each node connects a building group (containing five office buildings). The distribution system connects twenty office buildings in all. Each building contains twenty working areas and ten EVs. Because the ADMM method is used to decompose the original problem, the scale of the whole model decreases. In addition, the SOCR method is used to relax the model, which can further reduce the calculation cost. Thus, the

TABLE II
PARAMETERS OF BUILDINGS, HVAC SYSTEMS, AND EVs

Buildings		HVAC systems		EVs	
PARAM	Value	PARAM	Value	PARAM	Value
$R_{\text{wall(win)}}$	0.08 K/W	ρ	1.29 kg/m ³	SOC_{home}	0.40
R_{wall}	0.06 K/W	P_{static}	135 Pa	$\text{SOC}_{\text{max}}/\text{SOC}_{\text{min}}$	0.90/0.10
R_{win}	0.02 K/W	v	4 m/s	$P_{\text{max}}^c/P_{\text{max}}^d$	4 kW
$C_{\text{wall(win)}}$	2.6e+7 J/K	C_{cop}	3.0	E_B	24 kW·h
C_{wall}	7.9e+5 J/K	c_p	1005 J/kg·°C	κ	0.001
C_{room}	2.5e+5 J/K	$\eta_{\text{fan}}\eta_{\text{motor}}$	0.15	η^c/η^d	0.95
				W	0.149 kWh·km ⁻¹

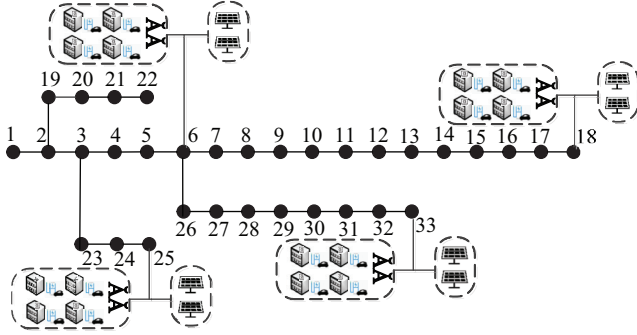


Fig. 6. Diagrammatic sketch of the ADN.

proposed method should have good scalability for the larger-scale problem. The testing of the method for a larger system will be investigated in a future study.

A. Energy Scheduling Results of Buildings and ADN

Under the given parameters, the stochastic and distributed optimal energy management of the ADN with office buildings is solved. The results of indoor temperatures and total HVAC system power of an office building cluster at different periods are depicted in Fig. 7. The HVAC systems are switched on after the office workers enter the office building. After a while, the indoor temperature of office buildings has been significantly increased and has reached the office workers' demands for a comfortable temperature (e.g., during 8:00–9:00). In parallel with the increase in the outdoor temperature and the PV power towards noon, the indoor temperature will continue to increase until it reaches the upper limit of office workers' comfort temperature, and the power of HVAC systems has a good tracking effect for PV power (e.g., during 11:00–14:00). However, as the outdoor temperature and PV power during the evening hour decreases, the indoor temperature will continue to decrease until it reaches the lower limit of the office workers' comfort temperature (e.g., during 16:00–18:00). To maintain employees' comfortable temperature demands, the power of HVAC systems continues to supply heat without tracking the PV power that eventually reduces to zero.

The SOC values and net EV charging power in an office building cluster at different periods are illustrated in Fig. 8. The EVs maintain a high total net charging power at 10:00–14:00. This is due to the higher PV power during the midday period, which causes an increase in SOC values of EVs dispatched in the parking lot up to the charging limit of EV batteries. However, as the expected SOC value of the workers

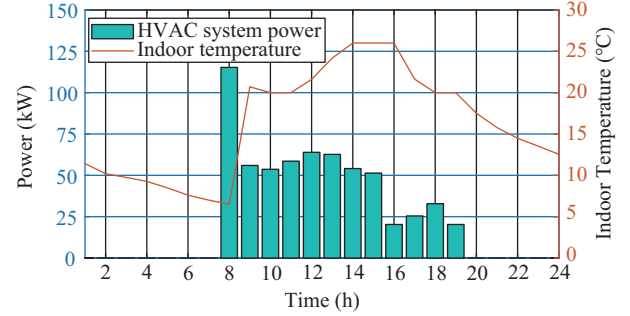


Fig. 7. Indoor temperature and HVAC system power of buildings.

