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**OPTIMIZATION OF CAPACITY,
ELECTRICITY TRADING AND
OPERATIONS OF INTEGRATED
COMMUNITY ENERGY SYSTEMS UNDER
BUILDING AND TRANSPORTATION
ELECTRIFICATION**

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**Optimization of Capacity, Electricity Trading
and Operations of Integrated Community
Energy Systems Under Building and
Transportation Electrification**

Liao Wei

**A thesis submitted in partial fulfilment of the requirements for
the degree of Doctor of Philosophy**

August 2025

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ABSTRACT

Abstract of thesis entitled: Optimization of capacity, electricity trading and operations of integrated community energy systems under building and transportation electrification

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The rapid electrification of building and transportation sectors is fundamentally transforming the landscape of energy demand, supply, and management in modern urban communities. As global cities strive to decarbonize their infrastructure and respond to ambitious climate targets, the integration of distributed energy resources (DERs) such as photovoltaics (PV), batteries, and electric vehicles (EVs) into local and district energy systems brings about unprecedented opportunities and challenges. These developments are further complicated by increasingly volatile loads, the need for flexible operation, and the imperative for resilience against both technical and environmental disruptions. Against this backdrop, the capacity design, energy trading, and operational strategies for community energy systems require rethinking and systematic optimization to ensure cost-effectiveness, grid reliability, and sustainability.

This thesis focuses on optimizing capacity electricity trading and operational strategies for integrated community energy systems, specifically considering the tight coupling between building and transportation electrification and the diversity of multiple communities. Based on a unique, high-resolution dataset from the integrated energy system serving a real-world campus, the study establishes a robust empirical dataset, which are used to evaluate the

proposed energy management and trading strategies, demonstrating the advantages of game-theory based peer-to-peer (P2P) strategy approaches in reducing costs, balancing supply and demand, and enhancing system flexibility. The work further addresses operational resilience under extreme events through short-term coordinated restoration strategies leveraging flexible resources such as DERs and vehicle-to-grid (V2G)-enabled EVs, and concludes with a multi-objective capacity planning framework that accounts for phased electrification and evolving long-term decarbonization targets.

Firstly, the study utilizes a comprehensive, high-resolution dataset spanning two decades, which was collected from a real-world campus distributed energy system in Japan. This dataset encompasses hourly records of energy generation and consumption, covering a wide array of supply-side resources including combined heating and power units (fuel cells, gas engines), absorption chillers, gas boilers, solar PV, and grid imports, as well as detailed load profiles for electricity, heating, cooling, and hot water at the level of individual buildings. By spanning the full operational lifespan of on-site generators, this dataset provides an unparalleled empirical foundation for descriptive analytics, model validation, and scenario analysis. It enables the rigorous evaluation of system efficiency, flexibility, and sustainability under evolving technological, operational, and policy conditions, while also serving as a benchmark for future research and policy-making in distributed energy systems.

Secondly, this study assesses conventional rule-based energy management strategies under both peer-to-grid (P2G) and P2P trading paradigms, to elucidate the differences in efficiency and techno-economic performance among different operational strategies within community-level energy systems. Four distinct energy management strategies are systematically compared, including the maximizing PV self-consumption (MSC) strategy, a cost-minimizing strategy based on time-of-use (TOU) tariffs, a P2P trading paradigm centered on the mid-market rate (MMR) principle, and a proposed demand response (DR)-based P2P strategy. Advanced

stochastic simulation techniques, including Monte Carlo integrated Markov Chain methods, are employed to capture the variability and uncertainty in vehicles' travel among different buildings, allowing for the dynamic generation of P2P prices that reflect real-time supply-demand balances within and across communities. The comparative results show that, relative to traditional mainstream operation strategies, strategies under P2P paradigm (especially incorporating DR) can provide substantial benefits in terms of reducing grid dependency, minimizing electricity costs, smoothing peak demand, and improving the effective utilization of renewable generation. Notably, the study shows that the optimal strategy choice depends on the specific role and characteristics of each building community, demonstrating the importance of context-sensitive, adaptive management strategies for maximizing system-wide benefits.

Thirdly, recognizing the limitations of rule-based and centralized trading strategies in increasingly decentralized, heterogeneous, and dynamic energy systems, the study develops a hybrid game theory-based P2P trading strategy for multi-microgrid systems to achieve optimal energy management and facilitate efficient, fair P2P electricity transactions. This proposed approach employs a non-cooperative game to determine optimal energy transactions and dynamic pricing among interconnected microgrids, while utilizing a cooperative game to fairly allocate revenues among buildings within each microgrid based on their individual contributions. The hybrid model accurately reflects both the competitive and collaborative dynamics that characterize real-world energy communities, capturing the complexities of decentralized decision-making, variable generation, and electricity demand. Through extensive simulation and case studies involving heterogeneous building communities and significant EV integration, this study demonstrates the effectiveness of the proposed approach. The results indicate that the hybrid game-theoretic P2P strategy significantly outperforms the TOU-based strategy under the P2G paradigm. Specifically, the proposed strategy reduces power imports from the utility grid for consumer-type microgrids by 30.4%, while also decreasing power

exports for prosumer- and producer-type microgrids by 33.2% and 25.9%, respectively, compared to the TOU-based approach. Furthermore, the flexible utilization of EVs and other responsive loads as dispatchable assets further amplifies system responsiveness and resilience, supporting the transition toward more robust, decentralized, and interactive power systems.

Fourthly, the study addresses the pressing challenge of enhancing operational resilience in power systems by facilitating rapid load restoration after outages caused by extreme weather events. Considering the effect of demand-side load rebound following outages, including building cold load pickup (CLPU) and the surge in EV charging load, the study develops a two-stage coordinated restoration strategy to ensure rapid restoration of demand-side load. This strategy is developed to optimize the post-outage restoration sequence of different loads across network nodes by coordinating all available generation and flexibility resources, including DERs, rooftop PV, and V2G-enabled EVs, based on the restoration weight of different load nodes. Meanwhile, the approach is evaluated across a range of grid architectures, especially hybrid AC/DC systems, which are emerging as a promising solution for next-generation grids. The results demonstrate that, under high-rebound scenarios, flexible resources such as rooftop PV and V2G-enabled EVs, can supply a majority share of the restoration power (up to 87.7%), significantly reducing dependency on traditional distributed generators (DGs) and enabling the restoration of critical loads up to 40% faster compared to conventional AC grid architectures. Voltage stability is also markedly improved, underscoring the value of distributed flexibility and advanced grid topologies in enhancing both the speed and robustness of power system restoration. These outcomes highlight the system's improved ability to withstand and recover from disruptions, reflecting a higher capability of operational resilience.

Finally, long-term capacity planning for community energy systems is approached through the development of a multi-objective optimization method that explicitly incorporates the dynamic impacts of phased electrification and evolving carbon reduction targets. Drawing on empirical

data for demand load, phased electrification, evolving carbon reduction targets, and heterogeneous power generation capacities and demand-load characteristics across diverse communities, the model evaluates optimal capacity planning decisions across a suite of decarbonization scenarios, including a 2010 benchmark and moderate and deep carbon reduction pathways for 2030 and 2050. The results reveal dramatic and transformative shifts in system configuration: the capacity of renewables such as PV and wind turbine are projected to increase by 300% from 2010 to 2030 and by an additional 230% by 2050, while installations of heat pumps for electrified heating and cooling are expected to rise by 1800% by 2030 and further by 182% by 2050. Deep decarbonization pathways yield a 43.4% higher share of renewables and a 17.3% reduction in fuel-dependent units compared to moderate scenarios, enabling technically feasible, seasonally carbon-neutral operation and dramatically expanding the scope for demand-side electrification. Under optimal configurations, the electrification ratio of buildings and transportation of community energy systems rises from 5–8% in 2010 to 20–28% by 2030, and reaches 53–77% by 2050, highlighting the transformative impact of integrated, forward-looking planning on decarbonization and sustainability outcomes. These findings reinforce the critical role of strategic planning that not only optimizes technical and economic performance but also supports the broader policy and societal objectives of deep electrification and sustainable development.

In summary, this study delivers a comprehensive and empirically validated methodology for the optimization of community energy systems at the intersection of building and transportation electrification. The comprehensive methodology developed in this thesis can offer essential guidance for researchers, policymakers, and stakeholders to assess the technical, economic, and environmental feasibility of integrated energy solutions. Furthermore, this work provides actionable tools and strategies to facilitate energy demand management, supply integration, storage deployment, and coordinated grid interaction, thereby supporting the development and

implementation of sustainable, decentralized, and resilient energy systems. Ultimately, the insights and frameworks presented contribute not only to the academic understanding of next-generation energy infrastructures, but also to practical policy formulation and strategic technology deployment, accelerating progress toward a low-carbon, electrified, and carbon-neutral future within urban environments.

RESEARCH OUTPUT DURING PHD STUDY

Journal Papers

- [1] **Liao W**, Xiao F, Li YX, Zhang HB, Peng JQ. A comparative study of demand-side energy management strategies for building integrated photovoltaics-battery and electric vehicles (EVs) in diversified building communities. *Applied Energy*. 2024;361.
- [2] **Liao W**, Xiao F, Li YX, Peng JQ. Comparative study on electricity transactions between multi-microgrid: A hybrid game theory-based peer-to-peer trading in heterogeneous building communities considering electric vehicles. *Applied Energy*. 2024;367.
- [3] **Liao W**, Jin XY, Ran Y, Xiao F, Gao WJ, Li YX. A twenty-year dataset of hourly energy generation and consumption from district campus building energy systems. *Scientific Data*. 2024;11(1).
- [4] **Liao W**, Xiao F, Li YX, Yu H, Peng JQ, Sun YJ. Capacity Optimization and Performance Assessment of Integrated Energy Systems Considering Building-Transportation Electrification in Long-Term Decarbonization Roadmaps. (*Under Review of Energy*).
- [5] **Liao W**, Xiao F, Yu H, Yan JY, Zhang HB. A coordinated load restoration strategy considering sophisticated demand-side load rebound and flexible resources across distribution grid architectures. (*Submitting to Advances in Applied Energy*).

Conference Presentations

[1] **Liao W**, Xiao F, Zhang HB. Comparative study on rule-based operation strategies for diversified building community grid connected photovoltaic cell systems combining building load and electric vehicle charging load. *Applied Energy Symposium 2023: Low Carbon Cities & Urban Energy Systems*. 2-7 September 2023. Matsue, Japan.

[2] **Liao W**, Xiao F. Enhancing integrated energy systems considering building-transportation electrification: capacity optimization and performance evaluation in long-term carbon emission roadmaps. *First International Conference on Digital Intelligence for Energy Systems*. 5-8 January 2025. Hong Kong.

[3] **Liao W**, Xiao F. Capacity optimization and operation of integrated energy symbiosis systems in the context of building-transportation electrification under multiple carbon emission scenarios. *Nexus Forum 2025 on Collaborative Innovation for Smart Sustainable Development*. 8-10 May 2025. Hong Kong.

Competition Awards

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NOMENCLATURE

Abbreviations

AC	alternating current
ACE	annual carbon emission
ADMM	alternating direction method of multiplier
AI	artificial intelligence
ATC	annual total cost
ASHP	air source heat pumps
BC	building community
BESS	battery energy storage system
BS	bill sharing mechanism
CCHP	combined cooling, heat, and power
CDA	continuous double auction
CLPU	cold load pickup
COP	coefficient of performance
DC	direct current
DERs	distributed energy resources
DG	distributed generator
DP	dynamic programming
DR	demand response
DRL	deep reinforcement learning
DSO	distribution system operator
EV	electric vehicle
ERP	electricity retail price
FiT	feed-in tariff
GA	genetic algorithm
GB	gas boiler
HP	heat pump
HEMS	home energy management system
HSS	heat storage state
ICT	information and communication technologies

IES	integrated energy system
IoT	internet-of-things
LCC	life cycle cost
LP	linear programming
MAS	multi-agent system
MCMC	Markov chain and Monte Carlo algorithm
MG	microgrid
MILP	mixed integer linear programming
MMR	mid-market rate
MPS	mobile power system
MSC	maximize self-consumption
NPV	net present value
NSGA	non-dominated sorting genetic algorithm
OIR	output-input ratio
ORC	organic Rankine cycle
PDF	probability density function
PFF	power fluctuation factor
PV	photovoltaics
PVB	PV-battery
P2G	peer-to-grid
P2P	peer-to-peer
RTP	real-time pricing
SCR	self-consumption rate
SDR	supply-demand ratio
SEI	system electricity independence
SOC	state of charge
SPT	stepwise power tariff
SSR	self-sufficiency rate
TCL	thermostatically controlled load
TESS	thermal energy storage system
TMY	typical meteorological year
TOU	time-of-use tariff
V2G	vehicle-to-grid

VSC	voltage source converter
WT	wind turbine

Symbols

A_i^D	pre-outage power level of TCLs
A_i^U	peak value of CLPU curve
A_m	power factor of VSC power loss model
C	cooling power
C_{DG-x}	DG-x power capacity
C_e	energy cost
$C_{i,B}$	cost of electricity transactions between the microgrid and the utility grid
$C_{i,L}$	comfort cost that the MG_i needs to pay as the transfer of flexible load
$C_{i,E}$	aging costs of the energy storage system of the MG_i
C_{inv}	initial investment cost
$C_{o\&m}$	operation and maintenance cost
C_{re}	replacement cost
C_i^t	duration between the decay start timeslot and time t
$C_i^{N,0}$	optimal operating cost of under the P2P paradigm
C_i^C	operating cost after conducting internal transaction under the P2P paradigm
$C_{MG_i_Game}$	cost of MG_i participating in the game based P2P paradigm
$C_{MG_i_breakpoint}$	the cost of MG_i independence operation under P2P paradigm
C_{P2G}^i	electricity cost of the building i under P2P paradigm
C_{P2P}^i	electricity cost of the building i under P2P paradigm
D_i	certain duration of peak value
$e_{i,t}$	i^{th} load energization symbol at time t
$E_{b,N}$	nominal capacity of the battery
$E_{hst,N}$	nominal capacity of the thermal storage tank
F_{ij}	virtual power flow of lines ij
H	heat power
$HHS_{max/min}$	minimum/maximum state of the TESS
$I_{ji}^{sqr,t}$	square current value of line ij at time t

$\bar{I}_{ij}^2$	square of line ij current limit
$l_{i,t}$	load demand after DR and game negotiation of MG_i at the time t
$L_{i,t}$	original load demand of MG_i at time t
L_i^t	CLPU value of i^{th} load at time t
L_i^{fix}	fixed load vector of i^{th} load
M	the number of microgrids in the game
P	electric power
$P_{b,ch/dis}$	charging and discharging power of the battery
$P_{ch/dis,max}$	maximum charging/discharging power of BESS
$P_{de_i_sh}$	electrical load shortage of building peer i
$P_{hst,ch/dis}$	charging and discharging power of the heat storage tank
$P_{hst,ch/dis,max}$	maximum charging/discharging power of TESS
P_{ij}^t	the trading electricity sold by MG_i to MG_j
P_{ac}	refrigeration power of absorption chiller
P_{load}	demand load of the TES
P_{orc}	net output power of the orc equipment
$P_{orc,t}$	power generated by expander of the orc equipment
$P_{orc,p}$	power consumed by pumps to pressurize the medium
$P_{pv_i_sur}$	surplus PV generated energy of building peer i
$P_{i,t}^{buyG}$	electricity purchased by microgrid i to the utility grid at time t
$P_{i,t}^{sellG}$	electricity sold by microgrid i to the utility grid at time t
P_{DG-i}^t/Q_{DG-i}^t	active/reactive power of i^{th} DG at time t
$P_{DG-i}^{max}/Q_{DG-i}^{max}$	active/reactive power output boundary of i^{th} DG
P_i^{sum}	total i^{th} load demand
P_{ij}^t/Q_{ij}^t	active/reactive power of line ij at time t
$P_{VSC_x}^{loss,t}$	power loss of VSC_x at time t
$P_{VSC_x}^t/Q_{VSC_x}^t$	active/reactive power ref. of VSC_x at time t
q_{ij}^t	the transaction electricity price between MG_i and MG_j
Q_{ac}	heat input power of the absorption chiller
Q_w	heat input power of the orc equipment
R_{buy}	grid electricity buying price, i.e. TOU
R_{sell}	grid feed-in-tariff subsidy

R_{DG-i}^+/R_{DG-i}^-	ramping up/down power rate of i^{th} DG
R_{ji}/X_{ji}	resistance/inductance of line ij
$SOC_{max/min}$	minimum/maximum state of the BESS
$s_{i,t}$	i^{th} load state at time t
$\overline{VSC}_x$	upper bound of VSC_x apparent power
$V_{i,t}^{sqr}$	square voltage value of node i at time t
t	timeslot
T	number of time segments in the whole period
U	equipment capacity
V_{cchp}	natural gas consumed by the CCHP
V_{ev}	natural gas consumed by the gas boiler
V_{gb}	gasoline consumed by the electric vehicles
V^{min}/V^{max}	allowable minimum and maximum voltage level
z_{ij}	line ij operation state
α_{ij}^t	ratio coefficient of the distribution line loss compensation cost caused by MG_i
β_{cal}	calendar aging coefficient of the energy storage system
β_{cyc}	cycle aging coefficient of the energy storage system
β_{ij}^t	ratio coefficient of the distribution line loss compensation cost caused by MG_j
δ_i	coefficient of compensation cost of the comfort due to the DR in MG_i
$\delta(t)$	son node assemblies connected to node i
ω_i	weighting factor of i^{th} load or i^{th} factor
$\eta_{ch/dis}$	charging/discharging efficiency of BESS/TESS
η_{orc}	thermoelectric conversion efficiency of the orc equipment
$\mu_{c,g}$	carbon emission factor of natural gas combustion
$\mu_{c,go}$	carbon emission factor of gasoline
$\mu_{c,e}$	carbon emission factor of electricity purchased from the utility grid
ξ	a binary number, 1 denotes battery charging and 0 denotes battery discharging
Ω_N/Ω_B	a set of nodes/bus lines
$\Omega_B^{Is}/\Omega_B^{Fa}$	a set of islanded nodes/fault lines
$\Omega_B^{Ns}/\Omega_{VSC}$	a set of lines without switch/ set of VSC

CHAPTER 1 INTRODUCTION

This chapter presents an overview of the thesis and is structured into three sections. Section 1.1 introduces the background and motivation for the research. Section 1.2 states the aims and objectives of the thesis. Finally, Section 1.3 outlines the structure of the thesis and provides a brief summary of each chapter.

1.1 Background and motivation

The intensifying climate crisis, predominantly driven by greenhouse gas (GHG) emissions, has evolved into one of the most urgent global issues of the 21st century. The building sector and transportation sector account for approximately 40% [1] and 33% [2] of total social energy consumption, and around 30% [1] and 37% [2] of global CO₂ emissions, respectively. As the international community rallies around ambitious carbon neutrality targets—with many countries pledging to achieve net-zero emissions by 2050 or sooner—the energy sector stands at the heart of both the problem and the solution [3]. Responsible for approximately three-quarters of global CO₂ emissions, the energy sector's transformation is essential for limiting global warming, safeguarding environmental sustainability, and ensuring long-term socio-economic development.

Within this context, the building and transportation sectors emerge as particularly critical. Together, they account for the majority of final energy consumption in modern societies: buildings require vast quantities of energy for heating, cooling, lighting, and appliances, while transportation has historically been dominated by fossil fuels and is a major source of urban air pollution [4]. Achieving substantial energy conservation and emissions reduction in these two sectors is pivotal for attaining global decarbonization objectives [5, 6]. Electrification has thus become a cornerstone strategy, offering a pathway for both sectors to transition from

dependence on carbon-intensive fuels towards cleaner, more sustainable alternatives powered increasingly by renewables [7].

The rapid advancement and deployment of renewable energy technologies, such as solar photovoltaic (PV) systems and wind turbines (WT), have fundamentally reshaped the energy landscape [8]. Solar PV, in particular, has witnessed significant breakthroughs in cell efficiency and cost reduction, resulting in its growing share in global power generation. For instance, PV panels accounted for around 12% of worldwide electricity production in 2023, with countries like China leading the way in distributed rooftop PV adoption to support their carbon neutrality goals [9]. These distributed energy resources (DERs), encompassing not only PV but also small-scale wind, batteries, and other local generation assets, have been widely introduced across residential, commercial, and institutional buildings [10]. Their integration has enabled on-site generation, enhanced energy self-sufficiency, and established interactive relationships with local microgrids, where surplus energy can be exchanged or traded to support grid flexibility and resilience, as illustrated in the system framework shown in Figure 1-1.

However, the integration of high shares of renewable generation presents notable technical and economic challenges. The intermittent and variable nature of resources like solar and wind leads to mismatches between generation and demand profiles, necessitating the deployment of energy storage systems (ESS) to ensure reliability [11]. While ESS technologies—especially batteries—offer crucial flexibility and backup, they also introduce additional investment and operational costs, highlighting the need for optimal system sizing and scheduling strategies [12]. Moreover, the growing scale of DERs deployment demands coordinated approaches to ensure that distributed assets contribute effectively not only to local self-consumption but also to broader grid stability and decarbonization efforts.

Parallel to the evolution of building energy systems, the transportation sector has been undergoing a profound transformation marked by the electrification of mobility. The global adoption of electric vehicles (EVs) has accelerated rapidly, driven by advancements in battery technology, supportive government policies, and widespread societal recognition of the need to reduce emissions [13]. Countries such as Norway have demonstrated the feasibility of large-scale EV adoption, with over 80% of new vehicle sales being electric, while other nations are following suit by expanding charging infrastructure and incentivizing EV purchases [14]. Electrified transportation not only reduces direct fossil fuel consumption and GHG emissions but also offers new forms of flexibility for the power system. Through technologies such as vehicle-to-grid (V2G), EVs can serve as mobile storage units, returning electricity to the grid during peak demand or emergencies and thus enhancing overall grid adaptability and system resilience [15].

The convergence of buildings and transportation on the path to electrification highlights the growing importance of integrated community energy systems (CES) [16]. These systems are characterized by the coordinated operation of diverse DERs, ESS, flexible loads, and advanced control technologies within a local community or district. By leveraging the synergies between building loads, EV charging, and distributed generation, CES can maximize local renewable energy utilization, support the implementation of peer-to-peer (P2P) and peer-to-grid (P2G) electricity trading mechanisms, and improve both economic and technical performance at the community level [17]. The transition toward such integrated systems is further motivated by the need to enhance energy system resilience in the face of escalating climate risks.

Furthermore, the frequency and severity of extreme weather events—such as hurricanes, wildfires, and heatwaves—have increased markedly as a direct consequence of climate change [18]. These events have exposed the vulnerabilities of traditional centralized power systems, as evidenced by incidents like the 2021 Texas winter storm, which caused sweeping blackouts

and underscored the fragility of existing infrastructure [19]. In this context, DERs offer crucial advantages in localizing energy production and enhancing the flexibility and resilience of supply [20]. Distributed generators (DGs), flexible demand-side resources, and advanced grid architectures such as hybrid AC/DC systems can accelerate post-outage restoration, support black-start capabilities, and reduce the risk of prolonged service interruptions [21]. Importantly, the integration of flexible loads—including thermostatically controlled loads (TCLs) and EV charging—enables dynamic demand response (DR), which can help balance supply and demand, especially during emergencies or system recovery [22]. However, these flexible resources also introduce new operational challenges, such as the rebound effect, where suppressed demand surges once power is restored [23]. Accurately modeling and managing these rebound effects is essential to maintain system stability and optimize restoration processes [24].

Despite these technological advances and conceptual frameworks, several key challenges remain in the practical realization of optimized, resilient, and sustainable community energy systems. First, there is a critical need for methodologies that can inform the optimal capacity design of DERs, storage, and flexible loads—balancing cost, reliability, and long-term sustainability, while accounting for the diverse and evolving needs of building and transportation electrification. Second, the development of effective electricity trading paradigms and market mechanisms—enabling efficient P2P and P2G exchanges among community stakeholders—is essential for unlocking the full value of distributed resources and fostering greater community engagement. Third, operational strategies must be robust and adaptive, capable of responding to variability in supply, demand, and external disruptions such as extreme weather. Finally, the evaluation of long-term performance and sustainability is hampered by the lack of comprehensive, high-resolution datasets covering the full operational lifespan of distributed community energy systems. This gap hinders our understanding of real-

world system adaptability, resilience, and carbon reduction potential under evolving socio-technical and climatic conditions.

In summary, the imperative to decarbonize the building and transportation sectors—supported by the rapid proliferation of distributed energy resources, electrified transport, flexible demand, and advanced management technologies—presents both unprecedented challenges and transformative opportunities. Addressing these challenges through integrated design, innovative trading and control mechanisms, and rigorous performance assessment will be essential to realize the full potential of community energy systems in achieving carbon neutrality, enhancing resilience, and contributing to a sustainable energy future.

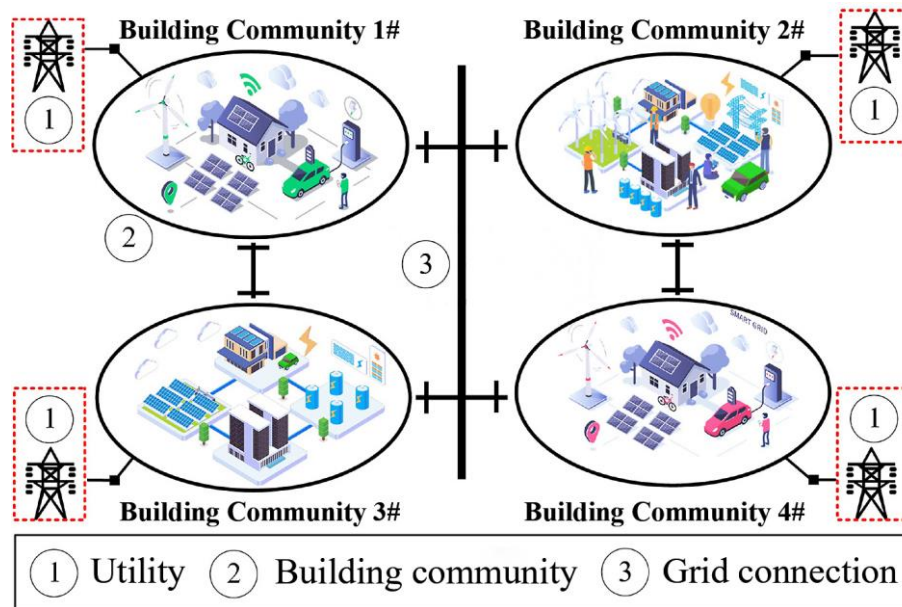


Figure 1-1 Schematic of the grid-connected hybrid building energy system integrated with diversified building communities

1.2 Aim and objectives

This PhD study aims to develop both theoretical frameworks and practical methodologies to optimize the capacity design, electricity trading mechanisms, and operational strategies of community energy systems in the context of increasing building and transportation

electrification. By addressing the technical, economic, and resilience-related challenges arising from the integration of DERs and EVs into building communities, the PhD study seeks to contribute to the realization of low-carbon, resilient, and efficient community energy systems.

The main aim and specific objectives of this thesis are as follows:

- i. To review and synthesize current research progress on the integration of EVs and DERs in building communities, with a particular focus on energy system management, flexible resources, demand-side response, and electricity trading paradigms.
- ii. To develop a comprehensive modeling framework for building-EV integrated community energy systems, including the simulation of building and EV load profiles, the modeling of district energy system components, and the formulation of internal energy trading mechanisms based on long-term, high-resolution datasets.
- iii. To evaluate and compare conventional and innovative energy management strategies under P2G and P2P electricity trading paradigms, assessing their impacts on system operation, energy balancing, self-consumption rates, and overall techno-economic performance.
- iv. To develop and validate a novel hybrid game theory-based P2P trading strategy for optimal energy management in multi-microgrid community systems, analyzing electricity transaction distribution, pricing dynamics, and revenue fairness among participants.
- v. To design and assess coordinated restoration strategies for community energy systems in response to power outages, considering flexible energy resources, load rebound effects, and advanced distribution grid architecture to enhance system stability and resilience.

- vi. To propose and implement advanced capacity design optimization methods for community energy systems, employing multi-objective and heuristic algorithms to balance investment cost, operational efficiency, carbon emissions, and system operation stability.
- vii. To conduct long-term distributed energy resource capacity planning that considers building and transportation electrification within decarbonization roadmaps, evaluating optimal planning results, supply-demand balance, operational performance, and electrification potential for diverse community energy scenarios.

Through the above objectives, this thesis aims to provide a holistic and practical foundation for the optimal planning, operation, and management of future-ready community energy systems, supporting the global transition towards carbon neutrality and sustainable urban development.

1.3 Research framework and organization of thesis

The overall research framework for the main body of this thesis (Chapters 3–8), focused on optimizing capacity, electricity trading, and operations in community energy systems, is illustrated in Figure 1-2. The framework consists of four main components: system modeling and test resources (Chapter 3); energy management and operation (Chapters 5–6); short-term coordinated load restoration (Chapter 7); and long-term energy system planning (Chapters 4 and 8).

This PhD thesis consists of nine chapters, each systematically addressing a critical aspect of demand-side load integration, electricity trading, energy system operation, and capacity design for community energy systems in the context of building and transportation electrification. The organization of the thesis is as follows:

Chapter 1 introduces the background, motivation, research aim, and objectives of the study. It highlights the significance of decarbonizing the building and transportation sectors, the role of distributed energy resources and electrification, and outlines the research gaps and contributions targeted in this thesis.

Chapter 2 presents a comprehensive literature review of recent advancements in EV-integrated building communities in the era of electrification, community-based multi-microgrid electricity transactions, demand-side energy system management, and energy system short-term operation and long-term planning. The chapter critically examines existing approaches in flexible energy resource integration, demand-side management, and both short- and long-term energy system transformations.

Chapter 3 details the overall research framework, methodology, and test resources adopted in the thesis. It describes the modeling of building-EV integrated community energy systems, including the simulation of demand-side load profiles, the development of district energy system and market trading models, and the construction of a long-term, high-resolution dataset from a campus energy system for validation.

Chapter 4 proposes advanced methods for the optimal capacity design of community energy systems. It covers the structure and operational principles of district energy systems, introduces the golden section method and multi-objective optimization approaches, and presents relevant performance evaluation metrics.

Chapter 5 assesses conventional rule-based energy management strategies for community energy systems under both P2G and P2P trading paradigms. The chapter evaluates the effectiveness of widely used demand-side management strategies and introduces a proposed demand response (DR) based P2P trading strategy, with comprehensive analysis of their techno-economic and operational performance.

Chapter 6 develops a novel hybrid game theory-based P2P trading strategy to optimize energy management in multi-microgrid community systems. It describes the structure and functioning of the proposed model, presents case studies for performance evaluation, and analyzes electricity transaction distribution, internal pricing dynamics, and revenue fairness.

Chapter 7 presents a short-term coordinated load restoration strategy for community energy systems, considering flexible energy resources and the rebound effects of building and EV charging loads after outages. The chapter details the two-stage restoration scheme, modeling of load rebound phenomena, and performance assessment under different restoration scenarios.

Chapter 8 addresses long-term distributed energy resource capacity planning by considering building and transportation electrification within decarbonization roadmaps. It discusses the development of electrification demand scenarios, optimal capacity planning methodologies, and provides in-depth analysis of supply-demand balance, operational performance, and electrification potential in diverse community contexts.

Chapter 9 summarizes the main contributions and key findings of this thesis, draws overarching conclusions, and provides recommendations for future research directions to further advance the development of sustainable and resilient community energy systems.

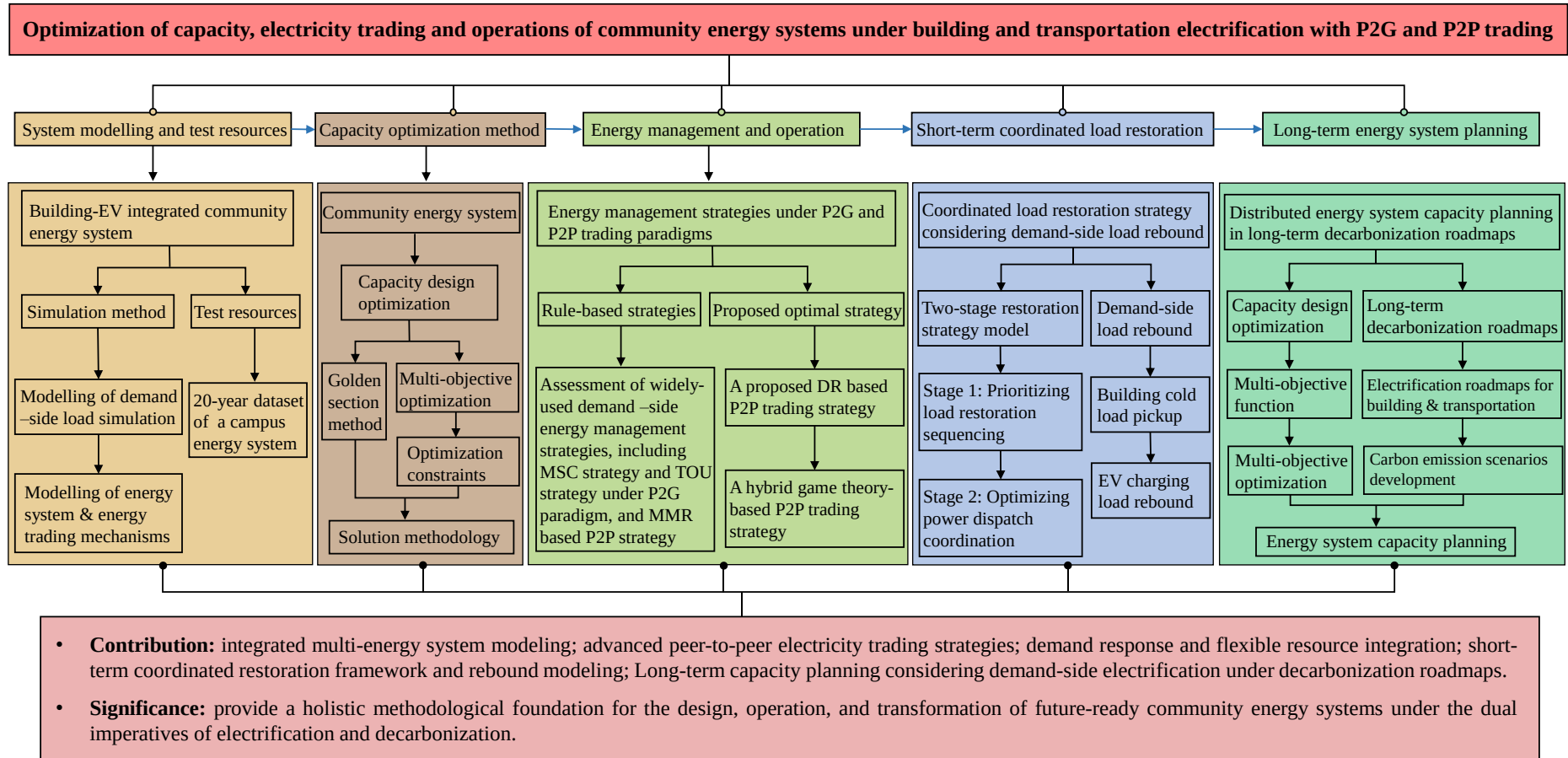


Figure 1-2 Overall research framework on optimizing capacity, electricity trading, and operations in community energy systems under building and transportation electrification.

CHAPTER 2 LITERATURE REVIEW

This chapter provides a comprehensive review of existing research relevant to the optimization and operation of community energy systems under building and transportation electrification. Section 2.1 examines the integration of EVs into building communities, highlighting the challenges, grid impacts, and operation methods for managing the combined building and transportation demand. Section 2.2 explores energy system management, including flexible energy resources, demand-side management, and the critical importance of communication and control between buildings, microgrids, and the utility grid. Section 2.3 reviews community-based multi-microgrid electricity transactions, focusing on the evolution from traditional peer-to-grid (P2G) trading mechanism to advanced peer-to-peer (P2P) trading paradigm. Section 2.4 discusses recent advancements in energy system upgrade and optimization, covering both long-term decarbonization pathways and short-term system restoration after outages, with an emphasis on capacity planning and resilience. Finally, Section 2.5 summarizes the key research gaps identified in the literature, such as the need for holistic modeling of diversified communities, synergistic electrification strategies, advanced trading mechanisms, robust restoration schemes, and comprehensive empirical data. Collectively, this chapter establishes the foundation for the research framework and methodologies proposed in the subsequent chapters.

2.1 EV-integrated building community

The global trend towards decarbonization and energy transition is fundamentally altering the structure and operation of building communities, placing electrification and distributed energy integration at the center of modern energy systems. The proliferation of renewable resources, particularly solar PV, and distributed energy technologies has enabled end-users to transform

from passive electricity consumers into active “prosumers” who can both generate and consume electricity [10]. This transformation is facilitated by advancements in storage technologies, such as batteries and EVs, which allow for autonomous balancing of local generation and consumption [25]. To further promote renewable energy adoption and stimulate user engagement in demand-side energy management, electricity markets worldwide have introduced mechanisms like feed-in-tariff (FiT) and time-of-use (TOU) pricing [26, 27]. Dynamic pricing models, including stepwise power tariffs (SPT) and real-time pricing (RTP), continue to incentivize users to participate in demand-side response and system optimization [28].

Within the context of the FiT scheme, prosumers can sell surplus electricity directly to the utility grid, operating within a P2G trading paradigm [29]. They can also benefit economically by exploiting the price differences between peak and off-peak hours through TOU strategies [30]. However, these traditional models limit trading interactions to the grid, restricting direct economic exchanges between prosumers and their peers, despite the mutual benefits and localized grid relief such interaction could bring [10, 31]. The intermittent nature of renewable generation, especially from PV and WT sources, introduces operational risks for the grid—such as power shocks and instability during periods of high variability—which in turn can burden the grid, diminish prosumer revenues, and increase consumer costs [32]. To address these systemic challenges, the P2P energy trading paradigm has emerged as a promising solution [33, 34]. P2P trading enables direct, decentralized transactions between users, aiming to alleviate grid stress from surplus generation while enhancing the economic benefits for all participants [18,20]. This paradigm is particularly attractive in power systems with high penetration of DERs, as it supports local balancing and provides enhanced resilience [35, 36].

Operational strategies for P2G and P2P paradigms have been examined extensively in the literature. Grid operators often promote self-consumption maximization (MSC) strategies,

leveraging storage to improve both grid stability and economic returns [37]. These MSC strategies are commonly deployed in distributed PV-battery (PVB) systems. Comparative studies, such as that by Zou et al. [38], have shown that MSC achieves a balanced performance between operational cost and grid power stability. From the perspective of end-users, TOU tariffs have been found to effectively align consumption with grid economics, relying on straightforward rule-based control (charging batteries during off-peak, discharging during peak periods) [27, 39]. However, while rule-based methods are easy to implement, they may not always provide optimal outcomes for grid stability or cost minimization. To overcome these shortcomings, advanced P2P strategies have been developed and assessed [33-36, 40]. For instance, Wang et al. [40] demonstrated that P2P trading allows prosumers to sell electricity at prices above FiT rates and enables consumers to purchase power at rates below grid retail prices, thereby enhancing both sides' benefits and improving grid stability. Despite these advances, comprehensive comparative analyses of P2G and P2P paradigms across diverse building communities remain scarce. Most studies focus on single building types or homogeneous clusters, neglecting the complex dynamics present in multi-type, multi-building communities. The integration of EVs into building energy systems further complicates the picture. As stated in the roadmap for the popularization of EVs in many countries and regions, EVs account for about 12% of private vehicle usage [41]. Furthermore, the integration of EVs into renewable energy systems in buildings has gained significant attention in recent years, driven by the need for decarbonization and the increasing popularity of EVs in many countries [42]. The widespread adoption of EVs introduces new challenges for building energy systems. Traditionally, energy demand in buildings encompassed operations such as heating, ventilation, air conditioning, lighting, and security [43]. However, with the inclusion of EVs, the total energy demand must consider not only the indoor requirements but also the energy needed to charge EVs for travel purposes [44]. This additional load places a strain on the building's

energy infrastructure and requires careful management to ensure grid stability. However, previous studies primarily concentrate on energy consumption characteristics that satisfy the indoor personnel's requirements within the building. With the growing prevalence of EVs, the energy consumption load on the building side must also incorporate the travel demand of individuals. In addition to considering the living demands and equipment load of personnel within the building, the charging load for EVs used for personal travel should also be considered when analyzing energy consumption demands on the building side. Furthermore, with the projected market share of EVs estimated to reach 10% by 2025 [45], managing EV charging loads becomes crucial for power grid stability. Inaccurate EV charging load prediction models and unmanaged charging practices may result in a significant surge in electricity demand during peak hours, potentially jeopardizing the stability and safety of the power grid [46]. Therefore, there is an urgent need to implement the efficient energy management system and reliable operation strategies to ensure that the entire system can effectively optimize and coordinate energy production, consumption, and storage within the entire energy system [47].

