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Simultaneous community energy supply-demand optimization by microgrid operation scheduling optimization and occupant-oriented flexible energy-use regulation

Chengyu Zhang¹, Yacine Rezgui², Zhiwen Luo³, Ben Jiang¹, Tianyi Zhao^{1,*}

¹ Institute of Building Energy, Dalian University of Technology, Dalian, China

² School of Engineering, Cardiff University, Cardiff, United Kingdom

³ Welsh School of Architecture, Cardiff University, Cardiff, United Kingdom

* Corresponding author: zhaotianyi@dlut.edu.cn

Abstract: Community microgrids represent a pivotal solution for addressing energy conservation and reducing carbon emissions. However, few studies focused on the methods of concurrently optimizing both the supply and demand sides within campus settings, a unique form of community. Moreover, few studies on energy demand optimization rarely delved into human-centered approaches and employed multi-strategy parallel flexible regulations, while few studies on energy supply optimization discussed the comprehensive environment-energy-society-investment benefits as optimization objectives with suitable algorithms for calculation. Consequently, this study introduced a novel approach to energy system supply-demand optimization by simultaneous flexible energy-use regulation and microgrid operation scheduling, to explore human-centered multi-strategy parallel flexible energy-use regulations, and comprehensive evaluation parameters for energy supply-demand optimization. (1) Regarding flexible energy-use regulation, this study proposed several adjustments including adjusting the start-up temperature of air conditioners (ACs), organized charging of electric vehicles (EVs), light or plug management, and course optimization. These parallel adjustments can reduce or shift 12.12% of energy demand during peak hours and 8.06% during sharp hours, yielding 4.449%–8.820% of the annual average benefits in different cases. (2) Regarding microgrid optimization scheduling, this study introduced novel objectives aimed at maximizing investment-environment-energy-society benefits and solving algorithms, the jellyfish search algorithm (JSA), for calculation. Results showed 10.085%–11.728% of the annual average benefits in different cases. Ultimately, the optimization integration of flexible energy-use regulations and microgrid operation scheduling yields 15.655%–18.016% of the annual average benefits in different cases.

Keywords: Microgrid operation scheduling optimization; flexible energy-use regulation; occupant-oriented regulation; multi-strategy parallel regulation; jellyfish search algorithm

Nomenclature

AC	Air conditioning or air conditioner
ACP	Alternating current power
BAT	Battery
CCHP	Combined cooling, heating, and power
CCHHP	Combined cooling, heating, hydrogen, and power
CNN	Convolutional neural network
CV-RMSE	Coefficient of variation of root mean square error
DCP	Direct current power
DE	Diesel engine
DG	Diesel generator
EBC	Energy in Buildings and Communities Programme of IEA
ESD	Energy storage device
EUI	Energy use intensity (kWh/a year·m ²)
EV	Electric vehicle
G2V	Grid-to-vehicle
GA	Genetic algorithm
GWO	Grey wolf algorithm
HSD	Hydrogen storage device
HVAC	Heating, ventilation, and air conditioning systems
IEA	International Energy Agency
LSTM	Long short-term memory neural network
MAE	Mean absolute error
MAPE	Mean absolute percentage error
JSA	Jellyfish search algorithm
MT	Microturbine
PCM	Phased change material
PSO	Particle swarm optimization
PV	Photovoltaic
R ²	Coefficient of determination
RMSE	Root mean square error
SE	Squeeze-and-excitation attention mechanisms
SOC	State of charge for batteries (%)
V2G	Vehicle-to-grid
WT	Wind turbine

1 Introduction

1.1 Background

With the continuous development of urbanization, energy, and environmental crisis may have been the main challenges all over the world. In 2021, buildings worldwide accounted for 30% of final energy consumption contributing to 37% of global energy-related CO₂ emissions from operational activities^[1–2]. Similarly, in China, building energy consumption and carbon emissions constituted 21% and 21.6% of the national total, respectively. Moreover, the annual growth rates of energy consumption and carbon emissions are 6.96% and 6.95% respectively, significantly higher than the previous year^[3–4].

Various measures have been proposed for these challenges, such as promoting the promotion of renewable energy sources. According to relevant statistics^[5], the global installed capacity of renewable energy witnessed an increase of around 260 GW in 2020, where solar photovoltaic power systems saw a surge of 127 GW in newly installed capacity, and wind power increased by 111 GW. Moreover, many governments have recognized transport electrification as a pivotal strategy for reducing CO₂ emissions, advocating for the transition from fossil fuel-based energy to renewable sources^[6].

In this context, community or urban microgrids have emerged as significant solutions. First, community microgrids can fully employ renewable energy sources thereby reducing reliance on external energy supplies while mitigating carbon emissions and lowering energy costs. Second, microgrids offer flexible energy supply and demand modes, fostering multi-level interactions among EVs, buildings, energy storage systems, photovoltaic (PV), and others. Finally, microgrids allow for localized solutions to energy problems and reduce the large number of losses during electricity transmission^[7–8].

Therefore, optimizing the operation of community microgrids becomes imperative, with flexible energy-use regulation and optimized scheduling energy supply as crucial endeavors.

1.2 Review on flexible energy-use regulation in buildings and communities

Annex 67 initiated by the EBC (Energy in Buildings and Communities Programme) under the IEA (International Energy Agency), has concentrated on ‘Energy Flexible Buildings’ yielding numerous achievements. This project has identified various flexible regulation strategies, such as adjustability of HVAC (Heating, Ventilation, and Air Conditioning) system use, EV charging, and plug load shifting^[9].

For example, Liang et al. presented a framework for flexible energy-use regulation employing dynamic electricity pricing mechanisms and batteries for energy storage. The results showed that the real-time pricing configuration resulted in a 30% decrease in demand and a 34% reduction in energy consumption, while the regulation with batteries improved the building self-sufficiency and the PV self-consumption by 17% and 20% from the baseline, respectively^[10]. Zhang et al. attempted to adjust the heating temperature setpoint profiles for each building, demonstrating a 22–27% peak demand reduction

on average compared to regular operation ^[11]. Sørensen et al. evaluated the interaction between EV charging and discharging supporting Vehicle-to-grid (V2G) mode in buildings with PV systems and discussed the influence of energy tariffs ^[12]. Ruan et al. found that preheating can achieve short-term energy flexibility during the heating season suggesting raising the preheating setting temperature to the upper limit of human thermal comfort (25 °C) and avoiding preheating during HVAC system startup ^[13]. Strauch et al. proposed demand flexibility strategies involving real-time pricing, demand limiting, and load shedding and shifting achieving significant reductions of 92%, 69%, 100%, and 100% during the peak hours on five winter days, respectively ^[14]. Yang et al. demonstrated substantial demand flexibility potential through the use of Phase Change Material (PCM) thermal storage with smart control, achieving a 338.3% reduction in electricity costs and a 98.5% shift in peak load for residential space heating ^[15]. Liu et al. found that introducing EV discharge in the net-zero energy building enhances PV utilization efficiency, load coverage, time-of-use grid flexibility performance, and system economy ^[16]. In summary, recent studies have discussed various flexible energy-use regulation strategies such as load cutting or shifting based on dynamic time-sharing electricity tariffs, the implementation of energy storage systems, adjustment of AC temperature setpoints, and orderly EV-building interactions ^[9–19].

However, there are also many irrespective challenges. First, many existing strategies for HVAC and related systems tend to prioritize environmental parameters over occupant thermal comfort. Similarly, strategies for load cutting or shifting often prioritize energy consumption reduction rather than considering occupants' perspectives such as human energy-use preferences and variability. These regulation solutions generally overlook factors such as comfort feelings, stochastic behaviors, and spatial and temporal distribution characteristics of occupants. Second, existing studies tend to focus on single regulation strategies, with few studies addressing regulation using multiple parallel strategies for multiple objectives. Few studies focus on parallel interactions among different loads, such as energy-use regulations for plugs, lights, and ACs at the building level, or buildings, EVs, PVs, and batteries at the community level. Moreover, although there are many buildings with completely different characteristics, functions, and energy use in communities, few studies have explored the linkage regulation and interactions among different types of buildings within communities.

Therefore, there is a pressing need to propose a flexible energy-use regulation framework that is human-centered, supports multiple parallel strategies, and considers various types of building objects.

1.3 Review on microgrid operation scheduling optimization

In a typical community microgrid, two primary modes of operation are typically employed: grid-connected and islanded. Standard components generally include PV systems, wind turbine (WT) power systems, batteries (BAT), buildings, EVs, diesel generators (DG), diesel engines (DE), microturbines

(MT), and others. Some systems may also incorporate special components like hydrogen storage devices. For community microgrid optimization, two main methods are commonly utilized: algorithm-based and software-based methods.

Software-based methods rely on simulation tools such as Homer^[28] or self-developed software^[29] for operation scheduling optimization. However, employing software often limits online capabilities, and some software may support limited components and operation modes. Moreover, the constraints and objective functions considered may be incomplete and not current (real-time policy impacts, etc.). Consequently, considering online abilities, flexibility, and comprehensiveness, this study emphasizes technical approaches that do not rely on simulation software.

On the other hand, algorithm-based methods generally involve several steps^[30]. First, objective functions and constraints will be established mathematically and algorithmically. The objective function typically aims for economic optimality, while constraints often include ensuring supply and demand power balance. Second, a suitable algorithm will be developed to calculate the optimization solutions, with various swarm intelligent algorithms commonly employed. Third, appropriate microgrid optimal scheduling strategies are proposed and described mathematically and algorithmically. Finally, proposed operation scheduling strategies can be solved through the optimization algorithm with specified objective functions and constraints, determining the optimal solution for electricity supply or consumption from the microgrid components. Table 1 reviewed some studies on microgrid optimization.

Table 1 Key contents of community microgrid optimization in recent studies

Components	Objective functions	Constraints	Solution algorithms
WT, PV, BAT, MT, and loads ^[20]	Economic benefits including fuel, startup, and shutdown cost	Supply-demand power balance, real power generation capacity, and battery limits	Balancing composite motion optimization (BCMO)
PV, WT, BAT, DG, and loads ^[21]	Economic benefits including cost of operation and maintenance, electricity transaction, fuel, pollutant treatment, and penalty	Supply-demand power balance, energy storage system capacity, and transaction constraints	Improved marine predators algorithm (I-MPA)
PV, WT, BAT, and loads ^[22]	Economic benefits including grid electricity sales profit, generator operating cost, and new energy-related cost	Power balance constraint, power limitation of generator set, limit of EV and battery charge state	Improved particle swarm optimization (I-PSO)
WT, PV, BAT, DG, and loads ^[23]	Economic benefits including cost of power generation and pollutant emissions	Supply-demand power balance, generation power limit of micro-source, interaction constraints, and energy storage constraint	Improved particle swarm optimization (I-PSO)

WT, PV, BAT, MT, and loads ^[24]	Economic benefits including cost of fuel, start-up or shut-down, and interactive power between the microgrid and the main grid	Supply-demand power balance, output limits, and charge or discharge constraints of storage	Improved manta ray foraging optimization (I-MRFO)
WT, PV, BAT, MT, DG, DE, and loads ^[25]	Economic benefits including cost of operation and pollution treatment	Supply-demand power balance, limits of power for different components, and transmission power limits	Improved particle swarm optimization (I-PSO)
WT, PV, BAT, and loads ^[26]	Minimum power cost, considering battery degradation	Supply-demand power balance, and battery limits	Particle swarm optimization (PSO)
PV, WT, BAT, DG, and loads ^[27]	Minimum operating cost in the distribution network	Supply-demand power balance, real power generation capacity, and battery storage constraints	Lightning search algorithm (LSA)

However, despite the focus on algorithm-based optimization scheduling methods in many studies, numerous challenges remain. First, there may be a lack of comprehensive and real-time construction of objective and constraint functions. Many contents have rarely been comprehensively addressed, such as the standby constraints for forecasting and grid fluctuations, count constraints of battery charging or discharging, environmental protection benefits, fines, subsidies, and whole-life depreciation costs, etc. Another significant challenge lies in selecting a suitable optimization algorithm. According to statistics ^[31], nearly 25% of the research in this area utilizes the particle swarm optimization (PSO) method, while the genetic algorithm (GA) and grey wolf algorithm (GWO) are utilized by nearly 10% and 5%. These early swarm intelligence optimization algorithms often suffer from drawbacks such as susceptibility to local optima, low accuracy, and efficiency, meaning more room for optimization and development.

Therefore, there is a pressing need to propose comprehensive and flexible objective functions and constraints and to develop suitable algorithms to solve the solutions of microgrid operation scheduling.

1.4 Challenges, targets, and works

Based on the observations outlined above, for flexible regulation of energy use, existing studies generally ignore thermal comfort feelings, stochastic behaviors, and spatial and temporal distribution characteristics of occupants, and ignore multiple parallel strategies for multiple objects. For microgrid optimization scheduling, existing studies rarely consider the environment-energy-economy-society benefits as objective functions, real-time comprehensive constraints, and suitable algorithms.

Therefore, in response to these deficiencies, on the one hand, for energy demand optimization, this study will propose a novel flexible energy-use regulation system. The innovation of the system is that it is occupant-oriented, respecting the occupant comfort feelings and energy-use habits. In addition, the

system can integrate several regulation strategies at the same time. On the other hand, for energy supply optimization, this study will propose a method for optimizing the scheduling operation of the community microgrid. The innovation of the method is that it will develop a suitable optimization algorithm and use the combined benefits and costs of the environment, energy, investment, and society as the objective function. Therefore, it may achieve simultaneous community energy supply-demand optimization. The traditional and proposed research architectures are shown in Figure 1 as follows.

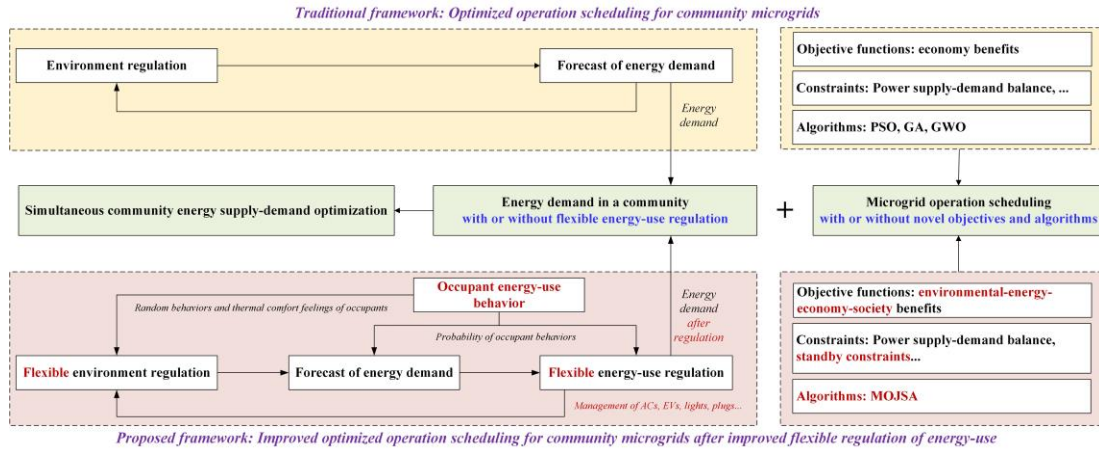


Figure 1 Comparison of the traditional framework and the proposed framework in this study

The remaining sections are organized as follows. Section 2 provides the related data acquisition and the related introduction for the sample buildings and community. Moreover, this section will introduce the microgrid system modeling process and results. Sections 3–4 introduce the methods. Section 3 introduces methods of microgrid operation scheduling optimization, including algorithmic and mathematical objective functions, constraints, and calculation algorithms. Section 4 introduces methods of occupant-oriented flexible energy-use regulation including adjusting AC start-up temperature, organized charging of EVs, lighting and plug management, and course optimization. Sections 5–6 introduce the results. Section 5 shows the results of flexible energy-use regulations in a single building or a community. Section 6 shows the optimized microgrid operation after common or radical occupant-oriented flexible energy-use regulations. Section 7 discusses the results with simultaneous flexible energy-use regulation and microgrid operation scheduling, the limitations, and future directions. Finally, section 8 shows the conclusions.