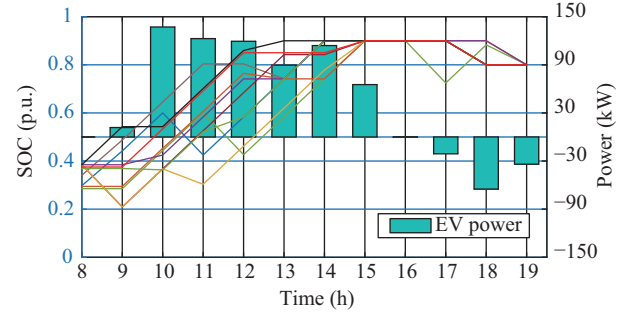


Fig. 8. SOC values and net charging power of EVs.

and the continuous reduction of the PV power during the evening hour, the total net charging power of the EVs becomes negative, and EV batteries are discharged until they reach the expected SOC value when the office workers leave (e.g., during 17:00–19:00).

Based on the stochastic and distributed energy management method of the ADN, the uncertainty of PV power is considered, and flexible resources in the office building are fully utilized. Hourly-based results of the operational power at an office building cluster and the network loss in the ADN are exhibited in Fig. 9. The office building's energy consumption possesses a good tracing performance on PV output. This promotes the local accommodation of PV power and improves the penetration of PVs in the system. Moreover, the ADN's economic operation can be further improved through reducing the network loss.

B. Impact of the Comfort Temperature Range

For HVAC systems, the intervals of the comfort temperature determine whether the building's thermal storage capacity can be fully utilized, and affect the tracking effect and the network

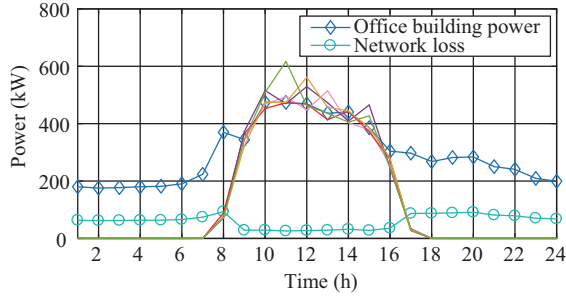


Fig. 9. Results of office building power and network loss.

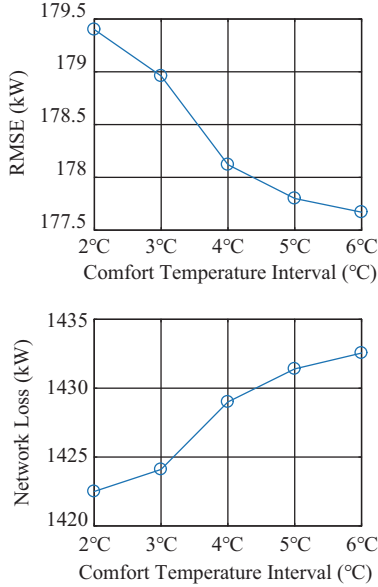


Fig. 10. Comparison of RMSE and network loss with various comfort temperature intervals.

loss. The interval of the comfort temperature changes from 2°C to 6°C. The contrast result of the root mean square error (RMSE) and network loss with different comfortable temperature intervals is shown in Fig. 10.

As shown in the figure, while the temperature interval turns from 2°C into 6°C, the RMSE decreases by 0.98%. The reason is that the heating power of the HVAC system can be used to track PV power without violating the comfort temperature constraints of workers when the comfort temperature interval increases. Similarly, while the temperature interval turns from 2°C into 6°C, the network loss of the ADN increases by 0.70%. The reason is that the heating power of the HVAC system will also increase accordingly when the upper limit of the comfort temperature increases. This increases the operational power of office buildings and thus increasing the network loss of the ADN.