In the field of operational optimization, selecting an appropriate strategy is crucial for achieving both efficiency and practicality. Broadly, two main approaches have been developed and widely adopted: rule-based strategies and optimization algorithms. Rule-based methods, grounded in expert knowledge, accumulated experience, and heuristic rules, are valued for their straightforward implementation and adaptability to specific operational contexts. These strategies often reflect domain expertise and can easily accommodate practical constraints encountered in real-world systems. On the other hand, optimization algorithms—such as genetic algorithms (GA), particle swarm optimization (PSO), linear programming (LP), and dynamic programming (DP) [48-51]—have been extensively employed due to their capability to systematically explore vast solution spaces and potentially achieve globally optimal solutions. These algorithms leverage mathematical models and computational power to seek

the best possible outcomes under defined objectives and constraints. However, a notable challenge arises in the application of these methods: while optimization algorithms can theoretically identify optimal solutions, they may overlook certain practical considerations that are difficult to formalize, such as operational safety margins, equipment aging, or human factors. Conversely, rule-based approaches, despite their practical advantages and ease of implementation, may be limited in their ability to discover truly optimal or innovative solutions due to their reliance on predefined rules. Given these contrasting strengths and limitations, comparative studies are essential to evaluate the relative effectiveness and applicability of rule-based strategies and optimization algorithms. Such investigations are particularly important in real-world scheduling scenarios, where both optimality and practicality must be balanced. Through systematic comparisons, it becomes possible to identify hybrid or adaptive approaches that combine the best aspects of both methodologies, ultimately enhancing operational performance in complex environments.

2.2 Demand-side energy system operation management

The integration of DERs into the power grid offers a multitude of advantages, including clean energy generation, reduced reliance on centralized grid, and enhanced environmental sustainability. However, this integration also poses potential challenges to grid stability, necessitating efficient control and coordination of their operation at the building level [8]. Demand-side management (DSM) represents a fundamental pillar supporting the integration of distributed renewable energy resources into modern energy systems [52]. DSM strategies, including FiT and TOU pricing, incentivize users to participate in energy management and facilitate the adoption of clean technologies [27]. Prosumers aim to achieve economic benefits through the FiT and the electricity price difference between peak and off-peak value of TOU price [30]. Liu et al. [39] conducted an investigation into the technical, economic, and

environmental aspects of PVB systems that employ a TOU strategy. The findings of their study revealed that the TOU strategy utilizes straightforward control rules, prioritizing the charging of batteries during periods of low electricity demand and discharging them to meet peak loads. Li et al. [27] conducted a rigorous case study to examine the implementation of the TOU strategy, utilizing real-world examples from the UK. The findings demonstrated that the TOU strategy effectively enhances the influence of DR on electricity consumption, resulting in significant reductions in energy costs and peak demand. Specifically, for residential households in the UK, implementing the TOU strategy can lead to a considerable reduction in electricity costs, ranging from 2.4% to 5.1%. Existing DSM strategies for DERs, encompassing rule-based control strategies and mathematical algorithms, predominantly concentrate on individual building-level operations by leveraging HEMSs to coordinate electricity usage within households [53]. However, these approaches exhibit limitations in effectively coordinating multiple buildings or building communities and ensuring a tradeoff between multiple stakeholders including user and utility grid within the context of the cyber-physical-social perspective of district energy systems. Therefore, these strategies have limited practical applicability for stakeholders involved in distribution network operators. There is an urgent need for a comprehensive and sustainable energy management approach that encompasses both the building and microgrid levels, promoting mutual benefits and ensuring long-term viability. Integrated energy systems (IES) incorporating DERs offer significant energy-saving and environmental benefits by combining renewable energy technologies—such as PV and WT—with energy storage solutions like battery (BESS) and thermal (TESS) systems to address intermittency challenges [54]. PV and WT are particularly effective for distributed and large-scale generation, respectively, while combined cooling, heat, and power (CCHP) systems enhance efficiency by simultaneously producing electricity and thermal energy, reducing emissions and primary energy consumption [55, 56]. Heat pumps further improve

sustainability by integrating renewables into heating and cooling [57]. As a holistic solution, IES with DERs meets local electricity, heating, cooling, and hot water demands, but optimizing their planning remains complex due to economic, environmental, and policy-related considerations, including evolving carbon emission policies tied to electrification trends [58].

Furthermore, electrification in buildings and transportation has grown significantly, yet complete electrification of building heating and cooling remains challenging. While residential and commercial sectors have increased electricity use since the 1960s with appliances like refrigerators and air conditioners [7], direct fuel consumption persists in space heating, water heating, and cooking [59]. Studies project substantial electrification by 2050—Mai et al. [60] estimate 61% of space heating, 52% of water heating, and 94% of cooking in U.S. buildings could shift to electricity, increasing demand by 38%, while Electric Power Research Institute (EPRI) [61] predicts 70% of building square footage may rely on electric heating and cooling. However, key barriers hinder widespread adoption: peak heating/cooling demands impose grid stress, electric alternatives may underperform high-efficiency gas systems in energy conversion, continuous operation requires unavailable large-scale storage, and retrofitting costs are prohibitive [62]. As a result, CCHP systems are considered the predominant energy framework for centralized management of heating and cooling in regional-level building communities. In contrast, building side electrification in the cooking field and EVs sector is more feasible. Cooking electrification is viable due to the relatively lower energy demands of cooking equipment. Electric stoves, induction cooktops, and electric ovens afford reliable heat sources with higher energy utilization efficiency compared to traditional gas stoves [62]. Additionally, electric cooking equipment offers precise temperature and timing control, enhancing cooking outcomes while eliminating safety concerns such as gas leaks. What's more, the electrification of the transportation sector, particularly the widespread adoption of EVs, has garnered significant attention as a promising solution for curbing greenhouse gas emissions

and lessening the environmental impact of transportation [63]. As the global community strives towards a sustainable and low-carbon future, the shift towards EVs presents substantial potential for attaining decarbonization objectives and enhancing air quality in urban regions. For instance, the U.S. federal government has set ambitious targets, aiming to electrify 50% of new light-duty vehicle sales by 2030 and reduce economy-wide greenhouse gas emissions by 50-52% by 2030, relative to 2005 levels [64]. Aligned with these objectives, forecasts suggest that EVs will represent 64% of U.S. light-vehicle sales and constitute 24% of the U.S. light-vehicle fleet by 2030 [65]. Under such scenario, EVs are projected to comprise 63% of the total light fleet by 2050 [66]. Moreover, to align with the 2°C climate targets, Milovanoff et al. [63] highlighted that electrifying 90% of the U.S. on-road fleet by 2050 would be necessary. Table 2-1 summarizes the electrification roadmaps for buildings and transportation sectors across different countries or regions, highlighting key targets and timelines for transitioning to low-carbon energy systems.

While the integration of demand-side distributed energy generation and consumption—through mechanisms such as DR and DERs coordination—plays a critical role in enhancing grid flexibility and reliability by actively engaging consumers in energy management, it also introduces new challenges. Specifically, although demand-side integration facilitates a more dynamic balance between energy supply and demand—particularly during peak load conditions or grid disturbances—it remains vulnerable to the load rebound effect that can occur following supply-side outages caused by frequent extreme weather events. This effect, characterized by a sharp increase in demand after power restoration, can severely undermine grid stability and reliability during post-disaster operations, and has therefore received considerable attention in recent studies. Existing literature on the demand-side load rebound effect has primarily focused on understanding its causes and developing models to predict its occurrence. Cold Load Pickup (CLPU), a specific manifestation of the rebound effect, has been

extensively studied in the context of TCLs [24]. HVAC systems, for example, attempt to restore indoor temperatures to pre-disturbance levels immediately after power restoration, leading to a substantial spike in electricity consumption. For brief power outage durations, the diversity of TCLs is not completely diminished, resulting in a CLPU curve that depends on the outage time. Agah et al. [23] explored the synchronization and rebound effects in residential devices participating in load control programs during power outages, showing that CLPU is influenced by factors such as outage duration, building insulation, and outdoor temperature. Song et al. [67] proposed a robust load restoration approach that incorporates time-dependent CLPU modeling and accounts for load uncertainty, providing valuable insights into CLPU impacts during grid restoration. Similarly, the rebound effect in EV charging has been identified as a critical issue, as EV owners often initiate charging simultaneously after an outage, creating additional stress on the grid [68]. However, compared to the extensive existing studies on building CLPU in TCLs, studies focusing on the rebound effect in EV charging load are relatively scarce, indicating a gap that warrants further exploration. Wei et al. [69] introduced a scheduling model for EVs by utilizing an equivalent aggregation method and a decomposition model, the model efficiently regulates EV population dynamics without sensitivity to private parameters. Anwar et al. [70] underscored the critical importance of effectively managing EV charging to alleviate grid strain and ensuring operational reliability. Managed EV charging offers crucial flexibility, benefiting both grid operations and EV owners.

Table 2-1 Electrification roadmaps for building and transportation sectors in different countries or regions

Country/Region	Building electrification		Transportation electrification		Reference
	2030	2050	2030	2050	
Africa	/	/	30% of light-vehicle fleet	50 % of light-vehicle fleet	[71]
South America	5%	42%	25% of light-vehicle fleet	50% of light-vehicle	[72, 73]
Britain	34% of space heating	58% of space heating	/	70% of vehicles	[74, 75]
China mainland	20%-30%	45–62%	More than 18%	32–59%	[76]
EU	36% of heating and cooling	58% of heating and cooling	/	60%	[77, 78]
Germany	14 – 45% of heating	45 – 66% of heating	19% of light-vehicle fleet	66% of light-vehicle fleet	[79]
Hong Kong	/	/	30 % of light-vehicle fleet	60–70 % of light-vehicle fleet	[80]
USA	24% of space heating, 17% of cooking	61% of space heating, 94% of cooking	24% of light-vehicle fleet	63% of light-vehicle fleet	[60, 65]

2.3 Community-based multi-microgrid electricity transactions

The evolution of distributed renewable integration has driven the emergence of new paradigms for electricity trading, fundamentally changing the operation of community energy systems. Traditional electricity market models—centralized, decentralized, and distributed—each have distinct characteristics that influence participation and scalability [81]. For example, the P2G trading markets facilitate decentralized trading and promote renewable energy integration into the existing grid infrastructure by enabling individuals or small-scale energy producers to sell excess energy directly to the grid; however, these markets face challenges in terms of limited

scalability and regulatory complexities arising from the coordination and balancing of energy transactions among numerous small-scale participants. To tackle the aforementioned challenges, researchers have put forward and assessed the effectiveness of P2P trading strategies. In response, recognizing the potential of the P2P sharing paradigm in the economic domain, i.e. P2P economy [82], an increasing number of researchers have undertaken exploration of P2P electricity transaction for multiple buildings [83], building communities [84], or even entire regions [33]. Indeed, P2P electricity trading has emerged as a disruptive concept in the energy sector, enabling direct energy transactions between energy producers and consumers [33, 84]. This decentralized approach offers numerous benefits, including increased energy efficiency, integration of renewable energy sources, potentially electricity cost saving, and reduced reliance on centralized utility grids. P2P electricity transactions present a viable solution for coordinating the generation and consumption balance among distributed energy systems within the region. Chen et al. [81] conducted an investigation of P2P electricity transaction among three distinct microgrids, and their study provided evidence that the adoption of the P2P paradigm facilitates flexible consumption of renewable energy within the region and effectively improves the overall operational efficiency and market competitiveness. Furthermore, the trading of surplus energy between individual buildings or building communities enhances the economic sustainability of the building sector. Wang et al. [40] demonstrated that under the P2P trading mode, prosumers can sell surplus electricity to peers at prices higher than the FiT tariff, while consumers can purchase electricity from peers at prices lower than the ERP from the utility grid. The implementation of effective P2P trading requires advanced models for pricing, resource allocation, and decision-making [25, 35]. Game theory and blockchain technologies have been recognized as a key enabler, offering transparency, trust, and security for decentralized electricity markets [85]. For example, Wu et al. [84] and Wang et al. [86] presented blockchain-based P2P frameworks that allow direct

participation in energy trading without intermediaries and enhance privacy protection. Nonetheless, the practical deployment of blockchain faces challenges such as scalability, transaction costs, legal and regulatory frameworks, and technological adoption barriers [87].

Alternative P2P trading models utilize mathematical relationships—such as the supply-demand ratio (SDR)—to link transaction quantities with prices. Liu et al. [35] demonstrated how higher SDRs typically result in lower prices and greater trading volumes, while Li et al. [25] developed a discriminative continuous double auction model to optimize both price and quantity dynamically. Other approaches, such as SDR-based, mid-market rate (MMR), and bill sharing (BS) mechanisms, have been compared by Zhou et al. [34], who found SDR-based models to be generally most effective, though the optimal choice depends on the specific context.

Thereupon, another model worth mentioning is the community-based energy trading approach that utilizes an optimization algorithm, where the electricity transaction quantities and prices between different buildings are treated as two independent variables. In this model, localized building communities, such as residential neighborhoods or commercial building communities, etc., establish their electricity exchange decision-making [88]. Participants within the communities can trade surplus energy generated from renewable sources, optimizing energy distribution and reducing reliance on the grid [89]. This model promotes local energy self-sufficiency, resilience, and promotes community engagement. Specifically, game theory-based approaches have gained significant attention due to their ability to capture the complex interactions and strategic decision-making among participants. Game theory of different game types, including cooperative games [81, 90], non-cooperative games [91], and Stackelberg games [92], have been explored in P2P electricity transaction models. These game models adeptly capture the intricate relationships and strategic decision-making processes among participating entities, thereby exhibiting heightened applicability and compatibility in real-world application. Game theory provides a robust mathematical framework for analyzing

strategic interactions among participants, empowering them to make optimal decisions within competitive environments [93]. By incorporating essential factors such as pricing strategies, resource allocation, and equilibrium analysis, game theory-based models effectively enhance the tradeoff between efficiency and fair distribution in transactions involving all participants, including the energy prosumers, energy consumers, and the utility grid. For example, Görgülü et al. [94] focused specifically on P2P energy trading among smart homes within a building community. Their work introduced the concept of DR and incorporated an interactive visual interface for monitoring. By integrating demand response mechanisms and user-friendly interfaces, their work aims to enhance the efficiency of energy trading among smart homes. Gökçek et al. [95] developed a decentralized multi-agent system for the P2P energy market using game theory, addressing challenges related to privacy protection and variable prosumer penetration. Their approach incorporates privacy measures and considers variable prosumer participation, contributing to the development of robust P2P energy trading systems. Additionally, Azim et al. [96] emphasized the importance of integrity in local energy markets through coalition game theory for P2P trading in a distribution network setting. Their work highlights the significance of integrity in local energy markets by considering coalition formation and game theory, providing insights into optimizing energy trading within distribution networks. Market power modeling and restraining aggregated prosumers in P2P energy trading are addressed in Ref. [97]. This study employs a game-theoretic approach to understand market dynamics and regulate prosumer behavior. By modeling market power and imposing restraints, this work contributes to ensuring fairness and efficiency in P2P energy trading. Fernandez et al. [98] presented an efficient P2P energy trading platform based on evolutionary games for prosumers in a community. Their work utilizes evolutionary game theory to optimize energy trading and foster collaboration among prosumers. The proposed platform offers a valuable framework for achieving efficient and cooperative P2P energy

trading. Ref. [99] provides a comprehensive review of research on P2P energy sharing and trading of renewable energy in smart communities. This work explores various aspects, including trading pricing models, decision-making processes, and agent-based collaboration. Furthermore, the rapid advancement of advanced information and communication technologies (ICT) and Internet-of-Things (IoT) technologies has provided substantial technological support for the digitization of energy in both the building and grid sectors [100]. Energy digitization has exerted a tremendous influence on the entire energy supply chain, leading to a transformation in the methods of energy sales and purchases [101]. This transformation has significantly elevated the interactive capabilities among building-side energy resources, market participants, and the utility grid. The development of digital communication and engagement tools has gained endorsement from policymakers globally [102, 103], thereby making it possible to facilitate electricity transactions between building communities. Specifically, to enable P2P electricity transaction among different buildings/building communities, it is necessary to establish power information communication and electricity transactions real-time control among the buildings/building communities, building-side aggregators, and the utility grid. This is crucial to ensure proper electricity usage within building communities and the seamless operation of the utility grid. However, relying solely on home energy management systems (HEMSs) at the individual building level cannot ensure effective communication and control of electricity transactions between building-building and building-grid [53]. Hence, it is essential to establish communication and control connectivity between the building side and the utility grid. Existing literature [33, 84, 104] indicates that microgrids are considered one of the most efficient approaches to provide advanced scheduling capabilities, flexibility, and standardized operation, control, and protection services to the utility grid. Microgrids offer an intermediary pathway to coordinate the cooperation between distributed market entities in interactive P2P energy markets and highly regulated large market entities. Microgrids, with

integration of distributed generators (DGs), storages, loads, can connect or disconnect from the utility grid acting as a controllable unit [104]. Thus, microgrids are commonly implemented within building communities, acting as coordinators for building clusters and establishing power information communication and transaction bridges with both the building side and the utility grid [33, 104].

2.4 Energy system short-term operation and long-term capacity planning

Currently, the rapid evolution of modern power systems has spurred growing interest in hybrid AC/DC distribution grids as a means to enhance energy efficiency, reliability, and adaptability [105]. The modernization and optimization of energy systems are increasingly driven by the adoption of hybrid AC/DC distribution grids, which combine the robustness of AC networks with the operational flexibility of DC subgrids. The integration of DC technology within subgrids has proven effective in consolidating diverse resources and addressing operation challenges, such as feeder power violations and imbalances arising from the increasing penetration of DGs and electrical loads [106]. Traditional AC distribution systems, while mature and widely deployed, struggle to integrate renewable energy sources, EVs, and other DERs due to limitations in handling bidirectional power flow and maintaining stability under high penetration of intermittent renewables [107]. In response, hybrid AC/DC distribution grids have emerged as a promising solution, which leverages the advantages of both AC and DC systems by integrating their respective subgrids. Recent studies have explored the technical and economic benefits of hybrid AC/DC grids. For instance, Biglarahmadi et al. [108] proposed a hierarchical control strategy to facilitate seamless coordination between AC and DC subsystems, demonstrating that hybrid grids can significantly reduce power losses and enhance voltage stability. Similarly, Tang et al. [109] highlighted the role of hybrid grids in facilitating efficient renewable energy integration, particularly for PV systems and wind turbines, by

providing a flexible platform for DC-based energy storage and direct coupling of renewables. Zhang et al. [105] investigated the practical implementation of hybrid grids, proposing a practical method for converting existing AC distribution lines into DC lines using voltage source converters (VSCs). Their findings demonstrated that through the reconfiguration of hybrid microgrids, substantial improvements can be realized in terms of feeder power capacity and DG penetration levels. Collectively, these studies underscore the potential of hybrid AC/DC grids to augment power flow management, grid performance, and resilience during disruptions. The flexible control capabilities of the hybrid AC/DC distribution grid not only enhance power flow management and grid performance but also enable the synchronized deployment of emergency power resources across different subgrids.

Power restoration has also emerged as a critical focus in modern distribution grid operation, particularly in improving grid reliability against faults and disturbances caused by various extreme events. Recent research has explored various restoration methods, frequently formulating the problem as a combinatorial optimization challenge. One prominent approach involves the use of multi-agent systems (MAS) for decentralized power restoration. Li et al. [110] demonstrated that MAS-based methods significantly reduce restoration time and enhance system reliability through real-time communication and decision-making among distributed agents. Sun et al. [111] proposed a rolling horizon optimization-based hybrid restoration framework for the New England 39-bus system with high penetration of DERs, achieving a balance between computational efficiency and scalability. Furthermore, recent advancements in machine learning and artificial intelligence (AI) techniques, such as deep reinforcement learning (DRL), have also enabled real-time optimization of restoration strategies. For instance, Essye et al. [112] conducted a hybrid DRL- Model predictive control method outperformed conventional heuristic algorithms in terms of speed and accuracy. While the aforementioned studies have conducted extensive research works on the planning and execution of restoration

tasks, they have primarily utilized a single-step optimization approach during the operational phase, neglecting the consideration of intermediate load restoration stages. The one-step methodology lacks the capability to address intermediate constraints spanning multiple time intervals, such as the ramp rate limitations of DGs and load rebound effect with time-varying power output. Consequently, the two-stage restoration approaches, which involve initial microgrid formation and subsequent optimal resource management, have emerged as practical alternatives [113]. For example, a multi-time step restoration methodology was proposed by Chen et al. [114], which effectively devises a sequence of control commands to appropriately coordinate DGs, load switches, and energy storage systems. Arif et al. [115] introduced a two-stage stochastic scheduling method to optimize distribution systems operations and repair crew routing for the restoration of outages following severe weather events. Their approach accounts for uncertainties in demand and repair times, presenting a novel decomposition technique and progressive hedging algorithm for the efficient management of large-scale outage scenarios, validated using IEEE distribution test systems. Lei et al. [116] further enhanced the resilience of distribution systems by employing Mobile Power Sources (MPSs) within a two-stage framework. Their strategy involves strategically positioning MPSs for swift pre-restoration actions before events and dynamically dispatching them post-event, thereby optimizing power recovery and grid resilience, as evidenced by experiments conducted on IEEE test systems.

Capacity optimization is critical for managing IES, as it addresses supply-demand mismatches and optimizes system performance [117]. The capacity planning of IES with DERs holds significant importance in ensuring efficient and sustainable energy management [118]. When addressing practical optimization problems, two main approaches are commonly employed: rule-based strategy optimization and optimization algorithms [119]. Rule-based strategies leverage professional knowledge and expertise to guide decision-making, while optimization algorithms employ various optimization algorithms and emerging techniques. These

algorithms include heuristic methods like GA [48, 120] and PSO [48, 49], mathematical programming methods such as LP [51, 121] and DP [48, 50, 122], and other state-of-the-art algorithms [123-126]. However, the optimization process based on optimization algorithms often focuses on finding the optimal solution in each step of the solution process, without always considering the actual situation based on expert knowledge. Current research predominantly focuses on optimizing the economy, environment, and energy stability objectives to determine optimal IES configurations. Typically, multi-objective optimization model is commonly used for the optimal planning of IES with DERs [127]. In contrast to single-objective optimization models, multi-objective approaches optimize competing objectives separately and apply preference-based decision-making to select the final scheme [128]. Therefore, multi-objective optimization of IES typically involves two stages: optimization and decision-making. Existing studies have explored the optimization of the capacity of IES with various energy resources. Shen et al. [129] explored the optimization of capacity configuration in an IES, focusing on economic and environmental considerations. Through a multi-objective optimization model, it aimed to achieve a harmonious balance between annual total cost and carbon emissions for improved system efficiency. Wei et al. [130] introduce a methodical retrofitting strategy for historic buildings, integrating multi-objective optimization with the energy system. Using energy simulation methodologies and the NSGA-II algorithm, this approach optimizes energy savings, carbon emissions, and net present value (NPV), resulting in notable enhancements. The outcomes showcased substantial reductions in energy consumption (up to 63.62%) and carbon emissions (60.48%), alongside an augmented NPV (151.84%). Zhao et al. [131] proposed an innovative optimization method for multi-energy CCHP systems, focusing on system simplification to enhance energy efficiency and environmental sustainability. Their study demonstrated a slight difference in hypervolume between the improved and original algorithms. Tian et al. [132] put forward an innovative

flexible multi-objective optimization planning method aimed at bolstering the operational flexibility of DERs. This method tackles the intrinsic variations in the temporal characteristics of objectives—such as economic viability, grid compatibility, and low-carbon emissions—by considering numerous operational scenarios. The findings illustrated that the suggested approach can enhance system flexibility by 6%–10% in contrast to traditional multi-objective planning methods, underscoring the significance of factoring in dynamic shifts in objective priorities for efficient and adaptable energy planning. Wang et al. [133] investigated the capacity and strategy optimization of CCHP systems integrated with PV and multiple energy storage technologies. Their investigation aimed to augment the overall advantages of energy supply systems by harnessing renewable energy sources and curbing environmental impact. The outcomes showcased that the proposed model, in conjunction with the NSGA-II and TOPSIS, could achieve a substantial reduction in pollutant emissions by 74.86%, primary energy savings of 36.83%, and annual cost savings of 13.04%.

2.5 Summary of research gaps

Based on the comprehensive literature review above, the following critical research gaps have been identified, guiding the direction of this thesis:

- Most existing studies tend to analyze the electrification of buildings and transportation in isolation or focus solely on homogeneous community types. This fragmented approach fails to capture the complex, synergistic, and interactive effects that emerge when both sectors undergo electrification within diverse communities. There is a pronounced need for integrated modeling frameworks that can holistically assess the joint impacts of building and transportation electrification on the operation, planning, and market participation of community energy systems. Furthermore, very few studies have quantified the combined benefits, challenges, and trade-offs of coordinated

electrification, nor have they developed actionable strategies for comprehensive energy system transformation at the community level.

- Current literature often analyzes either intra-microgrid (within community) or inter-microgrid (between communities) electricity trading, but rarely both in a unified framework. The decoupling of price and quantity in P2P markets, as well as the impact of EV migration and heterogeneous community profiles, remain underexplored.
- Demand-side management strategies in the literature are predominantly rule-based and building-centric, often lacking the flexibility required to accommodate diverse and dynamically changing community needs. Restoration strategies, particularly in the context of hybrid AC/DC microgrids, frequently overlook sequential, multi-stage operational constraints and fail to consider demand-side rebound effects following disruptions. This limits the effectiveness and resilience of energy systems, especially as electrification deepens and system complexity grows.
- There is a notable lack of high-resolution, long-term datasets for benchmarking distributed energy systems and for validating management or optimization models. Existing planning and validation approaches often do not sufficiently address the evolving pathways of electrification and decarbonization, impeding the development of robust, generalizable solutions for future energy systems.
- Traditional capacity planning models are generally inadequate for addressing the dynamic, multi-objective optimization problems posed by future energy systems. As electrification and decarbonization efforts intensify, energy systems must simultaneously balance reliability, cost, operational flexibility, and sustainability. Current models often lack the sophistication required to capture these competing

objectives and the uncertainties associated with rapid technological, regulatory, and behavioral changes.

In summary, this thesis systematically addresses the identified research gaps by proposing integrated modeling and optimization frameworks tailored for diversified, EV-integrated building communities. It introduces novel electricity trading paradigms incorporating hybrid game-theoretic approaches to facilitate efficient and equitable transactions in complex multi-microgrid environments. Furthermore, the thesis develops comprehensive, data-driven strategies for demand-side management, restoration, and capacity planning under scenarios of moderate to deep electrification and decarbonization. By bridging these critical gaps, the research advances both the theoretical foundation and the practical methodologies necessary for optimizing capacity design, electricity trading, and operational management in next-generation community energy systems.

CHAPTER 3 RESEARCH METHODOLOGY AND TEST RESOURCES

This chapter presents the research framework, methodology, and test resources for analyzing building-EV integrated community energy systems. Section 3.1 introduces the overview of building-EV integrated community energy system, including the demand-supply relationship of building-transportation-grid coupling and the research methodology. Section 3.2 details the development of demand-side load simulation, covering building prototype modeling, community load simulation, and EV charging load models for different communities. Section 3.3 focuses on energy system modeling and internal trading mechanisms, including district energy component models and electricity market paradigms. Finally, Section 3.4 describes a 20-year campus energy dataset, providing real-world testing data for diverse building communities. Together, these sections establish the foundation for the PhD study's analytical approach.

3.1 Overview of integrated community energy systems

The building-EV integrated community energy system is designed to optimize energy utilization and trading in diversified building communities, considering the rapid electrification of both buildings and transportation sectors. As illustrated in Figure 1-1, the system framework consists of several core components: onsite renewable generation (primarily rooftop solar PV), distributed energy storage systems, EVs, and flexible connections to the main utility grid via power transmission infrastructure. These elements are distributed across various building types, including residential, office, commercial, and campus communities.

The integration of these assets forms a hybrid energy system, enabling local generation, storage, and flexible consumption, while facilitating both P2G and P2P electricity trading. The system

is managed by a grid operator responsible for network stability, market operation, and balancing supply and demand. This interconnected network supports real-time energy dispatch, demand response, and coordinated operation across multiple communities, ultimately enhancing overall system efficiency, resilience, and decarbonization potential.

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The demand-supply relationship within the integrated energy system is characterized by the coupling of building electricity loads, EV charging demands, and grid interactions. Each building community exhibits distinct consumption profiles determined by occupant behavior, building function, and operational schedules. Simultaneously, the electrification of transportation introduces a new layer of dynamic, spatially and temporally distributed EV charging demands. The system's supply side is primarily composed of onsite solar PV generation and energy storage, which can be dispatched to meet local demand or exported to the grid. The demand side encompasses not only traditional building loads (e.g., lighting, HVAC, appliances) but also the flexible and stochastic charging loads of EVs. The grid serves as both a backup supply and an energy sink, enabling surplus electricity to be sold or deficit electricity to be purchased as needed. The interplay between these components requires sophisticated modeling to accurately capture the variability and correlation between building loads, EV charging, and renewable generation. An effective energy management strategy must account for the temporal coincidence and diversity of these demands, optimizing local energy use, enhancing self-consumption, and minimizing grid dependency.

3.2 Overview of research methodology

This study adopts a hybrid research methodology that integrates detailed simulation modeling with the use of onsite measurement data to analyze and optimize capacity design, electricity trading, and the operational strategies of building-EV integrated community energy systems, as illustrated in Figure 3-1. The methodological framework is structured to ensure both comprehensive scenario analysis and practical relevance of the findings.

Firstly, a simulation-based approach is developed to model the energy consumption characteristics of diversified building communities and the charging behaviors of electric vehicles. Prototype building models, drawn from established energy codes and standards, are used to represent typical building types—such as residential, office, commercial, and campus buildings—within each community. These models generate hourly and sub-hourly load profiles, reflecting the variations in occupancy, operation schedules, and equipment use. The simulation further incorporates a hybrid Markov Chain and Monte Carlo (MCMC) model to realistically capture the spatial-temporal dynamics of EV travel, parking, and charging activities. Through this approach, the simulation platform can represent the complex interactions between building loads, EV charging demands, distributed energy resources (such as rooftop PV and batteries), and the main utility grid.

In parallel, the research leverages high-resolution onsite measurement data collected from a real-world complex community and its energy station. This campus community comprises a diverse mix of teaching, research, office, and residential buildings, integrated with a district energy station. The measurement data, including detailed load profiles and renewable generation outputs, are utilized for calibrating and validating the simulation models, thereby ensuring that the simulated results closely reflect actual operational conditions. Furthermore, this empirical data allows for a realistic parameterization of user behaviors and system

constraints, and provides a valuable benchmark for the evaluation of proposed optimization and trading strategies.

By combining simulation results with real-world measurement data, the methodology enables a robust and holistic analysis of the integrated energy system. This dual approach supports scenario-based evaluation of various system configurations, electrification pathways, and operational strategies, including the implementation of P2G and P2P electricity trading. Ultimately, this research methodology ensures that the findings are both theoretically sound and practically applicable, providing actionable insights for the design and operation of future community energy systems.

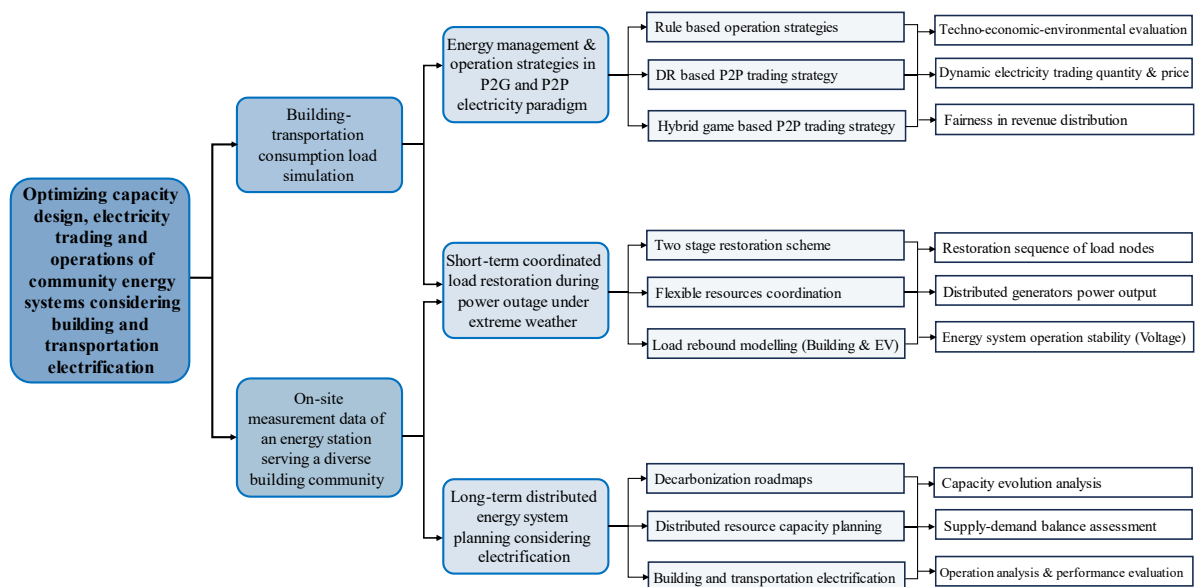


Figure 3-1 Overview of the research methodology

3.3 Demand-side load simulation

Accurate modeling of demand-side loads forms the foundation for effective planning and operation of the integrated community energy system. This section details the methodology for simulating two primary load components: building energy consumption and EV charging demand. The development of these load models requires careful consideration of the diverse

characteristics of different building types and their associated transportation patterns, as well as the temporal variations in energy use. By combining statistical approaches with physical modeling techniques, this study creates comprehensive load profiles that capture the essential features of real-world energy consumption while remaining computationally tractable for system optimization purposes. The load simulation framework must account for both regular patterns (daily, weekly, and seasonal variations) and stochastic elements (particularly in EV usage), enabling robust evaluation of system performance under various operating conditions. These models serve as critical inputs for subsequent analyses of energy management strategies, electricity trading mechanisms, and capacity planning described in later chapters.

3.3.1 Simulation platform and building prototype models

The building load simulation leverages established prototype models developed by the U.S. Department of Energy (DOE), which represent approximately 75% of the U.S. building stock and have been widely validated against real-world energy data. These prototype models cover major building types including residential (mid-rise and high-rise apartments), commercial (medium and large offices, standalone retail), and institutional (university campus buildings) structures. The simulation platform utilizes EnergyPlus and OpenStudio tools to generate detailed hourly energy consumption profiles for each prototype, incorporating factors such as building geometry, construction materials, HVAC systems, occupancy patterns, and equipment loads [134]. For specific applications like the university campus community, actual measured energy data from The Hong Kong Polytechnic University (PolyU) for 2015 is used to enhance model accuracy. The prototype approach provides a standardized methodology for comparing energy performance across different building communities while maintaining sufficient detail to capture the unique characteristics of each building type. This modular framework allows for flexible composition of various community configurations by combining appropriate prototype buildings in different proportions. Simultaneously, the charging model of EVs is simulated

using Python with the Monte Carlo Markov Chain algorithm (MCMC) as explained in Section 3.3.3. Then, the demand load of each building community is obtained by summing the building load and EV charging load, as illustrated in Figure 3-2.

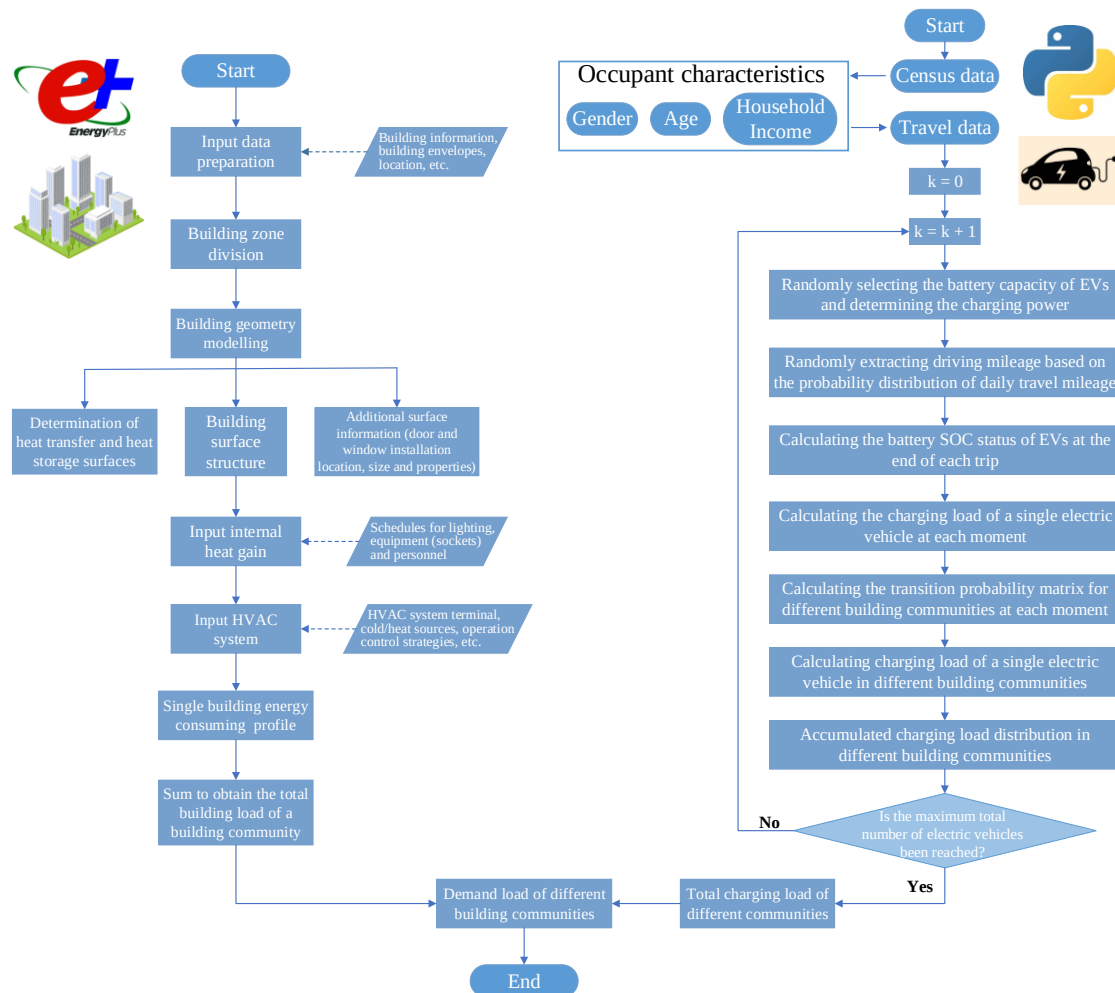


Figure 3-2 Schematic diagram of the demand-side load simulation modelling

3.3.2 Building community load simulation

The building community load simulation aggregates energy consumption from individual prototype buildings to form comprehensive profiles for four distinct community types: university campus, residential, office, and commercial retail. The relationship between these prototype buildings and the building community is depicted in Figure 3-3. The campus community model incorporates approximately 30 teaching and office buildings based on PolyU's actual building portfolio and energy use patterns. The residential community combines

20 mid-rise and 20 high-rise apartment buildings, while the office community comprises 20 medium and 20 large office buildings. The retail community consists of 20 standalone commercial buildings. Each community's load profile is developed by summing the simulated energy use of its constituent buildings, with appropriate diversity factors applied to account for simultaneous operation of multiple buildings. The resulting community-level load profiles exhibit distinct temporal patterns that reflect the underlying mix of building types and their associated usage schedules. For instance, the residential community shows prominent morning and evening peaks corresponding to household activities, while the office community displays a strong daytime load profile during working hours. These differentiated load characteristics are essential for evaluating how different community types interact with EV charging loads and participate in energy trading scenarios.