2 Data acquisition and microgrid system modeling

2.1 Example buildings and community microgrid

This community is a university campus with all types of buildings and facilities for living, learning, working, dining, and recreation, located in Dalian where the average yearly outdoor air temperature is 10.4°C. The average maximum temperature in summer is 27.3 °C with the relative humidity being 83%,

while the average minimum temperature in winter is -8.2°C with relative humidity being 58% [32]. The community and its microgrid are shown in Figure 2, which has buildings and EVs for energy demand, while PVs, batteries, and urban municipal grids for energy supply.

In this campus community, there are about seventy buildings while only twenty buildings have enough monitoring energy and environment data, which will be discussed in this study. Moreover, regarding PVs, most of the buildings have flat roofs with sufficient area for PV system installation. The configuration scheme is that PV panels will be installed on all available areas of the rooftops. Furthermore, regarding EVs, there are 106 EVs in the community, with an average battery capacity of 49.8056kWh and a driving range of about 8.297km/kWh. Additionally, there are 1,500 electric bicycles with a battery capacity of 1.25kWh and a driving range of 90km, equivalent to about 38 EVs.

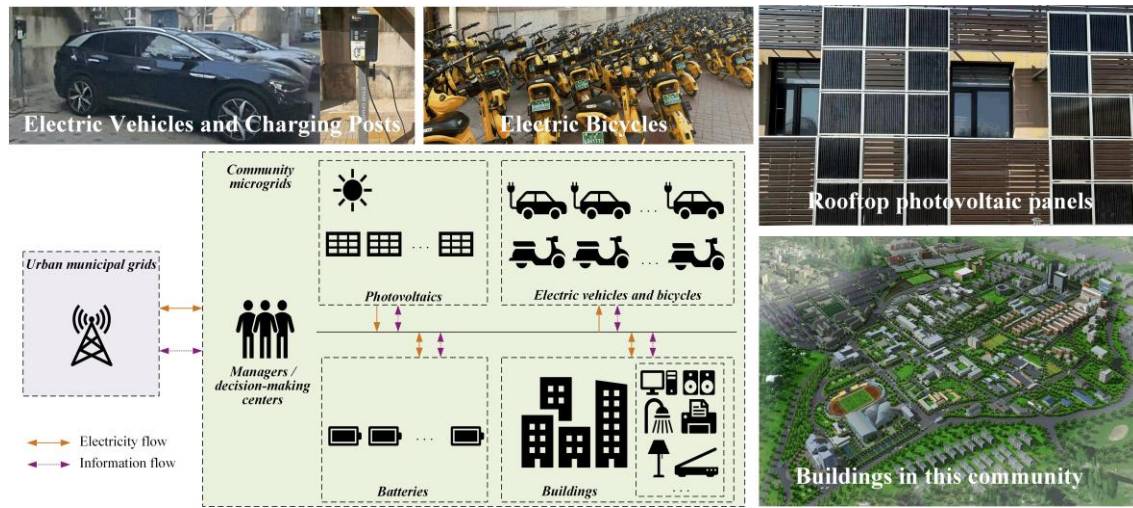


Figure 2 Schematic diagram of the community microgrid including the buildings, EVs, PVs, BATs, and grids

In this university, energy demand and PV power generation may be strongly influenced by different seasons. Referring to related studies [84–85] and actual energy data, firstly, in winter, the air temperature ranges from -6°C to 2°C generally. The largest source of load is heating, but since the community is centrally heated with municipal hot water, the power consumption here is very limited. In addition, there is almost no activity on campus during winter break (almost all of February). Therefore, the electrical load is lowest during the winter months. Secondly, in autumn, the air temperature ranges from 3°C to 25°C generally. This is a transition season for cooling and heating and thus there is still AC power consumption. Additionally, there are virtually no long vacations in autumn and the course schedules in autumn term are much higher than the rest of the year. Therefore, autumn has the highest power loads. The power loads during the spring and summer seasons are in the middle of the pack. Although ACs need to be turned on in summer, the power loads in spring are higher than in summer because Dalian is in the cold region, where most dormitories and academic buildings are not equipped with ACs. Moreover,

the course schedule in the spring term is much more than that in the summer because of the summer vacation which until about 40 days. In summary, power demand is ranked from largest to smallest as autumn, spring, summer, and winter. Moreover, summer typically has higher solar irradiance boosting PV generation, while winter has lower irradiance, reducing PV output.

And for studying flexible energy-use regulations for single buildings in this community, this study selected three representative buildings, designated as Buildings A–C in Table 2. These three buildings are typical of this campus and typical energy users of this community microgrid. The reason for this choice is that dormitories, academic buildings, and educational buildings are the most common building types on university campuses, while these three buildings have a large number of energy-using equipment, energy and environmental monitoring points, and active occupants. Academic buildings include laboratories, professors' offices, graduate students' studios, data centers (servers and computers), and various conference rooms, which are the special buildings on campus.

Table 2 The three sample buildings in this study

Code	Type	Heating and cooling systems	EUI (kWh/m ²)	Appearance
Building A	Academic building	Heating: District heating system with municipal hot water and using ACs as a supplement	87.61	
		Cooling: Split ACs in almost all rooms in this building		
Building B	Educational building	Heating: District heating system with municipal hot water and using ACs as a supplement	30.88	
		Cooling: Variable refrigerant flow multilink ACs in a few rooms in this building		
Building C	Dormitory building	Heating: District heating system with municipal hot water Cooling: None	28.33	

2.2 Data acquisition and system modeling

Related energy data were collected in 2021 from building energy monitoring platforms. These sample buildings were equipped with a monitoring and management system for energy use, capable of comprehensively recording current, voltage, and energy consumption changes in all energy-consuming items and branches with uploading relevant data to cloud platforms, as shown in Figure 3.



Figure 3 The monitoring and management of building energy consumption

In the city with policy in 2021, the electricity use will be divided into four periods in a day. 07:30–11:30 and 19:00–21:00 are peak hours, 22:00–05:00 on the next day are valley hours, and the rest are shoulder hours. Moreover, among them, 17:00–19:00 are the sharp hours. The ratio of the electricity tariff among sharp, peak, shoulder, and valley hours will be set to 1.875:1.5:1:0.5. It is worth noting that the target community has not yet adopted sectionalized electricity tariffs and currently employs flat electricity tariffs (0.5 RMB/kWh). However, sectionalized tariffs will be used as an important strategy for flexible energy-use regulation in some cases in this study.

The microgrid is modeled as follows.

(1) Energy demand from buildings

The building energy demand will be modeled using a data-driven approach, as demonstrated in recent studies [33–35, 37]. This enhanced system incorporates occupant energy-use behavior probabilities, including AC-related, plug-related, and light-related behavior models [33–35], alongside traditional inputs such as historical energy consumption, time, and outdoor air temperature [36]. To improve accuracy, the convolutional-neural-network (CNN) process and squeeze-and-excitation (SE) attention mechanisms are integrated into the Long Short-Term Memory (LSTM) neural network, resulting in a novel training algorithm referred to as CNN-LSTM-SE [36]. The process is shown in Figure 4, and the details will be available in previous studies [37].

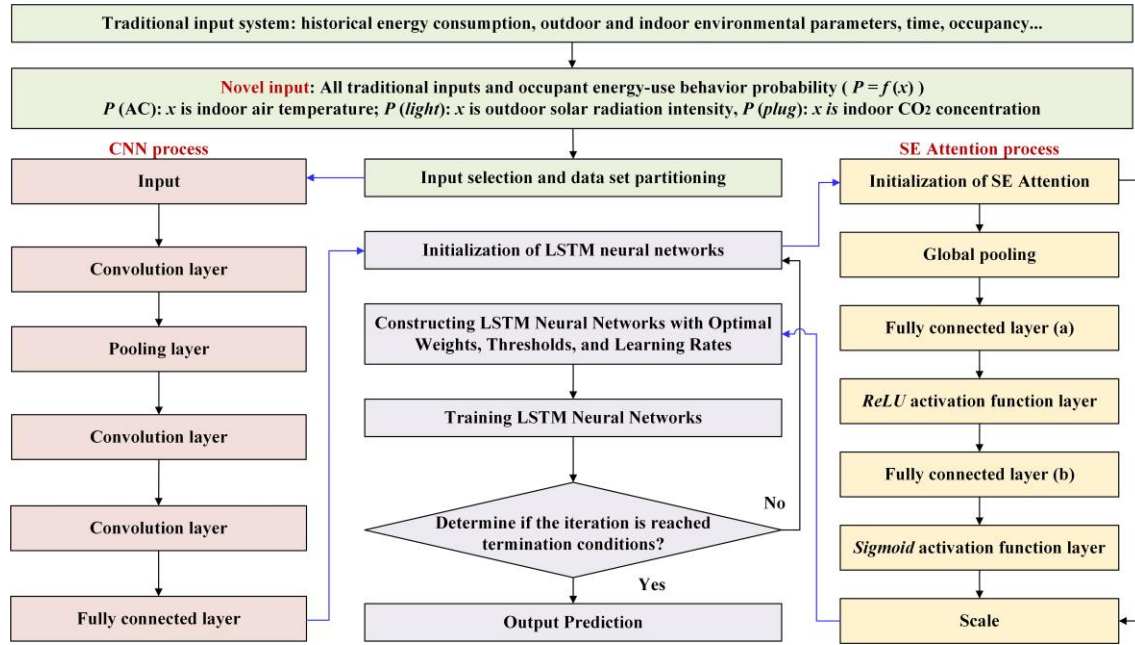


Figure 4 The enhanced building energy consumption prediction with novel inputs and CNN-LSTM-SE

To verify the proposed forecasting methods, this study attempted to forecast energy demand in Buildings A–C. The inputs include time, indoor air temperature, indoor CO₂ concentration, outdoor air temperature, historical energy demand at the last hour, and the probabilities of AC-, light-, and plug-related behaviors. The output is the energy demand at this hour. Other hyperparameter values will refer to recent studies ^[33–35, 37], and the advantages of the proposed methods were also shown in these studies. The results proposed energy demand forecasting for three sample buildings in this study will be shown in Figure 5 and Table 3.

Table 3 The results of proposed energy demand forecasting for three sample buildings in this study

Building	MAE	RMSE	MAPE	CV-RMSE	R ²	Time (s)
Building A	11.1113	17.8269	8.12%	0.1366	0.9588	214.6490
Building B	2.5389	3.8912	9.39%	0.1025	0.9891	252.709
Building C	2.8801	4.1513	13.09%	0.1748	0.9710	276.4860

Note: The performance of the proposed method is evaluated using five indices: the coefficient of determination (R²), mean absolute error (MAE), mean absolute percentage error (MAPE), root mean square error (RMSE), and coefficient of variation of root mean square error (CV-RMSE)

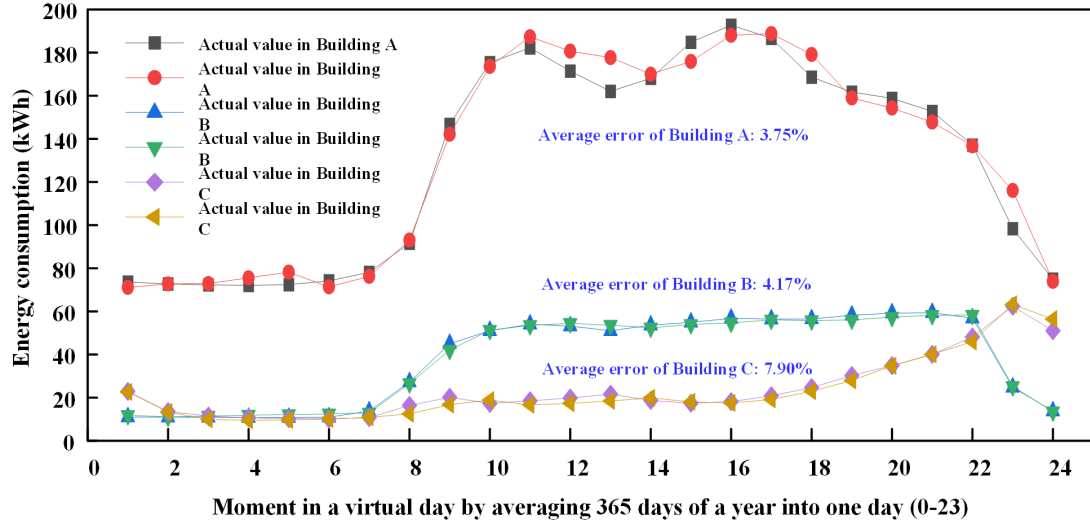


Figure 5 The enhanced building energy consumption prediction in example buildings on average

The model is validated by comparing the forecasted and actual values of the energy consumption of the buildings. Relevant international regulations are shown in Table 4. Therefore, the proposed forecasting methods may be effective [79].

Table 4 Relevant international regulations

Items	Technical code in China (JGJ176-2009)	IPMVP	FEMP
Error in one month	±15%	±20%	±15%
Error in one year	-	-	±10%

Note: Technical code in China (JGJ176-2009) is the Technical code for the retrofitting of public building on energy efficiency. IPMVP is the International Performance Measurement and Verification Protocol. FEMP is the US Federal Energy Management Program.

(2) Energy demand from EVs

This study proposes a Monte Carlo Stochastic Simulation model for EV charging load prediction, which has also been successfully applied in previous studies [38–41], with the steps shown in Figure 6. First, this approach requires the battery performance (miles that can be exercised per kWh) of EVs in the community. Second, the potential charging time will be calculated by Monte Carlo stochastic simulation based on the average mileage of the EVs (concerning the average daily commuting mileage of residents in the sample city) and the battery performance. Finally, the charging load per hour will be estimated based on the commuting time (the earliest start time and the latest end time for charging), the potential charging time, and the charging power of charging posts. The start time can be calculated by equation (1) while the end time can be calculated by equation (2).

$$f_s(t) = \begin{cases} \frac{1}{\sigma_s\sqrt{2\pi}} \exp\left[-\frac{(x-\mu_s)^2}{2\sigma_s^2}\right], \mu_s - 12 \leq x \leq 24 \\ \frac{1}{\sigma_s\sqrt{2\pi}} \exp\left[-\frac{(x+24-\mu_s)^2}{2\sigma_s^2}\right], 0 \leq x \leq \mu_s - 12 \end{cases} \quad (1)$$

$$f_e(t) = \begin{cases} \frac{1}{\sigma_e\sqrt{2\pi}} \exp\left[-\frac{(x-\mu_e)^2}{2\sigma_e^2}\right], 0 \leq x \leq \mu_e + 12 \\ \frac{1}{\sigma_e\sqrt{2\pi}} \exp\left[-\frac{(x-24-\mu_e)^2}{2\sigma_e^2}\right], \mu_e + 12 \leq x \leq 24 \end{cases} \quad (2)$$

Where, $f_s(t)$, and $f_e(t)$ are the start and end moments respectively (1–24 in a day). μ_s , and σ_s are the expected value and standard deviation at the starting moment respectively. μ_e , and σ_e are the expected value and standard deviation at the end moment respectively. The charging power can be calculated by equation (3) and the charging hours can be calculated by equation (4).

$$P_{EV} = \sum_{n=1}^N P_{ch} x_n \quad (3)$$

$$T_{ch} = \frac{(1-SOC)P_K}{\eta P_{ch}} \quad (4)$$

Where, P_{EV} is the EV charging load at moment t , kW. P_{ch} is the charging power of charging posts, kW (7.0 kW in this study). N is the number of EVs. x_n is the charging status of the n th EV (if the EV is charging, $x_n=1$, otherwise $x_n=0$). SOC is the state of charge for batteries, %. P_K is the rated battery capacity of each type of functional vehicle, kW. η is the charging efficiency (0.9 in this study). Moreover, the daily mileage traveling in this sample city using private vehicles may follow a lognormal distribution [38–41], as shown in equation (5).

$$f_m(x) = \frac{1}{x} \frac{1}{\sigma_m\sqrt{2\pi}} \exp\left[-\frac{(\ln x - \mu_m)^2}{2\sigma_m^2}\right] \quad (5)$$

Where, $f_m(x)$ is the daily mileage traveling in the city using private vehicles (km). μ_m , and σ_m are the expected value and standard deviation for the daily mileage respectively.