C. Impact of Expected SOC for Departing EVs

For workers' EVs, the expected SOC for departing EVs determines the net charge of EV batteries, and affects the tracking effect and network loss. Let the expected SOC values of EVs change from 0.70 to 0.90. The comparison of RMSE and network loss with various SOC at departure is shown in Fig. 11.

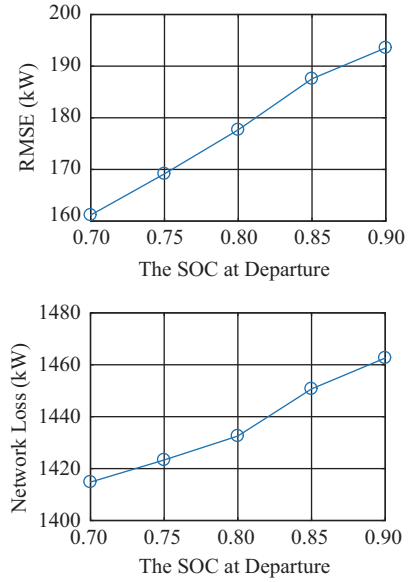


Fig. 11. Comparison of RMSE and network loss with various SOC at the departure.

As shown in the figure, when the expected SOC at departure changes from 0.70 to 0.90, the RMSE increases by 16.73%. The reason is that when the workers are off duty, the PV power has been reduced to zero, and the expected SOC at departure increases. This will lead to continuous EV charging to satisfy the travel demands of workers, and the PV power cannot be tracked by EV discharging. Therefore, the RMSE will increase as the expected SOC at departure increases. Similarly, when the expected SOC at departure changes from 0.70 to 0.90, the network loss of the ADN increases by 3.27%. The reason is that with the rising expected SOC at departure, the total net EV charging power increases accordingly. This increases the operational power of the office building and thus increases the network loss of the ADN.

D. Energy Management Results in Summer

In this section, case studies for the cooling scenario during summer time are carried out. The outdoor temperature in summer is referred to in [13]. The indoor temperature, HVAC system power, SOC values, and net charging power of EVs in the summer time case are shown below. As can be observed, the room temperature meets the temperature requirement of all the staff, and EV batteries can also reach the expected SOC value when the workers leave during the summer. In addition, through the coordinated scheduling of HVACs and EVs, the power of HVAC systems and EVs has a good tracing performance on PV output.

To verify the efficacy of the presented method during summer, the office building cluster load and ADN's network loss in the summer case are shown below. As can be observed, the profiles of the office building load and network loss are almost the same as in the winter case. Therefore, it further illustrates that the office building's flexible load also has a good tracking effect on PV power, and the network losses can be reduced in the summer case.

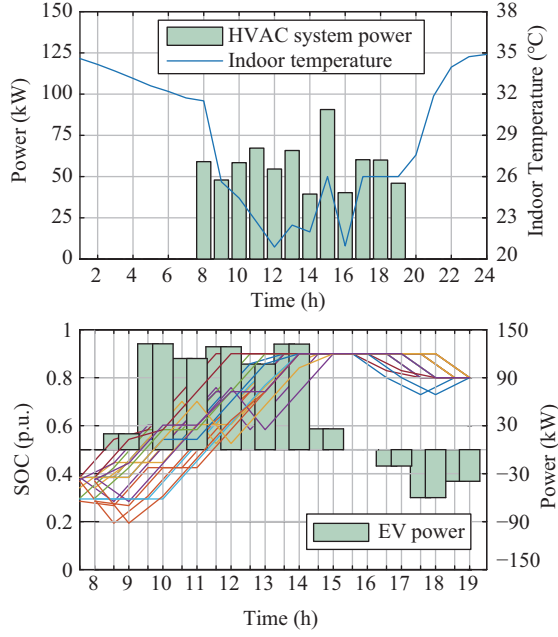


Fig. 12. Indoor temperature, HVAC system power of buildings, SOC values, and net charging power of EVs in the summer case.