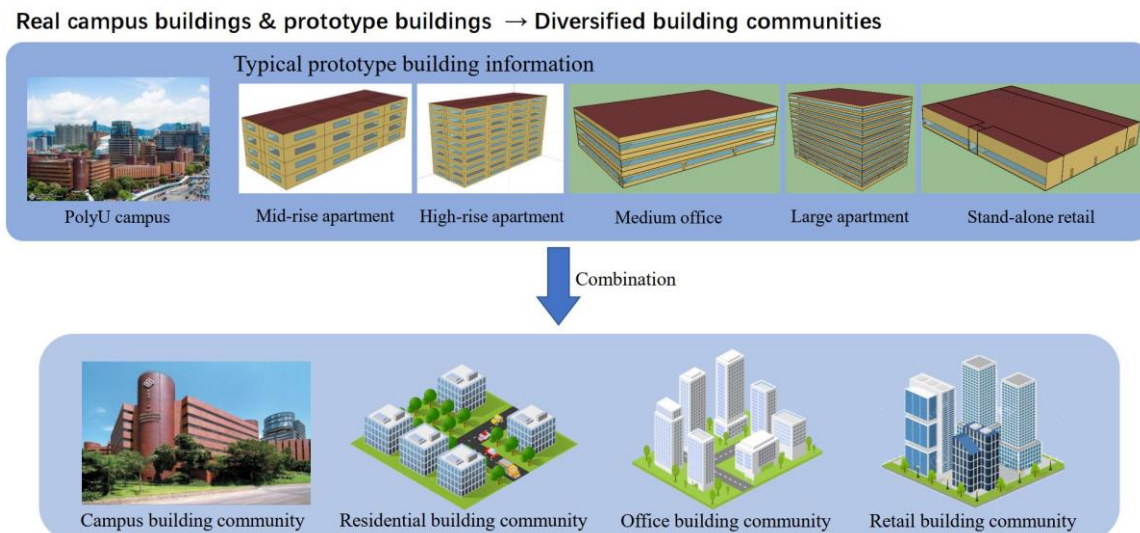


Figure 3-3 The relationship between prototype buildings and building community

3.3.3 EV charging load in different building communities

The thesis recognizes the importance of accurately generating the charging power characteristics of EVs at different times to facilitate a more objective comparison of energy dispatching and energy balance between the supply and demand sides under different operation strategies. In order to address this, the study proposed an integrated Markov Chain and Monte

Carlo algorithm (MCMC) to simulate the travel demand of EVs, considering diversified locations based on user characteristics, daily spatial-temporal distribution, transition probability of EVs, and probability distribution of travel distance. The structure of the simulation method for EVs and the flow of EVs' travel demand power calculation based on the MCMC algorithm are illustrated in Figure 3-4. This method enables the simulation of both individual and collective behavior of EVs, incorporating different traveling variable models such as first departure time, travel time, travel distance, and charging time, as well as a transport model comprising transition probability and travel destination.

The detailed simulation processes of the MCMC method are as follows:

1. Classification: The first step involves classifying occupant travel data based on characteristics such as gender, age, and household income.
2. Traveling variable models: Different traveling variable models, including first departure time, travel distance, travel time, and stay time (charging time), are constructed to simulate the daily typical travel demand and EVs' charging power in a specific region through Monte Carlo algorithm.
3. Transport model: A transport model based on the Markov Chain method is employed to calculate the probability of EVs staying in each building community as different destinations.
4. EV charging power simulation: The typical EV charging power at different times in different building communities is simulated by combining the traveling variable models, transport model, and EV charging model as constraints.

By following these steps, the MCMC method allows for the simulation of EV travel demand and the estimation of EV charging power of diversified building communities, considering various factors and characteristics.

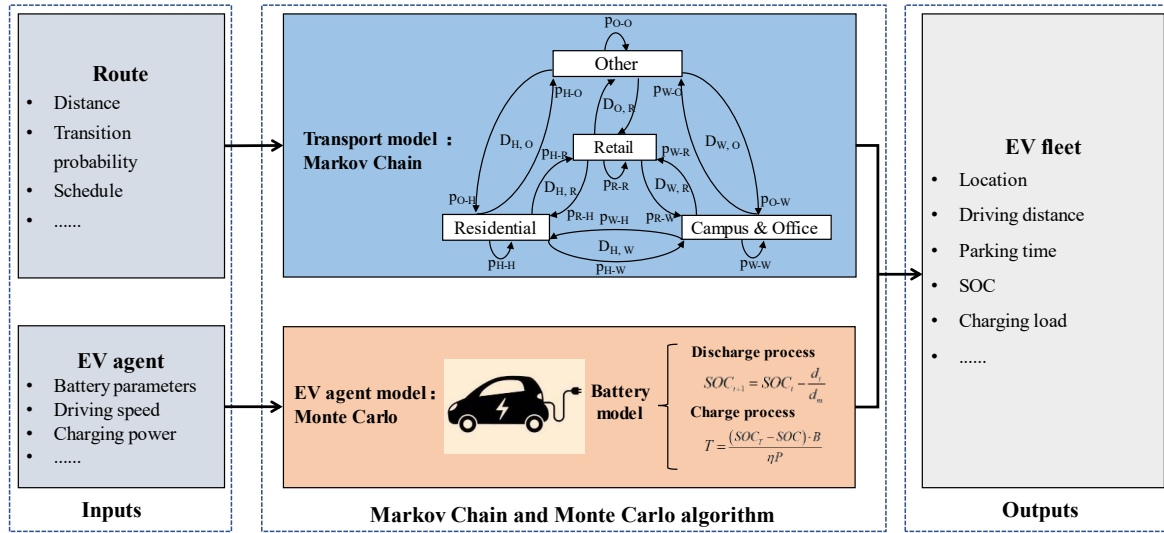


Figure 3-4 The EVs charging load spatial-temporal distribution simulation method based on the MCMC algorithm

3.3.3.1 Daily travel demand and EVs charging power

A. Probability distribution of daily mileage traveled

Considering that EVs are still relatively new and have a lower penetration rate compared to traditional fuel-consumed vehicles, the sample size of EV users is relatively small. Therefore, certain assumptions are made to account for this limited data availability. Firstly, it is assumed that EV users have similar vehicle usage habits to fossil-fuel vehicle users. This assumption allows for comparisons and analysis based on established patterns of vehicle usage, while acknowledging the differences in the technology and energy source. Secondly, it is assumed that EVs are fully charged before each trip. This assumption simplifies the analysis by assuming that EVs always start with a full charge, which is a common practice among EV users for daily routines. Moreover, the scope of this PhD study focuses on private vehicles used for daily travel. Other types of EVs, such as public transportation or commercial fleet vehicles, are not considered in this analysis. To support these assumptions, previous references [46, 135] have conducted statistical processing on household vehicle usage behavior data and population census data. These studies have concluded that the daily mileage of EVs follows a Lognormal

distribution, denoted as $S \sim \text{Log} - N(\mu_s, \sigma_s^2)$. The probability density function (PDF) of this Lognormal distribution is expressed by Eq. (3.1).

$$f_s(x) = \frac{1}{x} \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(\ln x - \mu_s)^2}{2\sigma_s^2}\right) \quad (3.1)$$

Where, the average value μ_s equals 3.2 and variance equals 0.88.

B. Probability distribution of initial charging time

The initial charging time of EVs within a day is determined based on publicly available statistical data to analyze the operating characteristics of EVs [46]. The distribution of the initial charging time, denoted as t_0 , is found to follow a normal distribution, represented as $t_0 \sim N(\mu_t, \sigma_t^2)$. The PDF of this normal distribution is expressed by Eq. (3.2).

$$f_t(x) = \begin{cases} \frac{1}{\sigma_s \sqrt{2\pi}} \exp\left(-\frac{(x - \mu_s)^2}{2\sigma_s^2}\right) & \mu_s - 12 < x < 24 \\ \frac{1}{\sigma_s \sqrt{2\pi}} \exp\left(-\frac{(x + 24 - \mu_s)^2}{2\sigma_s^2}\right) & 0 < x < \mu_s - 12 \end{cases} \quad (3.2)$$

Where, the average value μ_s equals 17.6 and variance equals 3.4.

C. Probability distribution of charging power

In building communities, considering the stability and reliability of the utility grid, the charging process of EVs normally belongs to conventional slow charging, with a relatively long time for constant charging. In contrast, the initial and end stages of non-linear charging behavior account for a very low proportion of the entire charging process. Therefore, in this study, the charging process is simplified without considering the flexibility of the charging process, and the impact of the start and end stages on the overall calculation is ignored.

D. Probability distribution of battery capacity

In current market, the battery capacity of available mainly range from 20kWh to 30 kWh. In simulation model, the PDF of the battery capacity distribution is expressed by Eq. (3.3).

$$f_c(x) = \begin{cases} \frac{1}{10} & 20 < x \leq 30 \\ 0 & \text{Others} \end{cases} \quad (3.3)$$

3.3.3.2 Transport model

The transport model incorporates a nonhomogeneous Markov Chain model with the Monte Carlo method to estimate the probability of a private electric vehicle staying in each building community as different destinations. This is achieved by considering the transition probabilities of the vehicle among different states at each time interval, representing state transitions [136]. Private EVs are commonly parked at various locations, including residential areas, campuses, offices, shopping malls, hospitals, and amusement parks. These parking spots serve as charging points for private EVs, allowing them to be charged for an extended period while parked [137]. Based on the parking and charging patterns of private EVs, the destinations are categorized into four main groups:

1. Residential building (H): This category includes locations where EV owners park and charge their vehicles at home, typically residential areas.
2. Campus and office (W): This group comprises locations such as office buildings and campuses where EVs are parked and charged during working hours.
3. Retail building (R): Locations like shopping malls, where EV owners park and charge their vehicles while shopping or running errands, fall under this category.
4. Other building (O): This category includes various public areas like hospitals, amusement parks, and other buildings where EVs are parked and charged for extended periods.

By considering these destination categories and incorporating the MCMC method, the transport model can estimate the probabilities of EVs staying in each building community, capturing the

diverse parking and charging patterns observed in private EV usage. Markov Chain is a discrete-time stochastic process in which the future state depends solely on the current state [138]. In the context of trips, assuming that each trip is usually related to the last destination, we can represent the current destination as $D_{i,t}$, and the destination in the next moment as $D_{j,t+1}$. The transition process between these destinations can be described using a Markov transition matrix based on Markov Chain and the single-step transition probability, which can be depicted by Eq. (3.4) and Eq. (3.5).

$$P_{ij,T} = P(D_{i,t} \rightarrow D_{j,T+1}) = P(D_{j,T+1} | D_{i,T}) \quad (3.4)$$

Discretizing the department time at a certain interval, the transition probability of travel purpose in the transport model can be expressed as Eq. (3.5) [31].

$$P_{T_k} = \begin{pmatrix} D_{11}^{T_k} & D_{12}^{T_k} & D_{13}^{T_k} & D_{14}^{T_k} \\ D_{21}^{T_k} & D_{22}^{T_k} & D_{23}^{T_k} & D_{24}^{T_k} \\ D_{31}^{T_k} & D_{32}^{T_k} & D_{33}^{T_k} & D_{34}^{T_k} \\ D_{41}^{T_k} & D_{42}^{T_k} & D_{43}^{T_k} & D_{44}^{T_k} \end{pmatrix} \quad (3.5)$$

Where, P_{T_k} is the spatial transition probability matrix in time interval k ; D_{ij} represents the transition probability of departure place i and destination j in time interval k .

3.3.3.3 EVs charging model

As different types of EVs, such as private cars, taxis, and buses, exhibit quite dissimilar electric charge patterns and power requirements, this study focuses solely on modeling personal private EVs. The detailed parameters of a single EV and total number of EVs in the communities in this study are depicted in the

Table 3-1. To illustrate the charging load modeling process, we will use a single EV as an example, and it is based on the travel behavior as follows:

- (1) Calculating the SOC of the EV battery before the trip begins is crucial. The current battery SOC during travel can be calculated by Eq. (3.6).

$$SOC_{i+1} = SOC_i - \frac{d_i}{d_m} \quad (3.6)$$

- (2) The situations that require charging are as follows: 1) When the current SOC cannot meet the requirements for the next trip; 2) When the battery charge level is lower than 20% of the battery capacity [135].
- (3) The charging power is determined based on the type of building community. Specifically, in residential buildings, offices, and campuses, the charging power is set at 3.5 kW, and the charging efficiency is 90%. On the other hand, in shopping malls or other public buildings, the charging power is 8.0 kW, while maintaining a charging efficiency of 85% [139].
- (4) Charging time is restricted by the available parking time, and it can be calculated using Eq. (3.7) and Eq. (3.8).

$$T = \frac{(SOC_T - SOC) \cdot B}{\eta P} \quad (3.7)$$

$$T \leq T_p \quad (3.8)$$

- (5) According to steps (1) - (4), the charging load of a single EV for a day can be obtained.
- (6) By repeating steps (1) - (5) and combining the Markov matrix results in section 3.3.3.2, the daily load profile of a single EV in different communities can be calculated, and the total load of each building community can be determined by stacking the load of each single EV accordingly.

Table 3-1 Specifications of EVs used in this study

Parameter	Value
Battery (kWh)	20-30
Charging power (kW)	Residential building, office and campus: 3.5 public building: 8
Charge/discharge efficiency (%)	Residential building, office and campus: 90 public building: 85
SOC _{min}	0.2
SOC _{max}	0.8
Total number of EVs	5000

3.4 Modelling of energy system components

This section establishes the comprehensive modeling framework for the district-level integrated energy system, as well as the internal electricity trading mechanisms among diversified building communities. The proposed system model is centered around an energy hub that integrates electricity, heating, cooling, and heat recovery subsystems to efficiently supply and manage energy flows within the community. Mathematical models for each equipment and subsystem are developed to capture their operational characteristics and interdependencies. Furthermore, this PhD study incorporates advanced market-based trading paradigms to facilitate flexible and economic energy exchanges both with the external grid and among peer building communities. The combined modelling framework supports rigorous analysis and optimization of system operation under various scenarios, including different carbon emission targets and electrification levels.

The district energy system is structured as a multi-carrier energy hub, integrating various energy conversion, storage, and supply technologies. By integrating these component models, the district energy system can flexibly manage energy supply and demand, optimize operation across different carriers, and adapt to fluctuations in renewable generation and user loads. The main components and their mathematical models are summarized as follows:

3.4.1 Photovoltaic (PV) system

PV system model is calculated by using solar irradiation data and ambient temperature data. The power output of a PV module is represented by an equivalent electric circuit and its I-V equation, as shown in Eq. (3.9), commonly known as the five-parameter equivalent diode model. This model dynamically reflects the nonlinear characteristics of PV modules under varying environmental conditions. The value of five parameters is dynamically fluctuated according to the change of solar irradiance and cell temperature, where these parameters under general conditions can be calculated by using the five parameters under standard testing condition (STC, i.e., 1000W/m² and 25 °C) [140]. The detailed specifications of the PV generation model are listed in

Table 3-2.

$$I_{pv} = I_{ph} - I_0 \left[\exp\left(\frac{V_{pv} + I_{pv}R_s}{n_0V_{th}} - 1\right) \right] - \frac{V_{pv} + I_{pv}R_s}{R_p} \quad (3.9)$$

$$V_{th} = \frac{N_s \cdot K \cdot T}{q} \quad (3.10)$$

$$I_{ph} = I_{L,ref} \frac{G_T}{G_{T,ref}} \quad (3.11)$$

$$G_T = G_b R_b + G_b \left(\frac{1 + \cos \alpha}{2} \right) + G \rho \left(\frac{1 - \cos \alpha}{2} \right) \quad (3.12)$$

$$\frac{I_0}{I_{0,ref}} = \left(\frac{T}{T_{ref}} \right)^3 \quad (3.13)$$

Table 3-2 Specifications of the PV generation model used in this study

Parameter	Value
Photon current I_{ph} (A)	5.13806
Diode saturation current I_0 (A)	1.35845×10^{-7}
Series resistance R_s (Ω)	0.454354
Parallel resistance R_p (Ω)	1852.48
Diode ideality factor n_0	1.37594
Boltzmann's constant K (J/K)	1.380653×10^{-23}
Absolute value of electron's charge q (C)	$1.60217646 \times 10^{-23}$
Reflectance of the ground ρ	0.2
Installation tile angle of PV array α ($^\circ$)	34-38

3.4.2 Wind turbine system

The wind power output is calculated based on Betz's law, considering wind speed, turbine technical parameters, and air density, as shown in Eq. (3.14). A commercial Vesta V117-4.2MW wind turbine model was adopted, and the technical parameters of the unit are listed in Table 3.3.

$$P_{Wind}^i = \frac{0.5(N_{Wind} \cdot C_p \cdot \rho \cdot A \cdot V_{Wind}^3)}{1000} \quad (3.14)$$

Table 3-3 The technical parameters of the Vesta V117-4.2MW wind turbine

Parameters	Value
Rated power (kW)	4000
Cut-in wind speed (m/s)	3
Cut-out wind speed (m/s)	25
Hub height (m)	84
Rotor diameter (m)	117
Swept area (m ²)	10751
Blade length (m)	57.2

3.4.3 Combined cooling, heating, and power (CCHP) System

The CCHP subsystem, primarily based on natural gas-fired gas turbines, supplies electricity, heating, and cooling. The mathematical model captures the interlinked generation processes, waste heat recovery, and efficiency parameters, supporting co-optimization of multiple energy outputs, represented by Eqs. (3.15) - (3.17).

$$H_{gt}(t) = Q_{gt}(t) \cdot h_{wh} \cdot d_{wh} \cdot e_{wh} \quad (3.15)$$

$$C_{gt}(t) = \frac{Q_{gt}(t) \cdot \eta_{wh,c} \cdot \delta_{wh,c}}{COP} \quad (3.16)$$

$$V_{gt}(t) = \frac{P_{gt}(t) \cdot \Delta t}{\eta_e \cdot L_{NG}} \quad (3.17)$$

3.4.4 Heat pump

Air Source Heat Pumps (ASHPs) are modeled to deliver both heating and cooling loads using electricity, characterized by their coefficient of performance (COP) as a function of temperature differences between heat sources and sinks. The mathematical model of ASHP is expressed by Eqs. (3.18) - (3.19) [141].

$$P_{ASHP}(t) = \frac{Q_{c/h}(t)}{COP} \quad (3.18)$$

$$COP = 6.08 - 0.09 \cdot \Delta T + 0.005 \cdot \Delta T^2 \quad (3.19)$$

3.4.5 Gas boiler

The gas boiler model represents the conversion of natural gas to heat, with efficiency and capacity parameters reflecting real-world operation. The mathematical model for the gas boiler is represented by Eqs. (3.20) - (3.21).

$$P_{gb}(t) = P_{gas,gb}(t) \cdot \eta_{gb} \quad (3.20)$$

$$P_{gas,gb}(t) = \frac{V_{gb}(t) \cdot L_{NG}}{\Delta t} \quad (3.21)$$

3.4.6 Absorption refrigerator model

The absorption refrigeration system utilizes recovered heat, with its performance described by the COP and energy conversion relationships. The mathematical model for a lithium bromide absorption chiller is expressed as Eq. (3.22).

$$P_{ac}(t) = Q_{ac}(t) \cdot COP_{ac} \quad (3.22)$$

3.4.7 Heat recovery model

In an integrated energy system, waste heat temperatures often provide a suitable source for driving an organic Rankine cycle (ORC) system. The heat recovery model predominantly relies on the ORC system, which utilizes an organic working medium as an energy carrier to generate electricity through the energy conversion cycle utilizing available heat. This approach represents an effective technical solution for recovering low-grade heat energy and implementing it within a distributed energy system. It enables the utilization of harvested heat and promotes resource conservation. The mathematical model for the ORC system is expressed by Eqs. (3.23) - (3.24).

$$P_{orc}(t) = P_{orc,t}(t) - P_{orc,p}(t) \quad (3.23)$$

$$\eta_{orc}(t) = \frac{P_{orc,t}(t)}{Q_w} \quad (3.24)$$

3.4.8 Energy Storage Systems

Both electrical (lithium-ion batteries) and thermal (heat storage tanks) storage devices are modeled. The battery status is represented by the state of charge (SOC), which is defined by Eqs. (3.25) - (3.26). The SOC represents the amount of energy stored in the battery as a percentage of its total capacity. It is a crucial parameter for energy storage management and control within the grid-connected hybrid building energy system. The heat storage model shares similarities with the battery model, encompassing both heat charging and heat release processes. The heat storage state (HSS) serves as the sole state variable that describes the charging and discharging processes of the heat storage tank. The mathematical model for the charging process of the heat storage tank can be expressed as Eq. (3.27). Table 3.4 provides detailed specifications of the battery and the heat storage tank employed.

$$SOC(t) = \frac{E_b(t)}{E_{b,N}} \times 100\% \quad (3.25)$$

$$SOC(t+1) = SOC(t) + \xi(t) \frac{P_{b,ch}(t) \cdot \Delta t \cdot \eta_{ch}}{E_b} - (1 - \xi(t)) \frac{P_{b,dis}(t) \cdot \Delta t}{E_b \cdot \eta_{dis}} \quad (3.26)$$

$$HSS(t+1) = HSS(t) + \xi(t) \frac{Q_{hst,ch}(t) \cdot \Delta t \cdot \eta_{ch}}{E_{hst}} - (1 - \xi(t)) \frac{P_{hst,dis}(t) \cdot \Delta t}{E_{hst} \cdot \eta_{dis}} \quad (3.27)$$

Table 3-4 Specifications of the battery and heat storage tank used in this study

Parameter	Value
Charge/discharge efficiency	0.90
Life cycle number	10000
SOC _{min}	0.20
SOC _{max}	0.95
HSS _{min}	0.20

$HSS_{\max}$	0.95
$P_{\text{ch}, \max}$ (kW)	0.15 * Battery capacity
$P_{\text{dis}, \max}$ (kW)	0.13 * Battery capacity
$Q_{\text{hst}, \text{ch}, \max}$ (kW)	0.15 * Heat storage tank capacity
$Q_{\text{hst}, \text{dis}, \max}$ (kW)	0.13 * Heat storage tank capacity

3.5 Electricity trading market mechanisms

To enable efficient and flexible energy management, this study incorporates two complementary electricity trading paradigms: the TOU pricing scheme with the utility grid, and an internal P2P trading mechanism among building communities. By integrating these market mechanisms, the district energy system can optimize both technical and economic objectives—maximizing renewable self-consumption, minimizing operational costs, and enhancing revenue streams for prosumers. The combined market model also supports scenario analysis of different trading structures, regulatory frameworks, and decarbonization pathways.

3.5.1 Time-of-Use (TOU) pricing model

The TOU pricing scheme is implemented as the external electricity tariff structure, with differentiated rates for peak, shoulder, and off-peak periods. This approach incentivizes load shifting and demand response, helping to balance supply and demand within the grid. The electricity tariff distribution for residential and commercial buildings is provided in illustrated in Figure 3-5 [142]. Surplus renewable energy generated within the community can be exported to the grid at a fixed feed-in-tariff (FiT), promoting local renewable integration.

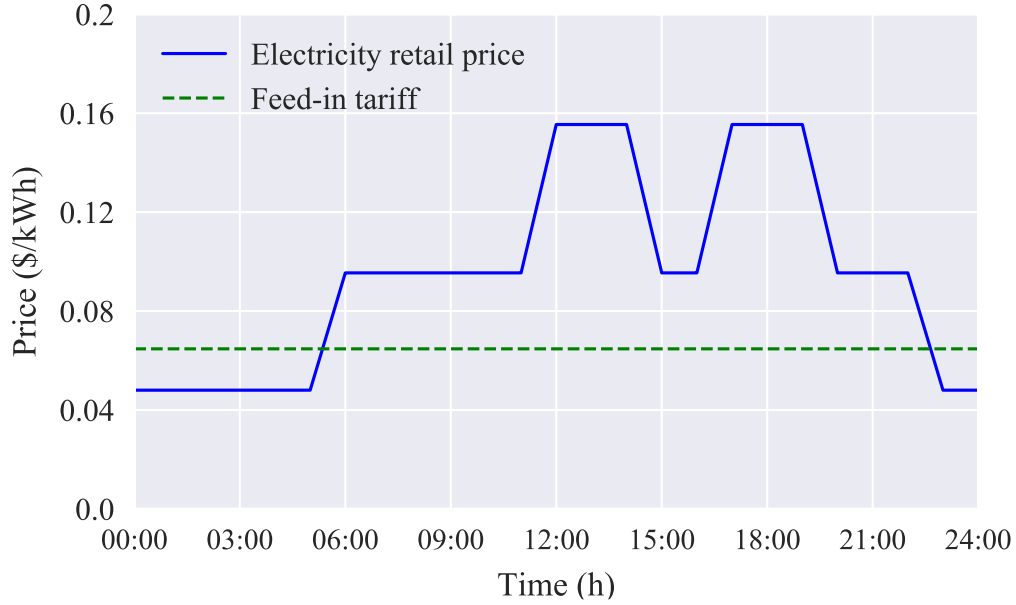


Figure 3-5 Distribution of daily retail TOU price and FiT subsidy

3.5.2 Peer-to-peer (P2P) pricing model

The P2P trading mechanism allows building communities to conduct direct energy transactions based on real-time local supply-demand conditions. the general P2P price model for multiple peers is developed on the basis of the total SDR of the whole peers assuming that the relationship between the price and SDR is inverse-proportional [36], as shown in Figure 3-6. In the figure, the symbols λ_{buy} and λ_{sell} correspond to the retail electricity price and the feed-in subsidy price at the calculation time, respectively. More specifically, the dynamic energy supply available for peer selling of the whole peers is the sum of surplus renewable energy remaining after each peer's self-consumption. On the other hand, the dynamic demand requiring purchasing from other peers is the sum of electrical load shortage after achieving self-sufficiency for each peer. Therefore, the SDR is formulated by Eq. (3.28).

$$SDR = \frac{\sum P_{pv_i_sur}}{\sum P_{de_i_sh}} \quad (3.28)$$

The P2P energy selling price ($P2P_{sell}$) model in the whole diversified building communities can be given a typical piecewise equation as Eq. (3.29) [36].

$$P2P_{sell} = f(SDR) = \begin{cases} \frac{R_{sell} \cdot R_{buy}}{(R_{buy} - R_{sell}) \cdot SDR + R_{sell}}, & 0 \leq SDR \leq 1 \\ R_{sell}, & 1 < SDR \end{cases} \quad (3.29)$$

The P2P energy buying price ($P2P_{buy}$) model in the whole diversified building communities is formulated as a piecewise equation as well, which is given by Eq. (3.30), and it depends on the selling price considering the economic balance [36].

$$P2P_{buy} = f(SDR) = \begin{cases} P2P_{sell} \cdot SDR + R_{buy} \cdot (1 - SDR), & 0 \leq SDR \leq 1 \\ R_{sell}, & 1 < SDR \end{cases} \quad (3.30)$$

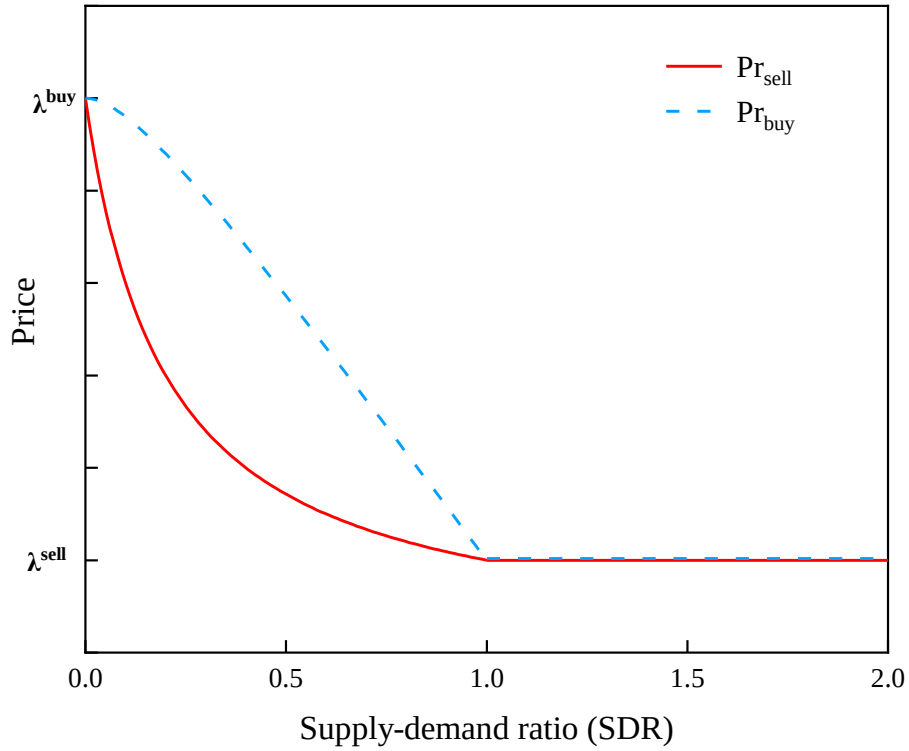


Figure 3-6 Uniform P2P trading price models in the diversified building communities

3.6 Twenty-year dataset of a campus energy system

A comprehensive, high-resolution dataset spanning two decades has been collected from the district energy system serving a campus. This long-term dataset provides valuable insights into the operation, performance, and evolution of a real-world distributed energy system, capturing hourly energy generation and consumption profiles from 2002 to 2021. The data cover both

supply-side and demand-side variables, including detailed records of electricity generation, gas consumption, heat recovery, and building energy loads. The availability of such an extensive dataset enables researchers and policymakers to conduct in-depth analyses of energy efficiency, system transitions, and operational strategies over the lifecycle of DERs.

3.6.1 Description of the integrated energy system serving the campus

The dataset was collected from the district building energy system situated in Kitakyushu Science and Research Park in Kyushu, Japan [143]. Detailed structure and energy flows of the energy station are depicted Figure 3-7. These buildings encompass two offices, a laboratory, a gymnasium, a library, a classroom and office complex building. This energy system was implemented in 2001, consisting of various components, namely rooftop solar PV panels, fuel cell, gas engine, gas boiler, and absorption chillers. The gas engine has a nominal power capacity of 160 kW, with a nominal power generation efficiency of 28.7%. The fuel cell has a power capacity of 200 kW, with a nominal power production efficiency of 40%. Fuel cell runs continuously for 24 hours every day, gas engine operates from 8:00 am to 10:00 pm throughout the year. The fuel cell and gas engine operate in a CCHP mode to supply simultaneous heat and power energy. The nominal capacity of the solar photovoltaic system is 153 kW and 13% module efficiency. All power generators operate in off-grid mode, PV generation is self-consumed, the on-site generators are operated to fulfill the baseload requirements, while grid import is utilized to cover the remaining electricity load. The absorption chillers have cooling and heating generating capacities of 2110 kW and 1780 kW, respectively. The nominal energy conversion efficiencies for cooling and heating supply are 1.1 and 0.93, respectively. The recovered waste heat from the CHP generators, along with city gas consumption, drives the operations of the absorption chiller systems for building space heating and cooling purposes. The gas boiler has a hot water generating capacity of 80 kW, it is responsible for meeting the daily hot water demand when the recovered waste heat is insufficient to fulfill the requirements.

The district energy system provides electricity, hot water, space heating, and cooling services to a total of six buildings within the park.

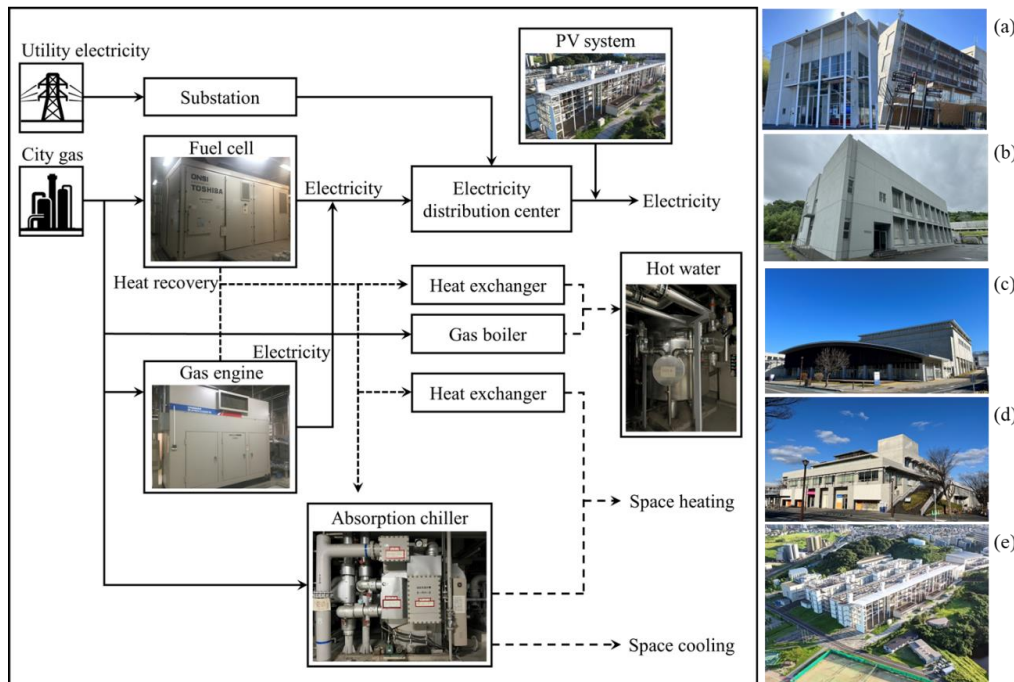


Figure 3-7 Schematic of the energy supply system and exteriors of buildings in Japan

3.6.2 Operational data of diverse building communities

To comprehensively evaluate the demand-side energy usage patterns, a dataset was collected involving a diverse building district in Japan, which encompasses campus, residential, and commercial communities, as illustrated in Figure 3-8. The selected district is composed of three primary community types: campus, residential, and commercial. Each community type exhibits distinct functional characteristics and energy usage patterns, thereby offering a rich context for the assessment of distributed energy system planning and operation. The campus community includes educational and administrative buildings with relatively high occupancy fluctuations and prominent daytime electricity consumption. The residential community consists of apartment complexes and housing units, characterized by morning and evening peaks in energy demand corresponding to occupants' daily routines. The commercial community encompasses office buildings and retail spaces, where energy consumption is typically aligned with business

hours and commercial activities. The diversity within this district enables a comprehensive evaluation of how different building types contribute to overall energy demand and how integrated system planning can optimize resource allocation.

The analysis period for the case study is carefully segmented into three representative seasons to accurately capture the variations in energy demand and system operation. The summer season spans from May 15 to October 15, totaling 154 days, during which space cooling becomes a predominant demand in response to elevated outdoor temperatures. The winter season, defined from December 4 to March 15 (102 days), is characterized by increased requirements for space heating due to colder climatic conditions. The remainder of the year is classified as the mid-season, with moderate temperatures resulting in transitional energy needs. This seasonal segmentation allows for the detailed examination of how heating and cooling loads fluctuate over the year and provides critical input for evaluating the flexibility and adequacy of energy supply systems under various operational scenarios.

In addition to seasonal energy demand fluctuations, the communities in the district maintain year-round requirements for electricity and domestic hot water. These persistent demands significantly impact the overall energy system design, as they establish a baseline load that must be consistently served alongside the more variable heating and cooling needs. The total annual heat demand within the district is thus composed of both space heating, which is primarily concentrated in the winter months, and domestic hot water, which is required throughout the year. Recognizing these patterns is essential for optimizing distributed energy resource planning and ensuring reliable system operation across all seasons.

Within this framework, space heating demand is considered only during the winter season, while space cooling is primarily addressed in the summer. Electricity consumption and domestic hot water demand are monitored continuously throughout the year, ensuring a

complete and accurate representation of annual building energy usage. The total heat demand for the community is calculated as the sum of space heating and domestic hot water requirements. By analyzing the demand-side data across different building types and seasons, the study provides valuable insights into the dynamic supply-demand balance and the specific characteristics of energy consumption in a real-world, mixed-use district environment.

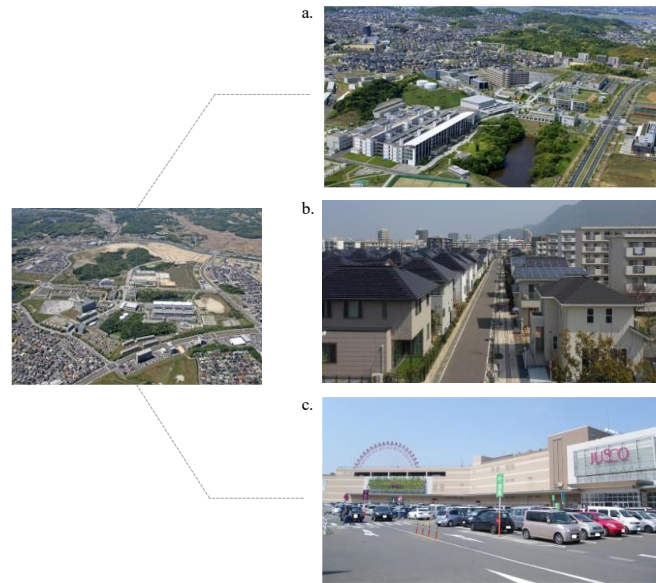


Figure 3-8 Schematic diagram of the diverse building district, a. Campus building community; b. Residential building community; c. Commercial building community

3.7 Summary

This chapter established a comprehensive foundation for the analysis and optimization of building-EV integrated community energy systems, presenting the research framework, methodology, and test resources adopted in the study. The chapter began with an overview of the integrated community energy system, emphasizing the importance of coupling building energy consumption, electric vehicle (EV) charging demands, and grid interactions to enhance energy efficiency, flexibility, and decarbonization. The system's hybrid structure—incorporating onsite renewables, distributed storage, EVs, and flexible grid connections—

enables advanced energy management strategies and supports both peer-to-grid (P2G) and peer-to-peer (P2P) electricity trading paradigms.

- A robust hybrid research methodology was introduced, combining detailed simulation modeling with real-world measurement data. Building prototype models were used to simulate diversified community load profiles across residential, office, commercial, and campus settings. A Monte Carlo Markov Chain (MCMC) approach was developed to capture the stochastic and dynamic nature of EV travel and charging behaviors within these communities. The integrated modeling of both building and EV loads enables a realistic evaluation of demand-side dynamics under different operational scenarios.
- The chapter further detailed the modeling of the district-level energy system, structured as a multi-carrier energy station that integrates electricity, heating, cooling, and heat recovery subsystems. Mathematical models for key components—such as PV panels, wind turbines, CCHP units, heat pumps, gas boilers, absorption chillers, and energy storage devices—were constructed to reflect their operational characteristics and interdependencies. Internal electricity trading mechanisms, including TOU tariffs and a dynamic P2P pricing model, were incorporated to facilitate flexible and economic energy exchanges among building communities.
- Finally, the chapter presented a unique, high-resolution 20-year dataset from a real-world campus district energy system in Japan, encompassing diverse building types and seasonal operational data. This dataset provides a valuable empirical basis for model calibration, validation, and scenario analysis, ensuring the practical relevance of the simulation results and optimization strategies developed in this research.

Overall, this chapter establishes the essential analytical and empirical groundwork, supporting subsequent chapters focused on system optimization, electricity trading, and policy evaluation for future integrated community energy systems.

CHAPTER 4 CAPACITY DESIGN OPTIMIZATION

METHOD FOR INTEGRATED COMMUNITY ENERGY

SYSTEMS

This chapter presents the capacity design optimization method for community energy systems, aiming at achieve an optimal balance among economic efficiency, system reliability, and environmental sustainability. Focusing on the integrated energy system (IES) within communities, the chapter first introduces the system structure and operational principles, highlighting the interactions among key components. The Golden Section Method is then employed as an effective approach for preliminary capacity sizing and narrowing the solution space. To address the competing objectives of economic efficiency, system reliability, and environmental sustainability, a multi-objective optimization method is developed, including the formulation of the optimization problem, constraint definition, and a hybrid solution methodology integrating advanced algorithms. The optimization results are subsequently analyzed, with detailed discussion on the performance and energy supply-demand balance of the optimized configurations. The chapter concludes by summarizing the key findings, providing a solid foundation for the subsequent evaluation and analysis.