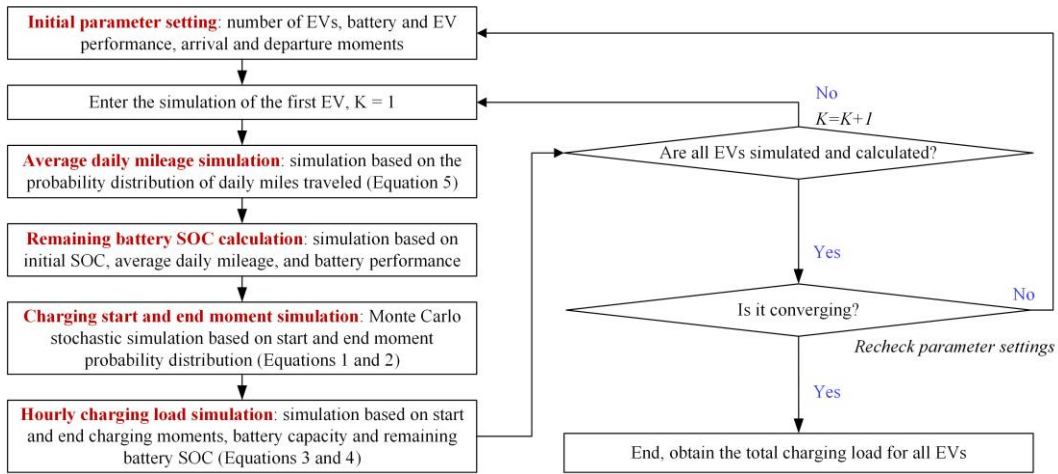


Figure 6 The process of calculating the EV charging load with the Monte Carlo Stochastic Simulation model

In this study, according to relevant surveys, the average mileage of Chinese research and education

personnel traveling in the city using private vehicles may be about 1,622 km/month ($\mu_m=55$ km/day). The working time on this campus is 8:00–17:00. Referring to related studies [86–88], since almost all EVs originate from teachers, and university community is a kind of work area for them. Therefore, if there is no guidance, teachers tend to charge immediately upon entering the university. According to the above data, the potential results are shown in Figure 7 including organized (encouraged for EV charging near 14:00 with μ_s being 14 with σ_s being 1.0) or unorganized EV charging (EV charging when entering this community at 8:00 with μ_s being 8 with σ_s being 1.0). The cumulative total load error for the two stochastic simulations was 0.4%, and the simulated data were considered informative. The reason for not enforcing exactly equal charging for both strategies is to preserve randomness.

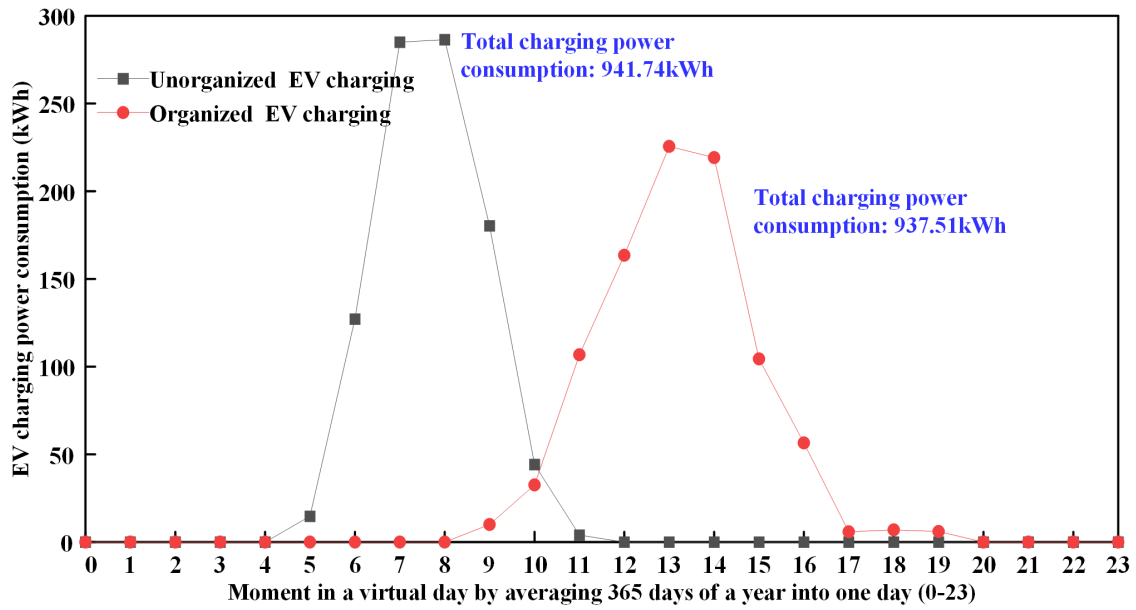


Figure 7 The potential results for EV charging consumption by different charging strategies

(3) Energy supply from PVs

Solar photovoltaic power generation can be calculated by equations (6–7).

$$P_{PV} = P_{STC} \frac{G_{ING}}{G_{STC}} \eta_{PV} [1 + k_T (T_C - T_{STC})] \quad (6)$$

$$T_C = T_{EN} + \frac{G_{ING}}{800} (T_n - 20) \quad (7)$$

Where, P_{PV} is the output power (kW) of the PV power generation system when the real-time solar radiation intensity is G_{ING} (W/m^2). P_{STC} is the maximum output power (200W in this study) when the PV power generation system is under standard conditions ($T_{STC}=25^\circ\text{C}$, $G_{STC}=1000 \text{ W}/\text{m}^2$). k_T is the temperature-power coefficient generally being $0.004\text{--}0.006/^\circ\text{C}$ ($0.0047/^\circ\text{C}$ in this study). T_C is the temperature of the battery panels and chips ($^\circ\text{C}$). T_{EN} is the environment temperature when the battery is in operation ($^\circ\text{C}$). T_n is the nominal operating temperature of the PV battery panels (42°C).

in this study). η_{PV} is the derating coefficient of the PV power generation system, meaning the attenuation percentage of generation in the current year compared to the first year (80% in this study). The accuracy and effectiveness of this method to model or calculate PV power generation has been verified in recent studies [80–83]. To further safeguard the supply-demand relationship, it is often necessary to also consider the fluctuations in PV power generation. Based on some researchers' suggestions [47, 77, 83], the PV fluctuations may generally be less than 10–15% of power.

(4) Energy demand and supply from batteries

In battery charge state calculations, the commonly adopted model is the Kinetic Battery Model (KiBaM) [42–44]. Assuming stable voltage at both ends of the battery, constant charging and discharging currents during the scheduling period, and neglecting the influence of environmental temperature on battery capacity, the battery charge state at moment t can be determined based on the charge state at moment $t-1$ (the previous moment). The process can be calculated by equations (8–9).

$$E_{SB}(t) = \begin{cases} E_{SB}(t-1) + \Delta t \times \eta_{SB} \left(\frac{P_{battery,c}(t)}{\eta_{inv}} \right), & \text{charging mode} \\ E_{SB}(t-1) - \Delta t \times \eta_{SB} \left(\frac{P_{battery,d}(t)}{\eta_{inv}} - P_{total}(t) \right), & \text{discharging mode} \end{cases} \quad (8)$$

$$\eta_{SB} = \begin{cases} \eta_c, & k(t) > 0 \\ 0, & k(t) = 0 \\ 1/\eta_d, & k(t) < 0 \end{cases} \quad (9)$$

Where, $E_s(t)$, and $E_s(t+1)$ represent the battery capacity at moment t and $t+1$, respectively (kWh). $P_{battery,c}(t)$, and $P_{battery,d}(t)$ denote the power of battery charging and discharging at moment t respectively (kW). η_{inv} , and η_{SB} represent the efficiency of the inverter and the efficiency of the battery, respectively. The inverter is a converter that transforms the DCP (direct current power, such as storage battery) into ACP (alternating current power, generally 220V and 50Hz sine wave), and if the building is in DCP, η_{inv} is considered 100%. η_c , and η_d denote the efficiency of charging and discharging the battery respectively (charging efficiency is assumed as 1, while the discharging efficiency is assumed as 0.8 in this study). $k(t)$ is the state of the energy storage operation (k is assumed as 1 during charging, 0 when neither charging nor discharging, and -1 during discharging in this study).

3 Methodology on microgrid operation scheduling optimization

3.1 Objective functions

To simplify the calculation process, the benefits of investment, energy, environment, and society are converted into economic benefits for easy accumulation. This method has been applied successfully in some studies, but few studies combine all the components, such as some omitting social benefits and costs and some omitting environmental costs [69–71]. For example, the environmental benefits represent the economic savings in pollutant treatment costs achieved by reducing pollutant emissions through

certain strategies. The calculation models for total energy-economy-environment-society costs and benefits are shown in equations (10-17) including all the costs over the full life cycle. The definition of different kinds of benefits and costs will be shown as follows:

(1) Investment costs: The CAPEX of construction, maintenance, and labor, including the costs of materials, construction, and maintenance of EV charging posts, battery systems, and PVs.

(2) Environment costs: These include the costs for treating pollutants such as CO₂, NO_x, SO₂, and others from electricity production processes.

(3) Energy benefits and costs: The discounted OPEX of energy, including the costs of purchasing electricity from municipal grids and the benefits of selling electricity back to the grid.

(4) Society benefits and costs: These include the benefits and costs from policies of local authorities, such as incentives for renewable energy use and fines for exceeding pollutant emission standards, which consider the electricity stability and sufficiency for all occupants. Moreover, it will consider keeping the AC setting temperature point value in the range of 20–28°C for occupant thermal comfort^[51–64].

$$F(Total) = F(CL) + F(CY) + F(CW) + F(EN) \quad (10)$$

Where, $F(Total)$ is the annual total cost. Considering that assigning weights to different benefits and costs is difficult (e.g., investment benefits, renewable energy incentives, etc.), this study considers using overall costs to construct a comprehensive function for single-objective optimization. In this way, the benefits and costs from different aspects can be directly added or subtracted since all of them can be converted to economic indicators. That is, coefficients such as the pollutant treatment cost (\$/kg) and renewable energy incentives (\$/kW) can be used instead of weights. Therefore, $F(Total)$ is the objective function, and the target is to minimize it.

$$F(CL) = \frac{m(1+m)^n}{[(1+m)^n - 1]} \times \sum_1^l N_k C_k \quad (11)$$

Where, $F(CL)$ is the initial investment (\$). N_k is the capacity of the k th equipment (W). C_k is the investment cost of k th equipment (\$/W). l is the number of equipment (pcs). m is the annual interest rate. and n is the service life of the equipment system.

$$F(CY) = F_G + F_B + F_D \quad (12)$$

$$F_G = \sum_i^l \sum_{j=1}^{24} (E_{ij,Gird} C_{ij,e}) \quad (13)$$

$$F_B = \delta P_{Bj}^2, k \in S_B \quad (14)$$

$$F_D = (a_{pv} + b_{pv} P_{PVj} + c_{pv} P_{PVj}^2) + (a_{ev} + b_{ev} P_{EVj} + c_{ev} P_{EVj}^2) \quad (15)$$

Where, $F(CY)$ is the annual operating cost (\$). F_G is the cost of electricity purchased from the municipal main grids when the battery and PV generation are insufficient (\$). $C_{ij,e}$ and $E_{ij,Gird}$ are the grid electricity price (\$/kWh) and the amount of electricity purchased (kWh) at day i , time j . F_B is

the cost of battery storage (\$). P_{Bj} is the flexible load power (kW). δ is the operation cost coefficient of energy storage. F_D is the cost of flexible power generation (\$), which is divided into two parts: PV power generation and EV charging pile power supply. P_{PVj} , and P_{EVj} are the power (kW) of PV power generation and charging pile power generation.

$$F(CW) = \varepsilon F(CL) \quad (16)$$

Where, $F(CW)$ is the annual maintenance cost (\$). ε is the maintenance cost factor.

$$F(EN) = \sum_i^I \sum_{j=1}^{24} C_q \left(\sum_{p=1}^P r_{pq} P_p(t) + a r_{Gridq} P_{Grid}(t) \right) \quad (17)$$

Where, $F(EN)$ is the cost of environmental treatment during microgrid operation (\$). a is the coefficient of concurrency and separation, with $a=1$ for grid-connected operation and $a=0$ for islanded operation. q is the type of pollutants released from the microgrid (mainly including CO₂, SO₂, NO_x, CO, soot, and PM2.5). C_q is the cost of treatment for each pollutant (\$/g). P is the total number of power generation units in the microgrid. r_{pq} , and r_{Gridq} are the emission coefficients of the pollutant q associated with the generation of electricity by the p th power generation unit of the local microgrid and the municipal main grids (g/kWh). $P_p(t)$, and $P_{Grid}(t)$ are the amount of electricity generated by the p th power generation unit of the local microgrid and supplied by the municipal main grid (kWh).

3.2 Constraints

(1) Electricity supply and demand balance constraints

It is important to ensure matching the supply and demand of electricity, as shown in equation (18). Moreover, this community does not yet support V2G technology for EVs. It means that this community only supports EV charging, rather than EV sales of electricity to the grid.

$$P_{PV}(t) + P_{bat,in}(t) + P_{grid,in}(t) = P_{Building}(t) + P_{bat,out}(t) + P_{EV,out}(t) + \delta \quad (18)$$

Where, $P_{PV}(t)$, $P_{bat,in}(t)$, $P_{grid,in}(t)$, $P_{Building}(t)$, $P_{bat,out}(t)$, and $P_{EV,out}(t)$ are the power of PV electricity generation, battery discharging, supplemental electricity from the municipal grid, total electricity demand of buildings in the community, battery charging, and EV charging respectively. δ is a real number greater than 0 but infinitely close to 0.

(2) Fluctuation, safety, and standby constraints

It is important to consider fluctuations in PV electricity generation, errors in demand forecasting, and power transmission losses when determining the total electricity demand in community microgrids, as shown in equations (19–21). The principle is to ensure enough electricity supply to meet demand in worst-case scenarios.

$$P_{actual\ supply}(t) = P_{actual\ demand}(t)(1 + \alpha) + \delta \quad (19)$$

$$P_{actual\ supply}(t) = P_{PV}(t) + P_{bat,in}(t) + P_{grid,in}(t) \quad (20)$$

$$P_{actual\ demand}(t) = P_{Building}(t) + P_{EV,out}(t) + P_{bat,out}(t) \quad (21)$$

Where, α is the fluctuation, safety, and standby factor. It will include two parts including reserve load capacity factor and forecast error factor. The reserve load capacity factor will be set to 10% to ensure that energy supply exceeds demand, considering transmission loss and other energy system losses [47–50, 77, 83]. While forecast error factor will consider fluctuations in PV electricity generation and building electricity load forecast errors, which will be set to 15% according to recent studies [47–50, 77, 83] and cases in this study (in Table 3). Therefore, in this study, α will be set to 25%. Moreover, for electricity safety, stability, and sufficiency, local authorities will give extra fine costs for charging or discharging and electricity supply or demand imbalance when the ratio of imbalance exceeds 5.0%.