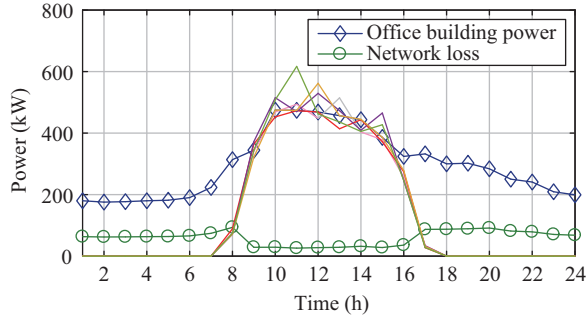


Fig. 13. Results of office building power and network loss in the summer case.

E. Accuracy Analysis of the SOCR

To further validate the SOCR correctness in this model, an error index $\Delta_{\text{diff}} = |P_{mn}^2 + Q_{mn}^2 - i_{mn}v_m|$ is defined [36]. The expected error scatters of each branch are shown in Fig. 14. Obviously, all deviations after SOCR are below 10^{-6} order magnitude, and the model accuracy for this study is able to satisfy the actual project demand.

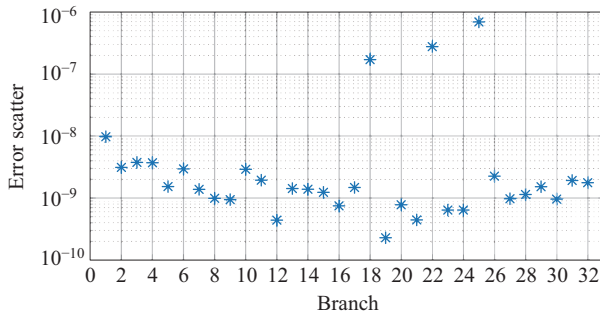


Fig. 14. Error scatter of each branch.

F. Convergence of the Optimization Model

To validate the accuracy of the presented distributed approach, the total target values obtained through the presented distributed approach and the centralized approach are compared, as shown in Fig. 15. As can be observed, the total objective value converges to a steady value after about 20 iterations, which is equal to the value of the centralized model.

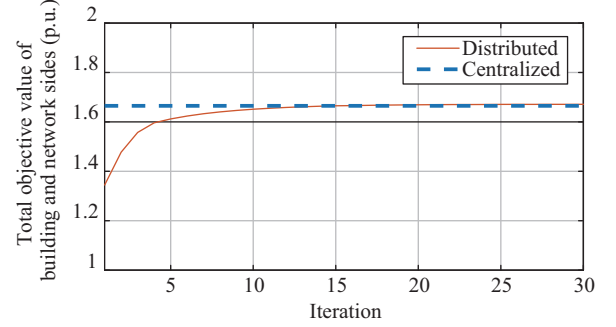


Fig. 15. Comparison of the total objective value obtained by the distributed and centralized methods.

The convergence curves of the primal and dual residuals of the stochastic and distributed optimal energy management approach to the ADN with office buildings are shown in Fig. 16. The feasibility tolerance of the stochastic and distributed optimization model is set to 10^{-3} . The convergence curves for both primal and dual residuals tend to decrease and eventually reach convergence accuracy. This further indicates that the solution of the algorithm can satisfy the constraints set by the ADN system with office buildings.

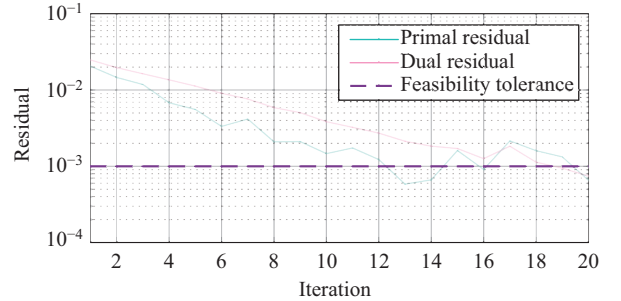


Fig. 16. Primal and dual residual versus iteration.