4.1 Description of the integrated energy system serving multiple communities

The district energy system represents a comprehensive and integrated approach to meeting the diverse energy needs of modern building communities. By leveraging multiple energy sources, advanced conversion technologies, and flexible storage solutions, the district energy system is designed to enhance energy efficiency, operational flexibility, and environmental sustainability.

The system architecture is characterized by the close coupling of electricity, heating, and cooling networks, enabling the optimal allocation and utilization of energy resources within the community. This section introduces the overall structure of the district energy system and elaborates on the operational principles that govern its efficient and sustainable functioning.

4.1.1 Integrated energy resources

The IES serving building communities is composed of four essential components: energy input, energy conversion, energy storage, and end-users. The energy input layer incorporates a variety of primary and secondary energy sources, including natural gas, solar radiation, wind energy, and electricity from the utility grid. The energy conversion layer consists of multiple devices, such as combined cooling, heating, and power (CCHP) systems, gas boilers (GB), solar photovoltaic (PV) panels, wind turbines (WT), absorption chillers (AC), and heat pumps (HP). These devices are responsible for transforming primary energy into usable forms of electricity, heating, and cooling according to the dynamic demands of the community.

Energy storage plays a pivotal role in balancing supply and demand fluctuations, enhancing system reliability, and enabling greater integration of renewable energy. The IES incorporates both electric storage (batteries, BAT) and heat storage tanks (HST), which store surplus electricity and thermal energy, respectively, for later use. The end-user layer comprises various types of buildings and facilities within the community, each with distinct electricity, heating, and cooling requirements. The interconnectedness of these components is illustrated in Figure 4-1, which depicts the energy supply-demand framework of the IES and highlights the bidirectional interactions with the external power grid.

In this configuration, the CCHP system serves as a central hub, simultaneously providing electricity and heat, while also enabling the recovery of waste heat for further utilization. Gas boilers and heat pumps supplement the heating supply, particularly during periods of high

demand or low renewable generation. PV panels and wind turbines contribute clean electricity, supporting the community's decarbonization goals. Absorption chillers and heat pumps are deployed to meet cooling loads, with their operation coordinated to maximize efficiency and minimize energy costs. The integration of energy storage units further enhances the system's flexibility, allowing for the temporal shifting of energy supply and demand, and facilitating participation in demand response and grid services.

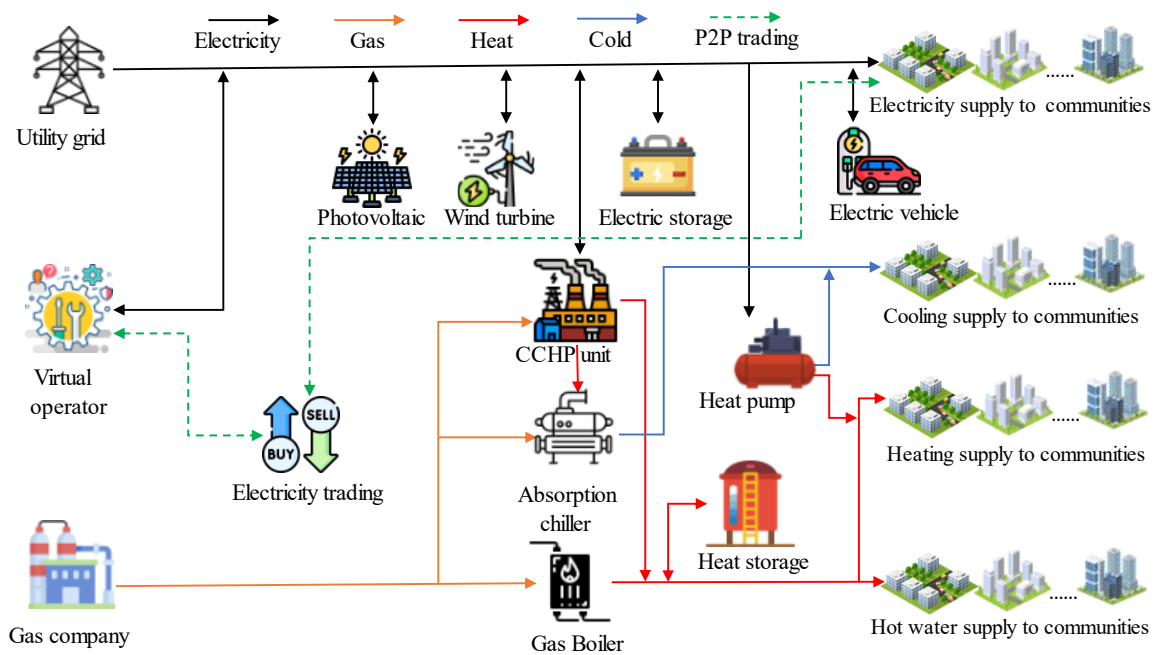


Figure 4-1 Schematic diagram of energy supply-demand structure of IES

4.1.2 Conventional operation principles

The operation of the IES is governed by a set of coordinated strategies that prioritize renewable energy utilization, optimize the use of available resources, and ensure reliable energy supply to all end-users. The overarching operational philosophy is to maximize the consumption of locally generated renewable energy, thereby reducing dependence on external energy sources and minimizing carbon emissions. The system follows the principles of “heating load follows cooling load” and “electricity load follows heating load,” which guide the sequential allocation of energy resources to meet the varying demands for cooling, heating, and electricity throughout the day and across seasons. The specific procedures for electricity, heating, and

cooling supply strategies are illustrated in Figure 4-2. By implementing these operation principles, the IES achieves a high degree of flexibility and resilience, enabling it to adapt to fluctuating energy demands, variable renewable generation, and external grid conditions. The integrated control of electricity, heating, and cooling supply, combined with the strategic use of energy storage, allows the system to deliver reliable, cost-effective, and low-carbon energy services to the community, supporting long-term sustainability and decarbonization objectives.

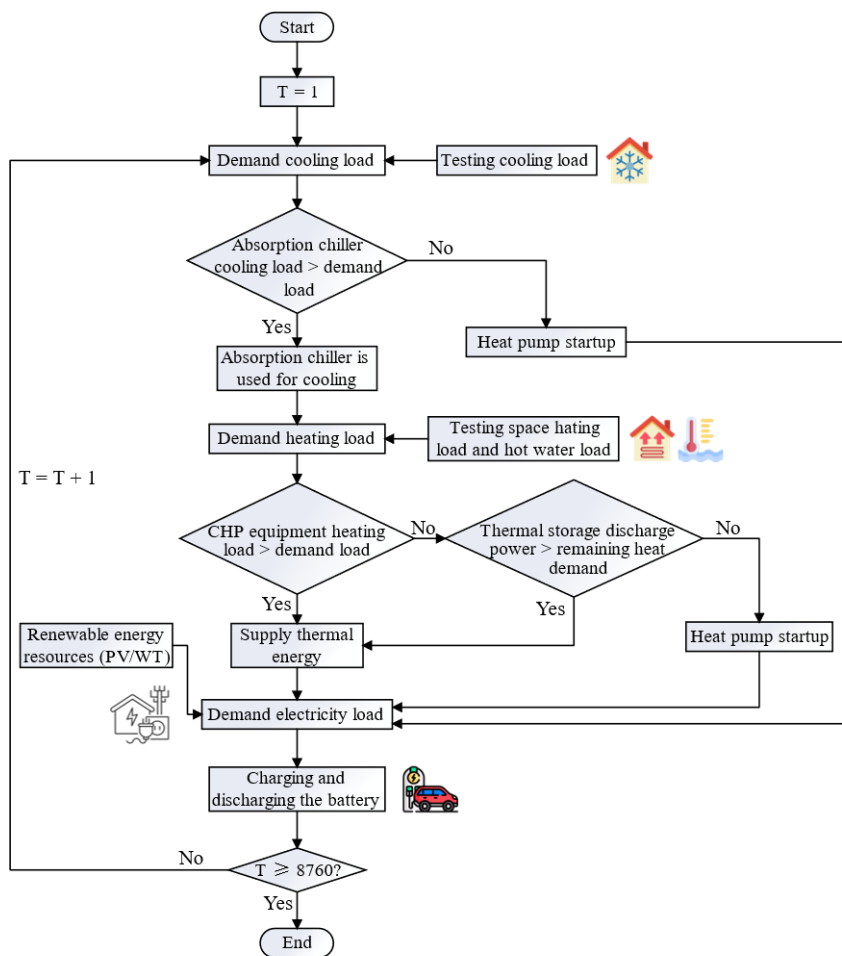


Figure 4-2 Flowchart of the energy complementary operation strategy of the IES

4.1.2.1 Electricity Supply Strategy

The IES prioritizes the use of electricity generated from PV panels, wind turbines, and the CCHP system to meet the community's electricity demand. Additionally, waste heat recovered from the CCHP process is utilized to generate extra electricity via ORC equipment, further improving overall system efficiency. Surplus electricity, after meeting immediate demand, is

stored in the battery. If the battery reaches its storage limit, any remaining excess electricity can be exported to the utility grid. Conversely, during periods of insufficient local generation, the system first discharges stored electricity from the battery to bridge the gap, and only resorts to purchasing electricity from the grid as a last resort to ensure uninterrupted supply.

4.1.2.2 Heating Supply Strategy

Heating demand is primarily met by the CCHP system, which provides both electricity and heat. When the heat output from the CCHP is insufficient, the system draws on stored thermal energy from the heat storage tank. If both the CCHP and HST cannot fully satisfy the heating load, the gas boiler is activated to provide additional heat. The heat pump operates as a supplementary device, particularly during peak demand periods or when other sources are unavailable, ensuring that the heating requirements of all end-users are consistently met.

4.1.2.3 Cooling Supply Strategy

Cooling is supplied mainly by the absorption chiller and the heat pump. The absorption chiller operates at its rated capacity to meet as much of the cooling load as possible. When the cooling demand exceeds the capacity of the absorption chiller, the heat pump is engaged to supply the remaining cooling requirement. This coordinated operation ensures that cooling loads are met efficiently, leveraging the strengths of both technologies and optimizing overall system performance.

4.2 Introduction to the golden section method

In this study, the golden section method is employed as an efficient approach to optimize the battery capacity within the IES. Serving as the first layer of the overall system optimization framework, this method focuses on determining the most cost-effective size of the energy storage system by minimizing the battery's life cycle cost (LCC), as illustrated in Figure 4-3.

The golden section method is a widely used interval search algorithm, renowned for its simplicity and convergence efficiency in solving unimodal optimization problems.

The optimization process begins by defining the objective function as the total LCC of the battery system, which accounts for both the initial investment and operational costs over its lifespan. By iteratively narrowing the search interval based on the golden ratio, the method efficiently identifies the optimal battery capacity that yields the lowest LCC. This enables the system to avoid over-sizing or under-sizing the storage, thereby achieving a balanced trade-off between investment and operational savings. Throughout the optimization, hourly input data for an entire year are utilized, ensuring that the battery dispatch is evaluated under realistic and dynamic energy demand and supply conditions. The dispatch performances of various energy management strategies are systematically compared, including PV self-consumption, grid interaction, utilization of storage systems, and overall cost performance. By integrating the golden section method into the system optimization framework, the study provides a robust, data-driven basis for battery sizing decisions, ultimately enhancing the economic and operational efficiency of the integrated energy system.

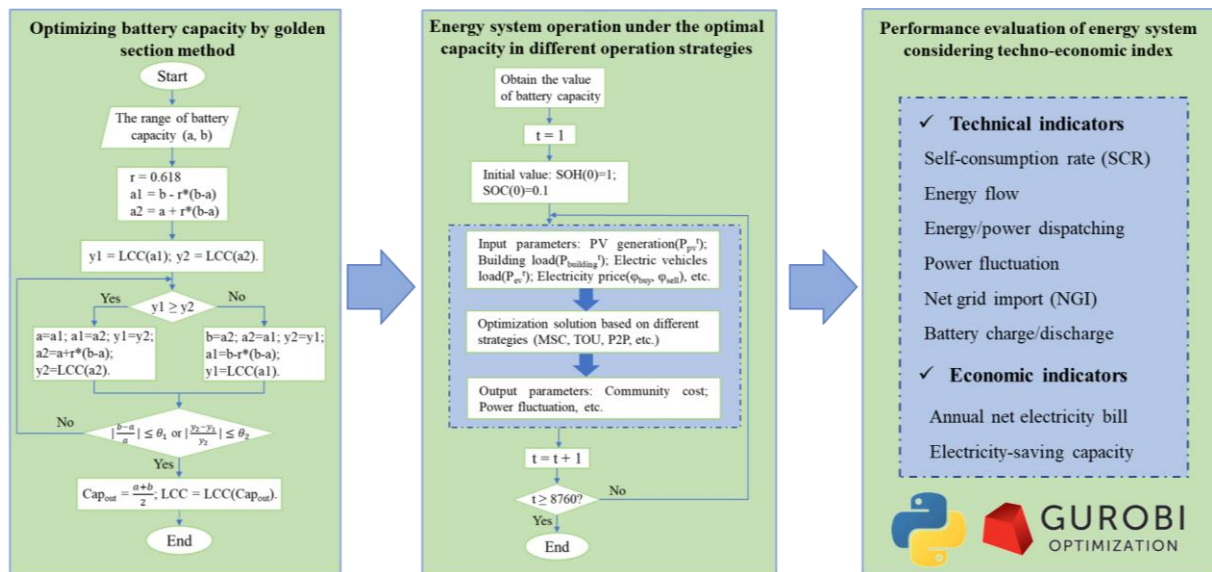


Figure 4-3 Schematic diagram of golden section method in energy system capacity optimization and performance evaluation

4.3 Multi-objective optimization method

The multi-objective optimization method developed in this study aims to determine the optimal capacity configuration of IES components by simultaneously considering economic, technical, and environmental objectives. By formulating a comprehensive multi-objective optimization model and employing a hybrid solution methodology, the approach ensures that the resulting IES design achieves a balanced trade-off among cost-effectiveness, system stability, and carbon emission reduction. The following subsections detail the formulation of the multi-objective optimization problem, the solution methodology, and the performance evaluation metrics adopted in the thesis.

4.3.1 Multi-objective optimization problem formulation

This study aims to determine the optimal capacity of IES components, focusing on three key aspects: economic efficiency, system stability, and carbon emissions. A multi-objective optimization model is developed to simultaneously address these objectives, evaluating the annual total cost to ensure economic efficiency, the system electricity independence to assess self-sufficiency in meeting electricity demand, and the annual carbon emissions to minimize environmental impact. By concurrently optimizing these three objectives, the study seeks to identify a capacity optimization strategy that balances cost-effectiveness, energy independence, and environmental sustainability, thereby establishing an efficient and sustainable IES capable of supporting long-term decarbonization goals.

In this study, the multi-objective function is employed to optimize the capacity of various energy-related equipment. The optimization process identifies the most appropriate capacity levels for generators, energy storage systems, boilers, chillers, and other pertinent components within the IES. The decision variables for the optimal capacity are delineated in Eq. (4.1), whereas the objective function is articulated in Eq. (4.2).

$$X = [U_{pv}, U_{wt}, U_{gt}, U_{ac}, U_{hp}, U_{gb}, U_{bat}, U_{hst}] \quad (4.1)$$

$$\min F = \omega_1 \cdot ATC + \omega_2 \cdot SEI + \omega_3 \cdot ACE \quad (4.2)$$

4.3.1.1 Technical objective

The system electricity independence (SEI) is recognized as a key technical objective to evaluate power grid stability, which is defined as the ratio of the power purchased from the utility grid to the total demand load of the system [31]. This relationship can be mathematically formulated using Eq. (4.3).

$$SEI = \frac{\sum_{t=1}^T P_{buy}^t}{\sum_{t=1}^T P_{load}^t} \quad (4.3)$$

4.3.1.2 Economic objective

The economic objective function minimizes the annual total cost (ATC) of the IES, incorporating various components. These elements consist of the initial investment cost (C_{inv}), operation and maintenance cost ($C_{o\&m}$), replacement cost (C_{re}), and energy cost (C_e). The ATC of the IES can be expressed as defined in Eq. (4.4).

$$ATC = C_{inv} + C_{o\&m} + C_{re} + C_e \quad (4.4)$$

The initial investment cost of the integrated energy system primarily comprises the acquisition expenses of the relevant equipment. Additionally, in line with the system's service life and the optimization objective of a yearly basis, the investment cost is distributed over each year. This distribution can be mathematically expressed using Eqs. (4.5) - (4.6).

$$C_{inv} = \sum C_k \cdot U_k \cdot F_{cr} \quad (4.5)$$

$$F_{cr} = \frac{i(1+i)^y}{(1+i)^y - 1} \quad (4.6)$$

The O&M cost of the integrated energy system primarily encompasses the expenses associated with maintaining and servicing the operational equipment. This cost can be expressed mathematically using Eq. (4.7).

$$C_{o\&m} = \sum_{t=1}^T \sum_k C_{o\&m,k} \cdot P_k^t \quad (4.7)$$

The replacement cost is determined based on the equipment's life cycle and initial investment. This cost is divided and allocated over each year to account for the replacement expenses of the equipment. The mathematical expressions for calculating the replacement cost of the equipment can be expressed as Eqs. (4.8) - (4.9).

$$C_{re} = \sum C_{r,k} \cdot F_{rk} \quad (4.8)$$

$$F_{rk} = \frac{1}{(1+i)^k} \cdot \frac{i(1+i)^y}{(1+i)^y - 1} \quad (4.9)$$

The energy cost in the IES includes the expenses associated with purchasing gas consumed by the gas turbine, gas boiler, and absorption chiller. Additionally, it encompasses the cost of purchasing electricity from the utility grid when the internal power generation of the system is insufficient. The energy cost can be mathematically represented by Eq. (4.10).

$$C_e = c_{gas} \sum_{t=1}^T \sum V_{gas}^t + c_{grid,p} \sum_{t=1}^T \sum P_{buy}^t \quad (4.10)$$

4.3.1.3 Environmental objective

The environmental objective minimizes greenhouse gas emissions, with a specific focus on reducing carbon dioxide emissions. Within the IES, carbon emissions primarily originate from direct sources such as natural gas combustion and fuel consumed by EVs, along with indirect sources arising from grid power procurement, depicted in Eq. (4.11).

$$ACE = \mu_{c,g} \sum_{t=1}^T (V_{CCHP}^t + V_{gb}^t) + \mu_{c,go} \sum_{t=1}^T V_{EV}^t + \mu_{c,e} \sum_{t=1}^T P_{buy}^t \quad (4.11)$$

4.3.1.4 Technical, economic, and environmental parameters

This section establishes and evaluates the key parameters necessary for the optimization process, focusing on the system's technical and economic aspect. The operational lifespan of the system is set as 20 years, with a 5% inflation rate and a 5% residual value rate. Additionally, the gas price for the IES is \$0.39 per cubic meter, and the electricity price includes the TOU rates and FiT subsidies for power purchase and sale, as shown in Figure 3-5 in Section 3.5.1. The technical characteristics of the equipment primarily include efficiency and rated power, while economic factors such as lifespan, initial investment outlay, and operation and maintenance expenses are also specified. These parameters are summarized in Table 4-1 and Table 4-2 [144, 145]. Furthermore, Table 4.3 provides carbon emission coefficients for natural gas combustion in gas-powered equipment and the indirect carbon emission factors from grid electricity purchases.

Table 4-1 Detailed technical parameters of equipment

Equipment	Parameters	Value
CCHP	Heat recovery rate from the harvest (η_{wh})	0.5
	Coefficient of heating from harvested heat (δ_{wh})	0.95
	Harvest heat heating efficiency (ε_{wh})	0.45
	CCHP power generation efficiency(η_e)	0.3
	Carbon emission factor for natural gas ($\text{kg} \cdot \text{kWh}^{-1}$)	0.21
AC	COP of absorption chiller	1.3
HP	COP when refrigerating (ASHP)	2.5
	COP when heating (ASHP)	3.3
GB	Heating efficiency (η_{gb})	0.9
BAT	Charging efficiency (η_c)	0.95
	Discharging efficiency (η_{dc})	0.95
	$\text{SOC}_{\max}$	0.8
	$\text{SOC}_{\min}$	0.2
HST	Heat charging efficiency($\eta_{c,h}$)	0.9
	Heat discharging efficiency($\eta_{dc,h}$)	0.9
	$\text{HSS}_{\max}$	0.8
	$\text{HSS}_{\min}$	0.2

Table 4-2 Technology costs and annual rate of decline estimated under different scenarios

Equipment	Economic parameters	2010	2030	2050	Annual rate
PV	Initial investment cost (\$·kW ⁻¹)	740	160	33	0.925
	O&M cost (\$·kWh ⁻¹)	0.05	0.05	0.05	/
	Operational lifespan (Year)	20	20	20	/
WT	Initial investment cost (\$·kW ⁻¹)	870	185	38	0.925
	O&M cost (\$·kWh ⁻¹)	0.03	0.03	0.03	/
	Operational lifespan (Year)	20	20	20	/
GT+ORC	Initial investment cost (\$·kW ⁻¹)	1700	1030	620	0.975
	O&M cost (\$·kWh ⁻¹)	0.05	0.05	0.05	/
	Operational lifespan (Year)	20	20	20	/
AC	Initial investment cost (\$·kW ⁻¹)	280	100	36	0.95
	O&M cost (\$·kWh ⁻¹)	0.048	0.048	0.048	/
	Operational lifespan (Year)	20	20	20	/
HP	Initial investment cost (\$·kW ⁻¹)	270	96	34	0.95
	O&M cost (\$·kWh ⁻¹)	0.06	0.06	0.06	/
	Operational lifespan (Year)	20	20	20	/
GB	Initial investment cost (\$·kW ⁻¹)	270	96	34	0.95
	O&M cost (\$·kWh ⁻¹)	0.04	0.04	0.04	/
	Operational lifespan (Year)	20	20	20	/
BAT	Initial investment cost (\$·kW ⁻¹)	540	156	45	0.94
	O&M cost (\$·kWh ⁻¹)	0.018	0.018	0.018	/
	Operational lifespan (Year)	10	10	10	/
HST	Initial investment cost (\$·kW ⁻¹)	37	11	3	0.94
	O&M cost (\$·kWh ⁻¹)	0.016	0.016	0.016	/
	Operational lifespan (Year)	10	10	10	/
EV	Additional cost (\$·kWh ⁻¹)	1645	24	0.4	0.81

Table 4-3 Parameters related to the environment

Parameters	Unit	Value	Notes and refs
Gasoline efficiency of private car	km·L ⁻¹	12.6	[146]
Gasoline price	\$·L ⁻¹	1.29	[146]
Gas price	\$·(m ³) ⁻¹	0.39	[147]
CO ₂ emission from gasoline	kg _{CO2} ·L ⁻¹	2.3	[148]
CO ₂ emission from electricity	kg _{CO2} ·kW ⁻¹	0.522	[144]
Low calorific value of natural gas	kJ·L ⁻¹	35.9	[147]
Carbon emission coefficient of natural gas	kg _{CO2} ·(m ³) ⁻¹	2.3	[148]
Utility grid carbon emission factor	kg·kWh ⁻¹	0.98	[145]
Fuel economy of EV	km·kWh ⁻¹	5.3	[144]

4.3.2 Optimization constraints

Two types of constraints should be considered in solving the optimization problems, including the system energy balance constraints and output constraints of energy devices. These constraints are vital in guaranteeing a balance between energy supply and demand, ensuring that the capacity of energy devices falls within specified limits, and that the operation of equipment complies with predefined conditions.

The energy equilibrium equations concerning electricity, cooling, and heat provision within the IES are delineated below. Within Eqs. (4.12) - (4.14), the left-hand side illustrates the cumulative energy output from diverse equipment at time t , whereas the right-hand side depicts the total energy demand at time t .

$$C_{ac}(t) + C_{hp}(t) = C_{load}(t) \quad (4.12)$$

$$H_{cchp}(t) + H_{gb}(t) + H_{hp}(t) + H_{hst}(t) = H_{load}(t) + H_{ac}(t) \quad (4.13)$$

$$P_{pv}(t) + P_{wt}(t) + P_{cchp}(t) + P_{buy}(t) + P_{orc}(t) = P_{load}(t) + P_{eb}(t) + P_{hp}(t) + P_{sell}(t) \quad (4.14)$$

Besides, the constraint on device output guarantees that the energy output stays within the designated minimum and maximum capacities of energy device k . Such constraint is mathematically represented as Eq. (4.15).

$$P_{k,\min}^t \leq P_k^t \leq P_{k,\max}^t \quad (4.15)$$

4.3.3 Solution for the multi-objective function

The Pareto solution set, comprising a collection of non-dominated solutions, is obtained by solving the multi-objective function (Eq.(4.2)), where each solution provides a trade-off among competing objectives. To address this multi-objective problem, our proposed method integrates the non-dominated sorting genetic algorithm III (NSGA-III), Shannon's entropy weighting method, and TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). By combining these methods, the approach ensures comprehensive exploration of the solution space, objective weighting of criteria, and effective identification of the best compromise solution, thereby enhancing the robustness and credibility of the decision-making process. As illustrated in Figure 4-4, the hybrid solution process involves three key steps: first, the Shannon's entropy weighting method calculates objective weights based on entropy values, with higher entropy indicating greater importance; second, NSGA-III, selected for its computational efficiency and robust convergence, employs evolutionary operators to identify the global Pareto-optimal solutions; and third, TOPSIS evaluates and ranks the solutions within the Pareto set to determine the best compromise. By combining these techniques, the approach effectively balances energy cost, grid stability, and carbon emissions, providing a robust framework for decision-making. The fundamental parameters of the algorithm include the population size, iteration times, crossover probability, and optimal population parameters. Table 4-4 provides specific details regarding the optimization parameters and the configuration

optimization boundaries. These parameters define the range within which the optimization algorithm operates and searches for optimal solutions.

Table 4-4 NSGA III algorithm optimization parameters.

Parameters	Unit	Value
Population size	/	200
Maximum number of iterations	/	100
Crossover probability	/	0.9
Optimal population parameters	/	0.3
Variation probability	/	0.1
PV configuration boundary	kW	[0,3000]
WT configuration boundary	kW	[0,3000]
GT configuration boundary	kW	[0,5000]
AC configuration boundary	kW	[0,3000]
HP configuration boundary	kW	[0,3000]
GB configuration boundary	kW	[0,3000]
BAT configuration boundary	kWh	[0,20000]
HST configuration boundary	kWh	[0,8000]

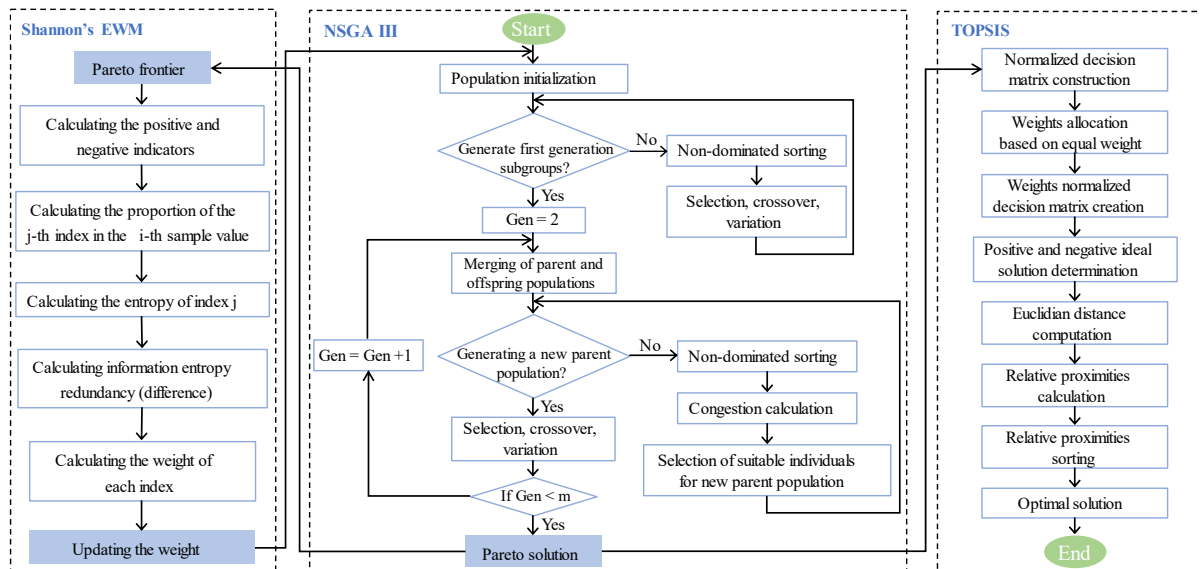


Figure 4-4 Process of the three-stage comprehensive solution method

4.4 Results and analysis

This section presents the key results and analysis of the IES modeling and optimization for the diverse building district. The findings encompass demand load characterization, optimal capacity design under the 2010 scenario, and the evaluation of energy supply-demand balance based on the optimal system configuration.

4.4.1 Demand load of diverse building communities

The demand profiles for the case study are constructed using comprehensive load data collected from three representative building communities: campus, residential, and commercial sectors. For the year 2010, a total of 8,760 hours of electricity, heating, and cooling load data were obtained for each community. These hourly loads were subsequently aggregated to establish a benchmark demand profile for the entire diversified building district. The resulting dataset captures the temporal and seasonal variations in energy demand across different building types, reflecting the complexity and heterogeneity of community-scale energy systems. The annual distributions of electricity, heating, and cooling loads under various carbon emission scenarios are illustrated in Figure 4-5, providing a foundational reference for subsequent optimization and scenario analysis.

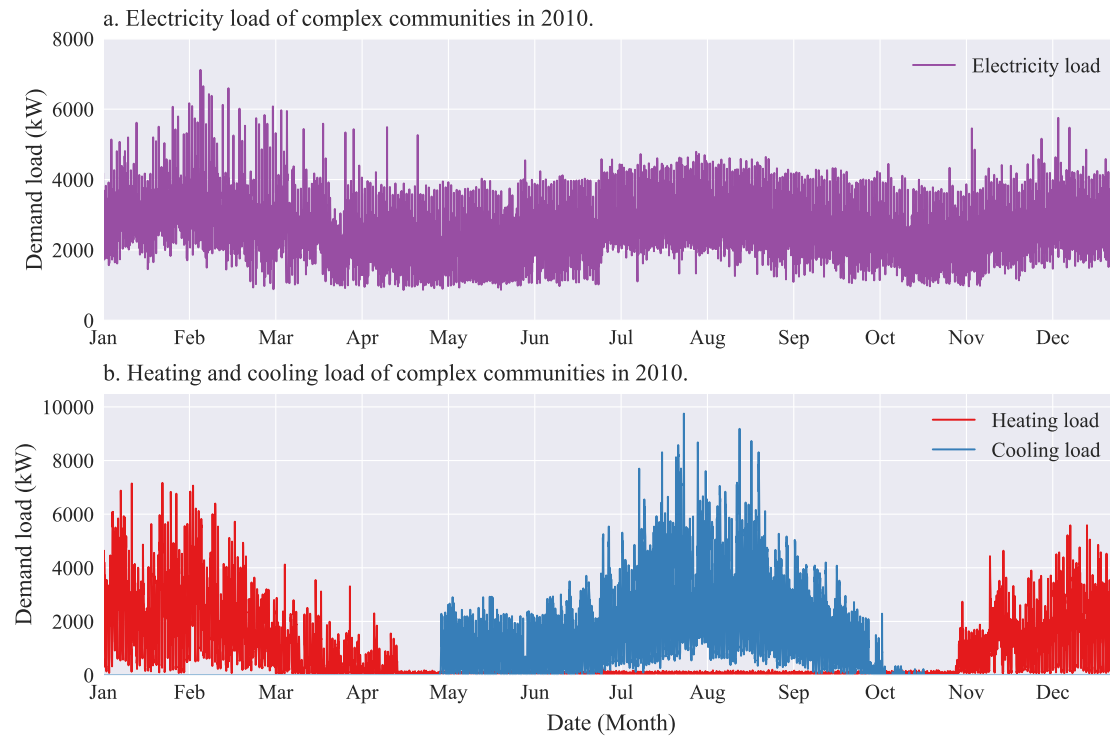


Figure 4-5 Demand load of complex communities in 2010

4.4.2 Optimized capacities of energy components

The optimal capacity configuration of the IES for 2010 was determined through multi-objective optimization using the NSGA-III algorithm. The optimization model simultaneously considers three key objectives: annualized total cost (ATC), system energy independence (SEI), and annual carbon emissions (ACE). The Pareto front, as depicted in Figure 4-6, visualizes the trade-offs among these objectives, forming a three-dimensional surface that represents 122 alternative design schemes under the 2010 scenario. The results clearly demonstrate the inherent conflicts between cost, independence, and emissions: improvements in one objective typically lead to compromises in others. To facilitate effective decision-making, the TOPSIS method is employed to rank the Pareto-optimal solutions and identify the most balanced and practical system configuration for further analysis.

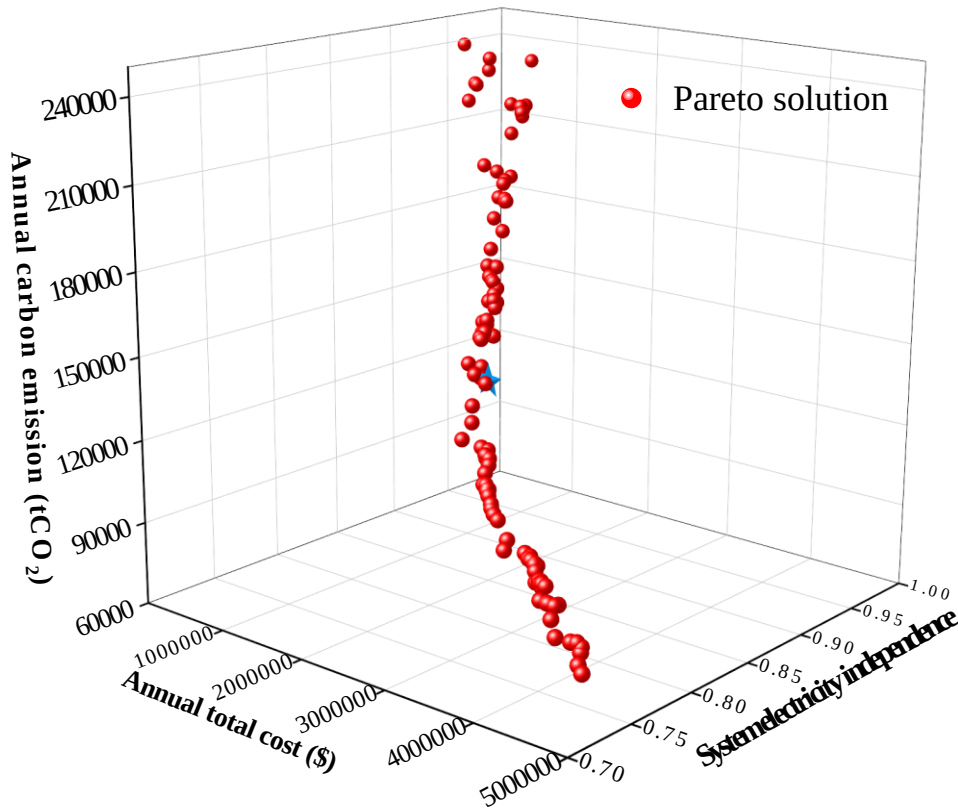


Figure 4-6 The obtained Pareto frontier in 2010 scenario by NSGA III algorithm

4.4.3 Energy supply and demand balance under the optimal capacity

Under the optimal capacity configuration identified for the year 2010, the energy supply and demand balance analysis reveal a heavy reliance on primary energy consumption and conventional technologies, as shown in Figure 4-7. The CCHP system is central to the district's energy supply, providing significant proportions of electricity, heating, and cooling. Specifically, 62.7% of the electricity demand is met by imports from the utility grid, while CCHP units supply 31.8%, and only 5.4% is covered by on-site renewable generation from PV and wind turbines. For cooling, the absorption chiller—primarily driven by waste heat from CCHP—accounts for 97.8% of the cooling load, while the remainder is met by electricity-driven heat pumps. Heating requirements are fulfilled mainly by gas boilers (59.8%) and CCHP (35.2%), with heat storage systems providing supplementary support during peak demand periods.

This configuration underscores the limited penetration of renewable and electrified technologies in 2010, as the energy system predominantly depends on fossil-fuel-based infrastructure due to prevailing cost, efficiency, and policy considerations. The preeminence of CCHP and gas boilers reflects the technological and economic landscape of the time, where reliability and established solutions were prioritized over emerging renewable alternatives. These insights provide a critical baseline for evaluating future transitions toward higher shares of renewables and electrification in district energy systems.

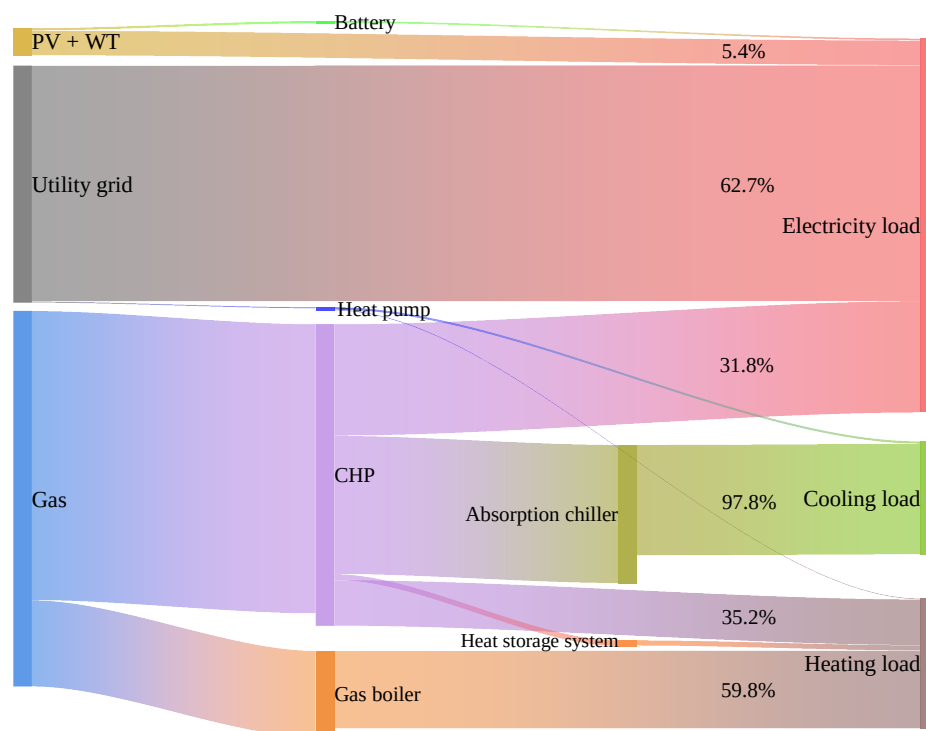


Figure 4-7 Energy supply-demand distribution under the optimal capacity in 2010 scenario

4.5 Summary

This chapter has systematically developed and demonstrated a comprehensive capacity design optimization framework for community integrated energy systems. Beginning with an overview of the district energy system's structure and operational principles, the chapter clarified how multi-energy coupling, advanced conversion technologies, and flexible storage solutions can be leveraged to enhance efficiency, reliability, and environmental sustainability

within community-scale applications. The operational strategies for electricity, heating, and cooling supply were detailed, emphasizing the importance of renewable integration, waste heat recovery, and coordinated use of storage.

- The golden section method was introduced as an effective first-layer tool for preliminary sizing of battery storage, enabling rapid solution space reduction and ensuring cost-effective investment in energy storage systems. By minimizing the battery's life cycle cost under realistic, hourly dispatch scenarios, the method provides a robust basis for subsequent, more complex optimization.
- A multi-objective optimization model was then formulated to address the conflicting goals of economic efficiency, energy independence, and carbon emission reduction. The hybrid solution methodology—integrating the NSGA-III algorithm, Shannon entropy-based weighting, and TOPSIS—proved effective in exploring the Pareto front of optimal capacity schemes and in objectively ranking the trade-off solutions.
- The results for the 2010 baseline scenario revealed the dominant role of conventional CCHP and gas boilers, reflecting limited renewable and electrified technology penetration at the time. Specifically, 62.7% of electricity demand was met by grid imports, 31.8% by CCHP units, and only 5.4% by on-site renewables. For heating, gas boilers and CCHP contributed 59.8% and 35.2%, respectively, while absorption chillers driven by CCHP waste heat accounted for 97.8% of cooling supply.