(3) Battery constraints

The battery system needs to comply with the following constraints, as shown in equations (22–28). Equations (22–23) show the power constraints of the battery charging and discharging. Equation (24) is for determining that batteries do not charge and discharge at the same time. Equations (25–26) are the constraints of the times of charging in a day and the capacity of the batteries. Finally, the electricity storage cycle constraint is shown in equation (27). That is, a cycle of 24 hours is used to ensure that charging and discharging are zeroed out (charging is equal to discharging) as much as possible during the same cycle, avoiding excessive energy loss and cost increase due to long-term electricity storage.

$$P_{bat,out}^{min} \leq P_{bat,out}(t) \leq P_{bat,out}^{max} \quad (22)$$

$$P_{bat,in}^{min} \leq P_{bat,in}(t) \leq P_{bat,in}^{max} \quad (23)$$

$$P_{bat,in}(t) \times P_{bat,out}(t) = 0 \quad (24)$$

$$N_{Bat} \leq N_{Bat}^{max} \quad (25)$$

$$SOC_{BAT}^{min} \leq SOC_{BAT}(t) \leq SOC_{BAT}^{max} \quad (26)$$

$$\sum_{t=1}^{24} (P_{bat,out}^t \times \eta_{bat,out} + \frac{P_{bat,in}^t}{\eta_{bat,in}}) = 0 \quad (27)$$

Where, $P_{bat,out}^{min}$, and $P_{bat,out}^{max}$ are the lower and upper limits of battery charging power respectively (kW). $P_{bat,in}^{min}$, and $P_{bat,in}^{max}$ are the lower and upper limits of battery discharging power respectively (kW). SOC_{BAT}^{min} , and SOC_{BAT}^{max} are the lower and upper limit of battery capacity respectively, while $SOC_{BAT}(t)$ is the battery capacity at moment t (%). $\eta_{bat,out}$, and $\eta_{bat,in}$ are the charging efficiency and discharging efficiency of the battery, respectively. N_{Bat} , and N_{Bat}^{max} are the time of charging and the maximum time of charging for the battery system.

(4) EV constraints

The EV system needs to comply with the following constraints, as shown in equations (28–30).

$$P_{EV,out}^{min} \leq P_{EV,out}(t) \leq P_{EV,out}^{max} \quad (28)$$

$$SOC_{EV}^{min} \leq SOC_{EV}(t) \leq SOC_{EV}^{max} \quad (29)$$

$$N_{EV} \leq N_{EV}^{max} \quad (30)$$

Where, $P_{EV,out}^{min}$, and $P_{EV,out}^{max}$ are the minimum and maximum values of the EV charging (kW). SOC_{EV}^{min} , and SOC_{EV}^{max} are the lower and upper limit of battery capacity of EVs respectively, while $SOC_{EV}(t)$ is the battery capacity of EVs at moment t (%). N_{EV} , and N_{EV}^{max} are the time of charging and the maximum time of charging for the batteries of EVs.

(5) PV constraints

The PV system needs to comply with the following constraints, as shown in equation (31).

$$P_{PV}^{min} \leq P_{PV}(t) \leq P_{PV}^{max} \quad (31)$$

Where, P_{PV}^{min} , and P_{PV}^{max} are the minimum and maximum values of the PV power generation, kW.

(6) Thermal comfort constraints

The AC setting temperature point value will be in the range of 20–28°C in the buildings with ACs to ensure that the room air temperature is in a comfortable range that is not too high or too low [51–64].

3.3 Solution algorithm: JSA

The essence of the community microgrid optimization may be an optimal solution search issue. That is, solving the solutions when the objective function, the energy-economy-environment-society costs shown in equation (10), is minimized under known hourly energy demand and certain constraints shown in equations (18–31) for the microgrid. These solutions will correspond to the optimal values of local power generation from the PVs, battery charging and discharging, and supplemental power from the municipal grid at each hour.

For optimal solution searching, swarm intelligent algorithms may be a suitable choice. In this study, the JSA proposed in 2020 will be used because of its strong searching ability and fast convergence speed. This algorithm simulates the foraging behavior of jellyfish in the ocean as they search for food which has two main movement modes as follows [45–46].

The first mode to move is to follow the ocean currents. The direction of the ocean current is calculated by averaging all vectors from each jellyfish to the best-positioned jellyfish (determined by fitness). The fitness is used to measure how well a given solution (jellyfish position) meets the optimization objective that is minimizing the total energy-economy-environment-society costs. The process can be calculated as shown in (32–34).

$$\overrightarrow{trend} = \frac{\sum \overrightarrow{trend}_i}{n_{pop}} = X^* - df \quad (32)$$

$$df = e_c u = \beta \times rand(0,1) \times u \quad (33)$$

$$X_i(t+1) = X_i(t) + rand(0,1) \times \overrightarrow{trend} \quad (34)$$

Where, the $\overrightarrow{trend}$ indicates the direction of the ocean current movement, influenced by the best jellyfish position. It represents the collective direction in which the algorithm is exploring the solution space. f means the fitness. $X_i(t + 1)$, and $X_i(t)$ are the position of jellyfish i at the moment i and $i+1$, respectively. The jellyfish location refers to a specific point in the solution space, which encodes a possible configuration for operating the microgrid. This configuration includes the values of local power generation from the PVs, battery charging and discharging, and supplemental power from the municipal grid at each hour. n_{pop} is the number of jellyfish. X^* is the best (minimum total costs) position in the current jellyfish population as determined by the factor e_c . u is the average position of all jellyfish. df is the difference between the current best position of the jellyfish and the average position of all the jellyfish. β is the allocation coefficient, which is taken as 3 in this study. $rand(0,1)$ means to take a random number from 0-1.

The second mode is to move inside the swarm of jellyfish. The second mode can be divided into two categories: active movements and passive movements. For passive movements using the second mode, the position of each jellyfish is shown in equation (35).

$$X_i(t + 1) = X_i(t) + \gamma \times rand(0,1) \times (U_b - L_b) \quad (35)$$

Where, U_b , and L_b are the upper and lower bounds of the search space, respectively. γ is the coefficient of movement which is taken as 0.1 in this study. For active movements using the second mode, it can be seen as populations moving toward each other based on the amount of food (measured in terms of fitness). When the amount of food at jellyfish i is greater than at jellyfish j , then jellyfish j moves towards jellyfish i and vice versa. This process can be expressed in equations (36–37).

$$X_i(t + 1) = X_i(t) + \overrightarrow{Step} \quad (36)$$

$$\overrightarrow{Step} = rand(0,1) \times \overrightarrow{Direction} = rand(0,1) \times \begin{cases} X_j(t) - X_i(t), f(X_i) > f(X_j) \\ X_i(t) - X_j(t), else \end{cases} \quad (37)$$

Where, X_i , and X_j are the position of jellyfish i and j , respectively.

A time control mechanism is used to switch between the movements, as shown in equation (38).

$$C(t) = |(1 - \frac{t}{MAX_{iter}}) \times (2 \times rand(0,1) - 1)| \quad (38)$$

Where, t and MAX_{iter} are the number of iterations and the maximum number of iterations. When $C(t) > 0.5$, the jellyfish will move as the first mode using equations (32–34). Moreover, when $C(t) < 0.5$, the jellyfish will move as the second mode. Further in the second mode, when $rand(0,1) > 1 - C(t)$, the jellyfish will move as the passive movements using equation (35) while when $rand(0,1) < 1 - C(t)$, the jellyfish will move as the active movements using equations (36–37).

To make the process of solving the microgrid operation schemes by using the JSA clearer and to show more details, Table 5 lists the pseudo-code of JSA including inputs, outputs, constraints, objectives,

and specific steps.

Table 5 Pseudo-code of JSA including inputs, outputs, constraints, objectives, and specific steps

Algorithm: Jellyfish search algorithm (JSA)

Inputs:

Data from file 'data.xlsx' // Contains information about power loads, generation, prices, etc.

Parameter values // values are listed in Table 9

Output:

Optimal power distribution for Photovoltaic system (PG_PV), Battery Energy Storage System (PG_BESS), and Municipal Grid (PG_grid)

BEGIN

Step 1: Obtain parameters and test problem information

MultiObj = GetFunInfo(TestProblem)

Step 2: Initialize the MOJS algorithm with the provided parameters

SET params.Np = PopulationSize

SET params.Nr = ArchiveSize

SET params.maxiter = MaxIterations

SET params.ngrid = GridNumber

Step 3: Run the MOJS algorithm to obtain the best position (Xbest) and best fitness (Fbest)

CALL ERP = MOJS(params, MultiObj)

SET Xbest = ERP.pos

SET Fbest = ERP.pos_fit

Step 4: Function GetFunInfo(TestProblem)

Input: TestProblem // Indicates the test problem number

Output: MultiObj // Object containing information about the problem

BEGIN

- 1: Obtain data from 'data.xlsx' for the specified test problem
- 2: Define upper and lower bounds for the particle values based on the problem constraints
- 3: Set the cost function considering energy costs, penalties, and environmental impact
- 4: Define the number of variables and objectives for the multi-objective problem
- 5: Return the information as a MultiObj object

END FUNCTION

Step 5: Function Fitness(x)

Input: x // Particle position

Output: c, result // Constraint status, fitness value

BEGIN

- 1: Handle power balance constraints and apply penalties if not satisfied
 - 2: Account for battery constraints and penalize violations
 - 3: Ensure battery charge-discharge balance and penalize violations
 - 4: Ensure PV constraints and penalize violations
 - 5: Ensure EV constraints and penalize violations
-

6: Evaluate energy costs and environmental costs (result is all the cost of microgrid operation)

7: Return constraint status and the calculated fitness value

END FUNCTION

Step 6: Implement constraints related to power generation and device capacity (Function Fitness(x))

Step 7: Validate the solutions to determine feasibility and constraints compliance (Function GetFunInfo(TestProblem))

Step 8: Identify the solution that minimizes the total cost and obtain the optimal power distribution (PG_PV, PG_BESS, PG_grid)

Step 9: Obtain the solutions for the microgrid optimization problem

Step 10: Visualize the power generation and distribution for different components

END

4 Methodology on flexible energy-use regulation

4.1 Occupant energy-use behavior modeling in buildings

The methods and results of AC-related, plug-related, and light-related behavior models have been shown in recent studies [33–35, 37]. This study will focus on elucidating the key steps rather than providing the whole process and all the details. The occupant energy-use behavior probabilities can be calculated by equation (39).

$$P_{(t_i-t_{i+1})} = \frac{\sum_{j=1}^n \Delta T_j}{n \times \Delta T_0} \quad (39)$$

Where, $P_{(t_i-t_{i+1})}$ is the occupant behavior probability during the moment t_i to moment t_{i+1} . i is a time index (e.g., if i is 2, then t_{i-1} , t_i , and t_{i+1} are 1:00, 2:00, and 3:00, respectively). j represents the code of each equipment. n is the total number of all equipment (e.g., if a building has 10 ACs, then n is 10 with j numbered from 1 to 10).

Occupant energy-use actions can be primarily categorized into three categories: environment-related, time-related, and random behaviors [33–35, 37]. Environment-related behavior can be expressed as equation (40). For example, occupants control ACs by their thermal comfort, which is correlated with indoor and outdoor air temperature. Time-related behavior can be expressed as equation (41). For example, ACs or lights are activated upon the arrival of the first occupant and switched off when the last occupant exits. Random behavior may be not influenced by specific physical parameters and encompasses actions such as charging cell phones, using microwave ovens, and watching TV. The random behavior is difficult to model while recent studies found that it can be indirectly reflected using the equation (40) with different influence factors (it is I in equations).

$$P_{(t_i-t_{i+1})} = f(I_{t_{i-1}-t_i}) = \frac{a+b(I-I_0)^n}{1+(I-I_0)^n} \quad (40)$$

$$P_{(t_i-t_{i+1})} = \begin{cases} c, & \text{some time or events} \\ 0, & \text{other time} \end{cases} \quad (41)$$

Where, I represents a physical parameter (external stimulus). Recent studies [33–35, 37] indicate that

I can be indoor air temperature for modeling AC-related behaviors, outdoor solar radiation intensity for modeling light-related behaviors, and indoor CO₂ concentration for modeling plug-related behaviors. f and g are mappings. a , b , c , and I_0 are constants.

4.2 Occupant-oriented flexible energy-use regulation

(1) Adjusting the start-up temperature of split ACs

AC-related behavior can be modeled by equation (40) and further converted into equation (42). Models shown in equation (42) have been verified in many recent studies and simulation software successfully [51–64]. In this study, flexible regulation for split ACs involves adjusting the start-up temperature which presents the lowest temperature when there is a probability for occupants to switch on the ACs, diverging from the conventional approach of altering the AC setting temperature. Compared to adjusting the AC setting temperature, the proposed AC start-up temperature adjustment can consider the complexities of AC usage, including occupant thermal comfort, randomness, and variability. By changing the start-up temperature while keeping other parameters constant, such as maintaining consistent thermal sensitivity, the updated AC-related behavior probabilities can be determined to assess changes in AC usage behavior before and after flexible regulations. The entire process is illustrated in Figure 8.

$$\frac{a+b(T-T_{su})^n}{1+(T-T_{su})^n} = P_{(t_i-t_{i+1})} = \begin{cases} 1 + P_{su} - e^{-\left(\frac{T-T_{su}}{l}\right)^k \Delta\tau}, & T \geq T_{su}, \text{ when occupied} \\ P_{su}, & T < T_{su} \end{cases} \quad (42)$$

Where, when discussing AC-related behaviors, T is the indoor temperature (°C) and T_{su} is the start-up temperature (°C). l is the scale parameter (°C), to nondimensionalize the temperature, and k is the shape parameter, presenting the thermal feeling sensitivity to the environment. $\Delta\tau$ is the time step used in measurement and simulation (1 hour in this study). p_0 is the baseline probability considering the continuous operation of certain ACs, such as those in restrooms or air curtains at main entryways.

Therefore, the crux lies in determining the suitable start-up temperature, often reliant on empirical judgment by technicians. Values documented in previous studies can serve as reference points [51–64], visually shown in Figure 9. Typically, start-up temperature may generally range from 20°C to 26°C in most cases. According to recent studies [53, 65], maintaining indoor air temperatures within the range of 20.0–23.0°C may enhance work performance, with productivity potentially declining beyond this range. Therefore, in cooling seasons, if the start-up temperature is excessively low such as 16°C (indicating occupants in a building initiate AC usage for cooling once the average indoor air temperature reaches 16°C), managers may recommend increasing the start-up temperature by 1–2°C. This proposed flexible regulation strategy for split ACs accounts for thermal comfort and energy conservation considerations. The adjusted AC-related behavior probabilities are then utilized to estimate energy demand with flexible

energy-use regulation, following the technical route depicted in Figure 4.