VI. CONCLUSION

This paper proposes a novel stochastic and distributed optimal energy management approach for the ADN with office buildings. According to the stochastic and distributed optimal model of the ADN, the flexible resources of office buildings can be dispatched in the optimal ADN operation with a distributed approach under stochastic scenarios.

During the optimal scheduling process, the BEMSs distribute the dispatching signals to the flexible resources in office buildings responding to the excitation signals of the DSO and uploading the feedback signals. On the other hand, the DSO sends the excitation signal to the buildings and receives the feedback signal uploaded by BEMSs. Therefore, the sub-goals

in the building and network can be achieved while respecting all the operational constraints of the ADN under multiple stochastic scenarios, and the office buildings cannot reveal their parameters to each other.

The main conclusions are the following:

1) According to the building thermal dynamics and the behavioral habits of workers, the loads of office buildings with integrated HVAC systems and EV charging piles are able to be leveraged to accommodate PV output to improve the PV generation penetration and decrease the ADN loss while meeting workers' heating and travel demands.

2) With increasing the comfortable temperature interval, the RMSE tends to decrease, and the network loss tends to increase. With increasing the SOC at departure, the RMSE tends to increase, and the network loss also tends to increase.

3) The global optimal energy management of the ADN with aggregated office buildings can be realized, and the privacy of the ADN and the office buildings is protected through the distributed optimization solution

This paper also shows some limitations, and these are considered as future studies to be conducted. First, the two-stage stochastic optimization approach for distributed optimal energy management in ADN with integrated office buildings will be studied. In addition, there are still binary variables in the optimization model. To provide an efficient solution for the ADMM, the method of removing binary variables will be further investigated [37]. Moreover, the proposed method considers incentive-based demand response. The energy management method can be further improved by studying the response subsidy policy in the future.