Overall, the approaches and results presented in this chapter provide a robust foundation for understanding and guiding the future evolution of community energy systems. The developed framework enables systematic evaluation of alternative capacity configurations under diverse objectives and constraints, thereby supporting informed decision-making for cost-effective, reliable, and low-carbon energy transitions at the district scale.

CHAPTER 5 ASSESSMENT OF CONVENTIONAL RULE-BASED ENERGY MANAGEMENT STRATEGIES UNDER PEER-TO-GRID AND PEER-TO-PEER TRADING PARADIGMS

This chapter systematically investigates the performance of conventional rule-based energy management strategies under both peer-to-grid (P2G) and peer-to-peer (P2P) trading paradigms in diversified building communities. Building upon the capacity optimization results and modeling framework established in the previous chapter, the study first reviews widely-used demand-side strategies, including the maximum self-consumption (MSC) strategy, time-of-use (TOU) strategy, and mid-market rate (MMR) based P2P strategy. A novel demand response-based P2P strategy is then proposed, with its mathematical formulation and operational constraints outlined to address emerging flexibility needs. The evaluation leverages realistic configurations and load profiles of representative building communities to ensure comprehensive assessment. Through comparative analysis of system operation and techno-economic performance, the chapter demonstrates the advantages of advanced P2P strategies—particularly those integrating demand response—in enhancing energy efficiency, economic benefits, and grid stability. The findings provide important insights for the development of future community energy management methods.

5.1 Introduction of widely-used demand-side energy management strategies

The effective management of electricity consumption in community energy systems is crucial for maximizing renewable energy utilization, reducing operational costs, and enhancing system flexibility. To this end, several rule-based energy management strategies have been developed

and widely adopted in practice. These strategies are typically categorized into peer-to-grid (P2G) and peer-to-peer (P2P) paradigms, each offering distinct mechanisms for energy allocation, trading, and cost optimization. This section reviews the operational principles of three mainstream strategies: the MSC rate based P2G strategy, the TOU based P2G strategy, and the MMR based P2P strategy.

5.1.1 Peer-to-grid strategy based on maximum self-consumption rate

The MSC strategy is a fundamental and commonly adopted rule in grid-connected PV-integrated storage systems. Its core principle is to prioritize the direct consumption of locally generated PV electricity by building loads and storage systems within the community. When PV generation exceeds the current load, the surplus energy is first stored in the battery system; if further excess remains, it is exported to the utility grid. Conversely, when PV generation cannot fully meet the load demand, the battery discharges to supplement the supply. If both PV and battery are insufficient, the system imports electricity from the grid. This sequential dispatch ensures maximum on-site utilization of renewable energy, reduces grid dependency, and can help lower overall energy costs. The detailed operational logic of the MSC strategy is depicted in the flow chart in Figure 5-1.

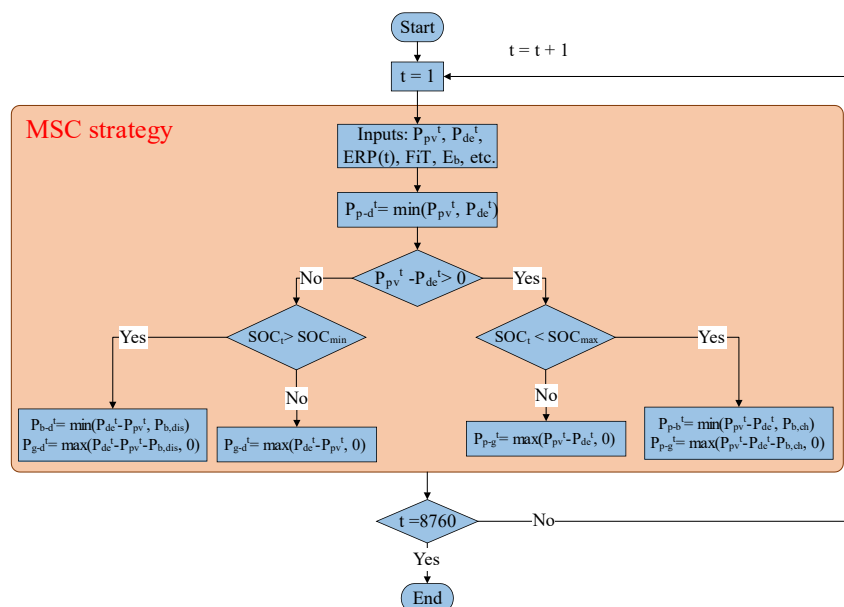


Figure 5-1 Flow chart of the MSC operation strategy

5.1.2 Peer-to-grid strategy based on time-of-use pricing

The TOU strategy leverages the temporal variation in electricity prices to optimize economic benefits. In this study, a uniform TOU tariff structure is applied across all building types, including residential, office, commercial, and campus communities, to ensure consistent economic signals and enable fair comparison of strategy performance. In this approach, the community energy management system actively schedules the charging of batteries during off-peak periods when electricity prices are low, either from the grid or from other communities with surplus generation. During peak periods, when prices are high, stored energy is discharged to meet local demand or even sold back to the grid or other communities. This strategy enables both cost savings for consumers and potential revenue generation by exploiting price differentials, while also contributing to load leveling and grid stability. The operational process for the TOU strategy is illustrated in Figure 5-2.

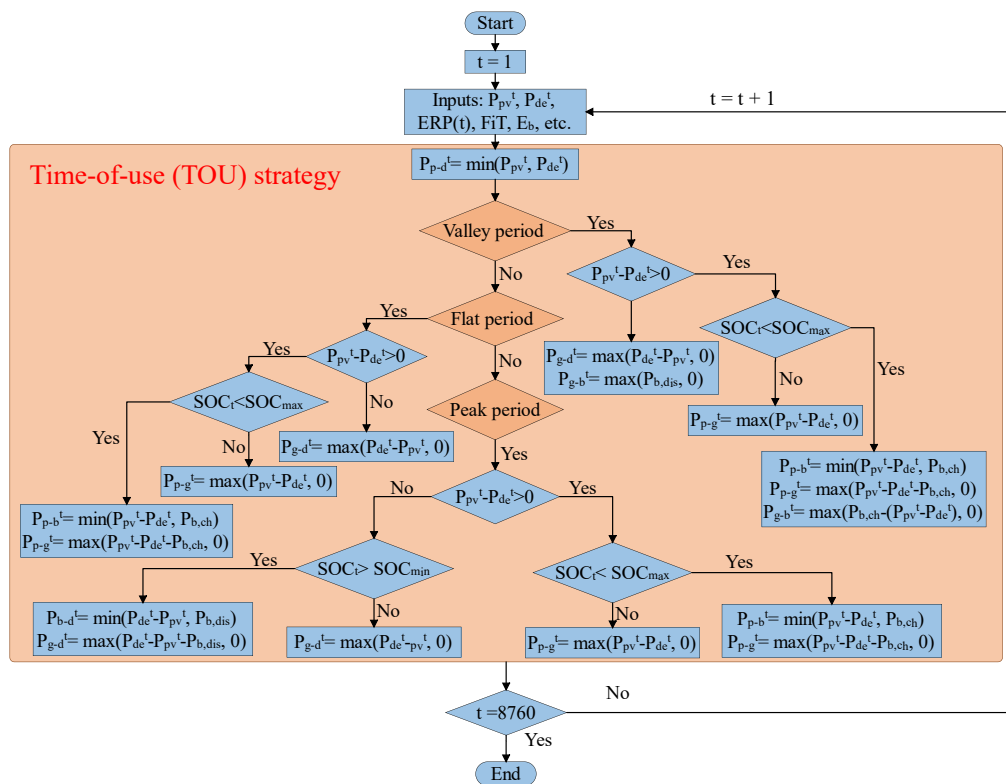


Figure 5-2 Flow chart of the TOU strategy

5.1.3 Peer-to-peer strategy based on Mid-market rate

The MMR based P2P strategy focuses on P2P trading of surplus renewable energy among community members based on a common mid-market rate. This strategy enables community members to sell and buy renewable energy from each other, optimizing energy utilization within the community. The MMR mechanism sets the internal energy trading price at the midpoint between the export price and the retail price, ensuring fair benefits for both energy producers and consumers [34]. Each prosumer provides separate energy bids for generation and demand, allowing for a balanced revenue distribution. The flow chart for the MMR based P2P strategy is illustrated in Figure 5-3. Based on the relationship between total electricity generation and demand within the diversified energy community, the internal prices under this strategy are defined in different scenarios:

- (1) If the generation is equal to demand, the internal buying and selling price are equal, taking the average of the export and retail price:

$$P2P_{buy, t} = P2P_{sell, t} = P_{average, t} = \frac{P_{retail, t} + P_{export, t}}{2}, \text{ if } \sum |E_{gen, t}| = \sum E_{dem, t} \quad (5.1)$$

- (2) When the power generation is less than the demand, the deficit generation must be compensated by importing electricity from the retailer (utility grid, etc.), and the cost of this import should be covered. Consequently, the internal selling price remains the same as the Eq. (B1), but the buying price is modified as shown in Eq. (5.2):

$$\begin{cases} P2P_{buy, t} = \frac{\sum |E_{gen, t}| \cdot P_{average, t} + (\sum E_{dem, t} - \sum |E_{gen, t}|) \cdot P_{retail, t}}{\sum E_{dem, t}}, & \text{if } \sum |E_{gen, t}| < \sum E_{dem, t} \\ P2P_{sell, t} = P_{average, t} = \frac{P_{retail, t} + P_{export, t}}{2} \end{cases} \quad (5.2)$$

- (3) Similarly, if the power generation exceeds the demand, the surplus needs to be sold to the retailer (utility grid, etc.) at the export price based on the Feed-in-tariff scheme. This

additional income should be distributed among all the prosumers who contributed electricity through generation and battery discharging. The P2P internal price is illustrated in Eq. (5.3):

$$\begin{cases} P_{2P_{buy}, t} = P_{average, t} = \frac{P_{retail, t} + P_{export, t}}{2} \\ P_{2P_{sell}, t} = \frac{\sum E_{dem, t} \cdot P_{average, t} + \left(\sum |E_{gen, t}| - \sum E_{dem, t} \right) \cdot P_{export, t}}{\sum |E_{gen, t}|}, \text{ if } \sum |E_{gen, t}| > \sum E_{dem, t} \end{cases} \quad (5.3)$$

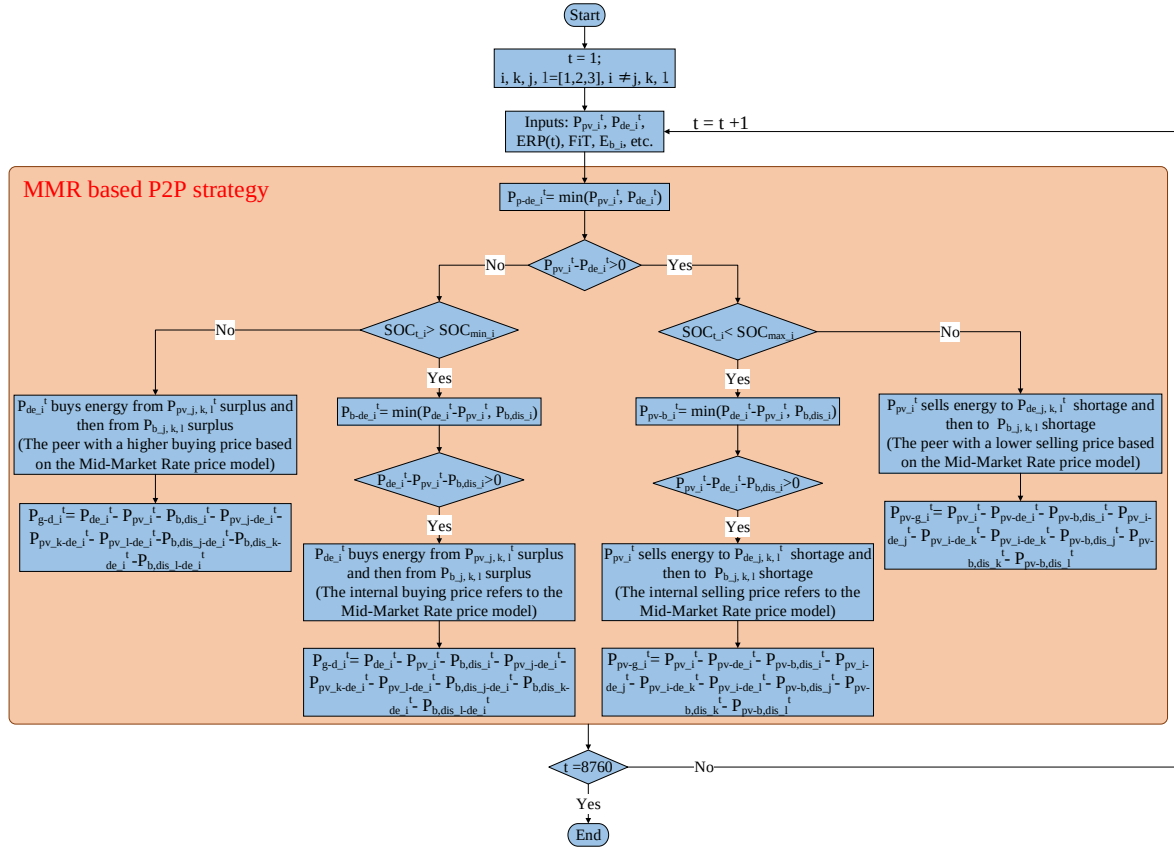


Figure 5-3 Flow chart of the MMR based P2P strategy

5.2 A novel peer-to-peer trading strategy based on demand response

Building on conventional P2P trading frameworks, this study proposes an advanced DR based P2P strategy that dynamically integrates user flexibility into the energy trading process. Unlike static rule-based schemes, the DR-based P2P strategy actively engages building communities by providing dynamic pricing signals, encouraging them to adjust consumption patterns in

response to grid or market conditions. Community members can shift or curtail loads during peak price periods, thereby optimizing energy utilization and creating new opportunities for local P2P trading.

5.2.1 Mathematical formulation of the strategy

This strategy incorporates demand response programs, allowing participants to voluntarily modify their energy usage in exchange for economic incentives. The price formation for P2P trading is based on a model described in Section 3.5.2, while the utility cost function integrates both power purchase expenses and the comfort costs associated with load shifting, as depicted in Eq. (5.4). The optimization problem is formulated as a non-cooperative game, where each building community acts as a player selecting its electricity consumption strategy to maximize profit (defined as the negative of the utility cost). The detailed flow chart demonstrating DR based P2P strategy is depicted in Figure 5-4.

$$C_{i,t}(x_{i,t}) = P_{i,t} \cdot (x_{i,t} - E_{pv,i}) + \alpha_i(x_{i,t} - E_{de,i}) \quad (5.4)$$

$$C_i = \sum_{t=1}^T C_{i,t}(x_{i,t}) \quad (5.5)$$

$$P_{i,t} = f(SDR_i) \quad (5.6)$$

In the diversified building communities, all building community form the game players. The optional strategy for building community i is its electricity consumption x_i for each time period, where $P_{ii} = -C_i$ is the profit function of building community i . This game can be defined as:

$$G = \{x_1, x_2, \dots, x_n; Pr_1, Pr_2, \dots, Pr_n\} \quad (5.7)$$

Besides, the trading behavior under different electricity prices among different building communities can form a non-cooperative game, and a distributed optimization method is utilized to solve the Nash equilibrium solution of the proposed strategy as shown in Eqs (5.8) and (5.9).

$$SOC_b^{\min} \leq SOC_b^t \leq SOC_b^{\max} \quad (5.13)$$

$$SOC_{ev}^{\min} \leq SOC_{ev}^t \leq SOC_{ev}^{\max} \quad (5.14)$$

(4) Demand response regulating power limit

In demand response regulation, the maximum regulated power of demand response is restricted to 10% of the total demand load. Additionally, it's important to note that the total load demand throughout the day remains the same even after the implementation of demand response regulation.

$$0.9E_{de, i} \leq x_{i, t} \leq 1.1E_{de, i} \quad (5.15)$$

$$\sum_{t=1}^{24} x_{i, t} = \sum_{t=1}^{24} E_{de, t} \quad (5.16)$$

5.3 Simulated community energy systems for strategy evaluation

This section outlines the configuration of representative building communities that serve as the basis for evaluating various energy management strategies. By selecting diversified community types and characterizing their respective load profiles, a robust and comprehensive framework is established for subsequent strategy assessment. The focus is on ensuring that the selected communities and their energy consumption patterns are both realistic and representative of typical urban environments.

5.3.1 Selection of representative building communities

To facilitate a comprehensive evaluation of energy management strategies, four distinct building communities are selected as representative case studies. These communities are chosen based on their prevalence in urban settings and their diverse energy consumption characteristics. Specifically, the targeted communities include: (1) a university campus community, which comprises approximately 30 teaching and office buildings; (2) a residential

building community, consisting of twenty mid-rise and twenty high-rise apartment buildings; (3) an office building community, made up of twenty medium-sized and twenty large office buildings; and (4) a commercial retail building community, which includes twenty standalone retail buildings. The relationship between these prototype buildings and the building community is depicted in Figure 3-3 in Section 3.3.2. The selection of these communities is informed by literature and relevant standards, ensuring that the study covers a broad spectrum of building functions and operational patterns. By focusing on these four community types, the evaluation framework is able to capture the unique energy demand profiles and operational characteristics associated with different building uses.

5.3.2 Community load characterization

The energy load profiles of the selected building communities are established using a combination of measured and simulated data. For the campus community, actual annual energy consumption and hourly load data from PolyU for the year 2015 are utilized, providing a realistic basis for analysis. For the residential, office, and retail communities, load profiles are generated through simulation based on prototype building models specified in relevant building energy codes and standards. These profiles reflect both the annual and hourly variations in energy demand, which are essential for accurately assessing the performance of different energy management strategies. Additionally, the integration of PV power generation is considered for each community, with the corresponding generation profiles derived from local solar irradiance data and available rooftop areas. The resulting load and generation data, as illustrated in Figure 5-5 and summarized in Table 2, provide a comprehensive foundation for the comparison and evaluation of energy strategies across the different community types.

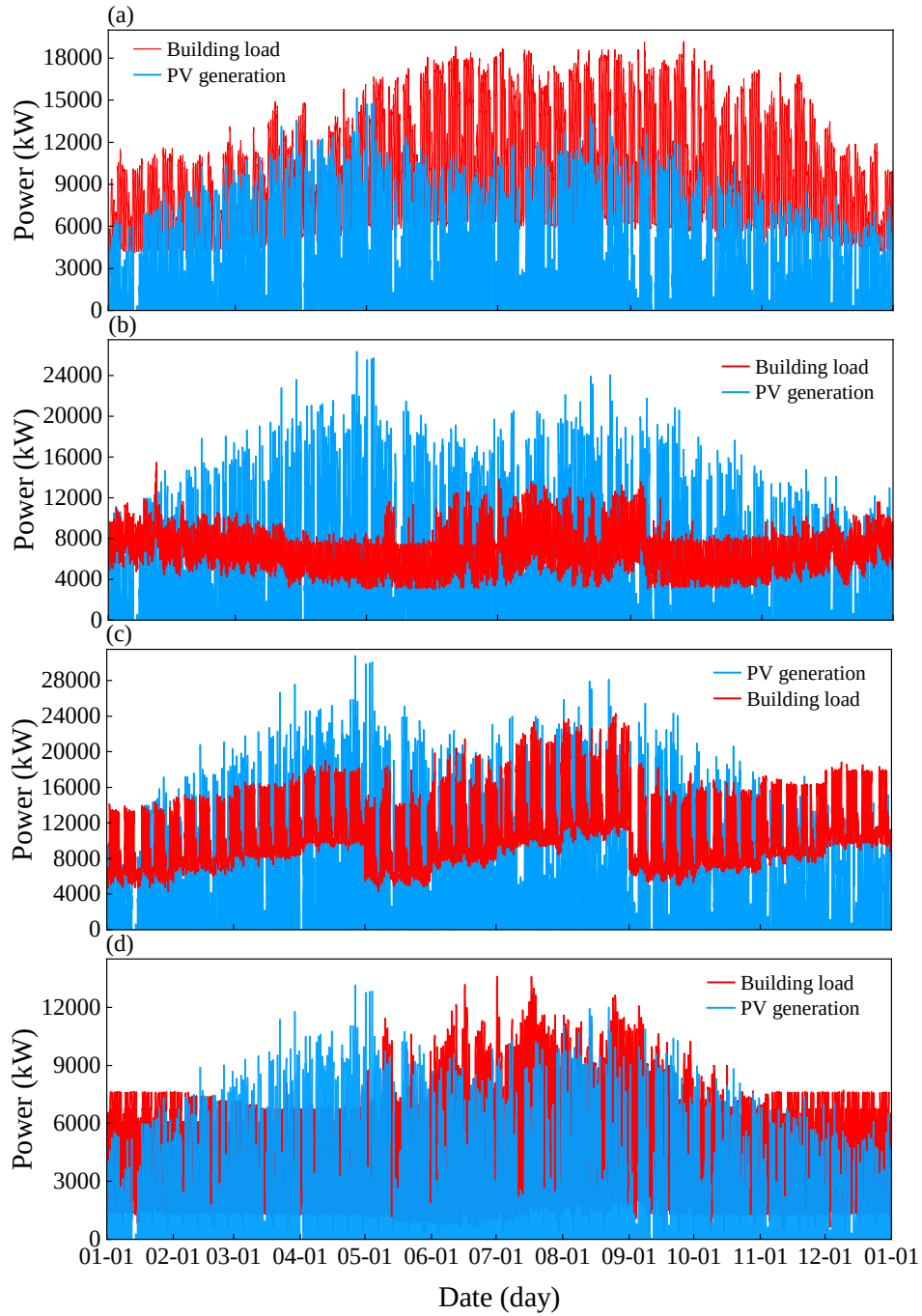


Figure 5-5 Demand load and power generation of building communities: (a) campus, (b) residential building, (c) office, (d) retail building

5.3.3 EV charging load

Using the MCMC method proposed in Section 3.3.3, the EV charging power for the diversified building communities is calculated based on census data. The EV charging power is categorized into weekday charging power and weekend charging power. Subsequently, the EV

charging power during typical workdays and weekends is determined by considering factors such as daily mileage demand, traffic models, and EV charging models. Figure 5-6 illustrates the distribution of EV charging power at different times. Significant variations in EV charging power exist among the different building communities in the region. In these diversified building communities, the residential building community and the commercial retail building community bear the primary EV charging load, accounting for approximately 40% and 30% of the total charging load, respectively. The office building community and the campus building community shoulder a charging load of around 5-10% of the total load, while the remaining charging power can be accommodated by other building communities. It is worth noting that the charging power and charging ratio of EVs in different building communities are influenced by EV policy incentives and the layout planning of EV charging stations in the city. The surveyed region in this study is located in Hunan Province, central China, where policy support for EVs is currently limited [44]. As a result, most EV charging stations are installed in residential building communities and commercial retail building communities. Therefore, these two building communities account for nearly 80% of the total EV charging power in the diversified building communities studied. Furthermore, the charging period for EVs in the region is predominantly concentrated during the mid-high or high electricity demand period, from 15:00 to 21:00, regardless of weekdays or weekends.

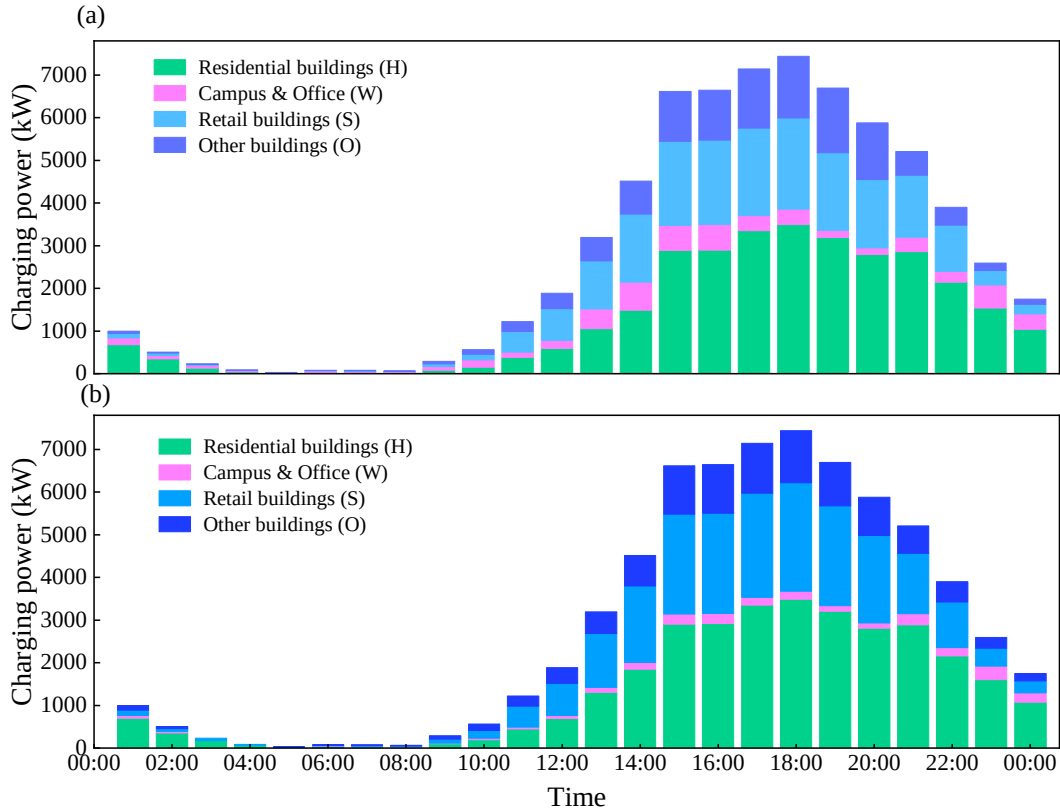


Figure 5-6 EV charging load distribution of diversified building communities: (a) weekdays, (b) weekends

5.3.4 Building load

By calculating the total building load and total EV charging load for each building community, the total demand load for each community can be determined. Table 5-1 presents the annual demand loads for the campus building community, residential building community, office building community, and commercial retail building community, which amount to 88,242,592 kW, 68,732,466 kW, 99,599,047 kW, and 47,634,609 kW, respectively. To provide an objective comparison of the differences in power generation and total electricity consumption among the various building communities, this study calculates the percentages of total power generation and total demand load for each community. The power generation and demand load ratios for the campus building community, residential building community, office building community, and commercial retail building community are 20.1%, 44.7%, 36.1%, and 32.2%, respectively.

Table 5-1 Annual power generation and consumption of diversified building communities

Building community	Power generation (kW)	Building load (kW)	Demand load (kW)	Power generation to demand load ratio (%)
Campus	17712794.0	86118157.6	88242592.0	20.1
Residential building	30735953.6	57330350.0	68732465.8	44.7
Office	35931685.9	97474612.3	99599046.6	36.1
Retail building	15353478.8	40681075.7	47634608.5	32.2

5.4 System operation and techno-economic performance analysis

This section presents a comprehensive analysis of the system operation and techno-economic performance of diversified building communities under four different operation strategies: MSC, TOU, MMR-based P2P, and DR-based P2P. The analysis covers dynamic energy dispatch, energy balancing, self-consumption rate, and total electricity cost, providing a holistic evaluation of the effectiveness and efficiency of each strategy in real-world scenarios.

5.4.1 Dynamic energy dispatch analysis

Figure 5-7 to Figure 5-10 depict the distribution of PV generation power and demand load, alongside the profiles of battery charging/discharging power and the variation of battery SOC over three consecutive weather days, considering four different operation strategies. The figures clearly indicate that the PV power generation in the campus community generally falls below the load demand for a significant portion of the time. Consequently, the campus community can be categorized as a typical building community lacking surplus generation power for storage in the battery or supply to the utility grid. Thus, the campus community primarily functions as a consumer within the broader spectrum of diversified building communities. In contrast, the residential building community demonstrates an excess of PV power generation during most daylight hours, enabling it to provide power to its battery, the

power grid, or other peer building communities. As a result, the residential building community operates as a prosumer within the diversified communities. Similarly, the office building community experiences surplus PV power generation during specific daylight hours, which can be utilized to charge its battery, supply the power grid, or contribute to other peer communities. Therefore, the office building community also functions as a prosumer within the diversified communities. Conversely, the commercial retail building community, akin to the campus community, has limited excess PV power generation available for supply to the power consumed side due to its substantial load demands.

Moreover, the battery power can be interpreted as follows: positive battery power indicates the charging power derived from surplus PV or grid generation, resulting in an increase in battery SOC. Conversely, negative battery power indicates the discharging power utilized to meet the building's load demand, causing a decrease in battery SOC. Similarly, positive power grid values indicate the importation of electricity from the grid, while negative power grid values signify the exportation of excess PV or battery power to the grid from the building community. Additionally, positive P2P power denotes the importation of excess electricity from other peer communities, whereas negative P2P power indicates the exportation of surplus PV power generation to other peer communities.

The figures demonstrate distinct charge/discharge processes and energy dispatch processes among the diversified building communities under the four operation strategies. In the MSC strategy, the battery's charge/discharge state and power are solely determined by the disparity between PV power and demand load. The battery charges when PV power surpasses the demand load and discharges otherwise. The rate of charge/discharge is proportional to the difference between PV power and load. Excess PV power beyond the battery's maximum charging capacity is exported to the grid. By comparison, in the TOU strategy, in addition to charging the battery when PV power exceeds the demand load, the battery is charged at the

maximum charging rate by the grid during the valley price period (00:00-07:00). The battery is discharged to meet the building and EV load during the peak price period (14:00-16:00, 19:00-21:00) when PV generation cannot fully cover them. The TOU strategy serves as a flexible arbitrage method by leveraging the price difference between peak and valley periods, and it helps alleviate pressure on the power grid by shifting load from peak to valley periods. Unlike the MSC and TOU strategies, the P2P strategies incorporate energy scheduling and electricity trading among different building communities through energy management systems. The P2P strategies achieve effective energy balance across the diversified building communities, reducing the dependence of the entire communities' demand load on the power grid and mitigating the impact of PV power generation on the grid. In the P2P strategy, when the PV power exceeds the community's demand load, the surplus power that would typically be exported to the grid is equally allocated and exported to other peer communities. The P2P strategy proves economically viable for both the entire diversified building communities and individual building community, as the purchasing and selling prices between peer communities fall between retail electricity prices (REP) and the feed-in-tariff (FiT) offered by the grid. Specific electricity prices are described in section 3.5. Moreover, within the P2P strategy, power dispatching priority is given to peer communities over direct electricity imports from the grid in cases where the load demand cannot be met. Similarly, when the generated power is in surplus, priority is given to exporting the excess power to peer communities rather than directly exporting it to the grid. This prioritization ensures efficient utilization of power resources within the P2P network. Thus, the P2P strategies treat power generation and consumption among different communities holistically, reducing the dependence and impact on the power grid by the diversified building communities. More importantly, the DR based P2P strategy comprehensively integrates the features of both the TOU and P2P strategies. On one hand, it enables arbitrage through battery charging and discharging during peak and valley

electricity price periods while shifting load from peak to valley demand periods. On the other hand, it leverages the P2P energy trading mechanism to balance the demand and supply among peer building communities. In the DR-based P2P strategy, the battery is charged during low-price periods and discharged during high-price periods to optimize the cost of electricity consumption. Additionally, excess PV power beyond the battery's capacity is allocated and traded among peer communities, ensuring efficient utilization of renewable energy resources.

Due to the varying characteristics of PV power generation and load demand across different building communities, the effectiveness of operation strategies differs accordingly. In building communities where PV power generation consistently falls short of the load demand throughout the day, such as the campus building community and commercial retail building community, reliance on power imports from the grid or peer communities is predominant. The MSC strategy is unsuitable for these communities as they lack surplus power generation for battery charging. However, the TOU strategy and P2P strategies have demonstrated greater efficacy in energy dispatch for these consumer-oriented communities. The TOU strategy effectively reduces dependence on grid power during peak electricity price periods, albeit leading to increased grid power imports during nighttime. Nevertheless, the dispatch capability of the TOU strategy is constrained by battery capacity and maximum discharge power. In contrast, the MMR based P2P strategy can further decrease grid power imports during daytime peak periods by importing electricity from peer communities, operating without power supply thresholds. The DR based P2P strategy offers even more substantial energy scheduling capabilities compared to separate TOU and MMR-based P2P strategy. Under the DR based P2P strategy, building communities can even export power to peer communities during peak load periods, significantly enhancing the distribution of grid power imports and contributing to the stable operation of the power grid. In contrast, residential and office building communities experience PV power generation that exceeds their load demand for most of the daytime,

resulting in significant surplus power. These communities act as prosumers, meeting their own demand while exporting excess power to the grid or peer communities. However, excessive power export to the grid during specific periods can potentially disrupt grid stability. For such prosumer-oriented communities, the TOU strategy enables power consumption to shift from daytime peak hours to nighttime valley hours. However, since peak hours coincide with maximum PV power generation, this leads to a higher power export to the grid and potential fluctuations in grid stability. In such scenarios, the P2P strategies proves effective in mitigating the concentration of excess power generation flowing into the grid. More importantly, the DR based P2P strategy treats all consumers and prosumers holistically within diversified building communities, prioritizing the export of surplus power to peer communities before exporting to the grid. This comprehensive approach ensures grid operation stability and offers substantial improvements over the other strategies.

In conclusion, the selection of an appropriate strategy depends on the specific characteristics of each building community within the diversified communities and their energy generation and consumption patterns. The MSC strategy, TOU strategy, and MMR based P2P strategy offer distinct advantages and trade-offs in energy dispatch, with the aim of optimizing self-consumption, achieving maximum economic efficiency, reducing reliance on the grid, and ensuring stable grid operation in diverse building community contexts. For consumer-oriented building communities, both the TOU strategy and DR based P2P strategy provide greater benefits in energy dispatch. However, for prosumer-oriented building communities, adopting the P2P strategies is a more suitable choice for their energy dispatch needs. In summary, the DR based P2P strategy treats all consumers and prosumers holistically within diversified building communities, prioritizing the export of surplus power to peer communities before exporting to the grid.

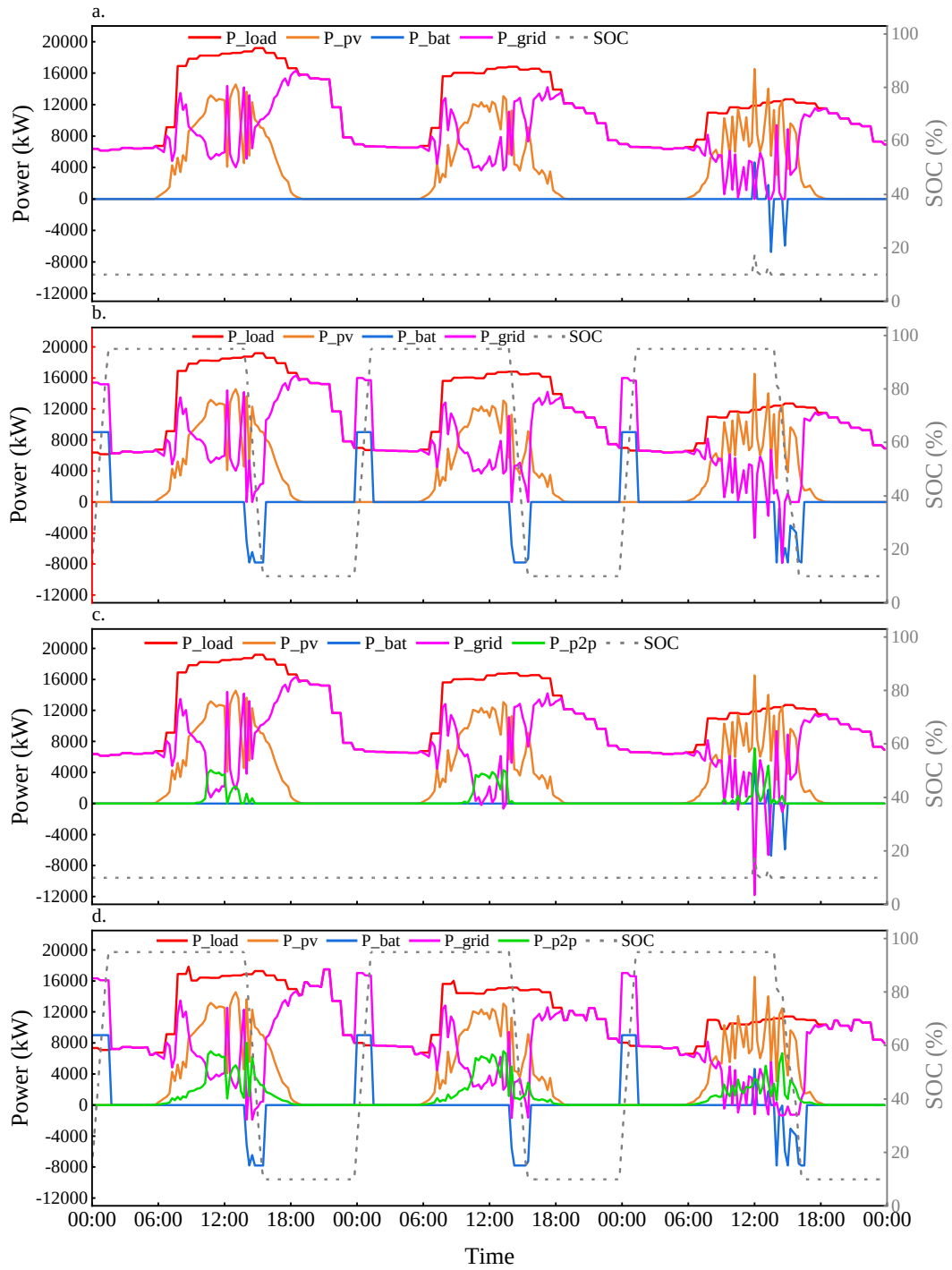


Figure 5-7 Energy dispatch distribution of campus community under different operation strategies: a. MSC strategy, b. TOU strategy, c. MMR based P2P strategy, d. DR based P2P strategy

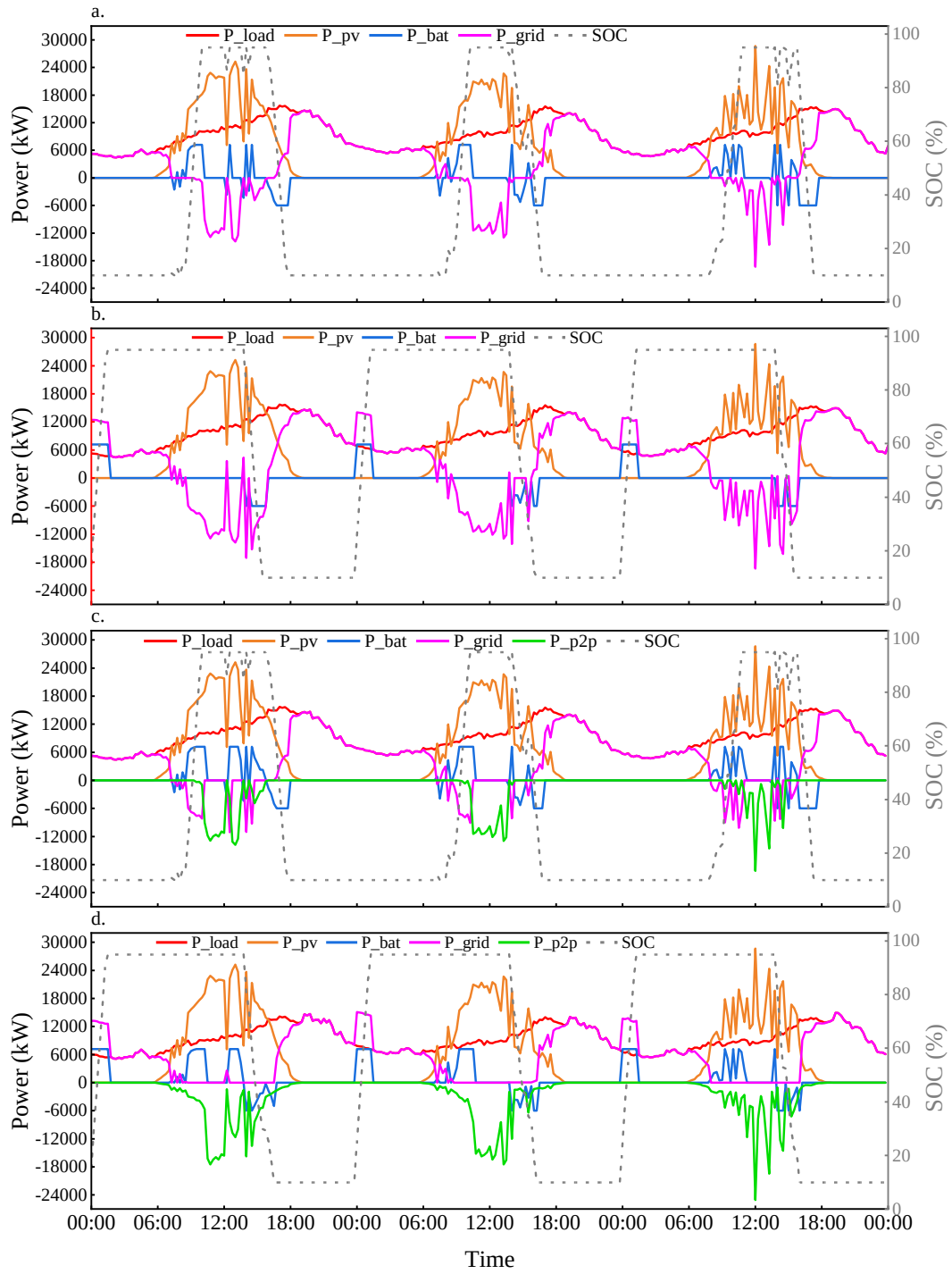


Figure 5-8 Energy dispatch distribution of residential building community under different operation strategies: a. MSC strategy, b. TOU strategy, c. MMR based P2P strategy, d. DR based P2P strategy