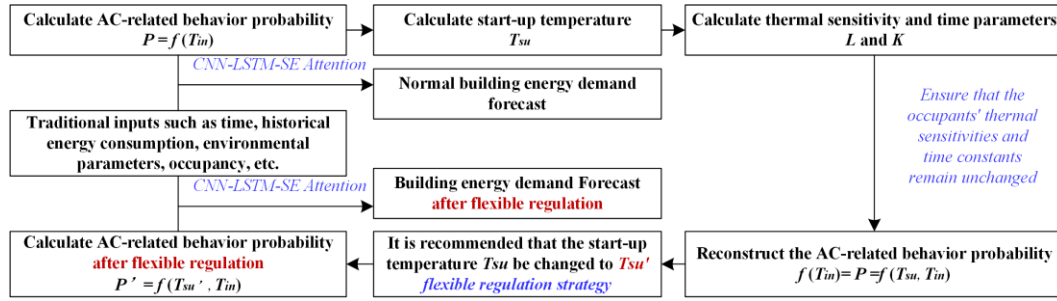


Figure 8 The whole process of flexible regulation of split ACs

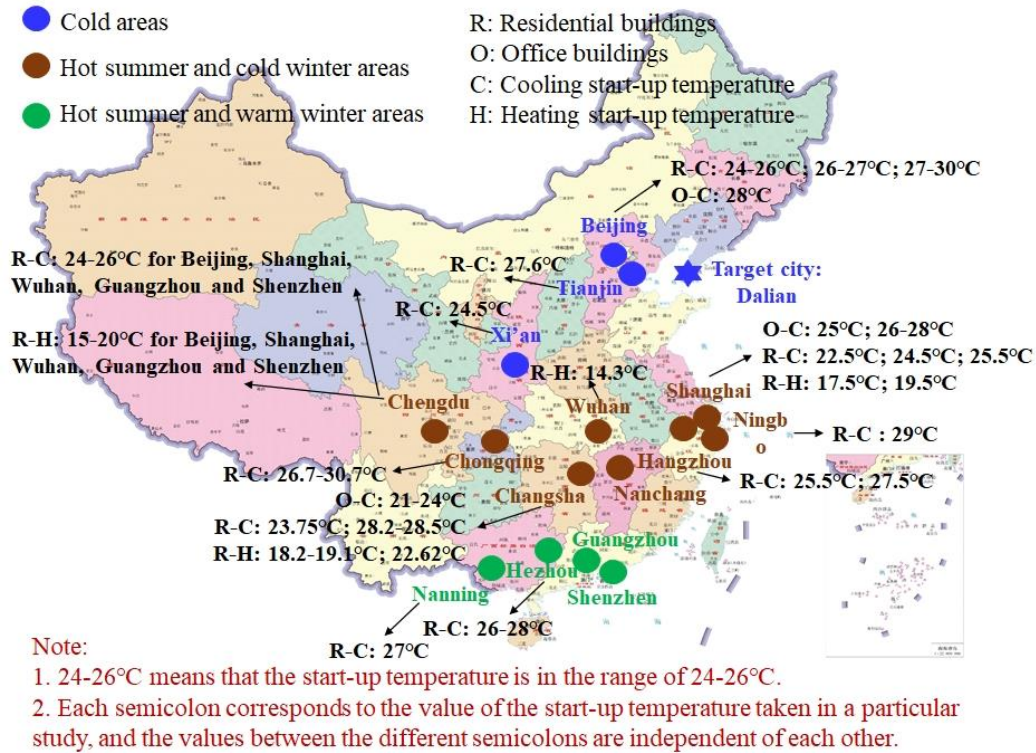


Figure 9 Some values of start-up temperature in different studies ^[51-64]

(2) Organized charging of electric vehicles

Electricity prices now follow a segmented schedule, prompting managers to suggest occupants charge their EVs during valley and shoulder hours while minimizing charging during peak or sharp hours. This strategy entails adjustments to parameters outlined in equations (1–5). For example, Figure 7 shows the results of the proposed charging for EVs at around 14:00 and 8:00.

(3) Lighting management and course optimization in educational buildings

Educational buildings are typical buildings in universities and are also the focus of energy waste. On the one hand, concerning lighting management, as shown in Figure 10, many unoccupied rooms

still maintain high-intensity operation of energy-using equipment, particularly in lighting. Numerous studies [66–67] have validated this observation. Consequently, managers may advocate for the deactivation of lighting in unoccupied areas. Based on the course schedule in this university, this phenomenon occurs most often at 17:00–18:00 (it is dinner time with no courses scheduled, but lighting is all on) and after 23:00 (the building is closed while lighting is usually on). This adjustment can be implemented by altering the lighting probability, with $P_{(17:00-18:00)}$ from 1 to 0. Then, the altered light-related behavior probabilities will be used to forecast the building energy demand after flexible energy-use regulation according to the technical route shown in Figure 4. Compared to the conventional method of simply reducing energy demand to 0, this technique considers the continued operation of other equipment (e.g., emergency lighting and fire alarm systems).

On the other hand, regarding course optimization [68], managers may recommend a schedule that prioritizes courses during valley and shoulder hours while minimizing them during peak or sharp hours. Since most courses during peak and sharp hours are elective, this adjustment can be accommodated due to the high level of autonomy enjoyed by professors and students, few people attending the classes, and few classes assigned. Managers may suggest redistributing 50% of peak-hour courses to other off-peak hours. This strategy can also be reflected in changing plug-related and light-related behavior probabilities and using the altered energy-use behavior probabilities to forecast building energy demand after flexible energy-use regulation according to the technical route shown in Figure 4.

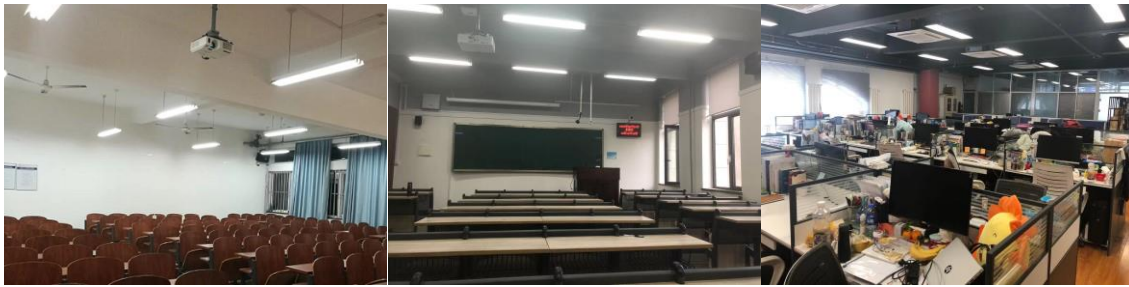


Figure 10 The phenomenon of energy waste in unoccupied rooms [37]

(4) Lighting and plug management in dormitory buildings

Similar to educational buildings, dormitory buildings within universities also grapple with lighting energy waste, akin to the scenario shown in Figure 10. Consequently, a flexible regulation strategy akin to that in educational buildings may be recommended for optimizing lighting use. Additionally, echoing course optimization strategies, managers may recommend reducing plug usage during peak hours (17:00–21:00), encouraging activities such as laundry to be shifted to off-peak periods (21:00–23:00). Since occupants tend to utilize plugs more frequently after 21:00 due to their needs and preferences as shown in Figure 11, a possible flexible regulation approach may involve redistributing 20% of the plug

load from 17:00–19:00 to 19:00–21:00 and 20% from 19:00–21:00 to 21:00–23:00.

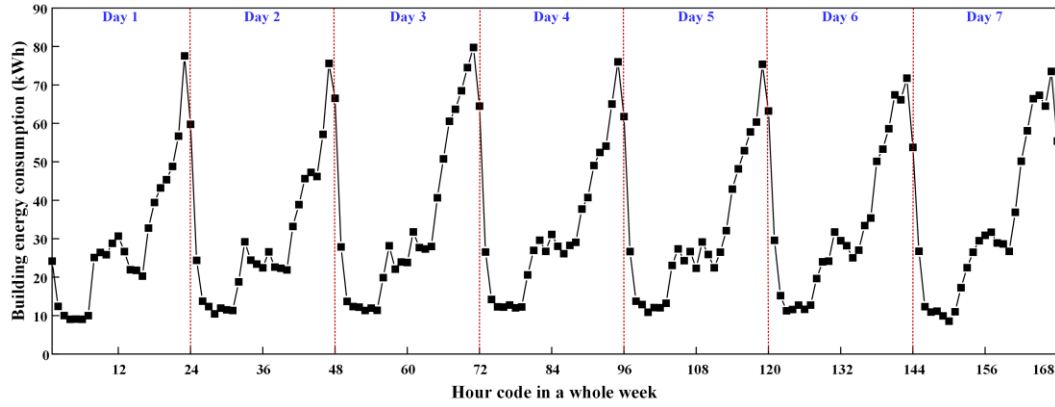


Figure 11 The energy consumption changes in Building C during 168 consecutive hours (one week)

Table 6 provides various flexible energy-use regulation strategies applicable to different building scenarios. Notably, the "ADVANTAGE" column in Table 6 delineates the benefits of the flexible energy-use regulations proposed herein compared to traditional methods. For instance, traditional methods involve adjusting AC setting temperatures, which is difficult to apply in regulation for split ACs and cannot determine human thermal feelings. While, the proposed method focuses on modifying AC start-up temperature maintaining the thermal comfort indicators such as thermal sensitivity unchanged, thereby considering the thermal feelings, randomness, and variability of occupants. Strategies a–c can be used in all buildings, and strategy d is generally used in educational buildings, and strategy e is generally used in dormitory buildings.

Table 6 The details of the proposed flexible energy-use regulation strategy in this study

Strategies	Change items	Category	Description	Advantages
a. adjusting AC start-up temperature	AC power	Reducing loads	Changing the start-up temperature from 18–20°C to 20–22°C for cooling, while changing the start-up temperature from 25–26°C to 23–24°C for heating.	Given occupant thermal feeling, randomness, and variability
b. organized charging of EVs	EV charging time	Shifting loads	Charging EVs more during valley and shoulder hours (12:00–17:00), while reducing charging during peak and sharp hours (8:00–11:00).	Given different working times in different universities
c. light management	Lighting use time	Interrupting loads	Turning off all the lights when the room is unoccupied.	Given equipment that cannot be turned off such as emergency lights.
d. course optimization	Course time	Shifting loads	Transferring 50% of the courses (only elective courses) during sharp and peak hours to other hours.	Given the characteristics and variability of elective courses
e. plug management	Plug use time	Shifting of loads	Transferring 20% of the plug loads from 17:00–19:00 to 19:00–21:00 and 20% of the plug loads	Given the needs and preferences of energy -use from university students

In summary, Figure 12 shows the comprehensive methodology and technical framework of flexible energy-use regulation and microgrid operation scheduling optimization, with potential results.

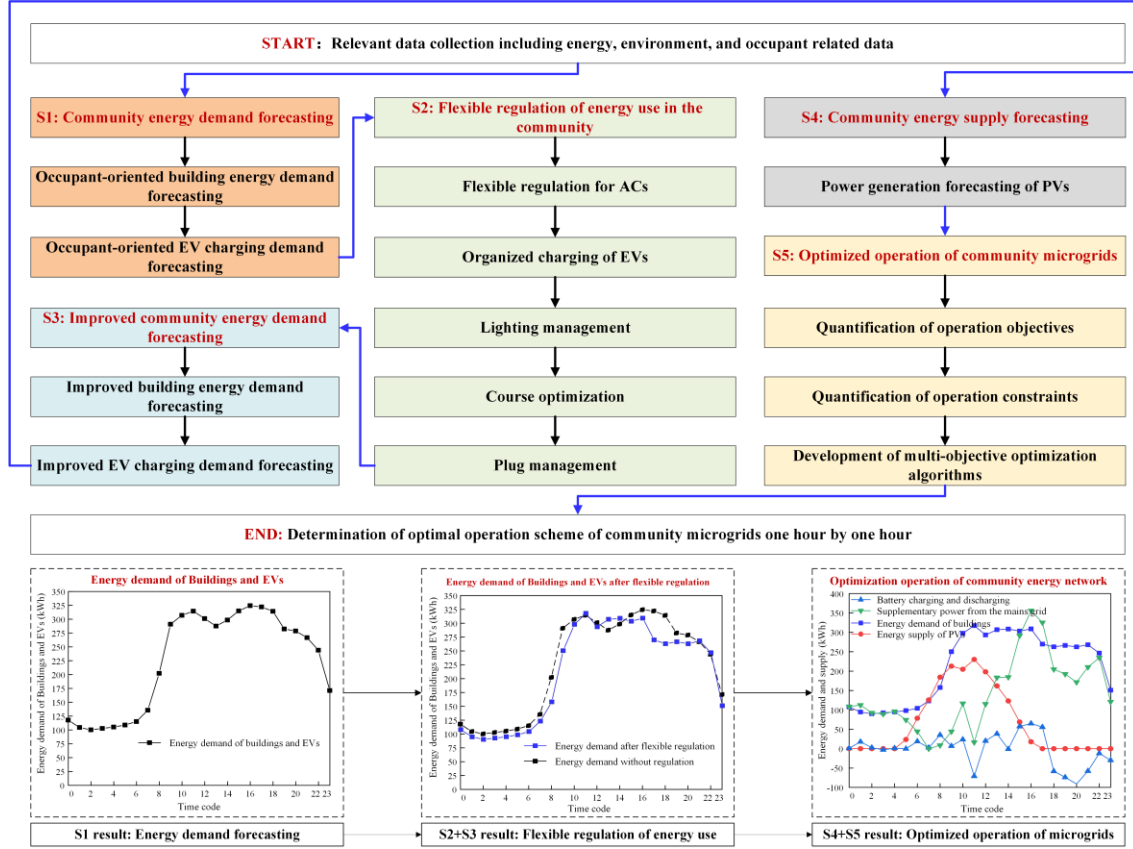


Figure 12 The complete technical framework and potential calculation results of this study

6 Results of flexible energy-use regulation

6.1 Results in single buildings

(1) Flexible regulation for start-up temperature of split ACs in a single building

Building A will serve as a case for the flexible regulation of split AC start-up temperature. The actual AC-related behavior probability is derived from Equation (43), computed using equations (39–41) based on recent studies^[33–35, 37]. Equation (43) yields $P_{su} = 4.70\%$ and $T_{su} = 19.17^\circ\text{C}$, indicating that AC usage averages 4.70% during working hours (7:00–23:00) in Building A, with AC activation occurring on average in this building at the indoor air temperature reaching 19.17°C . By solving for the remaining constants ($l = 13.00$ and $k = 3.78$), the AC-related probability can be expressed as equation (44). Managers may suggest raising the start-up temperature from 19.17°C to 21.00°C maintaining thermal sensitivity parameters and other parameters (l , and k) constant. Therefore, the changed probability can be shown in equation (45). Following this process, while holding other input

parameters such as time of day and meteorological parameters constant, the manager can forecast building energy demand with AC start-up temperature adjustment using methods in Figure 4. Comparisons are shown in Figure 13.

$$P\% = \begin{cases} 98750.62 + \frac{-98745.93}{1 + \left(\frac{x}{41.85}\right)^{20.77}}, & 7:00 - 23:00 \\ 0, & 23:00 - 7:00 \end{cases} \quad (43)$$

$$P\% = \begin{cases} 100 + 4.70 - e^{-\left(\frac{x-19.17}{13.00}\right)^{3.78}}, & x > 19.17 \text{ and } 7:00 - 23:00 \\ 4.70, & x < 19.17 \text{ and } 7:00 - 23:00 \\ 0, & 23:00 - 7:00 \end{cases} \quad (44)$$

$$P'\% = \begin{cases} 100 + 4.70 - e^{-\left(\frac{x-21.00}{13.00}\right)^{3.78}}, & x > 21.00 \text{ and } 7:00 - 23:00 \\ 4.70, & x < 21.00 \text{ and } 7:00 - 23:00 \\ 0, & 23:00 - 7:00 \end{cases} \quad (45)$$

The results indicate that implementing this strategy could potentially reduce total building energy demand (not solely AC energy demand) by approximately 9.41% annually in Building A.