REFERENCES

- [1] T. C. Zhang, J. X. Wang, H. W. Zhong, G. Y. Li, M. Zhou, and D. J. Zhao, "Soft open point planning in renewable-dominated distribution grids with building thermal storage," *CSEE Journal of Power and Energy Systems*, doi: 10.17775/CSEEJPES.2020.03660.
- [2] R. L. Li and S. You, "Exploring potential of energy flexibility in buildings for energy system services," *CSEE Journal of Power and Energy Systems*, vol. 4, no. 4, pp. 434–443, Dec. 2018, doi: 10.17775/CSEEJPES.2018.00360.
- [3] M. Ostadijafari, A. Dubey, and N. P. Yu, "Linearized price-responsive HVAC controller for optimal scheduling of smart building loads," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 3131–3145, Jul. 2020, doi: 10.1109/TSG.2020.2965559.
- [4] L. Yu, D. Xie, C. X. Huang, T. Jiang, and Y. L. Zou, "Energy optimization of HVAC systems in commercial buildings considering indoor air quality management," *IEEE Transactions on Smart Grid*, vol. 10, no. 5, pp. 5103–5113, Sep. 2019, doi: 10.1109/TSG.2018.2875727.
- [5] H. H. Chen, Z. N. Li, X. L. Jin, T. Jiang, X. Li, and Y. F. Mu, "Modeling and optimization of active distribution network with integrated smart buildings," *Proceedings of the CSEE*, vol. 38, no. 22, pp. 6550–6562, 2018.
- [6] D. T. Vedullapalli, R. Hadidi, and B. Schroeder, "Combined HVAC and battery scheduling for demand response in a building," *IEEE Transactions on Industry Applications*, vol. 55, no. 6, pp. 7008–7014, Nov./Dec. 2019, doi: 10.1109/TIA.2019.2938481.
- [7] X. L. Jin, J. Z. Wu, Y. F. Mu, M. S. Wang, X. D. Xu, and H. J. Jia, "Hierarchical microgrid energy management in an office building," *Applied Energy*, vol. 208, pp. 480–494, Dec. 2017.
- [8] Q. Yan, B. Zhang, and M. Kezunovic, "Optimized operational cost reduction for an EV charging station integrated with battery energy storage and PV generation," *IEEE Transactions on Smart Grid*, vol. 10, no. 2, pp. 2096–2106, Mar. 2019, doi: 10.1109/TSG.2017.2788440.
- [9] T. Jiang, Z. N. Li, X. L. Jin, H. H. Chen, X. Li, and Y. F. Mu, "Flexible operation of active distribution network using integrated smart buildings with heating, ventilation and air-conditioning systems," *Applied Energy*, vol. 226, pp. 181–196, Sep. 2018, doi: 10.1016/j.apenergy.2018.05.091.
- [10] M. Razmara, G. R. Bharati, M. Shabbakhti, S. Paudyal, and R. D. Robinett, "Bilevel optimization framework for smart building-to-grid systems," *IEEE Transactions on Smart Grid*, vol. 9, no. 2, pp. 582–593, Mar. 2018, doi: 10.1109/TSG.2016.2557334.
- [11] Z. N. Li, S. Su, Y. M. Zhao, X. L. Jin, H. H. Chen, Y. J. Li, and R. Z. Zhang, "Energy management strategy of active distribution network with integrated distributed wind power and smart buildings," *IET Renewable Power Generation*, vol. 14, no. 12, pp. 2255–2267, Sep. 2020, doi: 10.1049/iet-rpg.2020.0049.
- [12] M. Tavakkoli, S. Fattaheian-Dehkordi, M. Pourakbari-Kasmaei, M. Liski, and M. Lehtonen, "Bonus-based demand response using Stackelberg game approach for residential end-users equipped with HVAC system," *IEEE Transactions on Sustainable Energy*, vol. 12, no. 1, pp. 234–249, Jan. 2021, doi: 10.1109/TSTE.2020.2989583.
- [13] R. F. Zhang, T. Jiang, G. Q. Li, X. Li, and H. H. Chen, "Stochastic optimal energy management and pricing for load serving entity with aggregated TCLs of smart buildings: a Stackelberg game approach," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 3, pp. 1821–1830, Mar. 2021, doi: 10.1109/TII.2020.2993112.
- [14] S. S. Guggilam, E. Dall'Anese, Y. C. Chen, S. V. Dhople, and G. B. Giannakis, "Scalable optimization methods for distribution networks with high PV integration," *IEEE Transactions on Smart Grid*, vol. 7, no. 4, pp. 2061–2070, Jul. 2016, doi: 10.1109/TSG.2016.2543264.
- [15] W. Y. Zheng, W. C. Wu, B. M. Zhang, H. B. Sun, and Y. B. Liu, "A fully distributed reactive power optimization and control method for active distribution networks," *IEEE Transactions on Smart Grid*, vol. 7, no. 2, pp. 1021–1033, Mar. 2016.
- [16] M. Xie, X. Ji, X. T. Hu, P. J. Cheng, Y. X. Du, and M. B. Liu, "Autonomous optimized economic dispatch of active distribution system with multi-microgrids," *Energy*, vol. 153, pp. 479–489, Jun. 2018, doi: 10.1016/j.energy.2018.04.021.
- [17] Z. M. Li, L. Wu, and Y. Xu, "Risk-averse coordinated operation of a multi-energy microgrid considering voltage/var control and thermal flow: an adaptive stochastic approach," *IEEE Transactions on Smart Grid*, vol. 12, no. 5, pp. 3914–3927, doi: 10.1109/TSG.2021.3080312.
- [18] T. Y. Zhao, J. H. Zhang, and P. Wang, "Flexible active distribution system management considering interaction with transmission networks using information-gap decision theory," *CSEE Journal of Power and Energy Systems*, vol. 2, no. 4, pp. 76–86, Dec. 2016.
- [19] J. Liu, P. L. Zeng, H. Xing, Y. L. Li, and Q. W. Wu, "Stochastic optimal operation of flexible distribution networks for security improvement considering active management," *CSEE Journal of Power and Energy Systems*, doi: 10.17775/CSEEJPES.2020.02860.
- [20] Z. M. Li, Y. Xu, X. Feng, and Q. W. Wu, "Optimal stochastic deployment of heterogeneous energy storage in a residential multienergy microgrid with demand-side management," *IEEE Transactions on Industrial Informatics*, vol. 17, no. 2, pp. 991–1004, Feb. 2021.
- [21] R. Z. Lu and S. H. Hong, "Incentive-based demand response for smart grid with reinforcement learning and deep neural network," *Applied Energy*, vol. 236, pp. 937–949, Feb. 2019.
- [22] A. Triviño-Cabrera, J. A. Aguado, and S. de la Torre, "Joint routing and scheduling for electric vehicles in smart grids with V2G," *Energy*, vol. 175, pp. 113–122, May 2019.
- [23] Z. M. Li and Y. Xu, "Temporally-coordinated optimal operation of a multi-energy microgrid under diverse uncertainties," *Applied Energy*, vol. 240, pp. 719–729, Apr. 2019.
- [24] J. García-Villalobos, I. Zamora, P. Eguia, J. I. San Martín, and F. J. Asensio, "Modelling social patterns of plug-in electric vehicles drivers for dynamic simulations," in *2014 IEEE International Electric Vehicle Conference (IEVC)*, Florence, Italy, Dec. 2014, pp. 1–7.
- [25] Z. N. Li, S. Su, X. L. Jin, H. H. Chen, Y. J. Li, and R. Z. Zhang, "A hierarchical scheduling method of active distribution network considering flexible loads in office buildings," *International Journal of Electrical Power & Energy Systems*, vol. 131, pp. 106768, Oct. 2021.
- [26] S. Su, Z. N. Li, X. L. Jin, K. Yamashita, M. C. Xia, and Q. F. Chen, "Energy management for active distribution network incorporating office buildings based on chance-constrained programming," *International Journal of Electrical Power & Energy Systems*, vol. 134, pp. 107360, Jan. 2022.
- [27] M. Farivar and S. H. Low, "Branch flow model: relaxations and convexification—Part I," *IEEE Transactions on Power Systems*, vol. 28, no. 3, pp. 2554–2564, Aug. 2013, doi: 10.1109/TPWRS.2013.2255317.