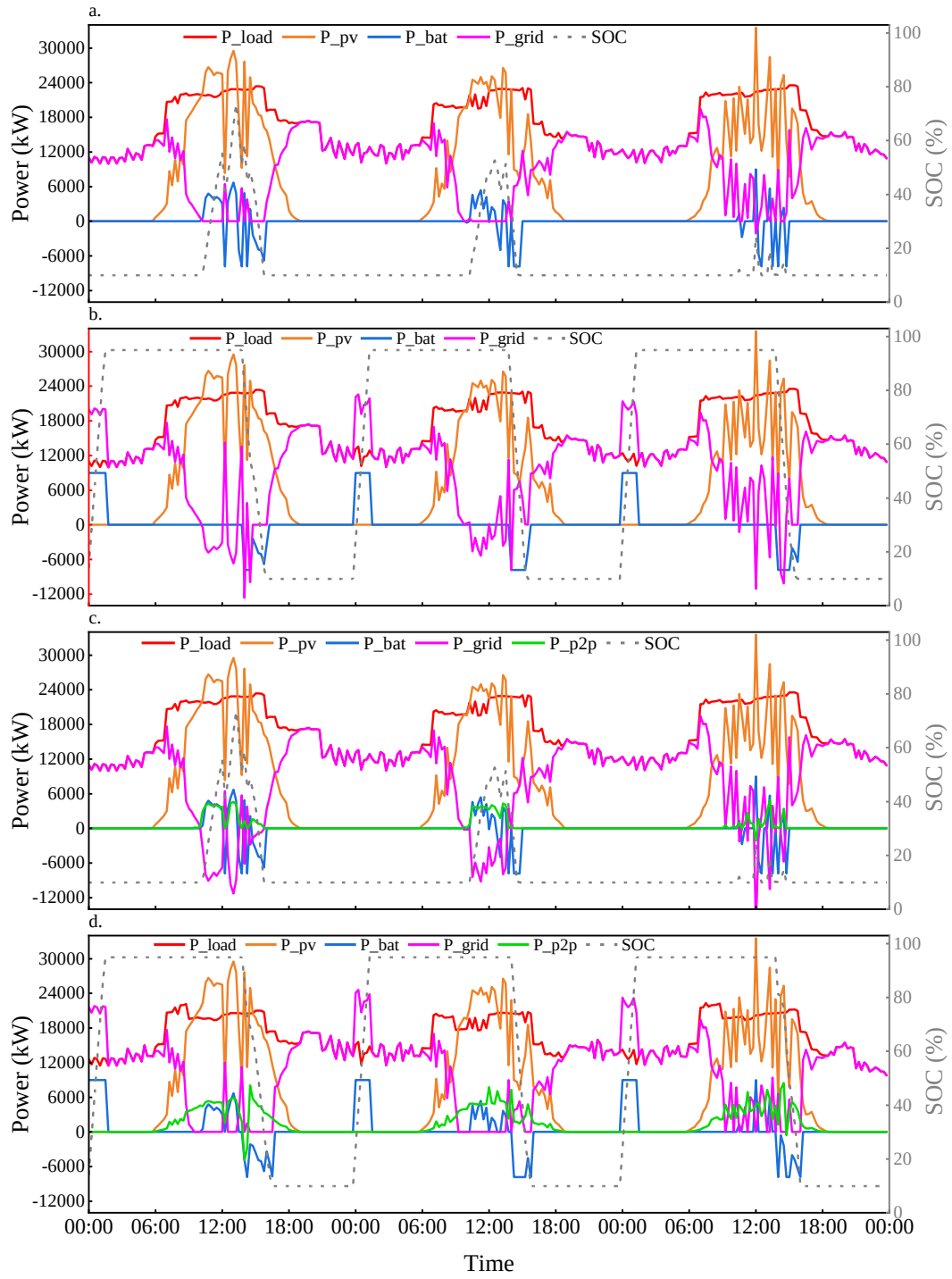


Figure 5-9 Energy dispatch distribution of office community under different operation

strategies: a. MSC strategy, b. TOU strategy, c. MMR based P2P strategy, d. DR based P2P

strategy

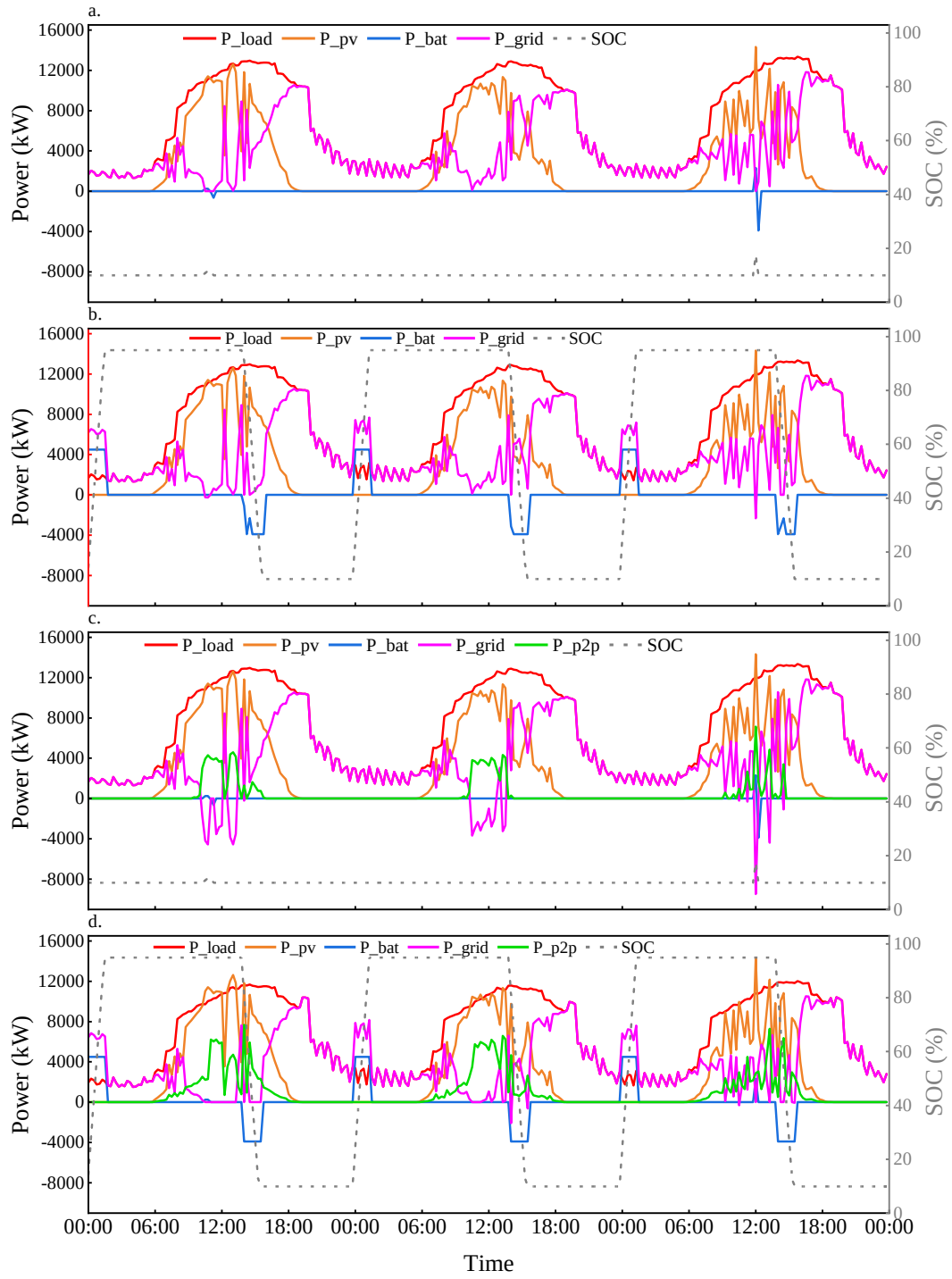


Figure 5-10 Energy dispatch distribution of retail building community under different operation strategies: a. MSC strategy, b. TOU strategy, c. MMR based P2P strategy, d. DR based P2P strategy

5.4.2 Energy supply-demand balance

The energy flow within diversified building communities under various operation strategies is presented in Table 5-2 and illustrated in Figure 5-11. Table 5-2 provides the percentage distribution of the entire building communities across different operation strategies, including grid import, PV generation to load, battery discharge, and electricity import from other peer communities. It is worth noting that the MSC strategy and TOU strategy do not involve electricity trading with other communities, resulting in zero electricity purchases from such sources. Under the MSC and TOU operation strategies, the diversified building communities account for approximately 98% and 94% of the total building electricity consumption, respectively. This consumption is achieved through electricity purchases from the power grid and on-site utilization of PV power generation. The key distinction between these two strategies lies in the comprehensive utilization of battery storage for peak-to-valley energy arbitrage in the TOU strategy. This approach minimizes the cost of building-side electricity purchases and reduces reliance on the power grid during peak electricity price periods. In contrast, the P2P operation strategies involve additional energy transactions with other peer communities in addition to grid power import, on-site PV consumption, and battery discharge. For instance, in the MMR-based P2P strategy, electricity input from the grid and on-site consumption of PV energy are roughly equal to the MSC and TOU strategies, accounting for 67.8% and 27.9% of the total energy consumption, respectively. Battery discharge represents 2.5% of the total energy consumption between the MSC and TOU strategies, while energy transactions with other peer communities contribute to 1.8% of the total energy consumption. Furthermore, the DR-based P2P strategy maximizes the benefits of energy trading between peer communities. Compared to other operation strategies, the DR-based P2P strategy reduces the proportion of electricity imported from the power grid and on-site PV consumption to total electricity consumption, reaching 62.1% and 23.5%, respectively. Notably, battery discharge

and electricity trading with other peer communities represent 5.6% and 8.8% of the total electricity consumption, respectively. In summary, P2P strategies, particularly the DR-based P2P strategy, offer significant advantages over the mainstream MSC and TOU operation strategies. They effectively alleviate pressure on the power grid by actively responding to electricity demand during peak hours and utilizing excess renewable energy generation from other building communities. These strategies promote electricity balance during peak and valley periods, enhancing the stability and reliability of electricity consumption within the diversified building communities.

Besides, Figure 5-11 provides an overview of the energy distribution among diversified building communities with varying power generation and consumption characteristics under different operation strategies. Specifically, residential and office building communities with a relatively high power generation to demand load ratio exhibit the following characteristics when participating in the MSC and TOU operation strategies. The proportion of PV power generation to the total electricity consumption in these building communities is approximately 37% and 32%, respectively. These values are lower than the ratios of PV power generation to building demand, which are 44.7% and 36.1%, respectively. In the MSC and TOU strategies, surplus electricity is exported to the grid at the feed-in-tariff price. Conversely, in the P2P operation strategies, the surplus PV power generated by residential and office building communities is primarily sold to other peer communities with lower ratios of PV power generation and building power consumption. This approach enhances the electricity balance across the entire diversified building communities, reduces dependence on the power grid, mitigates the impact of frequent electricity import and export, and achieves economic efficiency through price differences between the P2P trading price and the feed-in-tariff price. Moreover, for campus building community and commercial retail building community with a relatively low power generation to demand load ratio, these communities mainly rely on

electricity imports from the power grid to meet their electricity demands during periods of insufficient electricity consumption under the MSC and TOU operation strategies. However, importing significant amounts of electricity from the power grid during peak electricity price periods increases both the pressure on the power grid and the cost of purchasing electricity for the building community. In contrast, the DR-based P2P strategy enables building communities with lower power generation proportions to dynamically procure electricity from other peer communities at relatively low P2P trading prices during peak electricity price hours. This approach reduces the total electricity purchase cost for the building community while minimizing the impact on the stable operation of the power grid.

Furthermore, to provide a more comprehensive assessment of the impact of energy flow on the overall fluctuation of the power grid under different operation strategies, this section conducts a detailed analysis of the total energy inflow and outflow between different building communities and the power grid, as well as among different building communities throughout the year, as illustrated in Figure 5-12. Figure 5-12, it is observed that under the MSC and TOU operation strategies, all building communities primarily engage in electricity import and export with the power grid, indicating a significant dependence on the grid. However, under the P2P strategies, notable differences in the interaction between building communities and the power grid are observed. Residential building community and office building community, which have a high proportion of electricity generation, primarily import electricity from the grid when their power supply is insufficient. Surplus electricity generated on the building side is rarely exported to the grid. Instead, substantial electricity transactions occur between the building community and other peer communities. This highlights the efficient utilization of excess electricity within the P2P network and reduces reliance on the power grid. In contrast, under the P2P operation strategies, campus building community and commercial retail building community, with a relatively low proportion of power generation, not only import electricity

from the power grid but also receive electricity imports from other peer communities. This additional energy exchange further enhances the balance and complementarity of power generation and consumption within the diversified building communities. Furthermore, the DR based P2P strategy, compared to the MMR based P2P strategy, enables increased electricity trading with other peer building communities by actively participating in demand response measures during peak and off-peak electricity usage hours. The DR based P2P strategy allows for more significant electricity transactions between building communities, promoting efficient energy utilization and reducing dependence on the power grid.

To summarize, the P2P operation strategies effectively regulate the diverse power generation and consumption characteristics among building communities, enhancing the complementarity and balance of energy flow within the entire diversified building communities. Additionally, it reduces the total electricity cost for the building community by leveraging the price difference between P2P transaction prices and retail electricity prices or grid feed-in-tariff prices. Moreover, the P2P operation strategy decreases the dependence on the grid and mitigates its impact on building-side electricity consumption. These benefits are particularly significant in the case of the DR-based P2P strategy.

Table 5-2 The proportion of various energy flows in diverse energy communities under different operating strategies

Energy flow percentage (%)	MSC	TOU	MMR based P2P	DR based P2P
Grid import	69.8	67.8	67.8	62.1
PV generation to load	28.3	26.5	27.9	23.5
Battery discharge	1.9	5.7	2.5	5.6
Peer import	0	0	1.8	8.8
Total	100	100	100	100

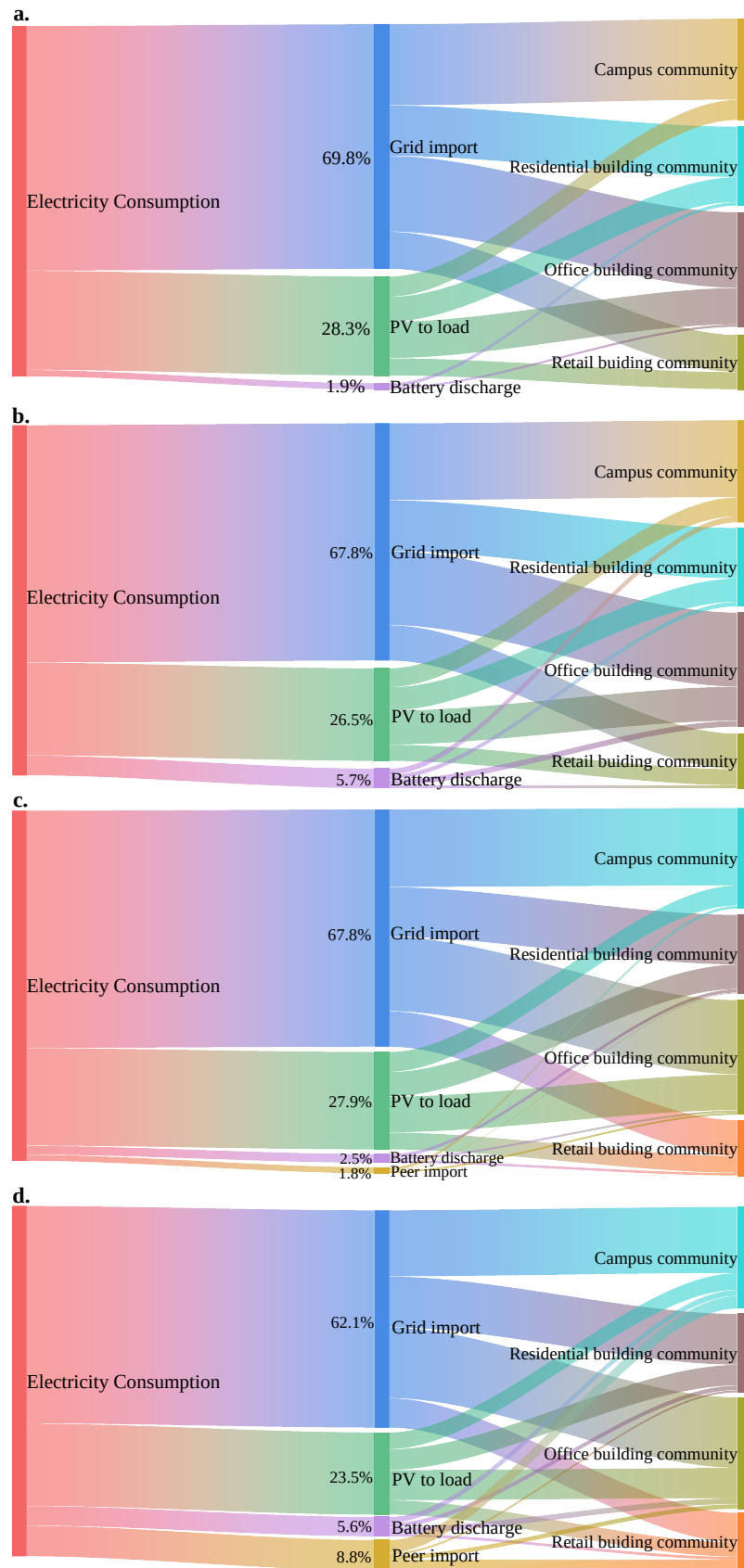


Figure 5-11 Distribution of electricity consumption in different building communities under different operating strategies: a. MSC strategy, b. TOU strategy, c. MMR based P2P strategy, d. DR based P2P strategy

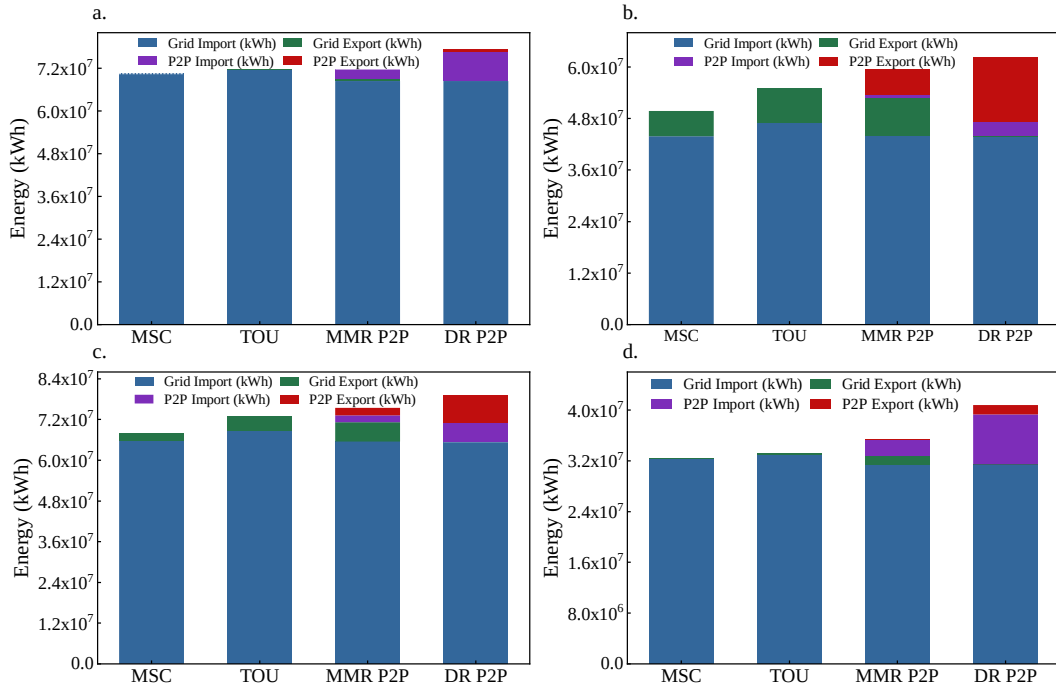


Figure 5-12 Energy flow of building communities under different operation strategies: a.

Campus building community, b. Residential building community, c. Office building community, d. Retail building community

5.4.3 Self-consumption rate

Table 5-3 and Figure 5-13 (a) provide valuable insights into the distribution of SCR among diversified building communities under four different operation strategies. From Fig. 16a, it is evident that the SCR of PV power generation in different building communities exceeds 70%. Building communities with a low proportion of power generation, such as campus building community, achieve SCR values higher than 96% under all strategies and can even reach 99.95% under the MSC strategy. On the other hand, building communities with a high proportion of PV power generation, like residential building community, exhibit relatively lower SCR values of around 70-80% due to the surplus PV generation during the daytime. Furthermore, the impact of different operation strategies on the SCR varies across different building communities. Under the MSC strategy, which prioritizes on-site generation consumption, PV power is first supplied to the building, and any excess PV power is used for battery charging.

As a result, the SCR remains relatively high for diversified building communities. The campus building community and commercial retail building community, with low PV generation proportions, achieve remarkable SCR of 99.9% and 99.6%, respectively. The residential building community and office building community, with high PV generation proportions, also maintain relatively high SCR at 80.9% and 93.7%, respectively. In the TOU strategy, the goal is to capitalize on price differences between peak and off-peak electricity periods through battery charging and discharging, maximizing economic efficiency. PV power generation is prioritized to meet building loads during peak electricity prices, with any excess generation exported to the grid. However, since PV generation remains relatively high during most peak periods, the overall SCR in diversified building communities decreases compared to the MSC strategy. This reduction is particularly evident in residential building community and office building community, where PV generation accounts for a significant proportion of the demand load. The SCR for these two types of building communities decreases to 73.5% and 88.4%, respectively, under the TOU strategy. In addition, the P2P operation strategies also impact the SCR of different building communities to varying degrees. Under the MMR based P2P strategy, the SCR decreases further compared to the TOU strategy, with the extent of reduction varying across building community types (ranging from 3% to 8%). In the MMR based P2P strategy, during peak hours, each building community aims to sell excess PV and battery power due to relatively high P2P selling prices, resulting in reduced self-supply of PV power. However, there is a significant difference in the SCR of PV power generation under the DR based P2P strategy compared to the MMR based P2P strategy. In the DR based P2P strategy, while participating in demand response during peak hours, priority is given to consuming PV power generation. The building community first utilizes PV power to meet its own energy needs and stores in the battery. The remaining PV power is sold to other peer communities. Consequently, the SCR of

different building communities significantly improves under the DR based P2P strategy, second only to the MSC strategy.

In summary, a higher level of SCR for building communities indicates increased consumption of PV power generation, thereby reducing the operational risk associated with unstable PV output to the power grid. In terms of SCR indicators, the MSC strategy and DR based P2P strategy enhance the stability of interactions between diversified building communities and the power grid while considering the conditions of renewable energy systems.

Table 5-3 Distribution of PV self-consumption rate in different building communities under different operating strategies

Building community	MSC	TOU	MMR based P2P	DR based P2P
Campus building community	99.95%	99.58%	96.11%	97.81%
Residential building community	80.86%	73.52%	70.33%	81.09%
Office building community	93.69%	88.43%	84.06%	93.07%
Retail building community	99.63%	98.62%	90.32%	95.75%
Diversified building communities	93.53%	90.04%	85.21%	91.93%

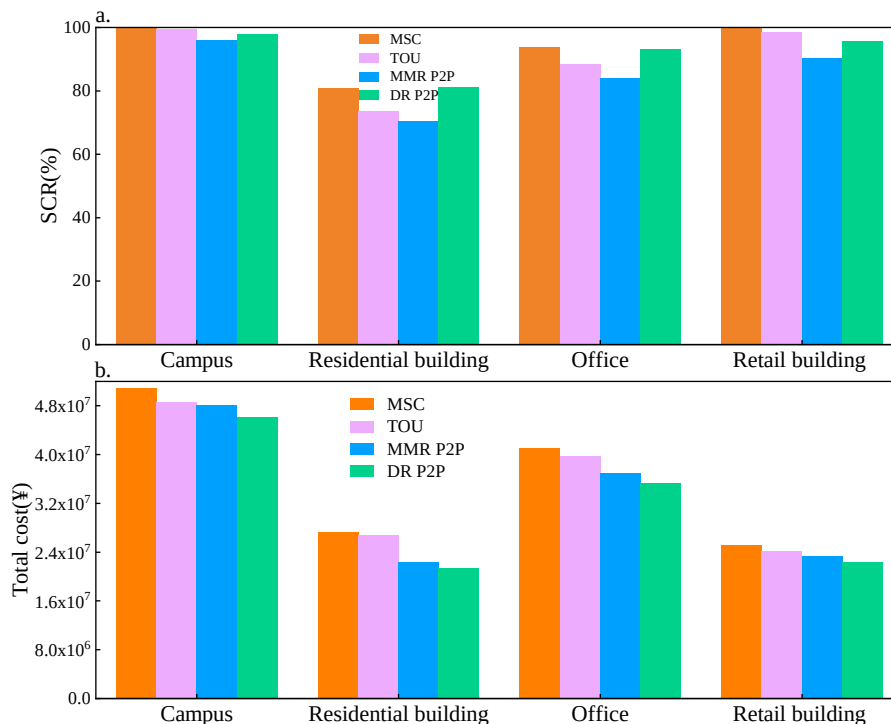


Figure 5-13 Techno-economic parameter distribution of building communities under different operation strategies: a. Self-consumption rate (SCR), b. Total electricity cost

5.4.4 Total electricity cost

Table 5-4 and Figure 5-13 present the total electricity costs for different building communities under various operation strategies. The MSC strategy, focused on maximizing self-consumption of PV power, shows weak economic performance with high power supply costs. The TOU strategy, utilizing energy storage to take advantage of price differences, offers a 3.5% reduction in total electricity purchase costs compared to MSC. However, limited battery capacity limits further improvements. In contrast, P2P strategies significantly enhance economic efficiency by enabling surplus PV power to be utilized by other communities through more economical P2P prices. The MMR-based P2P strategy reduces total electricity costs by approximately 6.1% compared to the MSC strategy, facilitating cost savings through internal transactions between building communities. More importantly, the DR-based P2P strategy considers demand response characteristics and load shifting, achieving electricity purchasing economy through improved P2P prices and demand response. Compared to the MSC strategy, the DR-based P2P strategy can reduce total electricity costs by up to 13.3%.

In summary, different operation strategies result in varying total operating costs for diversified building communities. P2P strategies based on the peer-to-peer (P2P) paradigm, such as MMR-based and DR-based approaches, outperform traditional rule-based strategies (MSC and TOU) within the peer-to-grid (P2G) paradigm. Notably, the DR-based P2P strategy, with demand response considerations, offers further improvements in economic performance. This approach holds significant benefits for achieving maximum economic efficiency in cases involving interactions between building communities and power grids.

Table 5-4 Distribution of total electricity cost in different building communities under different operating strategies

Building community	MSC	TOU	MMR based P2P	DR based P2P
Campus	5.09E+07	4.86E+07	4.81E+07	4.61E+07
Residential building	2.73E+07	2.69E+07	2.24E+07	2.14E+07
Office	4.10E+07	3.98E+07	3.69E+07	3.53E+07
Retail building	2.52E+07	2.41E+07	2.34E+07	2.24E+07
Total cost savings level (%)	/	3.5%	6.1%	13.3%

5.5 Summary

This chapter comprehensively evaluated the performance of demand-side energy management strategies for diversified building communities, considering the overall demand load encompassing building load and electric vehicle charging load. Four strategies were assessed, including two P2P-based strategies (common Mid-Market Rate (MMR) based P2P strategy and a novel demand response (DR) based P2P strategy) and two rule-based strategies based on P2G paradigm (maximizing self-consumption (MSC) strategy and time-of-use (TOU) strategy). The analysis focused on energy dynamic dispatching and the overall techno-economic aspects of a grid-connected photovoltaic-battery (PVB) system within the district energy system comprising the four building communities. The main findings are summarized as follows:

- The choice of strategy depends on the role of the building community, whether as a consumer or a prosumer. For consumer communities, both the TOU strategy and DR based P2P strategy provide greater economic benefits. For prosumer communities, adopting the P2P strategies (MMR based P2P strategy and DR based P2P strategy) is a more cost-effectiveness choice for energy management.
- Compared to the mainstream MSC and TOU operation strategies, P2P strategies,

especially the DR based P2P strategy, effectively alleviate pressure on the power grid by actively responding to electricity demand during peak hours and utilizing excess renewable energy generation from other communities. These strategies promote electricity balance during peak and off-peak periods, resulting in more stable and reliable electricity consumption for the entire diversified building communities.

- In terms of SCR indicator, the overall SCR for diversified building communities varied across strategies: 93.53% for MSC, 90.04% for TOU, 85.21% for MMR-based P2P, and 91.93% for DR-based P2P. Both the MSC strategy and DR based P2P strategy enhance the stability of interactions between diversified building communities and the power grid. In addition, the P2P strategies (MMR based P2P strategy and DR based P2P strategy) yield better economic outcomes compared to traditional rule-based strategies under the P2G paradigm. In terms of electricity costs, compared to MSC, the TOU, MMR-based P2P, and DR-based P2P strategies saved 3.5%, 6.1%, and 13.3%, respectively. The DR-based P2P strategy demonstrates significant advantages in these regards.

Overall, the study compares the technical and economic performances of four different energy management and operation strategies based on P2G and P2P paradigms in diversified building communities. Besides, this study develops an energy management strategy for integrating EVs and building loads, including the power requirements of both the building side and the EV side at various times in different building communities. It emphasizes the benefits of the novel DR-based P2P strategy in achieving stable and reliable electricity consumption, reducing grid pressure, and improving economic efficiency.

CHAPTER 6 DEVELOPMENT OF A HYBRID GAME THEORY-BASED PEER-TO-PEER TRADING STRATEGY FOR OPTIMAL ENERGY MANAGEMENT

This chapter develops a hybrid game theory-based peer-to-peer (P2P) trading strategy to achieve optimal energy management in multi-microgrid systems. Building on the comparative analysis and limitations identified in previous rule-based and demand response strategies in Chapter 5, this chapter introduces a novel trading paradigm that leverages cooperative game theory for intra-building optimization and non-cooperative games for inter-microgrid transactions. A detailed case study is conducted to assess the effectiveness of the proposed game-theoretic P2P strategy, enabling a comprehensive evaluation of dynamic energy dispatch and techno-economic performance compared to conventional time-of-use peer-to-grid benchmarks. Further analysis explores electricity transaction distributions and revenue fairness, examining import and export patterns, internal P2P pricing mechanisms, and equitable revenue allocation among participants. The findings underscore the potential of advanced game-theoretic approaches to enhance operational efficiency and fairness in decentralized community energy systems, providing important implications for future smart grid development.

6.1 Multi-microgrid electricity trading paradigm

The rapid proliferation of distributed renewable energy resources has spurred the evolution of electricity trading paradigms from traditional centralized models toward more decentralized and flexible frameworks. In this study, a hierarchical management strategy framework for energy dispatch is established, as illustrated in Figure 6-1, to accommodate different electricity

trading paradigms—namely, the traditional P2G and the emerging P2P trading models. The framework is structured into three layers: the microgrid layer, the energy dispatch layer tailored to each trading paradigm, and the optimization result analysis layer.

At the foundational microgrid layer, DERs such as PV systems, WT, and battery storage systems are integrated with local loads, including building demands and EV charging. Microgrids, as flexible and autonomous subsystems, enable the optimized coordination of generation, storage, and consumption within a localized boundary. Under the P2G paradigm, microgrids primarily interact with the utility grid, exporting excess generation or importing electricity as needed, following conventional management strategies such as TOU scheduling. However, P2G markets face challenges related to limited scalability and the regulatory complexity of coordinating energy transactions among numerous small-scale participants.

In contrast, the P2P paradigm enables direct energy transactions among multiple interconnected microgrids, facilitated by decentralized trading mechanisms. This approach enhances flexibility, improves grid resilience, and allows for more granular optimization of energy flows. Nevertheless, the lack of centralized control in P2P markets can introduce challenges related to trading stability and efficiency. To address these issues, this study adopts a hybrid management approach: the traditional TOU strategy is utilized under the P2G paradigm, while a game theory-based decentralized management method is implemented for the P2P paradigm. This dual approach enables a comprehensive evaluation of the operational, economic, and regulatory implications associated with each electricity trading model.

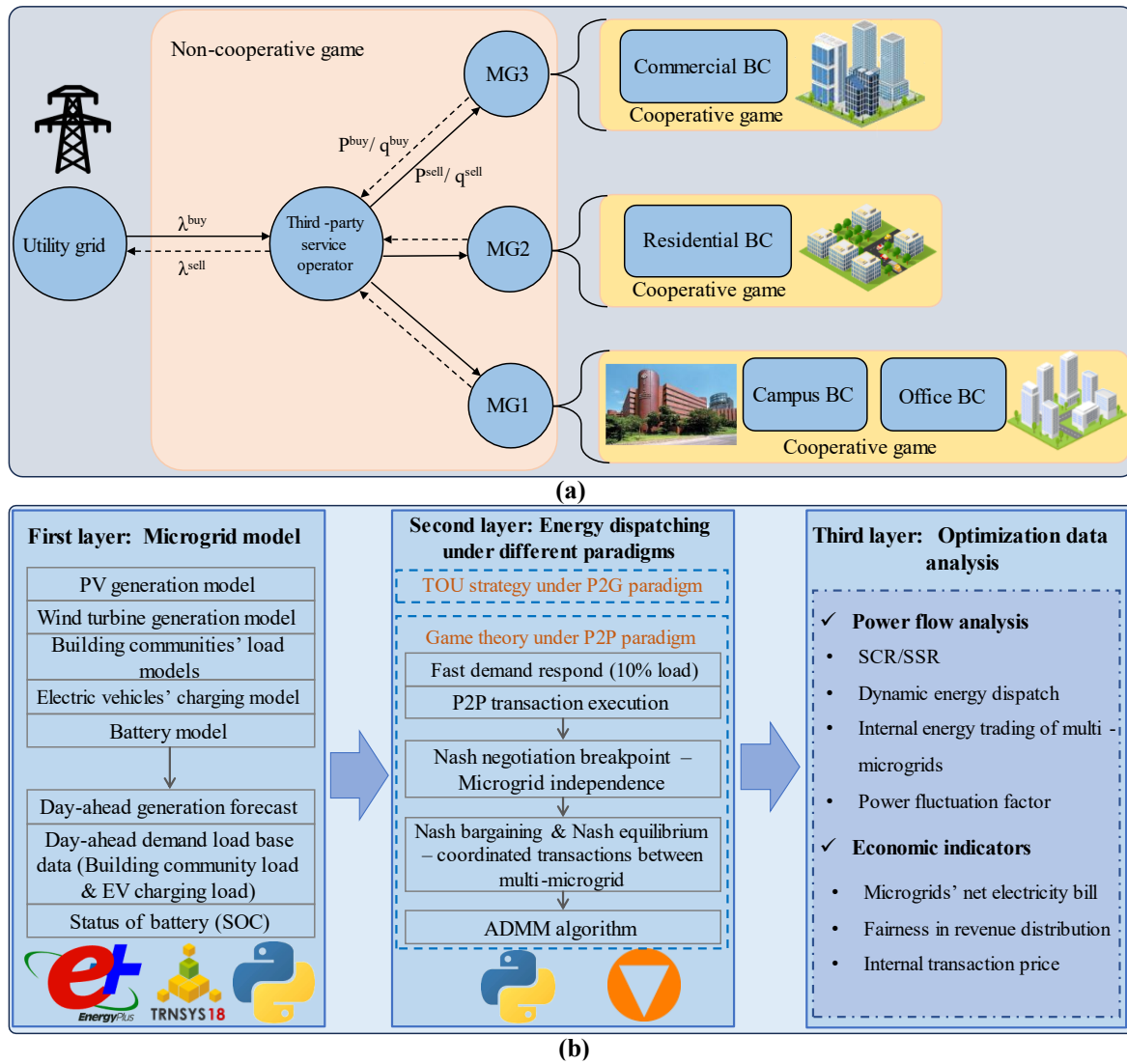


Figure 6-1 Hierarchical management strategy framework under different power paradigms:

- (a). The game relationship between multi-microgrids and diversified building communities;(b). The three-layer framework of the energy management strategies

6.1.1 Description of multi-microgrid serving building communities

Within the proposed hierarchical framework, microgrids are composed of diverse building communities that serve as the fundamental units of distributed energy systems. Each microgrid typically integrates a heterogeneous mix of residential, commercial, and institutional buildings, each with distinct load profiles and energy consumption patterns. In addition to traditional building loads, microgrids also incorporate flexible loads such as EV charging stations, which further increase the potential for demand-side management and load shifting.

The core components of a building community-based microgrid include local renewable generation assets (e.g., rooftop PV panels, small-scale wind turbines), battery energy storage systems, and a smart energy management system (EMS) for real-time monitoring and control. By aggregating the energy resources and flexible loads of multiple buildings, the microgrid can achieve higher efficiency and reliability through coordinated generation, consumption, storage, and trading.

Microgrids can operate either in isolation, managing their internal energy balance autonomously under the P2G paradigm, or as part of a larger network of interconnected microgrids under the P2P paradigm. In the latter case, microgrids can engage in direct energy trading with neighboring communities, facilitated by decentralized market mechanisms and peer-to-peer contracts. This structure not only optimizes local resource utilization but also enhances the overall resilience and adaptability of the community energy system, paving the way for a more sustainable and participatory electricity market.

6.1.2 A new hybrid game theory based P2P trading strategy

The multi-microgrid participation is situated within a distributed electricity market. The market participants include microgrid operators, large grid/distribution network operators, and internal microgrid users, as depicted in Figure 6-2. Microgrid operators represent the system's interests, managing internal distributed energy dispatch and load demand response regulation while engaging in external market transactions. Electricity transactions between microgrids are coordinated via a multi-microgrid trading platform established through an alliance chain. Utility grid/distribution network operators charge appropriate grid service fees for microgrids internal transaction and purchase/sell surplus or shortage electricity from/to microgrids. The energy management system is administered by microgrid operators. Renewable energy systems like PV and WT are typically the preferred electricity resources for microgrids. If local load demand exceeds renewable power generation, electricity can be procured from the utility grid

through the energy management system or released from energy storage systems. However, if renewable energy generation surpasses local load demand, excess electricity can be sold to the utility grid or stored in energy storage systems. The energy management system also encompasses local demand response functions, optimizing supply and demand across different time periods. This increases local renewable energy consumption ratio and overall energy system flexibility. Moreover, the bidding mechanism for multi-microgrid should employ different game models tailored to specific markets. Therefore, this study employed a hybrid non-cooperative and cooperative game models to calculate electricity transaction quantities and electricity transaction prices between multi-microgrid, aiming for improved overall performance. Specifically, it establishes a non-cooperative game relationship among three independent microgrids: the campus community and office building community microgrid, the residential building community microgrid, and the commercial building community microgrid. Meanwhile, within the microgrid comprising the campus community and office building community, a cooperative game relationship exists between them, aiming at maximizing economic efficiency.