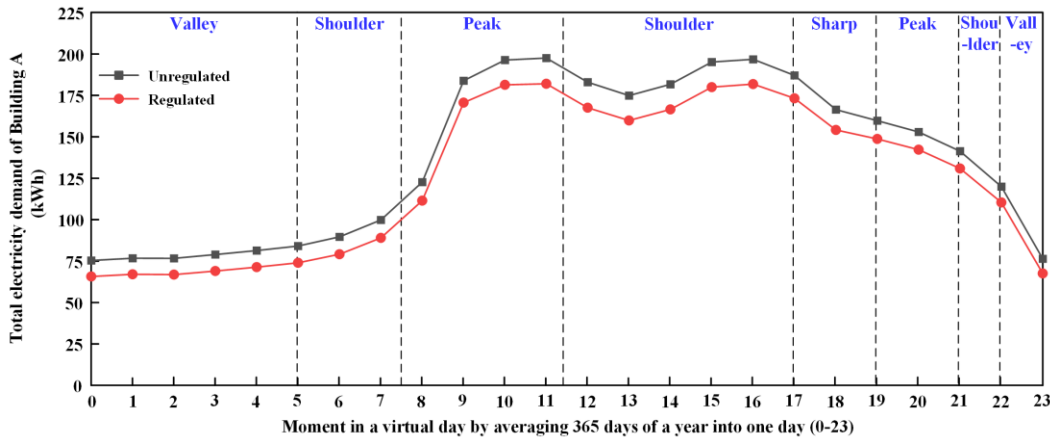


Figure 13 Comparison of building energy demand without or with flexible regulation for split ACs in a virtual day by averaging every hour in 2021

(2) Organized charging of electric vehicles nearby buildings

Building A and its adjacent charging posts will serve as a case for the organized charging strategy for EVs. Referring to equations (1–5) in section 2.2 for detailed methods and parameter selection, since most of the EVs in this university belong to teachers, managers suggest prioritizing EV charging during valley and shoulder hours (12:00–17:00) while minimizing charging during peak and sharp hours (8:00–11:00). In contrast, if no strategy is employed, charging would be uniform and random. Figure 14 presents a comparison of energy demand for Building A and its nearby charging posts.

The results indicate that this strategy could shift approximately 50.91% of electricity demand for EV charging from peak and sharp hours to valley and shoulder hours.

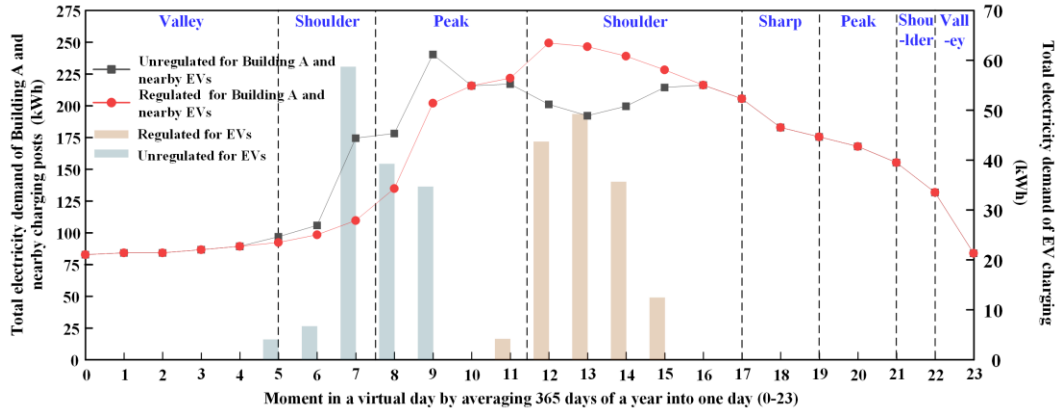


Figure 14 Comparison of energy demand for Building A and charging posts nearby Building A without or with organized charging of EVs in a virtual day by averaging every hour in 2021

(3) Lighting management and course optimization in an educational building

Building B will serve as a case for lighting management and course optimization in educational buildings. Managers suggest turning off lights in unoccupied rooms, primarily during 17:00–18:00 and 23:00–5:00 on the next day, and transferring 50% of elective courses from peak to shoulder hours. Figure 15 compares energy demand for Building B under this strategy.

The results show that if the strategy is achievable, it would reduce total building energy demand by about 7.26% during valley and shoulder hours and about 4.00% during other hours in one day.

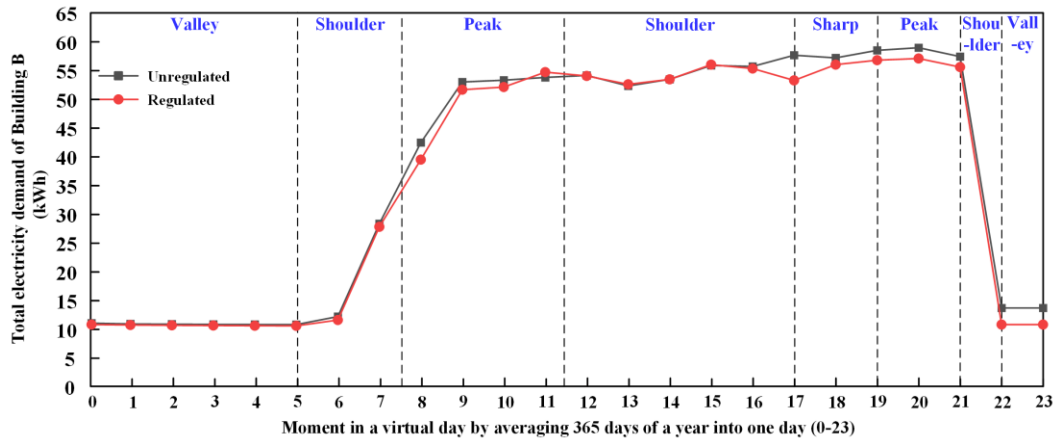


Figure 15 Comparison of building energy demand for Building B without or with lighting management and course optimization in a virtual day by averaging every hour in 2021

(4) Lighting and plug management in a dormitory building

Building C will serve as a case for lighting and plug management in dormitories. Managers suggest turning off lights in unoccupied rooms and transferring 20% of plug loads from 17:00–19:00 to 19:00–21:00 and 20% from 19:00–21:00 to 21:00–23:00. Figure 16 shows the comparison for Building C.

The results show that if the strategy is achievable, it would transfer about 10.15% of total building energy demand from sharp and peak hours to other hours.

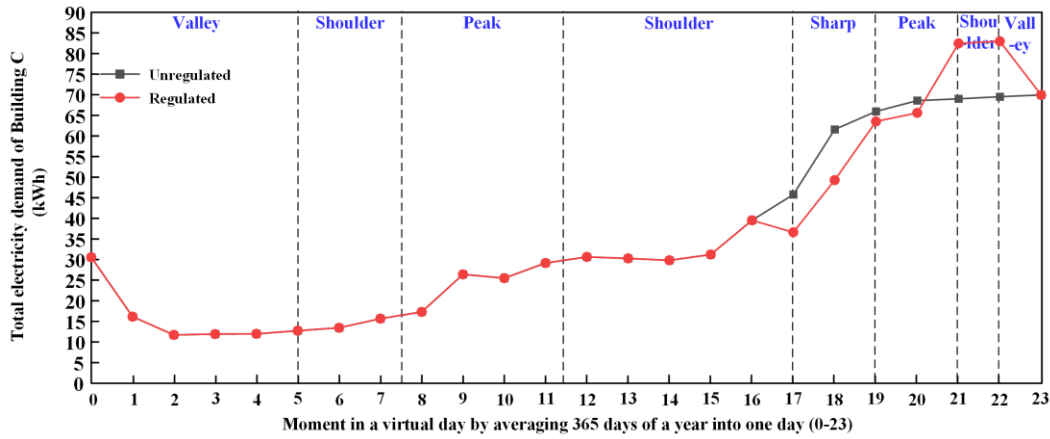


Figure 16 Comparison of building energy demand for Building B without or with lighting management and course optimization in a virtual day by averaging every hour in 2021

In summary, this study introduces four flexible energy-use regulation strategies in various buildings:

Strategy a: Flexible regulation for start-up temperature of split ACs;

Strategy b: Organized charging of EVs nearby buildings;

Strategy c: Lighting management and course optimization for educational buildings;

Strategy d: Lighting and plug management for dormitory buildings.

Considering all strategies concurrently for Buildings A-C and their nearby charging posts on a virtual day by averaging every hour in 2021, energy demand will be shown in Figure 17. These parallel strategies could reduce and shift 15.13% of energy demand from peak hours and 8.57% from sharp hours. Additionally, there is a 5.18% reduction in energy demand during valley hours.

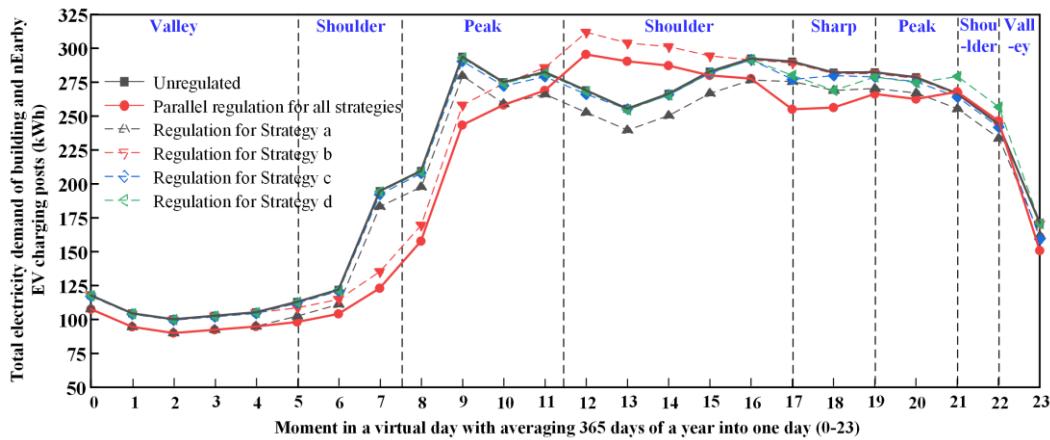


Figure 17 Comparison of building energy demand for Buildings A-C and charging posts nearby Buildings A-C without or with parallel flexible regulation in a virtual day by averaging every hour in 2021

6.2 Results in the whole community

Combining all buildings with enough energy and environmental data as a community, detailed information on these buildings is presented in Table A-1 in Appendix A. These buildings will undergo studies for flexible energy-use regulation using Strategies a–d. Based on the building functions, Strategy a will be implemented in Buildings A and D–H, Strategy b in Buildings A–K, Strategy c in Buildings B and I–K (educational buildings), and Strategy d in Buildings L–T (dormitory buildings).

Regarding AC start-up temperature adjustments, specific details are shown in Table 7. Analysis reveals that actual AC start-up temperature in buildings may often deviate from optimal values depicted in Figure 9. Therefore, managers may recommend adjusting the AC start-up temperature by $\pm 1\text{--}2^\circ\text{C}$ to stabilize the cooling and heating start-up temperature around $21\text{--}24^\circ\text{C}$. The symbol ‘–’ indicates a relatively appropriate start-up temperature, where no adjustment is advised to maintain thermal comfort.

Table 7 The flexible regulation of energy use for split ACs in every building which has ACs

Building	Type	T_{su} ($^\circ\text{C}$)	P_{su}	T_{su}' ($^\circ\text{C}$)
A	Cooling	{19.17, 7:00 – 23:00 0, 23:00 – 7:00}	{4.70%, 7:00 – 23:00 0.00%, 23:00 – 7:00}	{21, 7:00 – 23:00 0, 23:00 – 7:00}
D	Heating	{23.52, 9:00 – 22:00 22.37, 23:00 – 07:00 21.99, 7:00 – 9:00, 21:00 – 23:00}	{0.00%, 9:00 – 21:00 0.00%, 23:00 – 07:00 0.00%, 7:00 – 9:00, 21:00 – 23:00}	{22, 7:00 – 9:00, 21:00 – 23:00 21, 9:00 – 21:00 21, 23:00 – 7:00}
D	Cooling	{21.00, 9:00 – 22:00 20.47, 23:00 – 07:00 19.33, 7:00 – 9:00, 21:00 – 23:00}	{6.00%, 9:00 – 21:00 3.00%, 23:00 – 07:00 1.80%, 7:00 – 9:00, 21:00 – 23:00}	{22, 7:00 – 9:00, 21:00 – 23:00 22, 9:00 – 21:00 22, 23:00 – 7:00}
E	Cooling	{22.72, 7:00 – 23:00 0, 23:00 – 7:00}	{6.18%, 7:00 – 23:00 0.00%, 23:00 – 7:00}	{24, 7:00 – 23:00 0, 23:00 – 7:00}
F	Cooling	17.69	5.90%	20
G	Cooling	{20.49, 7:00 – 9:00, 21:00 – 23:00 19.14, 9:00 – 21:00 0.00, 23:00–next 7:00}	0.00%	{21, 7:00 – 9:00, 21:00 – 23:00 20, 9:00 – 21:00 0, 23:00–next 7:00}
H	Heating	{27.18, 9:00 – 22:00 25.47, 23:00 – 07:00 26.20, 7:00 – 9:00, 21:00 – 23:00}	{9.60%, 9:00 – 21:00 9.30%, 23:00 – 07:00 9.40%, 7:00 – 9:00, 21:00 – 23:00}	–
H	Cooling	{24.16, 9:00 – 22:00 20.81, 23:00 – 07:00 21.42, 7:00 – 9:00, 22:00 – 23:00}	{21.50%, 9:00 – 22:00 5.60%, 23:00 – 07:00 8.70%, 7:00 – 9:00, 22:00 – 23:00}	{–, 7:00 – 9:00, 21:00 – 23:00 22, 9:00 – 21:00 22, 23:00–next 7:00}

The results depicting community energy demand with or without Strategies a–d for a virtual day by averaging every hour in 2021 are tabulated in Table 7 and visualized in Figure 18. Furthermore, all data in Table 8 represent energy demand in kWh. These parallel strategies could reduce and shift 12.12% of energy demand from peak hours and 8.06% from sharp hours on average. Although the proportion of cuts and regulations may be not large, the flexible regulations may be significant. On the one hand, the benefits are high. That is the cost of regulation is small (no additional equipment additions, building modifications, etc.) while regulation is mostly targeted at times of high electricity costs. On the other hand, regulation fully respects the comfort and energy habits of the occupants, and will not require the

occupants to sacrifice energy demand to save energy.