- [28] L. H. Wang, Q. Q. Li, R. Ding, M. S. Sun, and G. R. Wang, "Integrated scheduling of energy supply and demand in microgrids under uncertainty: A robust multi-objective optimization approach," *Energy*, vol. 130, pp. 1–14, Jul. 2017.
- [29] S. Boyd, N. Parikh, E. Chu, B. Peleato, and J. Eckstein, "Distributed optimization and statistical learning via the alternating direction method of multipliers," *Foundations and Trends® in Machine Learning*, vol. 3, no. 1, pp. 1–122, Jan. 2010.
- [30] A. Mallem and O. Boudebouz, "Economic dispatch on a power system network interconnected with solar farm," in *2019 1st International Conference on Sustainable Renewable Energy Systems and Applications (ICSRESA)*, Tebessa, Algeria, Dec. 2019, pp. 1–6, doi: 10.1109/ICSRESA49121.2019.9182477.
- [31] L. D. Zhang, Y. Li, H. Zhang, X. D. Xu, Z. L. Yang, and W. Xu, "A review of the potential of district heating system in Northern China," *Applied Thermal Engineering*, vol. 188, pp. 116605, Apr. 2021.
- [32] ASHRAE Standard 55P, "Thermal environmental conditions for human occupancy," Atlanta, USA: American Society of Heating, Refrigerating and Airconditioning Engineers, 2003.
- [33] J. F. Busch, "Thermal comfort in Thai air-conditioned and naturally ventilated offices," in *Standards for Thermal Comfort: Indoor Air Temperature Standards for the 21st Century*, J. F. Nicol, M. Humphreys, M. Sykes, and S. Roaf, Ed. London: Taylor and Francis, 1995, pp. 114–131.
- [34] Z. N. Li, S. Su, X. L. Jin, and H. H. Chen, "Distributed energy management for active distribution network considering aggregated office buildings," *Renewable Energy*, vol. 180, pp. 1073–1087, Dec. 2021.
- [35] S. Su, Z. N. Li, X. L. Jin, K. Yamashita, M. C. Xia, and Q. F. Chen, "Bi-level energy management and pricing for community energy retailer incorporating smart buildings based on chance-constrained programming," *International Journal of Electrical Power & Energy Systems*, vol. 138, 107894, Jun. 2022.
- [36] H. J. Gao, J. Y. Liu, X. D. Shen, and R. Xu, "Optimal power flow research in active distribution network and its application examples," *Proceedings of the CSEE*, vol. 37, no. 6, pp. 1634–1644, May 2017.
- [37] Z. M. Li, Y. Xu, S. D. Fang, X. D. Zheng, and X. Feng, "Robust coordination of a hybrid AC/DC multi-energy ship microgrid with flexible voyage and thermal loads," *IEEE Transactions on Smart Grid*, vol. 11, no. 4, pp. 2782–2793, Jul. 2020.