In the context of adjacent N independent microgrids, their varying scales of renewable energy installations, geographical locations, and energy consumption characteristics result in different renewable power outputs and load demand electricity consumption patterns. However, these microgrids can be coordinated through interconnections of transmission networks and communication equipment, enabling internal scheduling among multi-microgrid. This coordination facilitates greater energy reciprocity and complementary advantages, leading to a higher cost advantage in cross energy supply chain competition. Consequently, it improves the economic performances and system reliability of microgrids. To understand the game relationship within multi-microgrid, it is essential to clarify the interests of entities participating in the electricity market. Balancing and optimizing the profits of participants becomes crucial

in determining the optimal strategies for different decision-makers and stakeholders within the system. The coordination and scheduling among multi-microgrid mentioned above constructs a game theory model. Detailed information regarding the basic conditions, construction principles, and mathematical models of game theory refers to Appendix.

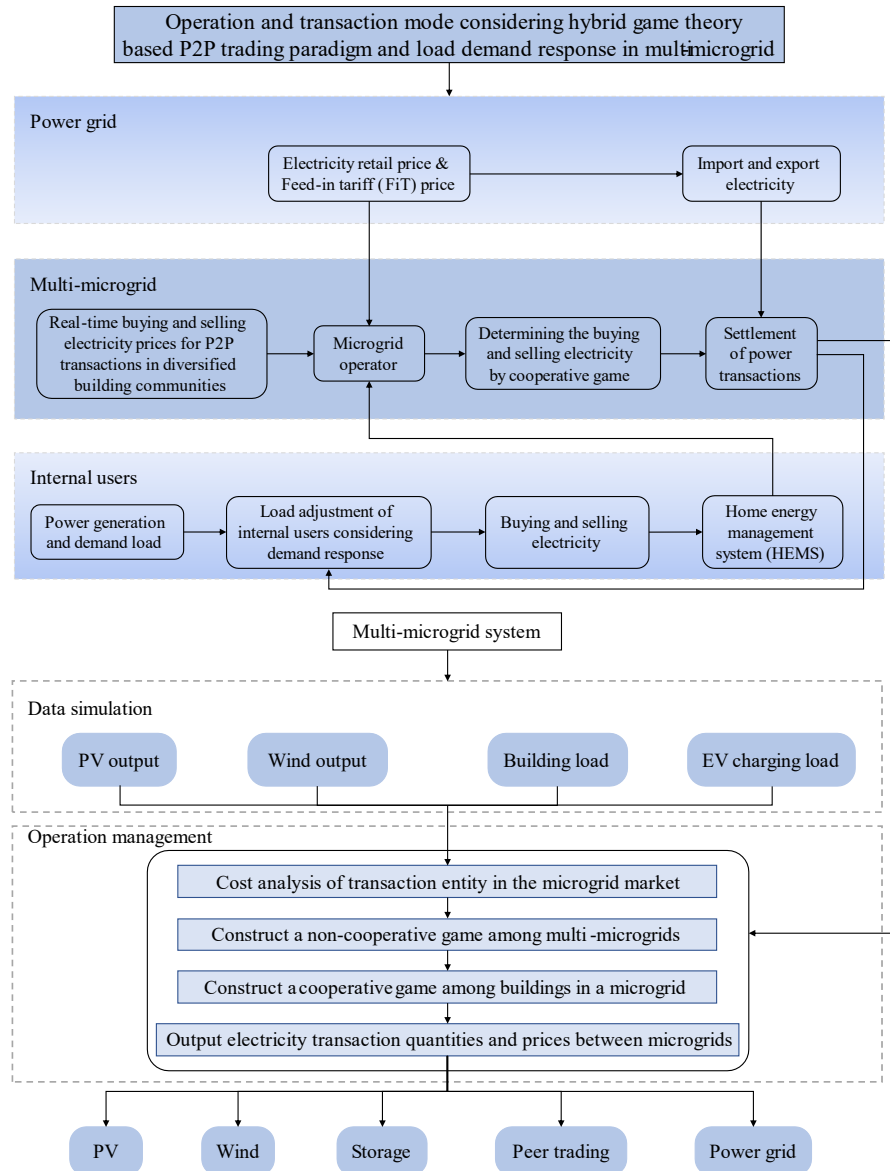


Figure 6-2 Schematic diagram of electricity trading mechanism and multi-microgrid optimal scheduling and transaction

6.1.2.1 Cooperative game for intra-building optimization

In the study, a cooperative game relationship can be established among buildings within the same microgrid to maximize overall economic benefits. The microgrid system comprises

multiple buildings equipped with energy systems composed of electricity generation, consumption, and storage. Initially, each building formulates its individual electricity purchasing and selling strategies to maximize its own economic benefits. These strategies may involve factors such as the timing and quantity of electricity purchases, as well as the timing and quantity of electricity sales. Subsequently, buildings engage in information exchange and negotiation to coordinate their strategies and execute Nash bargaining of cooperative game. After Nash bargaining, the strategies of each building are interdependent, and overall economic benefits can be maximized through mutual cooperation.

Furthermore, the overall economic benefits of the microgrid are allocated to each building based on their contribution levels. Contribution levels refer to the cumulative proportion of electricity purchased from and sold to the grid by different buildings. According to Homans' social exchange theory, distributive fairness is defined as the attainment of proportional output to input within an exchange relationship [149]. Hence, to assess the fairness of revenue distribution among diverse buildings in the microgrid with cooperative game relationships under the P2P paradigm, it is essential to consider the correlation between inputs and outputs within each microgrid. In this study, the Output-input ratio (OIR) indicator, as defined in Ref. [31], is represented by Eqs. (6.1) - (6.3).

$$OIR_i = \frac{(C_{P2G}^i - C_{P2P}^i) / \sum_{i=1}^{N_i} (C_{P2G}^i - C_{P2P}^i)}{E_{P2P}^i / \sum_{i=1}^{N_i} E_{P2P}^i} \quad (6.1)$$

$$RD_j = OIR_j \cdot ER_{MGi} \quad (6.2)$$

$$ER_{MGi} = C_{MGi_Game} - C_{MGi_breakpoint} \quad (6.3)$$

6.1.2.2 Non-cooperative game for inter-microgrids transaction

For the combined multi-microgrid, the set of all microgrids is represented as $N = \{1, 2, \dots, n\}$. All non-empty subsets L in N , denoting the microgrids within the alliance L , collaborate with each other. This collaboration involves comprehensive optimization and adjustment of power generation, energy storage, load, market-traded electricity, and electricity transaction prices, and etc. The objective is to achieve either the minimum overall operating cost or reliable power supply for the alliance L . Based on the supply and demand of electricity within the system and economic considerations, microgrids determine the amount of electricity and electricity prices to be traded with other microgrids or distribution networks in the wholesale market. Furthermore, for the multi-microgrid, the optimal cost of independent operation under the P2G paradigm for each microgrid serves as the breakpoint for Nash negotiation in the non-cooperative game and as a constant reference for the subsequent stages of the non-cooperative game.

6.1.2.3 Nash negotiation breakpoint - microgrid independence operation under P2G paradigm

The renewable energy equipment possesses several advantages, such as a simple equipment structure, long lifespan, high reliability, and low maintenance requirements, resulting in relatively low maintenance costs [150]. On the other hand, the energy storage units are generally costly and require frequent replacement, thus the aging cost of energy storage systems is factored into the cost calculation. In the P2G paradigm, all microgrids can only purchase and sell electricity from the distribution network to ensure internal power balance. Thus, the total operating cost of multi-microgrid system within one operating cycle T ($T=24$ hours) encompasses the following three components: the cost of electricity transaction between the microgrid and the distribution network to address internal production and demand imbalances, the comfort compensation cost associated with load transfers for users, and the

aging cost of energy storage systems. The cost model for multi-microgrid is expressed as Eq. (6.4).

Objective function:

$$\min C_i = C_{i,B} + C_{i,L} + C_{i,E} \quad (6.4)$$

$$C_{i,B} = \sum_{t=1}^T (P_{i,t}^{buyG} \cdot ERP - P_{i,t}^{sellG} \cdot FiT) \quad (6.5)$$

$$C_{i,L} = \sum_{i=1}^T \delta_i (l_{i,t} - L_{i,t})^2 \quad (6.6)$$

$$C_{i,E} = (\beta_{cal}(T) + \beta_{cyc}(T)) \cdot c_i^{es} \quad (6.7)$$

6.1.2.4 Nash equilibrium - coordinated internal transactions between multi-microgrid

When the collection of microgrids in a region $N = \{1, 2, \dots, n\}$ forms an electricity supply alliance between them, transaction agreements are made among the microgrids. Following the attainment of a Nash equilibrium, electricity can be directly traded between them. For the bargaining process between microgrids, the sum of the operating cost of any selling party MG_i and any purchasing party MG_j in the alliance should also include the cost of conducting the transaction C_{ij}^M , as well as the over-grid fee C_{net}^{ij} levied by the distribution network on the microgrid during the electricity transaction process between multi-microgrid [81].

(1) Cost of purchasing and selling electricity

The cost of purchasing and selling electricity when MG_i participates in a multi-microgrid alliance is depicted in Eq. (6.8). The internal electricity transaction price should also meet the restriction of Eq. (6.9).

$$C_{i,j}^M(P_{ij}^t, q_{ij}^t) = \sum_{t=1}^T \sum_{j \in M/i} P_{ij}^t \cdot q_{ij}^t \quad (6.8)$$

$$FiT < q_{ij}^t < ERP \quad (6.9)$$

(2) The over-grid fee levied by the distribution network

After the Nash equilibrium between microgrids, the power flow between multi-microgrid requires the use of the power transmission network of the distribution network. Therefore, the distribution network will charge over-grid service fees based on the electricity trading behavior between microgrids. In the study, the over-grid fee is determined by utilizing the segmented grid electricity price, which is based on the relationship between P_{ij}^t and a certain grid power base P_0 [81]. When P_{ij}^t is less than or equal to P_0 , the distribution network does not charge over-grid fees to encourage electricity transaction between multi-microgrid. When P_{ij}^t is larger than P_0 , the quadratic function related to P_{ij}^t is used to evaluate the line loss caused by transmission between multi-microgrid on the distribution network, which serves as the basis for charging the corresponding over-grid service fee, as illustrated in Eq. (6.10).

$$C_i^{net}(P_{ij}^t) = \begin{cases} 0 & P_{ij}^t \leq P_0 \\ \frac{\sigma+1}{2} \sum_{t=1}^T \sum_{j \in M/i} (\alpha_{ij}^t (P_{ij}^t)^2 + \beta_{ij}^t P_{ij}^t) & P_{ij}^t > P_0 \end{cases} \quad (6.10)$$

Therefore, the objective function of MG_i under the P2P paradigm is to minimize the total operating cost in the bargaining and transaction processes between microgrids, as depicted in Eq. (6.11), including the electricity transaction costs with the distribution network, the transaction costs between microgrids, and the over-grid service fees paid to the distribution network. Eq. (6.12) represents the internal power balance constraint of MG_i when there are electricity transactions between microgrids.

$$\min C_i^C = C_i^N(P_{i,t}^c, P_{i,t}^d, l_{i,t}, P_{i,t}^{buyG}, P_{i,t}^{sellG}) + C_{ij}^{net}(P_{ij}^t) + C_{ij}^m(P_{ij}^t, q_{ij}^t) \quad (6.11)$$

$$s.t. \quad P_{i,t}^{PV} + P_{i,t}^{WT} + P_{i,t}^d - P_{i,t}^c + P_{i,t}^{buyG} - P_{i,t}^{sellG} - \sum_{j \in M/i} P_{ij}^t = l_{i,t} \quad (6.12)$$

Since each microgrid is independent, it can freely choose any trading agent in the market. If the microgrid is more inclined to choose Nash equilibrium result in the microgrid when conducting transactions, certain conditions need to be met. This condition is that microgrids can further reduce their operating cost by the proposed hybrid game models based P2P paradigm. If the above conditions cannot be met, MG_i will not choose to participate in multi-microgrid alliances for internal transactions. That is to say, internal transactions between microgrids should comply with Eq. (6.13).

$$C_i^{N,0} \geq C_i^C \quad (6.13)$$

If it is assumed that all microgrids in the region can reduce operating cost through non-cooperative game, then Eq. (6.14) is satisfied.

$$\begin{cases} \max \prod_{i=1}^M (C_i^{N,0} - C_i^C) \\ \text{s.t. } C_i^{N,0} - C_i^C > 0 \end{cases} \quad (6.14)$$

Where, microgrid i (MG_i) is a participant in the non-cooperative game. M is the number of microgrids in the game. The bargaining strategy of microgrid i in the game model is $\{P_{ij}^t, q_{ij}^t\}$, which refers to the electricity transaction quantity and price between MG_i and MG_j . The two together form a Nash equilibrium strategy set. The solution of Eq. (6.14) is the Nash equilibrium solution strategy $\{P_{ij}^{t*}, q_{ij}^{t*}\}$ for the multi-microgrid electricity transaction problem in the study. It is obvious that Eq. (29) has two optimization variables simultaneously, namely electricity transaction quantity P_{ij}^t and electricity transaction price q_{ij}^t , which is a nonlinear non-convex optimization problem and difficult to solve. In the study, the distributed Alternating Direction Method of Multipliers (ADMM) algorithm is utilized to find the optimal electricity transaction scheme accepted by all microgrids. Throughout this process, the distribution of benefits for all microgrids in terms of purchasing and selling electricity is

considered, ensuring maximization of overall benefits while avoiding sacrificing individual interests.

6.1.3 Performance evaluation metrics

The evaluation of energy management strategies requires a comprehensive comparison of multiple factors. In this regard, three distinct evaluation factors are considered: the technical factor (e.g., self-consumption rate (SCR) and self-sufficiency rate (SSR)), economic factor (e.g., total electricity cost within and across building communities), equality factor (e.g., fairness in revenue distribution within the building community), and energy reliability factor (e.g., power fluctuation factor (PFF) in the utility grid) [31, 151].

6.1.3.1 Technical indicator

In the energy system, the SCR and SSR are two main factors used to analyze the energy flow between the building community and the utility grid. Generally, the SCR is a metric that quantifies the proportion of energy consumed by an entity within an energy system, relative to the energy generated by that same entity. It serves as a measure to evaluate the self-sufficiency and energy utilization efficiency of the energy system. The SSR is a metric that quantifies the proportion of energy generated by an entity within the total energy consumption of the energy system. It is used to assess the independence and sustainability of the energy system. The SCR and SSR demonstrate the local consumption rate of renewable generation and the proportion of the distributed energy in load demand, respectively, depicted as Eqs. (6.15) - (6.16).

$$SCR = \frac{\sum_{t=1}^T \left(\left(\sum_{i=1}^{N_i} P_{du}^i(t) + \sum_{i=1}^{N_i} P_{P2P,sold}^i(t) + \sum_{i=1}^{N_i} P_{ch}^i(t) \right) \times \Delta t \right)}{\sum_{t=1}^T \left(\left(\sum_{i=1}^{N_i} P_{PV}^i(t) \right) \times \Delta t \right)} \quad (6.15)$$

$$SSR = \frac{\sum_{t=1}^T \left(\left(\sum_{i=1}^{N_i} P_{du}^i(t) + \sum_{i=1}^{N_i} P_{P2P,bou}^i(t) + \sum_{i=1}^{N_i} P_{dis}^i(t) \right) \times \Delta t \right)}{\sum_{t=1}^T \left(\left(\sum_{i=1}^{N_i} P_{load}^i(t) \right) \times \Delta t \right)} \quad (6.16)$$

6.1.3.2 Economic indicator

The economic factor in a microgrid energy system represents the financial expenditure associated with purchasing electricity from external sources. The total electricity cost for building community is regarded as the economic factor in this study, which consists of the cost battery aging during the charging and discharging process, the cost of electricity imported from the grid, the cost of electricity bought from other peer communities through P2P transaction, and revenue from selling electricity to grid and peer communities. This factor is illustrated as Eq. (6.17).

$$C_{com} = \sum_{t=1}^T C_{bou,grid}^t + \sum_{t=1}^T C_{bou,P2P}^t + \sum_{t=1}^T C_{bat}^t - \sum_{t=1}^T C_{sold,grid}^t - \sum_{t=1}^T C_{sold,P2P}^t \quad (6.17)$$

6.1.3.3 Power fluctuation indicator

PFF is an indicator used to measure the stability and variability of power generation in an energy system. It quantifies the degree of fluctuation or variability in the output power of renewable energy sources, such as solar and wind, within a given time period. For energy system in this study, power fluctuation refers to the variability or instability in the supply and demand of electrical power within different building communities, which can have significant implications for energy management and overall system reliability towards utility grid. Besides, the power fluctuation factor represents the impact of community power consuming and generating behavior on the utility grid, and it is defined as Eqs. (6.18) - (6.19).

$$F = \frac{1}{T} \sum_{t \in T} \left[\left(\sum_{i=1}^{N_i} P_{bou,grid}^i(t) - \sum_{i=1}^{N_i} P_{sold,grid}^i(t) \right) - P_A \right]^2 \quad (6.18)$$

$$P_A = \frac{1}{T} \left(\sum_{i=1}^{N_i} P_{bou,grid}^i(t) - \sum_{i=1}^{N_i} P_{sold,grid}^i(t) \right) \quad (6.19)$$

6.1.3.4 Revenue distribution fairness in the community

According to Homans' social exchange theory, distributive fairness is defined as the attainment of proportional output to input within an exchange relationship. Hence, to assess the fairness of revenue distribution among diverse building community multi-microgrids with cooperative game relationships under the P2P paradigm, it is essential to consider the correlation between inputs and outputs within each microgrid. In this study, the input denotes the quantity of electricity transacted by the community through participation in P2P transactions, while the output refers to the reduction in the community's electricity bill. The OIR indicator is represented by Eq. (6.20).

In Eq. (6.20), the OIR is calculated as the ratio of each community's electricity cost reduction (output) to its total electricity transaction volume (input) within the P2P trading framework. A higher OIR value indicates that a community receives greater economic benefit per unit of electricity traded, while consistent OIR values across all participating communities suggest equitable revenue distribution. This metric enables quantitative assessment of whether the cooperative game mechanism allocates benefits proportionally to each participant's contribution to the coalition.

$$OIR_i = \frac{(C_{P2G}^i - C_{P2P}^i) / \sum_{i=1}^{N_i} (C_{P2G}^i - C_{P2P}^i)}{E_{P2P}^i / \sum_{i=1}^{N_i} E_{P2P}^i} \quad (6.20)$$

6.2 Case study for evaluating the proposed strategy

A real case of a multi-microgrid is selected for case analysis. The chosen scenario is situated in Hung Hom, Kowloon Peninsula, Hong Kong, at a latitude of 22°18' north and a longitude of 114°10' east [152]. This area comprises various typical building clusters, including residential buildings, commercial buildings, and public buildings, as shown in Figure 6-3. The

selection of this specific area makes it suitable as a representative building community for the case analysis conducted, as shown in Table 6-1.

Considering the unique geographical location and spatial characteristics of diversified building communities, distinct renewable energy systems are paired with each community. Specifically, for residential and commercial building communities situated along the coast, a hybrid configuration comprising photovoltaic panels and wind turbines is adopted. Conversely, non-coastal campus and office building communities primarily rely on solar photovoltaic panels. The specific parameters of the renewable energy systems and energy storage systems for each building community are presented in Table 6-1.

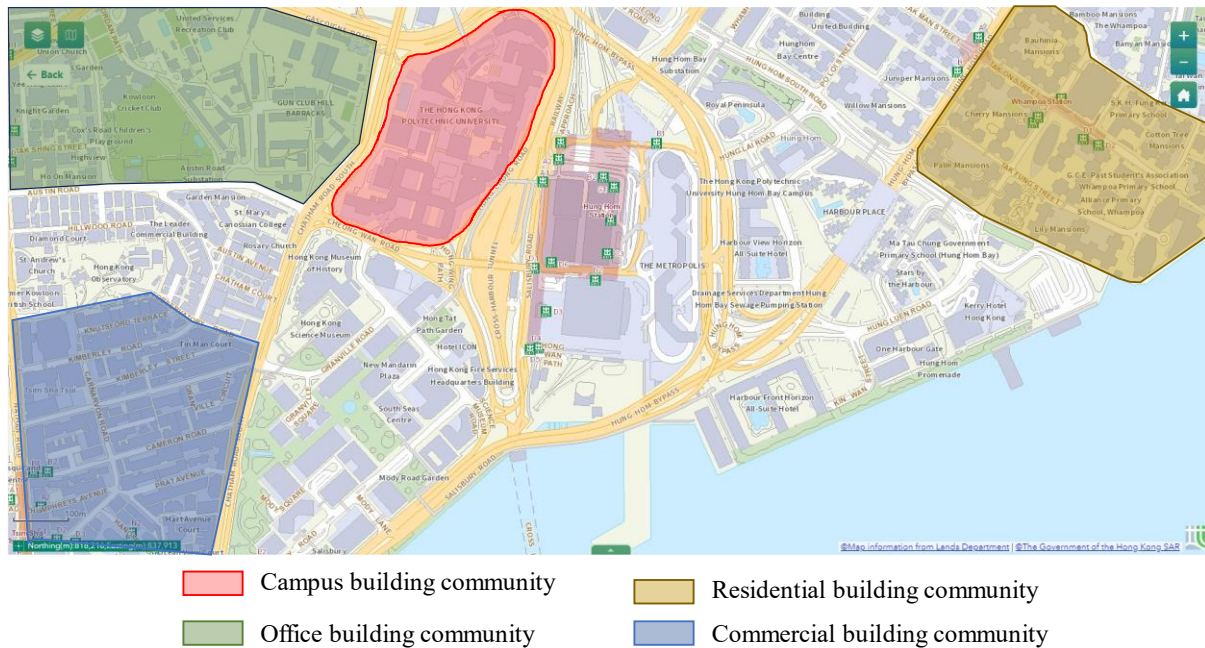


Figure 6-3 Distribution map of multi-microgrid building communities in a real scenario

Table 6-1 Information of energy system in multi-microgrid building communities

Microgrid	Community	Location information	DERs type	Energy storage capacity /kWh	Charging/discharge limit / kW
MG ₁	Campus	The PolyU campus	PV	40000	6000 / 5200
	Office	Blocks and Towers	PV		
MG ₂	Residential	Mansions	PV + Wind	15000	2400 / 2000
MG ₃	Commercial	Commercial centers	PV + Wind	10000	1500 / 1300

Figure 6-4 and Table 6-2 present the daily load profiles, power generation distribution, and total annual electricity generation and consumption for the above three microgrids. The annual electricity generation to consumption ratios for MG₁, MG₂, and MG₃ are 29.2%, 139.6%, and 304.6%, respectively. In practice, building communities within the utility grid lack independent power control and communication capabilities [84]. Consequently, they are commonly categorized as distinct community microgrids for the purpose of power dispatch and regulation. Based on the established definitions of microgrid-level power generation and consumption characteristics, MG₁ can be categorized as consumer due to their significantly lower power generation levels throughout the year. However, building communities of MG₂ and MG₃, located along the coast, are equipped with specific wind turbines, ensuring a considerable level of electricity generation throughout the day. Consequently, the power generation capacity of these two microgrids surpasses that of MG₁ which rely solely on a single rooftop PV system. MG₂, in particular, demonstrates a unique characteristic as it exhibits periods of surplus electricity generation exceeding consumption, as well as periods where consumption exceeds generation. This dual role of MG₂, functioning both as a producer and a consumer, is commonly referred to as a prosumer. On the other hand, MG₃, leveraging its substantial potential for wind power generation, consistently produces more electricity than it consumes over extended periods. Consequently, MG₃ is primarily considered as an energy producer.

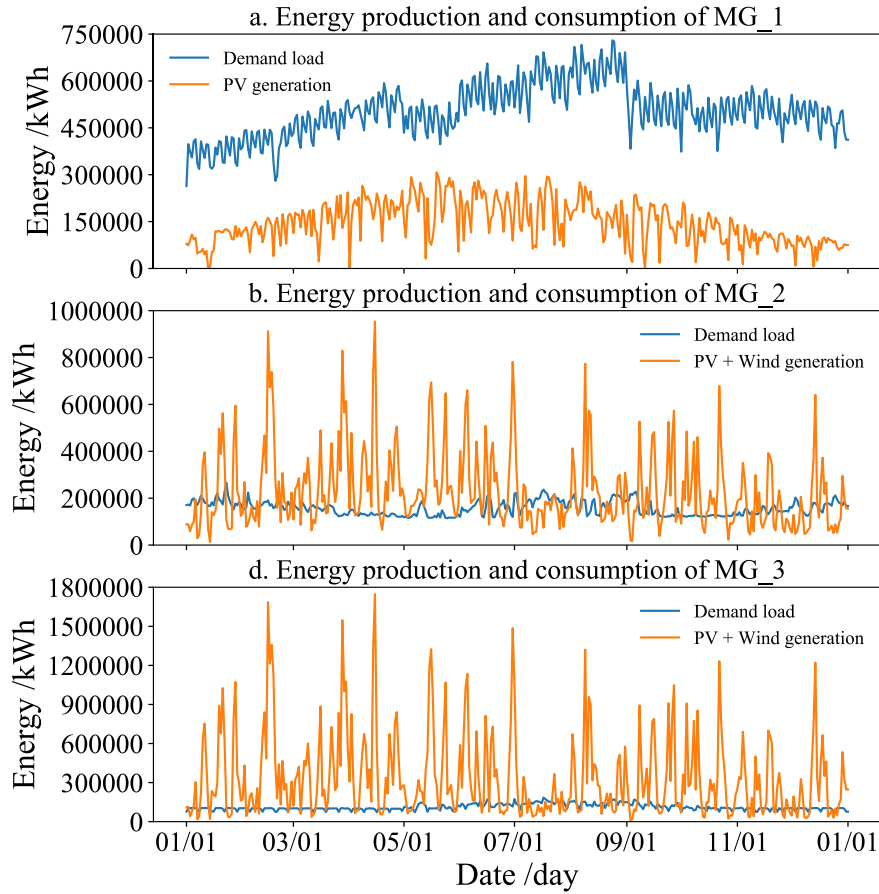


Figure 6-4 Distribution of electricity production and consumption in multi-microgrid

Table 6-2 Total annual electricity generation and consumption of the multi-microgrid

Microgrid type	Demand load (kWh)	Power generation (kWh)	Power generation to demand load ratio (%)
MG ₁	183592769.9	53644480.0	29.2
MG ₂	57330350	77014852.6	134.3
MG ₃	40681075.7	123911276.9	304.6

In the study, the power dispatch and energy consumption behaviors of typical days in summer, mid-season, and winter are compared and analyzed under different energy trading paradigms within the multi-microgrid. The aim is to evaluate the advantages of P2P energy trading paradigm based on the hybrid game models in comparison to the existing P2G paradigm. Figure 6-5 illustrates the power generation and consumption distribution among three types of microgrids during typical days. The trend indicates higher load demand and PV power

generation during summer, while wind power generation exhibits greater volatility, particularly in the mid-season. By analyzing the power dispatch, electricity purchasing and selling characteristics of three microgrids in various seasons under different paradigms, this study offers a comprehensive and objective evaluation of the advantages and potential of the proposed hybrid game theory-based P2P electricity transaction paradigm.

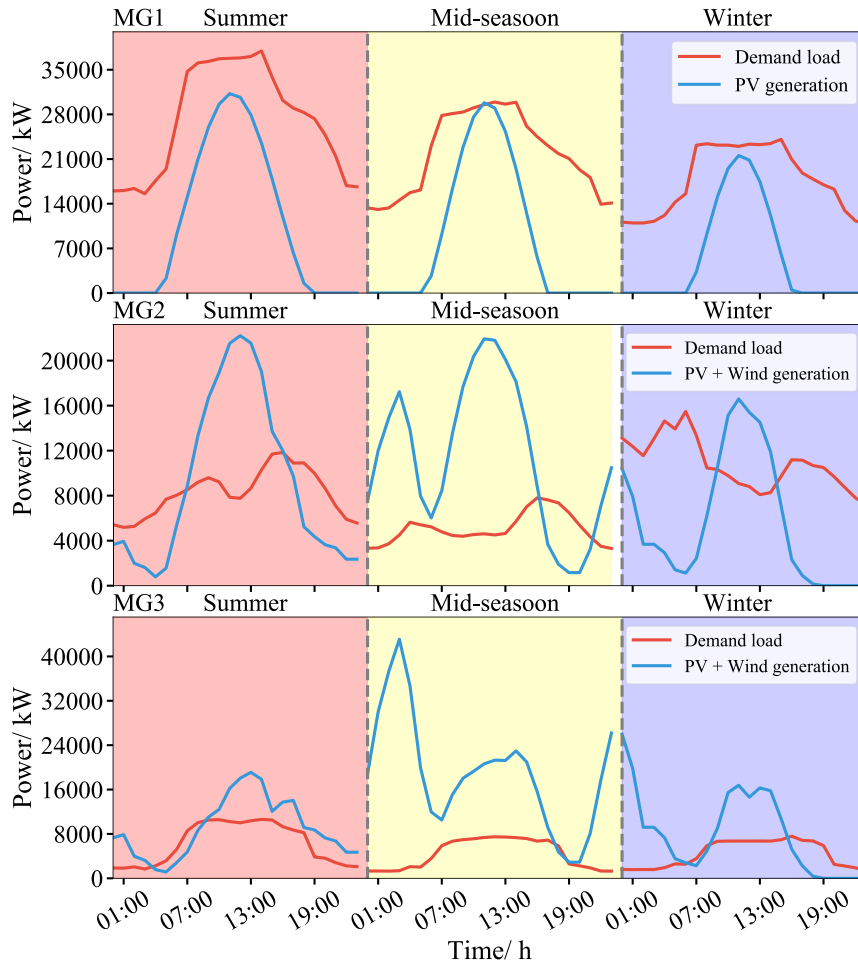


Figure 6-5 Electricity generation and consumption distribution of three different microgrids in summer, mid-season, and winter typical days

6.3 Dynamic energy dispatch under different electricity trading paradigms

This section presents a comparative analysis of dynamic energy dispatch within a multi-microgrid system under two contrasting electricity trading paradigms: the conventional P2G

paradigm and the proposed hybrid game-based P2P paradigm. By evaluating typical days in summer, mid-season, and winter, the study investigates the operational characteristics, grid interactions, and techno-economic performances of each paradigm, highlighting the advantages and limitations inherent to each approach.

6.3.1 Time-of-use peer-to-grid trading paradigm – a benchmark strategy

The power dispatch distribution of typical days in different seasons within the multi-microgrid under the P2G paradigm is illustrated as Figure 6-6. For comparative evaluation, taking a typical summer day as an example, the power dispatch distribution of multiple microgrids under the P2G paradigm and the proposed hybrid game-based P2P paradigm. In the configuration of the building-battery-grid system based on the P2G paradigm, the power generation and consumption on the building side are closely linked to the utility grid, resulting in a heavy dependence on the utility grid for electricity demand. During periods of 09:00 to 15:00, when PV and wind power generation are significant, the electricity purchased from the distribution network by the multi-microgrid is generally lower compared to other times. In fact, in microgrids with high power generation capacity, such as MG₂, there may even be a surplus of electricity sold back to the distribution network. Besides, the dynamic dispatch of electricity in the multi-microgrid system also shows variations on typical days across different seasons. Overall, the instability and intermittency of renewable energy systems, particularly wind power generation, have a notable impact on the stable operation of the utility grid. During typical summer days, when power consumption on the building side remains stable and there is consistent renewable energy generation, the power import and export between the multi-microgrid system and the utility grid tend to remain relatively stable. However, during mid-season day and winter day characterized by significant fluctuations in power generation, both the prosumer-type MG₂ and the producer-type MG₃ significantly export electricity to the grid, which might have adverse effects on the stable operation of the utility grid. Furthermore, for

the consumer-type MG₁, under the P2G power paradigm, the power dispatch distribution remains relatively consistent on typical days across different seasons. The distribution of electricity purchases from the utility grid is also maintained at a similar level.

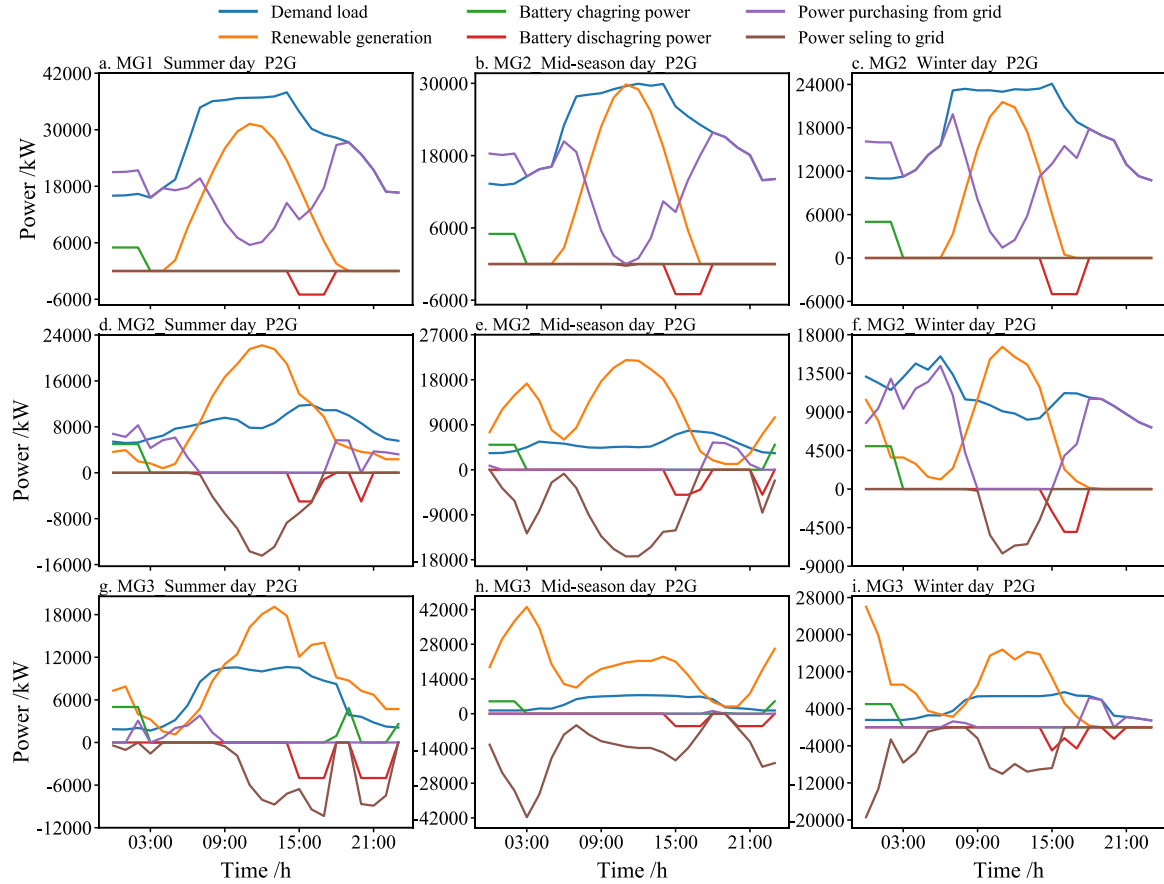


Figure 6-6 Power dispatch distribution of typical days within the multi-microgrid system under the P2G paradigm

6.3.2 Hybrid game based P2P trading strategy

The power consumption and dispatch distribution on typical days across different seasons for the multi-microgrid under the proposed hybrid game-based P2P paradigm is depicted as Figure 6-7. In the building-battery-grid system configuration under the P2P paradigm, compared to the traditional P2G paradigm, there is a noteworthy reduction in the building side's electricity production and consumption directly linked to the distribution network, resulting in a decreased dependence on the utility grid. Through mutual electricity transactions between microgrids

with diverse generation and consumption characteristics, the multi-microgrid, consisting of consumer-type MG_1 , prosumer-type MG_2 , and producer-type MG_3 , effectively reduces electricity imports from and exports to the utility grid on typical days across different seasons. This helps to minimize interactions with the utility grid and maintain lower reliance on external electricity sources. Moreover, by implementing DR for transferable loads on the building side and shifting electricity consumption from peak hours to off-peak hours, the electricity import from the utility grid by the multi-microgrid can be further leveled out, which can reduce the adverse impact of frequent electricity dispatch with the utility grid. However, despite the effectiveness of internal P2P electricity transactions in reducing the multi-microgrid system's dependence on the utility grid, the intermittency of renewable energy systems, especially wind power generation, can still result in certain extreme moments. For example, MG_3 , with a large WT capacity, may export a significant amount of electricity to the utility grid during the time period of 01:00-03:00 on typical days of mid-season and winter. This export will create imbalances in the supply-demand dynamics of the distribution network, which in turn may strain its stability and overall operation.

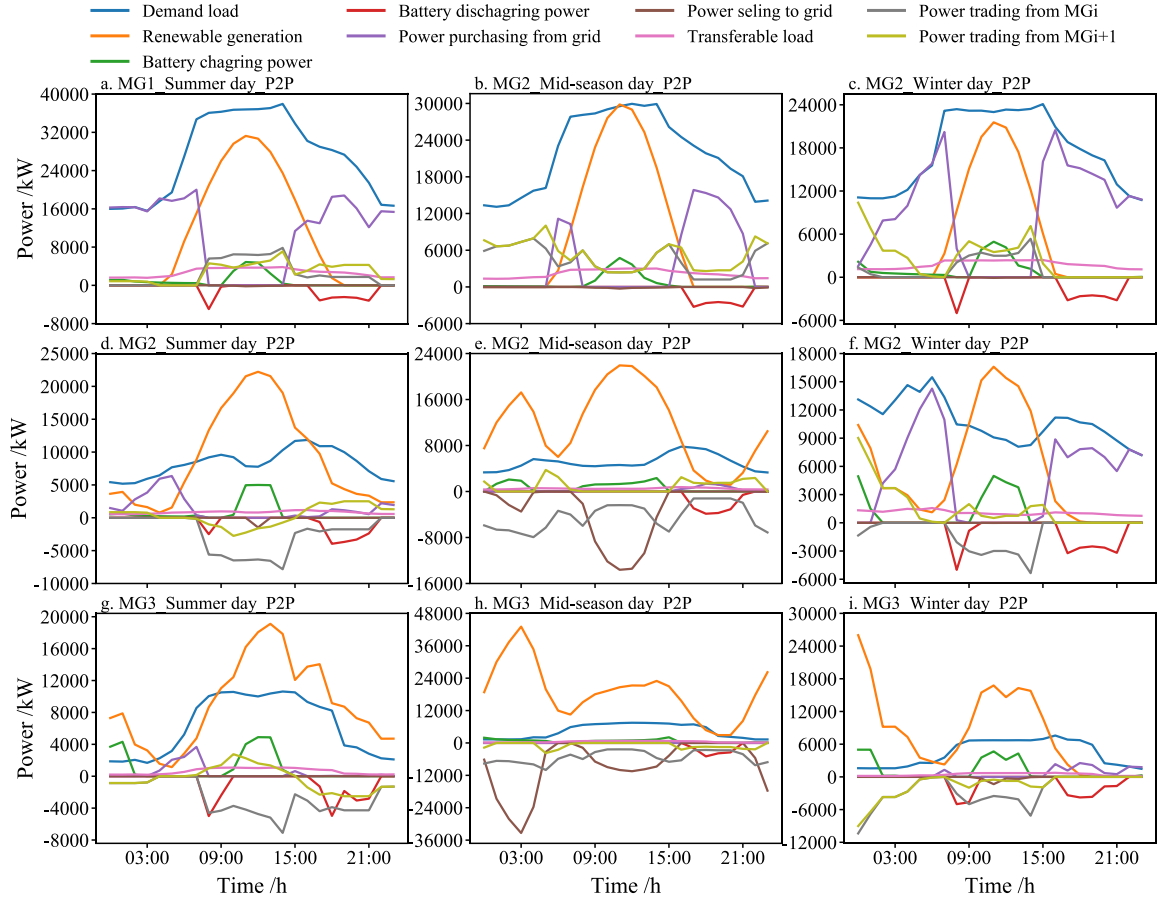


Figure 6-7 Power dispatch distribution of typical days within the multi-microgrid system under the hybrid game-based P2P paradigm

6.3.3 Techno-economic performances

A detailed comparison of key techno-economic indicators—namely SCR, SSR, and PFF—offers quantitative insights into the relative advantages of the two paradigms.