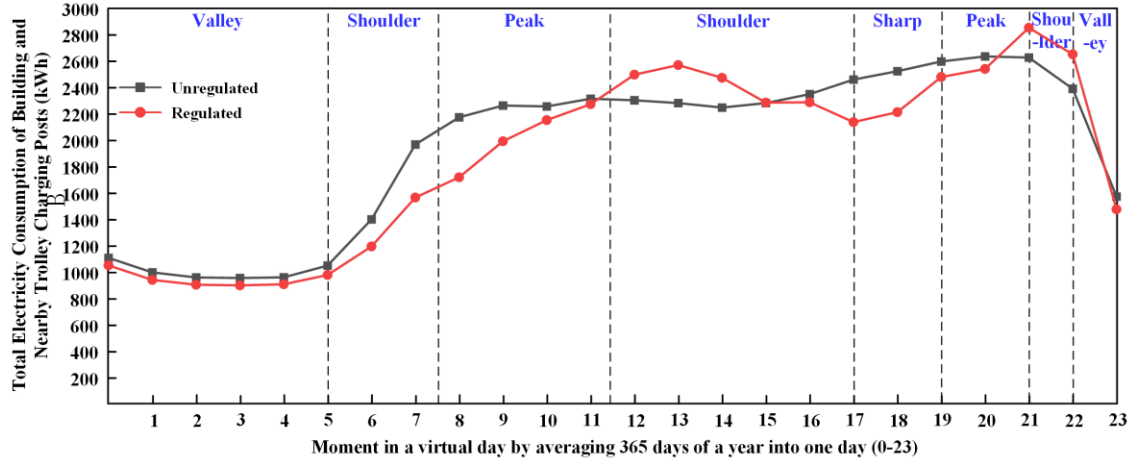


Figure 18 Comparison of community energy demand for all Buildings and charging posts without or with parallel flexible regulation in a virtual day by averaging every hour in 2021

Table 8 The results of community energy demand with or without flexible energy-use regulation strategies

Start moment	Buildings A and D–H		EV charging posts		Buildings B and I–K		Buildings L–T	
	Without	With	Without	With	Without	With	Without	With
	Strategy a	Strategy a	Strategy b	Strategy b	Strategy c	Strategy c	Strategy d	Strategy d
0:00	621.3060	571.1708	0.0000	0.0000	182.4471	176.1883	301.2462	301.2462
1:00	610.8518	561.0684	0.0000	0.0000	173.9708	167.2178	208.7556	208.7556
2:00	599.1069	550.8935	0.0000	0.0000	170.6553	163.3722	184.8930	184.8930
3:00	596.1359	548.5803	0.0000	0.0000	169.5406	161.6902	183.4210	183.4210
4:00	595.9015	551.7445	0.0000	0.0000	169.9725	161.6713	187.6440	187.6440
5:00	596.9241	551.9570	17.6188	0.0000	168.6654	160.0193	258.1939	258.1939
6:00	665.0311	612.5494	144.0651	0.0000	165.7116	156.9800	416.5483	416.5483
7:00	814.3096	744.9070	324.1725	0.0000	237.3975	229.0087	582.1714	582.1714
8:00	913.7648	848.6491	383.8794	0.0000	304.2640	298.1947	561.6300	561.6300
9:00	1096.4134	1028.4002	195.5742	0.0000	378.5453	371.2043	581.3810	581.3810
10:00	1191.6056	1119.9284	23.7274	0.0000	394.5556	386.4618	633.5474	633.5474
11:00	1213.6690	1139.0348	5.2931	47.5380	397.7340	387.9107	684.9257	684.9257
12:00	1190.7021	1120.5845	0.0000	274.1267	384.8775	374.7275	713.1257	713.1257
13:00	1144.6794	1077.6633	0.0000	363.4970	368.1108	360.6759	753.2848	753.2848
14:00	1142.2130	1078.8104	0.0000	296.2244	392.0705	385.2267	697.1491	697.1491
15:00	1165.5114	1106.1229	0.0000	68.6815	403.0754	397.0302	695.6767	695.6767

16:00	1163.3606	1104.5184	0.0000	2.1641	407.2238	401.7677	760.9941	760.9941
17:00	1160.5445	1105.1632	0.0000	0.0000	408.1213	315.5359	872.0725	697.6580
18:00	1084.8619	1024.6954	0.0000	0.0000	404.5573	356.4990	1013.7040	810.9632
19:00	1024.4549	964.9874	0.0000	0.0000	413.3107	408.1935	1138.0163	1084.8275
20:00	995.6155	934.9206	0.0000	0.0000	398.7061	405.4017	1218.6583	1177.6674
21:00	927.3669	871.0262	0.0000	0.0000	367.8292	422.4064	1308.8726	1536.4758
22:00	771.0742	736.5155	0.0000	0.0000	310.7464	362.3450	1284.5047	1528.2364
23:00	623.4120	577.7592	0.0000	0.0000	180.1031	128.6664	744.2894	744.2894

7 Results of microgrid operation scheduling optimization

7.1 Microgrid operation scheduling with common flexible energy-use regulation

Following the discussion on flexible energy-use regulations in the community, the optimized microgrid operation scheduling solution can be simulated, with key parameters detailed in Table 9. For comparison purposes, four kinds of cases are proposed, and the results are shown in Figure 19. Moreover, it is important to note that positive and negative values in Figures 19(a)–19(d) are used only to distinguish between supply and demand and have no other meaning. Moreover, comprehensive benefit reflects the reduction in total cost, which is the annual average cost in the full life cycle discounted by a conversion factor, considering the initial investment, incentives, penalties, and all other costs.

Case a: Electricity sourced from municipal grids without flexible regulation;

Case b: Electricity sourced from municipal grids with multi-strategy parallel flexible regulation;

Case c: Electricity sourced from municipal grids and local microgrids without flexible regulation;

Case d: Electricity sourced from municipal grids and local microgrids with multi-strategy parallel flexible regulation.

Table 9 Key parameters for simulation of microgrid operation solutions ^[47–50, 69–71]

Parameters	Explanation of the parameters	Values
Population size	Population size of jellyfish	100
Maximum number of iterations	Maximum number of iterations for JSA	2000
Archive size	The number of potential solutions for JSA stored in the archive for comparison throughout the optimization process	500
Number of grids in each dimension	The search space can be divided into multiple grids, and this number determines how discrete the algorithm to the search space	50
Construction cost		PVs: 207.19\$/kW
	Construction costs of photovoltaic systems, battery systems, and	Batteries: 138.12\$/kW
	EV charging posts, estimated based on equipment specifications	Posts: 865.21\$/a post

Life cycle	Years of full-life microgrid operation	20 years
Annual interest rate	Annual interest rate in the full life cycle	8.0%
Maintenance cost factor rate	Maintenance cost from labor (2.0%) and others (1.5%)	3.5%
Pollutant discharge factor	Emissions of CO ₂ , NO _x , SO ₂ , and other pollutants from thermal (municipal) power generation.	CO ₂ : 960g/kWh NO _x : 15g/kWh SO ₂ : 30g/kWh
Pollutant treatment cost factor	Treatment costs for CO ₂ , NO _x , SO ₂ , and other pollutants for calculating potential environmental benefits.	CO ₂ : 0.0032\$/kg NO _x : 1.1040\$/kg SO ₂ : 0.8280\$/kg
Energy storage cost factor	The cost of energy storage using batteries	0.0777\$/kWh
Battery limit of capacity	Maximum capacity of the batteries	1000kWh
Battery limit of charge state	Maximum and minimum charge state of the batteries	30%–90%
Number of equivalent trams	Overall number of EVs after approximate equivalence of electric bicycles to EVs through battery performance	144
Number of EV charging posts	The number of EV charging posts that have been built	31
Electricity sales costs	The cost of selling electricity to the main municipal grid	0.0517\$/kWh
Basic electricity costs	Electricity costs from the municipal grid in the shoulder hours	0.0691\$/kWh
Power balance penalty factor	Penalty costs for charging or discharging and electricity supply or demand imbalance when the ratio of imbalance exceeds 5.0%	100\$/kWh
Subsidy factor	Subsidy costs for renewable energy generation (PV in this study).	0.0442\$/kWh
Reserve load capacity factor	Margin to ensure that supply exceeds demand	10%
Forecast error factor	Margin to consider the energy demand or supply forecast error	15%
AC temperature setting value	The range of AC temperature setting values to ensure that the room temperature is in a comfortable range that is not too high or too low	20–28°C

The conclusions can be analyzed according to the simulation results:

(1) Comparing Cases a to c and Cases b to d, combining municipal grids and local microgrids may yield greater benefits. Constructing a community microgrid could result in an 11.725% comprehensive benefit increase with parallel multi-strategy flexible energy-use regulation strategies, while an 11.728% benefit increase without any flexible regulation strategies.

(2) Comparing Cases a to b and Cases c to d, flexible energy-use regulation strategies may offer additional benefits. Parallel multi-strategy flexible energy-use regulation could result in a 4.449% comprehensive benefit increase when a microgrid has been constructed, while a 4.452% benefit increase when only the municipal main grid supplies electricity.

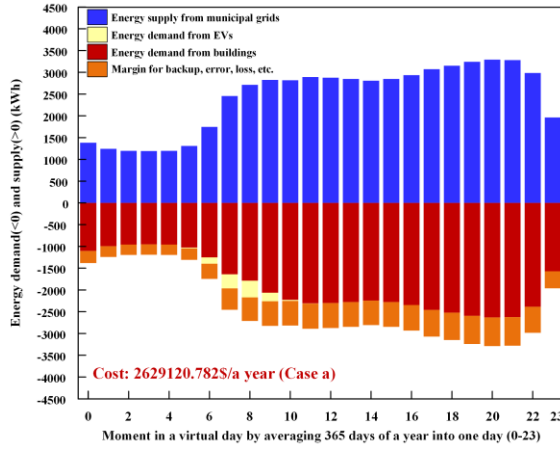


Figure 19(a) Case a

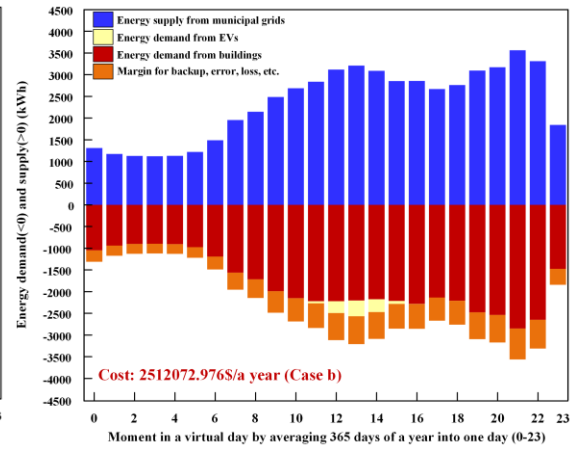


Figure 19(b) Case b

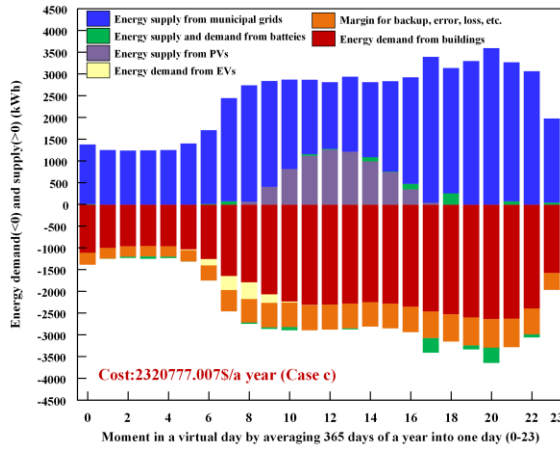


Figure 19(c) Case c

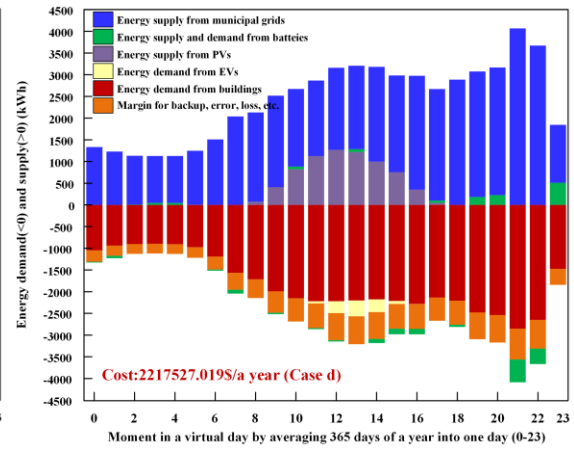


Figure 19(d) Case d

Figure 19 The optimized operation solutions of community microgrids with different cases

7.2 Microgrid operation scheduling with radical flexible energy-use regulation

In this study, the flexible regulations were notably conservative, as evidenced by several factors:

(1) The AC start-up temperature for cooling was only regulated to about 20–22°C, a value still considered low. In addition, considering that the target building groups are situated in a cold region of China, many buildings on this campus (e.g., all dormitory buildings) do not necessitate ACs for cooling in summer, or the AC demand is weak. Therefore, the start-up temperature can be further increased.

(2) Lights and plugs were managed equally conservatively. This study focused on energy wastage during the evening break (17:00–18:00) and after the building closes (after 23:00) only in dormitories and educational buildings. However, at other times, there were still a large number of devices running when no occupants in the room in other buildings such as academic buildings. As shown in Figure 10, the first graph is for educational buildings at 17:00, the second graph is for educational buildings at 14:00, and the third graph is for academic buildings at 12:00. In addition, only 20% of the plug load has

been recommended to be shifted to other moments in this study, which was also conservative.

(3) The number of EVs was based on statistics in 2021. However, the number of EVs in China has risen dramatically in recent years due to rapid technology development and government incentives. With approximately 4,000 vehicles on this campus, the number of EVs set in this study was conservative according to the estimation of the proportion of new-energy vehicles in China.

Given these considerations, this section proposes radical flexible energy-use regulation strategies, including adjusting the AC start-up temperature to 24°C for cooling and 20°C for heating, organizing EV charging with the number of EVs set to 20% of total vehicles, and shifting 50% of plug loads from peak and sharp hours to shoulder or valley hours. And no radical adjustments of course and lights will be used for normal and necessary activities in this university. The results are shown in Figure 20.

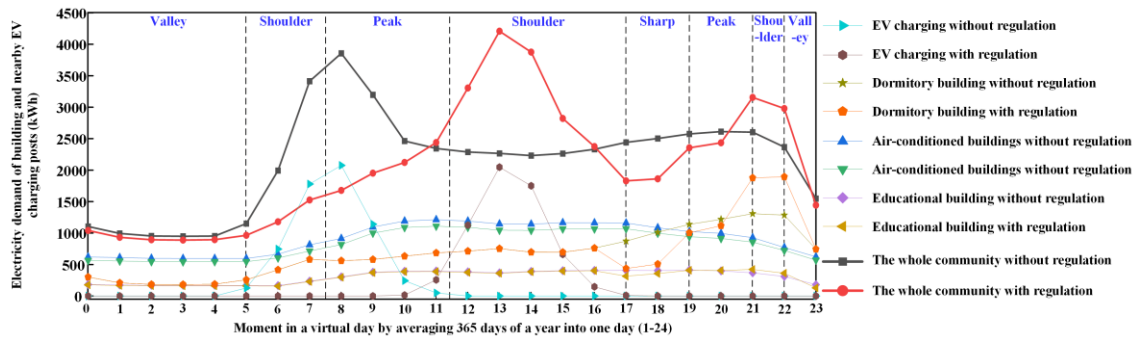


Figure 20 Comparison of community energy demand for all Buildings and charging posts without or with the proposed radical flexible energy-use regulation in a virtual day by averaging every hour in 2021

Additionally, this study explores four additional cases with or without radical flexible energy-use regulation strategies for microgrid operation scheduling optimization, as shown in Figure 21. It is crucial to note that the number of EVs will be adjusted from 144 to 20% of the total vehicles, and the number of charging posts will be proportionally increased, resulting in a total of 172 charging posts.

Case e: Electricity sourced from municipal grids without flexible regulation, with an increased number of EVs;

Case f: Electricity sourced from municipal grids with radical flexible regulation, with an increased number of EVs;

Case g: Electricity sourced from municipal grids and local microgrids without flexible regulation, with an increased number of EVs;

Case h: Electricity sourced from municipal grids and local microgrids with radical flexible regulation, with an increased number of EVs.