Zening Li received the M.S. degree in Electrical Engineering from Northeast Electric Power University, Jilin, China, in 2019, and the Ph.D. degree in Electrical Engineering from Beijing Jiaotong University, Beijing, China, in 2022. He is currently a lecturer with the College of Electrical and Power Engineering, Taiyuan University of Technology, Taiyuan, China. His research interests include smart building, active distribution network, and integrated energy system.



Su Su received the B.S. and Ph.D. degrees in Electrical Engineering from Tohoku University, Sendai, Japan, in 2006 and 2009, respectively. She is currently a Professor with the School of Electrical Engineering, Beijing Jiaotong University, Beijing, China. Her current research interests include active distribution network energy management, electric vehicle charging station planning and optimal scheduling, and analysis and modeling of electric vehicle user driving behavior.



research interests include energy management of multi-energy buildings and their integrations with integrated energy systems, and the energy & flexibility markets solutions.



Mingchao Xia received the B.S. and Ph.D. degrees in Electrical Engineering from Tsinghua University, Beijing, China, in 1998 and 2003, respectively. He is currently a Professor with the School of Electrical Engineering, Beijing Jiaotong University, Beijing. His current research interests include energy internet, smart power distribution system control and optimization, power electronics in power distribution, and flexible load control.



Qifang Chen received the B.S. and M.S. degrees in Communication Engineering and Electric Engineering from Xiangtan University, Xiangtan, Hunan, China, in 2010 and 2013, respectively, and the Ph.D. degree in Electrical Engineering from North China Electric Power University, Beijing, China, in 2017. He is currently an Associate Professor with the School of Electrical Engineering, Beijing Jiaotong University, Beijing. His research interests include microgrid, renewable energy vehicles, and integrated energy systems.



Koji Yamashita received the B.S. and M.S. degrees in Electrical Engineering from Waseda University, Tokyo, Japan, in 1993 and 1995, respectively, and the Ph.D. degree in Electrical and Computer Engineering from Michigan Technological University, Houghton, MI, USA, in 2020. He was a Visiting Researcher with Iowa State University, Ames, IA, USA, from 2006 to 2007. He was a Research Scientist with the Power System Division, CRIEPI, Tokyo, from 1995 to 2018. He is currently a Post-Doctoral Scholar with the University of California at Riverside, Riverside, CA, USA, cultivating machine learning techniques for power system dynamics.