Similar to Figures 21(a)–21(d), the conclusions can be analyzed according to the simulation results:

(1) Comparing Cases e to g and Cases f to h, constructing a community microgrid could bring

10.085% of the comprehensive benefits without radical flexible regulation with an increased number of EVs, while 10.397% of the benefits with radical flexible regulation strategies.

(2) Comparing Cases e to f and Cases g to h, using radical flexible energy-use regulation will bring 8.503% of the comprehensive benefits without microgrids with an increased number of EVs, while 8.820% of the benefits with microgrids.

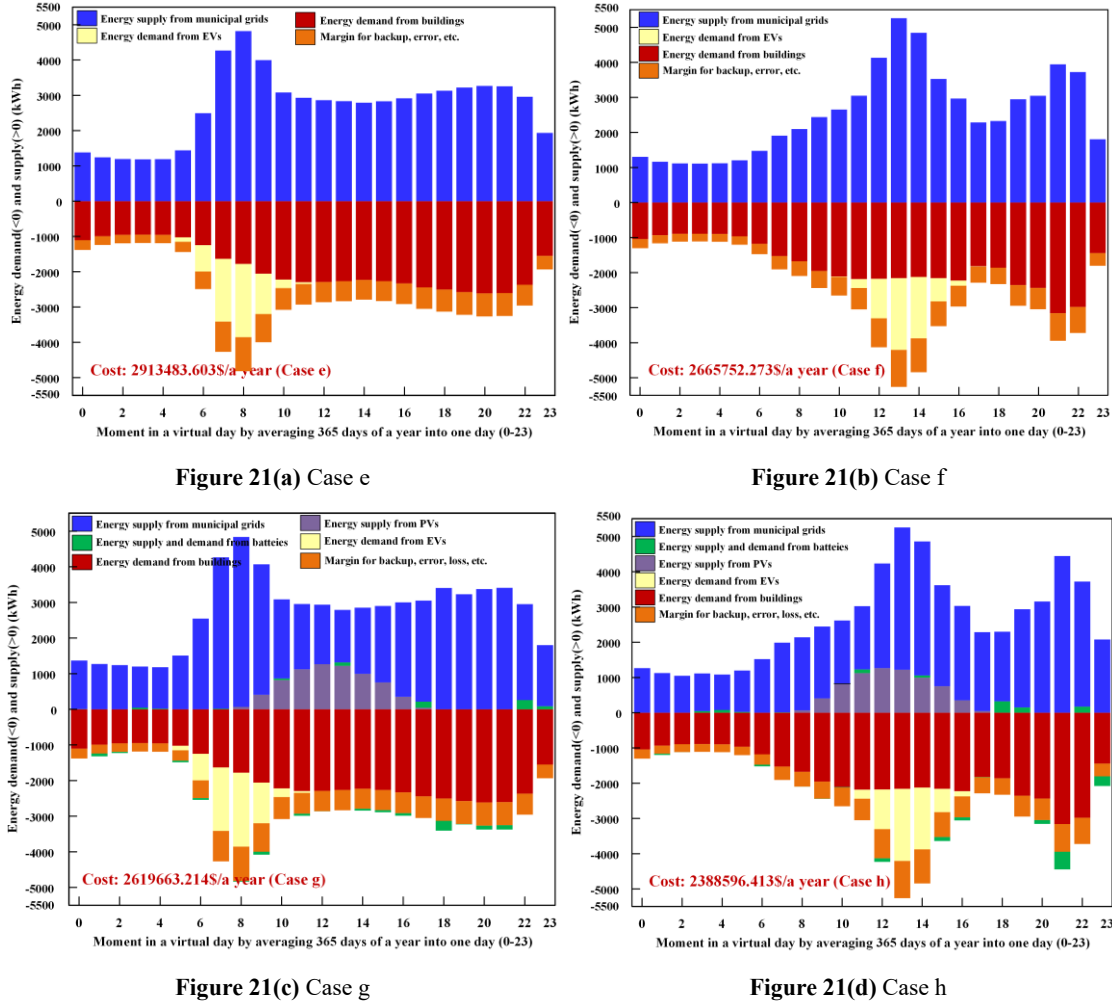


Figure 21 The optimized operation solutions of community microgrids with proposed novel cases with the proposed radical flexible energy-use regulation and more EVs

In summary, comparing Cases a to d and Cases e to h, using flexible energy-use regulation with constructing a community microgrid will bring 15.655%–18.016% of the total benefits on average. Considering the matter separately, using common flexible energy-use regulation will bring 4.450% of the comprehensive benefits on average, whereas radical flexible energy-use regulation provides 8.662% of the total benefits. Thus, the improvement rate from common regulation to radical regulation is 48.619%. Moreover, constructing a community microgrid will bring 10.984% of the benefits on average,

while the benefit changes may be not significant in different simulation cases.

8 Discussions

8.1 Result analyses of adjusting and scheduling

This study proposes a community energy system optimization method that considers energy supply and demand through proposed flexible energy-use regulations and microgrid operation scheduling optimization simultaneously. The results indicate 15.655% of the average annual benefits using common flexible regulation strategies with microgrids and 18.016% using radical regulation strategies also with microgrids. Table 10 outlines some existing studies on microgrid operation optimization.

Table 10 The existing studies about microgrid operation optimization

References	System	Regulations	Estimation	Performance
This study	EV, PV, building, and BAT	Adjusting AC start-up temperature; organized charging of EVs; light and plug management; course optimization; battery energy storage	Investment-energy-society-environment costs and benefits	165.655%–18.016% of the average annual benefits
Yan et al. [73]	EV, PV, WT, ESD, and CCHP	Energy storage of cooling, heating, and power; reducing unnecessary energy loads; V2G and G2V regulation for EVs	Carbon emission and energy (gas and power) bill costs	26.88% of cost-saving
Jasim et al. [74]	EV, PV, building, and BAT	Shifting the energy loads from peak to off-peak hours	Power bill costs	14.08%–38.88% of cost decrease
Huy et al. [75]	WT, PV, DG, BAT, and CCHP	Encouraging users to voluntarily reduce their electricity consumption during periods of high demand or when grid reliability is threatened	Operational (system operation and maintenance costs, fuel costs, and subsidies) costs	5.95% of cost decrease
Mota et al. [76]	PV, and building	Shifting the loads to PV availability hours, or if not possible, to off-peak hours	Household energy bill costs	1.5%–26.8% of cost decrease
Zhang et al. [77]	WT, ESD, HSD, CCHHP, and loads	Battery, thermal, and hydrogen energy storage; suggesting CCHHP-based MG operator has bidirectional energy trading with electricity and district heating markets	Operational (system operation and Maintenance costs, energy bill costs, and subsidies), and pollutant treatment costs	15.44% of cost-saving (2275.645\$ to 1924.18\$)
Yang et al. [78]	PV, WT, BAT, EV, MT, and building	Organized charging of EVs, real-time power cost adjustment, and encouragement	Investment, operational (system operation and Maintenance costs, energy bill costs, and subsidies), and pollutant treatment costs	25.50% of cost-saving

Note: The nomenclature includes ESD (energy storage device), HSD (hydrogen storage device), CCHP (combined cooling, heating, and power), CCHHP (combined cooling, heating, hydrogen, and power), and MG (Microgrid).

Various studies focus on different regulations, such as demand response, EV charging management, and energy storage optimization. Moreover, microgrids vary in components and modes of operation (grid-connected or islanded). However, despite these differences, discounted benefits generally range from 5–40%, consistent with the simulation results of this study.

8.2 Time scale election

This study conducts flexible regulation of energy use and optimal scheduling of energy networks on an hourly basis, with one day (24 hours) as a cycle. However, the data corresponding to a certain hour represents the average of all data for that hour over 365 days of the year. Thus, the results are for a virtual day by averaging every hour for a whole year.

This approach facilitates comparing the operation of a year as a whole. However, in practice, actual daily operational data should inform flexible energy-use regulation and microgrid operation scheduling optimization instead of relying on averaged data over a year. For example, adjusting the AC start-up temperature for cooling should only affect hours during the cooling season, offering better benefits compared to averaging data over the entire year, as shown in Figure 22.

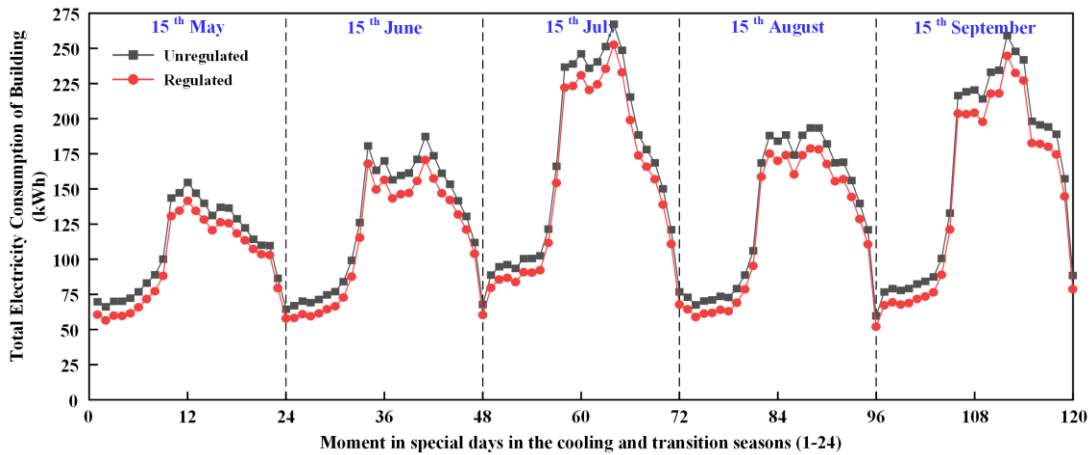


Figure 22 Comparison of building energy demand without or with flexible regulation for split ACs in actual days (every 15th in the cooling and transition seasons) in 2021

8.3 Limits and future works

This study has certain limitations:

(1) The community has not completed the construction of the microgrid, meaning the research relies on simulated models rather than actual operating cases. Consequently, although the study used the real monitored operational data, it also depends on the energy supply and demand forecasting. That means the proposed method is more effective for the preliminary assessment of the design phase. If it will be used in the operation phase, it may need further studies and work.

(2) The study suggests flexible regulation of energy use at a managerial level rather than mandating

occupant actions due to privacy concerns, freedom, and individual differences. Thus, the study can only assess potential energy use reduction or transfer.

(3) The proposed microgrid is conservative and atypical because it does not consider wind power or larger-scale energy storage systems.

Therefore, in the future, these works will be considered:

(1) The future work is to propose more accurate and scientific energy demand or energy usage prediction models. However, the prediction for EV charging consumption stays on Monte Carlo stochastic simulation of which accuracy needs to be further strengthened. In addition, EV battery performance is based on averaged data, with no individualized analysis of each EV, which also needs to improve.

(2) The future work is to develop a prompt program based on cell phones, bracelets, or watches to send real-time energy-use optimization suggestions to occupants, for enhancing the applications of flexible regulation strategies.

(3) More typical and comprehensive microgrid optimal studies will be conducted. For example, wind power generation and large-scale energy storage systems will be considered.

9 Conclusions

This study proposed a community energy system optimization method that considers energy supply and demand through proposed flexible energy-use regulations and microgrid operation scheduling optimization simultaneously, and the conclusions were as follows.

(1) This study proposed methods for occupant-oriented flexible energy-use regulations leveraging occupant behavior models instead of depending on physical parameters (such as the power of equipment) as traditional methods. This approach will consider energy use preference, thermal comfort feelings, special activities, and stochastic behaviors of occupants. Furthermore, the proposed strategies consider the interaction among buildings, EVs, PVs, and energy storage systems. The proposed method could achieve occupant-oriented and multi-strategy parallel flexible energy-use regulations by using novel parameters, and the occupant behavior probabilities.

(2) Implementation of the proposed common flexible regulation strategies in a single building, alongside nearby EV charging posts, demonstrated a 15.13% adjustment (reduction and transfer) of energy demand during peak hours and 8.57% during sharp hours. Additionally, there is a 5.18% reduction in energy demand during valley hours. When extended to the entire community, comprising twenty buildings and all charging posts, these strategies resulted in a 12.12% adjustment (reduction and transfer) of energy demand during peak hours and 8.06% during sharp hours.

(3) This study proposed methods for microgrid operation scheduling optimization. This study

proposed improved objective functions simultaneously considering the benefits and costs of investment, environment, energy, and society. In addition, this study proposed multiple constraints that considered the operational status of each component, supply and demand balance, transmission losses, standby, and fluctuations. Finally, this study proposed suitable solving algorithms, JSA.

(4) Results from microgrid optimization scheduling, conducted over a 20-year cycle with all costs converted to annual averages, revealed significant benefits. When common flexible regulation strategies were used in parallel, it could result in 4.449% of the annual average benefits (with microgrids) or 4.452% of the combined benefits (no microgrids). When radical flexible regulation strategies were used, it could result in 8.820% of the average annual benefits (with microgrids) or 8.503% of the benefits (no microgrids). On average, using common regulations will bring 4.450% of the comprehensive benefits, while 8.662% when using radical regulations, meaning 48.619% of improvement. Moreover, the results show that constructing a microgrid will bring 11.728% of the annual average benefits (the number of EVs is counted in 2021) or 10.085% of the benefits (the number of EVs will be forecasted as the current development rate) without flexible regulation, while 11.725% and 10.397% of the benefits with flexible regulation strategies respectively.

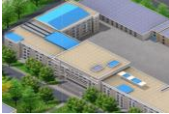
(5) The proposed methods for flexible energy-use regulations and microgrid operation scheduling optimization contribute to the development of an energy system optimization framework that considers energy supply and demand simultaneously. The results indicate 15.655% of the average annual benefits with common flexible regulation strategies while 18.016% with radical regulation strategies.

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Appendix A All Buildings with enough related data in this community

Table A-1 Details of buildings with enough related data in this community

Code	Type	Appearance	Energy items	Area (m ²)	Roof Area (m ²)	Floors	EUI (kWh/m ²)	Regulation strategies
A	Educational building		ACs, lights, plugs	11000	3872	7	87.61	a, b
B	Educational building		lights, plugs	9084	2304	4	30.88	b, c
C	Dormitory building		lights, plugs	3527	1034	6	28.33	d
D	Office building		ACs, lights, plugs	35998	6682	6	24.93	a, b
E	Exhibition building		ACs, lights, plugs	3647	2054	4	43.68	a, b
F	Hotel		ACs, lights, plugs	5818	3562	19	199.19	a, b
G	Academic building		ACs, lights, plugs	36500	1789	19	24.39	a, b
H	Academic building		ACs, lights, plugs	32291	1222	7	50.17	a, b
I	Educational building		ACs, lights, plugs	11676	4403	9	60.87	b, c
J	Educational building		ACs, lights, plugs	27700	6102	7	18.93	b, c
K	Educational building		ACs, lights, plugs	17540	4268	7	37.06	b, c
L	Dormitory building		lights, plugs	11463	1709	6	51.04	d

M	Dormitory building		lights, plugs	8496	1385	6	50.00	d
N	Dormitory building		lights, plugs	11813	1938	6	70.72	d
O	Dormitory building		lights, plugs	11463	1709	6	39.42	d
P	Dormitory building		lights, plugs	11707	1890	6	50.54	d
Q	Dormitory building		lights, plugs	11676	1890	6	73.28	d
R	Dormitory building		lights, plugs	11676	1890	6	65.36	d
S	Dormitory building		lights, plugs	6113	1062	6	70.05	d
T	Dormitory building		lights, plugs	7373	1215	6	52.84	d

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