6.3.3.1 Self-consumption rate (SCR) and Self-sufficiency rate (SSR)

In the context of the energy system, the SCR assesses how much of the self-generated energy is consumed internally within the system, while the SSR measures the contribution of self-generated energy to the overall energy consumption of the system. Figure 6-8 and Figure 6-9 illustrates the distribution of SCR and SSR in the multi-microgrid under the P2G and P2P electricity transaction paradigms. Regarding the SCR indicator, the consumer-type MG₁ exhibits a consistent SCR level of approximately 99% under the TOU strategy under the P2G

paradigm and the hybrid game-based P2P paradigm. In contrast, for the prosumer-type MG₂ and the producer-type MG₃, the SCR level under the hybrid game-based P2P paradigm is significantly higher compared to the P2G paradigm. For MG₂, the SCR increases from 59.5% under the P2G paradigm to 91.0% under the P2P paradigm, and for MG₃, the SCR increases from 41.9% under the P2G paradigm to 84.9% under the P2P paradigm. This is attributed to the internal electricity transactions and dispatching between microgrids facilitated by the P2P paradigm.

Similarly, for the SSR indicator, the P2P paradigm enables internal electricity transactions between microgrids, allowing microgrids to purchase excess electricity from peer microgrids when their electricity consumption exceeds production. This leads to an increase in the SSR level on the multi-microgrid. Consumer-type MG₁ and prosumer-type MG₂ benefit from the P2P paradigm by sourcing more electricity from producer-type MG₃ during periods of insufficient power generation, significantly improving their SSR levels. For MG₁, SSR increases from 35.7% under the P2G paradigm to 63.0% under the P2P paradigm, and for MG₂, SSR increases from 64.8% under the P2G paradigm to 78.1% under the P2P paradigm. On the other hand, producer-type MG₃, which has relatively low electricity import from other microgrids in the P2P paradigm, maintains an almost consistent SSR level ranging from about 90% to 92% under both the P2G paradigm and the P2P paradigm. In summary, the P2P paradigm allows for internal electricity transactions between microgrids, improving both SCR and SSR levels for certain microgrids, while maintaining consistent levels for others.

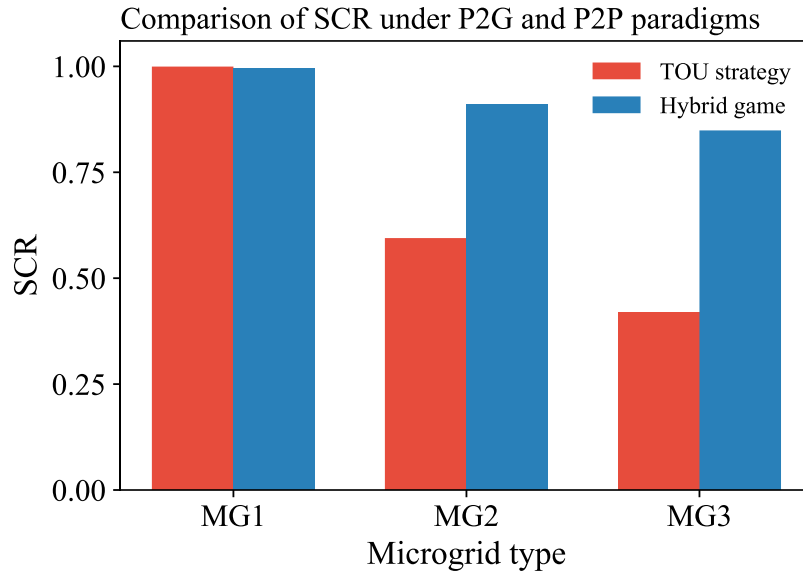


Figure 6-8 Distribution of SCR in the multi-microgrid under the P2G and P2P paradigms

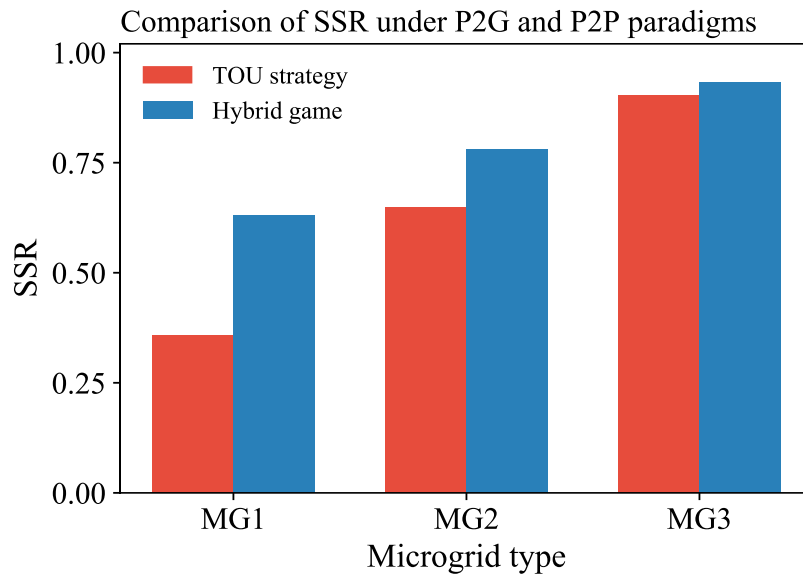


Figure 6-9 Distribution of SSR in the multi-microgrid under the P2G and P2P paradigms

6.3.3.2 Power fluctuation factor (PFF)

The PFF is indeed a crucial metric for assessing renewable energy integration, grid stability, and energy management. It quantifies the level of power fluctuation in renewable energy generation and energy consumption, with higher PFF values indicating greater variability and lower values representing more stable power generation. Figure 6-10 illustrates the PFF distribution in the multi-microgrid under the P2G and P2P paradigms on typical days across different seasons, significant differences in power interaction between the multi-microgrid and

the utility grid can be observed. The P2P paradigm demonstrates notable advantages in terms of PFF indicators. Compared to the P2G paradigm, the proposed hybrid game-based P2P paradigm achieves a considerable reduction in PFF levels. On average, the PFF decreases by approximately 70%, with the average PFF value decreasing from 1.6×10^{10} under the P2G paradigm to 4.4×10^9 under the P2P paradigm. Overall, this outcome underscores the effectiveness of the hybrid game-based P2P paradigm energy management approach in enhancing the performance of renewable energy sources and improving grid stability. By mitigating power fluctuations, this approach optimizes the operation of the power system, leading to more reliable and efficient utilization of renewable energy resources.

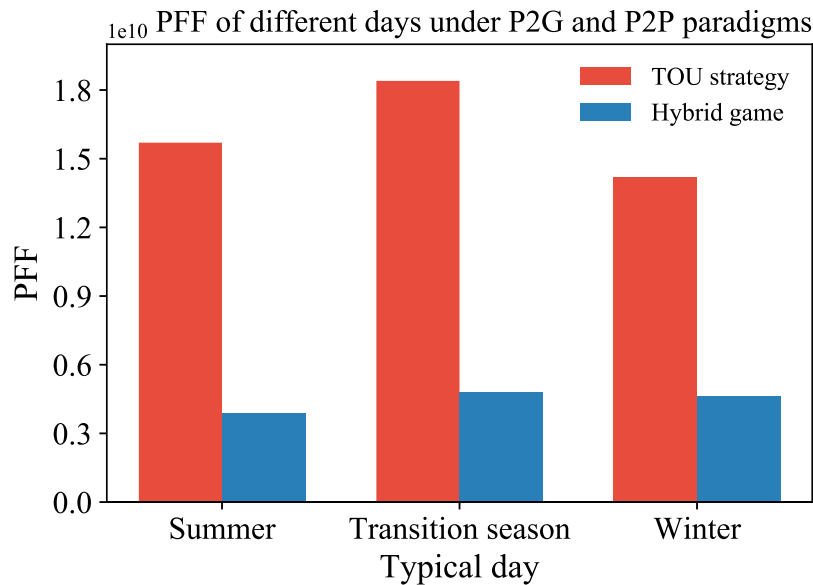


Figure 6-10 Distribution of PFF in the multi-microgrid under the P2G and P2P paradigms

6.3.3.3 Total electricity cost

Total electricity cost for each microgrid and building community is also an important metric that provides insights into the economic implications and financial performance of the multi-microgrid. Figure 6-11 illustrates the distribution of total electricity purchase costs for the multi-microgrid and diversified building communities on typical days across different seasons under the P2G and P2P paradigms. The result implies that both power-importing microgrids

and power-exporting microgrids can ensure economically viable electricity costs, making it feasible for the multi-microgrid to effectively reduce the total cost of electricity purchases compared to the P2G paradigm. Specifically, for consumer-type MG₁, the total electricity cost decreases significantly from 114,670 \$ under the P2G paradigm to 66,955 \$ under the P2P paradigm. Besides, for prosumer-type MG₂, the total electricity cost remains relatively low under both the P2G paradigm (7,144 \$) and the P2P paradigm (-1,058 \$). The negative value of the electricity cost indicates that it can obtain benefits from power dispatching and electricity transactions, resulting in potential savings or revenue generation. Similarly, for producer-type MG₃, both the P2G and P2P paradigms can ensure the multi-microgrid in a profit state for power dispatching and electricity transactions on typical days across different seasons. However, the P2P paradigm allows MG₃ to further maximize its economic efficiency by conducting internal electricity transactions with other microgrids. The total electricity revenue of MG₃ increases from 30,992 \$ under the P2G paradigms to 50,495 \$ under the P2P paradigms. These findings demonstrate that the P2P paradigm, specifically the hybrid game-based P2P paradigm, can substantially reduce the total electricity cost for consumer-type microgrids and provide cost-saving benefits to prosumer and producer-type microgrids through power dispatching and internal electricity transactions. This highlights the P2P paradigm's potential to enhance economic efficiency and optimize costs in multi-microgrid energy systems.

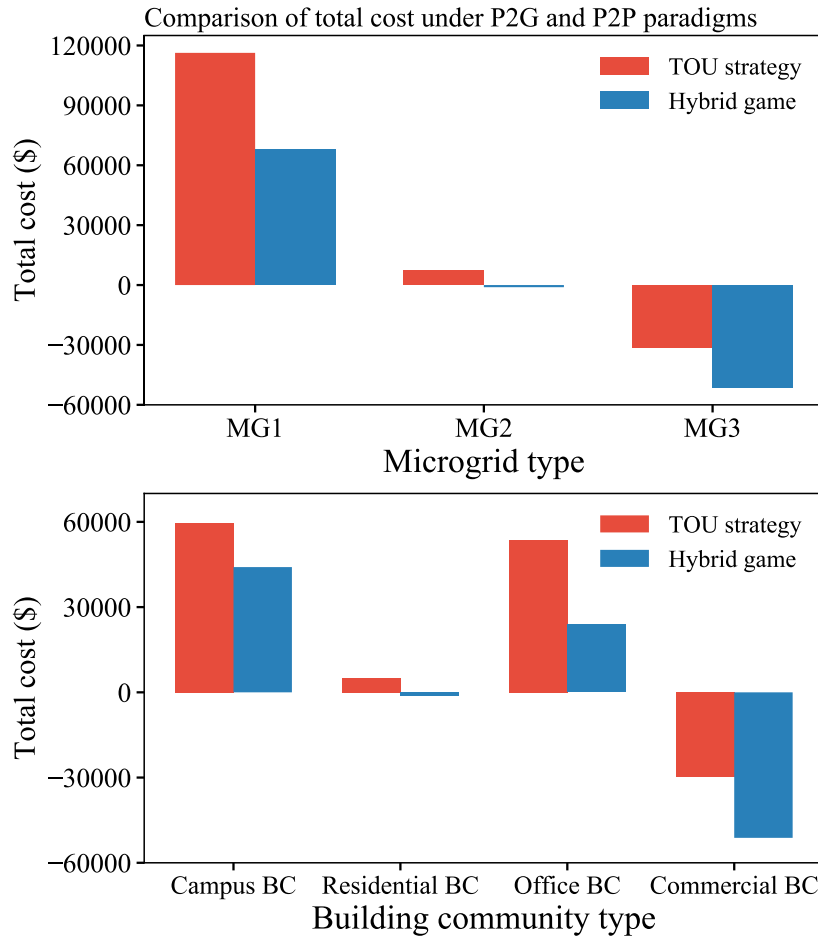


Figure 6-11 Distribution of total electricity purchase costs for multi-microgrid and diversified building communities under the P2G and P2P paradigms

6.4 Analysis of electricity transaction and fairness in revenue distribution

This section focuses on the comprehensive analysis of electricity transaction patterns and the fairness of revenue distribution within the multi-microgrid system, under both the traditional P2G and the proposed P2P trading paradigms. By examining the spatial and temporal characteristics of electricity imports and exports, the internal pricing mechanisms, and the allocation of trading revenues among microgrids, this study aims to provide a holistic understanding of the operational and economic impacts of different electricity market structures.

6.4.1 Imported and exported electricity

Electricity import and export distribution involves the transfer of electrical power between different entities or systems, typically within a larger energy network such as a microgrid or utility grid. It encompasses the procurement of electricity from external sources through imports and the distribution of electricity generated within a specific system to other microgrids or utility grid through export. The importance of electricity import and export distribution lies in its crucial role in ensuring a reliable and balanced energy supply. By providing access to additional power, it addresses situations where local generation capacity is insufficient or where energy diversification is desired. Furthermore, the exportation of surplus electricity allows for the efficient utilization of renewable energy resources and presents the opportunity for economic benefits through revenue generation for the entity exporting the electricity.

6.4.1.1 Traditional TOU strategy under P2G paradigm

Figure 6-12 illustrates the distribution of electricity import and export components within the multi-microgrid operating under the P2G paradigm. The TOU strategy governs the order of power import and export for the multi-microgrid, which is relatively straightforward. Alongside charging and discharging the batteries, the microgrid primarily engages in trading the required or excess electricity with the utility grid. For consumer-type MG₁, approximately 99.2% of the power generation is directly utilized by the building, supporting its electricity needs. Additionally, 7.75% of the generated power is charged to the matched battery for storage purposes. The remaining electricity demand, which accounts for approximately 63.6% of the total load demand, is fulfilled by the utility grid. For prosumer-type MG₂, under the TOU strategy, approximately 47.2% of the power generation is directly utilized by the building, satisfying about 51.0% of the demand load. The charging of the battery constitutes 8% of the power generation, while its discharging meets 8.3% of the demand load. Notably, the utility grid plays a significant role in the multi-microgrid, serving as the primary interaction point. Around 44.8% of the power generation is directly exported to the utility grid, while the system

imports 40.7% of the demand load electricity from the grid to meet its own electrical demands. For producer-type MG₃, a relatively smaller proportion of power generation, specifically 29.2%, is consumed directly by the microgrid itself, which satisfies about 69.8% of the demand load. While batteries serve as power buffers, with 6.8% of the power generation dedicated to charging and 20.6% of the demand load met through discharging, a significant proportion of power generation is still directly exported to the grid. About 64.0% of the generated power is exported, while only 9.6% of the demand load is imported from the grid.

Indeed, the import and export of electricity within the multi-microgrid under the P2G paradigm heavily relies on the utility grid, which can impact the system's stability. The multi-microgrid's operation is susceptible to disruptions in the external electricity supply, such as interruptions or price increases, which can result in insufficient power supply or increased costs. Additionally, regulating the import and export of electricity requires coordination with the demand and operation conditions of the utility grid to maintain stability and load balance. To ensure smooth electricity imports and exports, cross-regional cooperation and coordination are essential. Establishing a suitable mechanism for electricity cooperation and trading becomes crucial in facilitating efficient and reliable energy exchange.

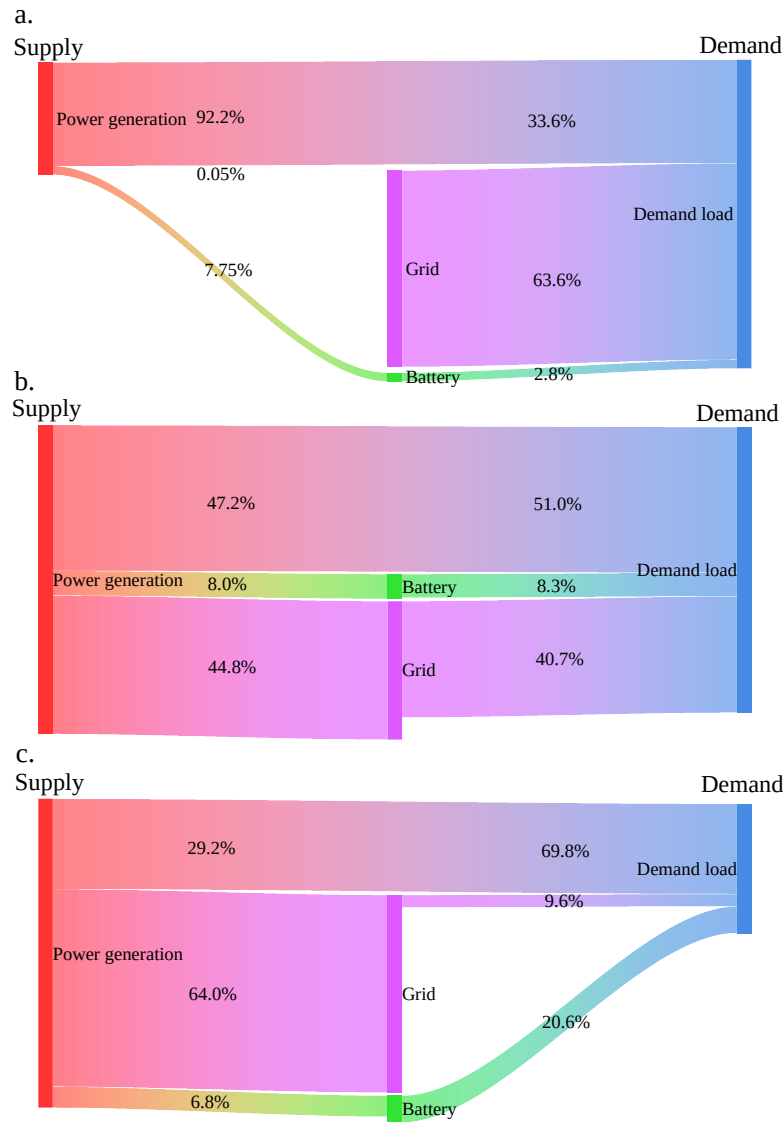


Figure 6-12 Distribution of electricity import and export components within the multi-microgrid under the P2G paradigm: (a) MG₁, (b) MG₂, (c) MG₃

6.4.1.2 Hybrid game-based P2P paradigm

The distribution of electricity import and export within the multi-microgrid, operating under the proposed hybrid game-based P2P paradigm, is illustrated in Figure 6-13. This paradigm introduces more intricate methods for power import and export within the multi-microgrid. In addition to the standard charging and discharging of the matched battery, the power required for the building or surplus power can be adjusted through transferable load demand response and import/export transactions with the utility grid and other peer microgrids. For consumer-type MG₁, the direct consumption level of power generation remains similar to that of the TOU

strategy. However, under the P2P paradigm, the power import from the utility grid for MG₁ can be reduced from 63.6% of the demand load under the P2G paradigm to 33.2%. This reduction is achieved through demand response adjustments of transferable load and internal electricity transactions with other microgrids. Regarding the prosumer-type MG₂, the power export to and import from other microgrids under the hybrid game-based P2P paradigm account for 31.2% of the generated power and 11.8% of the demand load, respectively. Furthermore, internal electricity transactions significantly impact the interaction between the multi-microgrid and the utility grid. Under the P2P paradigm, the power export of MG₂ to the utility grid and power import from the utility grid are reduced to 11.6% and 23.9%, respectively, compared to 44.8% and 40.7% under the P2G paradigm. Similarly, for the producer-type MG₃, the internal electricity export to and import from other microgrids under the hybrid game-based P2P paradigm are 23.5% and 6.1%, respectively. Additionally, the electricity export to and import from the utility grid are reduced to 38.1% and 2.9%, respectively, compared to 64.0% and 9.6% under the P2G paradigm. Furthermore, for all types of microgrids, including MG₁, MG₂, and MG₃, the demand response at the transferable load under the hybrid game-based P2P paradigm can shift approximately 9% of the load from peak time to valley time, thereby enhancing energy dispatching efficiency and achieving greater economic benefits for the multi-microgrid. By adjusting the electricity transaction paradigm, the multi-microgrid can significantly reduce its dependence on the utility grid and increase its self-sufficiency, benefiting from enhanced energy management strategies and localized internal electricity transactions within the hybrid game framework.

To sum up, the electricity import and export distribution under the hybrid game-based P2P paradigm reduces reliance on the utility grid by facilitating internal transactions among multiple microgrids, thereby positively impacting the stable operation of the utility grid. Through internal electricity transactions, the multi-microgrid can enhance energy autonomy,

improve grid stability, promote energy efficiency, and foster community participation and energy sharing to achieve greater economic benefits. The decentralized nature of this electricity transaction mode supports sustainable energy development and facilitates the transformation of the power system. It provides a suitable approach for cross-regional electricity cooperation and coordination, fostering collaboration and synergy among microgrids. Overall, the hybrid game-based P2P paradigm holds promise for advancing the power sector towards a more sustainable and efficient future.

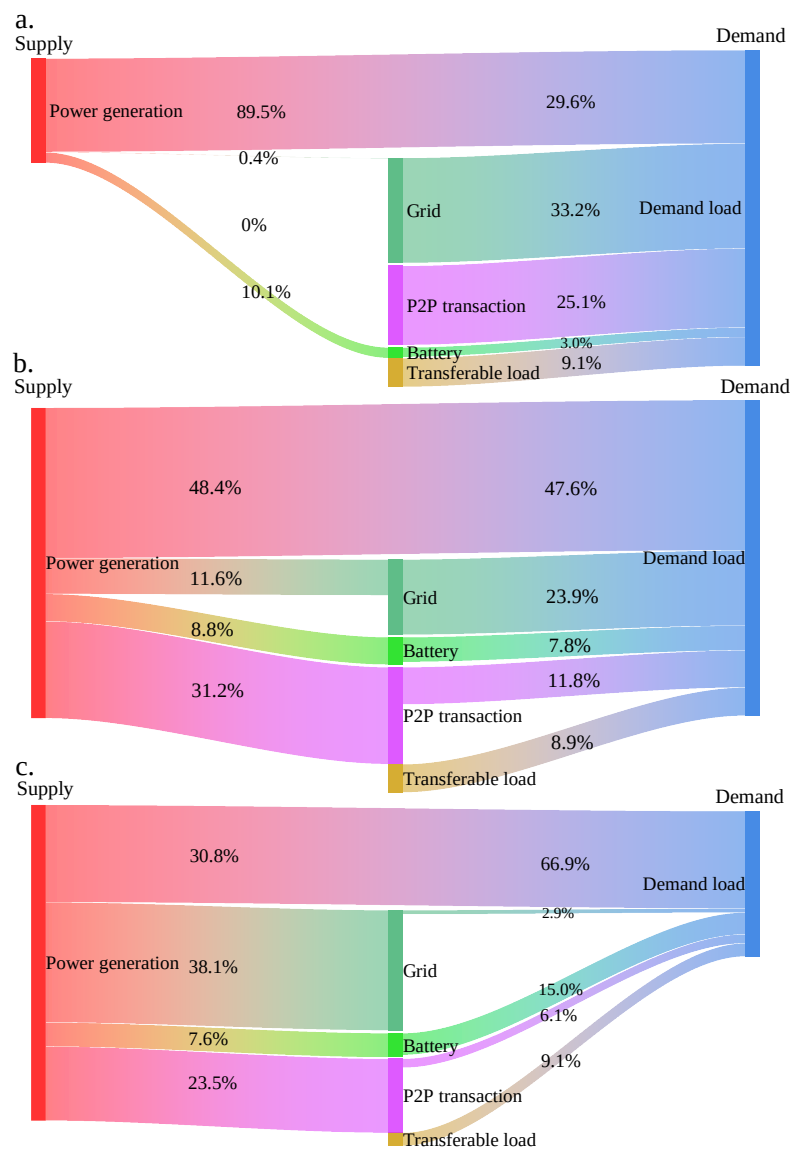


Figure 6-13 Distribution of electricity import and export within the multi-microgrid under the proposed hybrid game-based P2P paradigm: (a) MG₁, (b) MG₂, (c) MG₃

6.4.2 Internal P2P pricing dynamics

According to Figure 6-14, the distribution of internal electricity transaction prices within the multi-microgrid system at different times on different typical days under the hybrid game-based P2P paradigm is depicted. These internal electricity transaction prices are calculated based on the non-cooperative game and fall between the FiT and the REP. This ensures that the game relationship between microgrids and between the multi-microgrid and utility grids satisfies the requirements of Nash equilibrium. In the hybrid game-based P2P paradigm, the internal transaction prices between different microgrids are independently negotiated and determined based on their respective economic interests. Each microgrid can set its optimal pricing according to its generation costs, demand situation, and electricity market conditions. Unlike existing P2P electricity transaction price models based on SDR [83, 153], the electricity transaction price under the P2P paradigm is not strongly related to the single variable of supply-demand relationship. However, the internal electricity transaction price can be influenced by market supply and demand. When a microgrid's power supply exceeds its demand, it may sell excess electricity to other microgrids at a lower price. Conversely, when a microgrid's demand exceeds its power supply, it may purchase power from other microgrids at a higher price. Furthermore, the internal electricity transaction price may vary based on factors such as time, location, and the types of microgrids involved in the transaction. For example, the transaction price between producer-type microgrids and consumer-type microgrids tends to be higher, while the transaction price between producer-type microgrid and prosumer-type microgrid may be lower.

To summarize, the internal transaction price between different microgrids under the P2P paradigm is determined through negotiation considering market supply and demand, as well as the transaction types of the microgrids and their economic interests. The internal electricity transaction price under the P2P paradigm is an independent variable and does not exhibit a

strong linear or nonlinear relationship with the electricity transaction quantity through SDR. Therefore, in the calculation process of power dispatch under the P2P paradigm, the transaction electricity and transaction electricity price should be optimized separately. In existing literature [83, 153], it is commonly observed that the transaction electricity and transaction electricity price are often unified through an intermediate variable, which may introduce significant errors and requires further study.

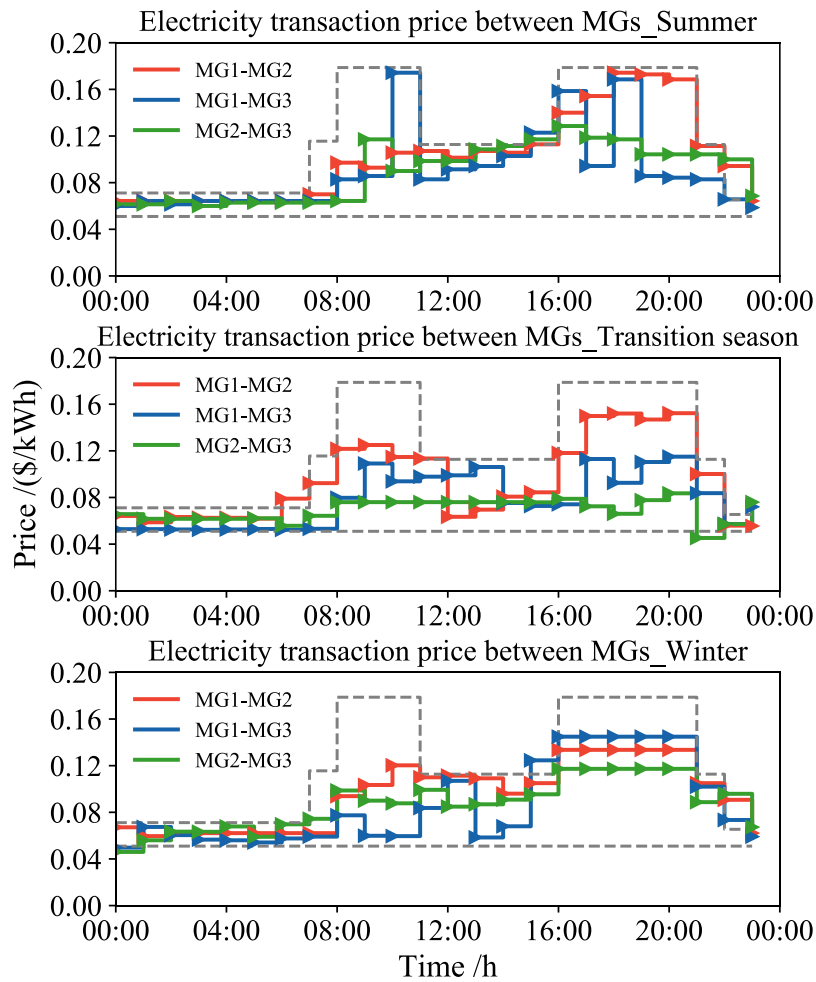


Figure 6-14 Distribution of internal electricity transaction prices within the multi-microgrid system under the bargaining game-based P2P paradigm

6.4.3 Fairness in revenue distribution

In the context of the P2P paradigm, the pursuit of equitable revenue distribution is a significant objective. Figure 6-11 illustrates the distribution of electricity purchase costs across multiple

microgrids and the revenue distribution among diverse building communities, considering both the P2G and hybrid game-based P2P paradigms. In the hybrid game-based P2P paradigm, the relationship between different microgrids can be characterized as a non-cooperative game. This non-cooperative game encourages the establishment of competitive relationships among microgrids, fostering efforts to maximize benefits through pricing and transaction strategies. Consequently, resource allocation becomes more efficient, leading to improved economic outcomes. However, in this non-cooperative game, each microgrid strives to maximize its individual interests without a centralized coordination mechanism, potentially resulting in unfairness. Microgrids prioritize their economic interests, sometimes overlooking the interests of other microgrids. As a consequence, there is a risk of unfairness in revenue distribution. Conversely, within the same microgrid, the relationship between different building communities can be characterized as a cooperative game. These building communities collaborate and negotiate to determine the electricity transaction arrangements among them, leveraging the output-input ratio. For instance, in MG1, the campus building community and office building community engage in P2P electricity transaction to achieve a more equitable income distribution. Within the cooperative game, building communities can collectively establish rules and guidelines to ensure fair energy trading and income distribution while sharing economic benefits.

6.5 Summary

The rising penetration of renewable energy in buildings and the electrification of transportation present challenges in maintaining a reliable energy supply-demand balance. In this study, a hybrid game-based P2P energy management method is proposed, and a comparative analysis of electricity transactions is conducted in a multi-microgrid with diverse building communities, considering EVs. The study considers a hybrid game-based P2P electricity trading paradigm

and compares it with a traditional TOU strategy under the P2G paradigm. The proposed method is evaluated using three typical days across different seasons in the multi-microgrid, considering dynamic electricity demand, technical aspects, economic factors, and more. The analysis has yielded the following conclusions:

- Under the typical P2G paradigm with TOU strategy, the power dispatch distribution in multi-microgrids shows a heavy dependence on the utility grid for electricity demand, particularly during periods of significant PV and wind power generation. In contrast, the proposed hybrid game-based P2P paradigm reduces the multi-microgrid's reliance on the utility grid by facilitating mutual electricity transactions between microgrids with diverse generation and consumption characteristics, minimizing imports and exports.
- The hybrid game-based P2P paradigm improves SCR and SSR for prosumer and producer-type microgrids, reducing PFF by 70%, and lowers total electricity costs for consumer-type microgrids. This paradigm enables internal electricity transactions, enhances economic efficiency, reduces costs, and optimizes renewable energy utilization in multi-microgrid systems.
- The hybrid game-based P2P paradigm reduces power imports from the utility grid for consumer-type microgrids by 30.4% and power exports to the utility grid for prosumer and producer-type microgrids by 33.2% and 25.9% respectively. It also enables a 9.0% shift in demand response for transferable load. Overall, this paradigm enhances energy autonomy, grid stability, efficiency, and economic benefits in the multi-microgrid.
- Under the hybrid game-based P2P paradigm, internal electricity transaction prices are determined through negotiation considering energy supply and demand, transaction types, and microgrid economic interests. The transaction price is independent of the supply-demand relationship.

In summary, this chapter highlights the potential of the hybrid game theory-based P2P paradigm in facilitating efficient and sustainable electricity exchange within microgrid ecosystems. It contributes to the advancement of energy management strategies, promotes the integration of variable renewable energy, and supports the optimization of electricity transactions in heterogeneous building communities with EVs. Further studies need to focus on conducting comprehensive economic analyses to assess the capital investments required for implementing microgrids and evaluate the feasibility of hiring staff and acquiring equipment. This will pave the way for translating this study into real-world practical applications, ensuring the sustainable development of community-based energy systems. In future research, it is also important to investigate the implications of the proposed P2P framework on the central grid, considering the need for enhanced ramping capabilities and centralized control to manage the introduced fluctuations. This will provide a more comprehensive understanding of the practical implications and pave the way for the implementation of P2P energy trading at a larger scale.

CHAPTER 7 A SHORT-TERM COORDINATED LOAD RESTORATION STRATEGY CONSIDERING CONSUMPTION SIDE LOAD REBOUND AND FLEXIBLE ENERGY RESOURCES

This chapter develops and evaluates a short-term coordinated load restoration strategy that explicitly considers demand-side load rebound and the integration of flexible energy resources. Building on the multi-microgrid energy management and peer-to-peer trading strategies established in Chapters 5 and 6, the focus here shifts to enhancing system resilience and operational recovery following disturbances in community energy systems. Previous work has addressed optimal capacity planning and steady-state operation, while this chapter addresses the dynamic restoration phase, where rapid and efficient recovery is critical. The proposed approach introduces a two-stage coordinated restoration scheme, comprising an overall framework and a mathematical model designed to optimize both the sequence of load node restoration and the dispatch of distributed energy resources. Special attention is given to modeling demand-side load rebound, such as building cold load pickup (CLPU) and electric vehicle (EV) charging load rebound, which significantly affect system stability during restoration. By incorporating these phenomena, the strategy ensures a more realistic and effective approach to system recovery. A comprehensive case study is conducted, including test system configuration, the definition of multiple restoration scenarios, and comparative case analysis. Results are presented and discussed with respect to load rebound profiles, restoration sequences, distributed generator and voltage source converter performance, and node voltage stability. The findings underscore the importance of advanced grid architectures and flexible distributed energy resource integration for improving restoration efficiency and resilience. By

explicitly considering demand-side dynamics and coordinated control, this chapter offers practical insights for strengthening the operational reliability of future community energy systems.

7.1 Two-stage coordinated restoration scheme

This section presents the design and implementation of a two-stage coordinated restoration scheme for hybrid AC/DC interconnected distribution grids. The proposed scheme aims to accelerate the restoration process following extreme events, enhance system resilience, and optimize the utilization of DERs, including DGs, PV systems, and EVs. The two-stage approach systematically integrates topology reconfiguration, load prioritization, and optimal power dispatching to achieve rapid and resilient restoration while minimizing network losses.

7.1.1 Coordinated restoration scheme description

The proposed coordinated restoration scheme systematically integrates the grid topology layer, information layer, and restoration flow layer, as illustrated in Figure 7-1. This hybrid topology is designed to facilitate the rapid restoration of critical loads during power outages while simultaneously enhancing power quality through the optimal utilization of DERs and flexible resources [154]. In extreme disaster scenarios, the framework isolates faulty grid sections into subgrids, each adhering to radial topology constraints, and optimally dispatches DGs for load restoration [155]. Topology reconfiguration and tie-switch operations are employed to optimize the utilization of local DGs, prioritizing the restoration of crucial loads whenever feasible.

The restoration process addresses several challenges, including demand-side load rebound phenomena (e.g., CLPU and EV charging surges), limited DG ramping capabilities, and mismatches between resource availability and load demand. By leveraging DC

interconnections, the framework coordinates multiple power resources to overcome these challenges and optimize restoration process. Prior to restoration, the distribution system operator (DSO) collects essential data, including load rebound profiles, grid topology, PV generation, EV status, and DG capacities [156]. Based on this information, a two-stage optimization scheme is employed to determine optimal load restoration sequences, EV discharging references, VSC dispatching strategies, and DG schedules. These directives are iteratively executed through remote switches and other grid devices until full restoration is achieved. The two-stage optimization process holistically integrates scheduling and operational decision-making, demonstrating significant advantages in managing complex demand-side rebound effects, enabling faster restoration, and optimizing distributed resource utilization. A detailed comparison among conventional approaches, our prior work, and the proposed framework is presented as Table 7-1. The proposed scheme demonstrably outperforms existing methods by effectively mitigating intricate demand-side load rebound challenges and optimizing the utilization of distributed and flexible resources, thereby achieving rapid and efficient power system restoration.

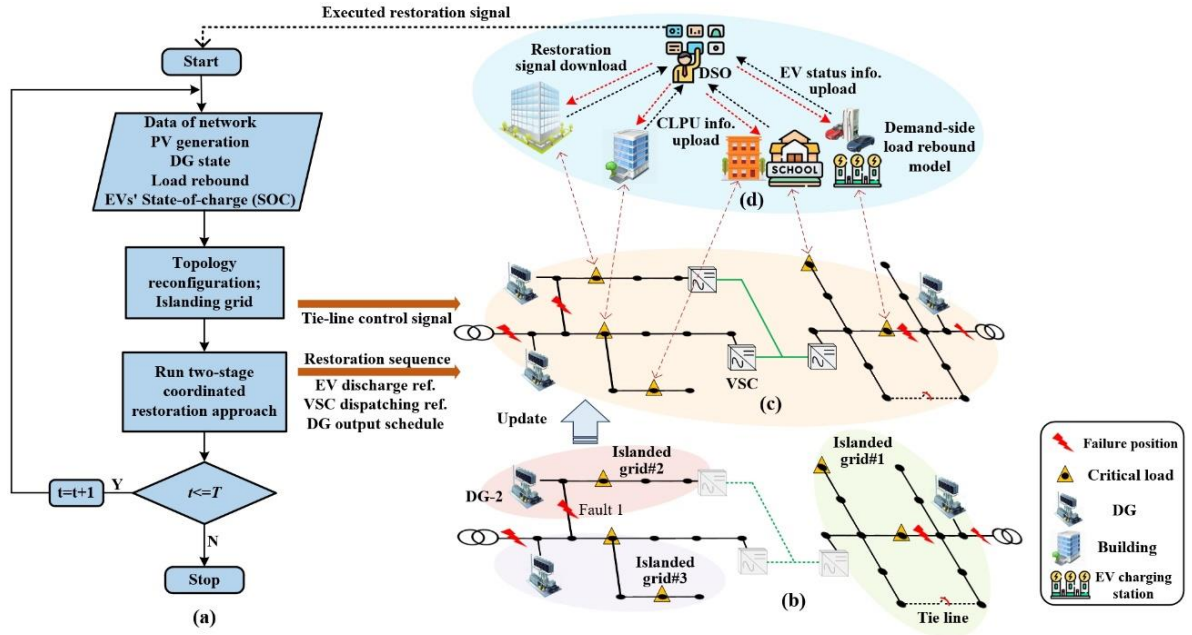


Figure 7-1 The proposed two-stage coordinated restoration scheme. (a) Developed restoration flow chart; (b) Traditional AC distribution grid with fault incidents; (c) Hybrid AC/DC distribution grid with fault incidents; (d) Information interaction process between demand-side users (building and transportation) and DSO

Table 7-1 Power restoration scheme comparison of conventional approaches, our prior work, and the proposed framework

Restoration scheme	CLPU	EV charging load rebound	Distributed resources utilization	Flexible resource (e.g. V2G)	Multi-step restoration	Backup black start resource	Grid islanding	Topology reconfiguration
Conv. scheme [157]	/	/	/	/	✓	/	✓	✓
Our prior work [156]	✓	/	/	/	✓	✓	✓	✓
Proposed framework	✓	✓	✓	✓	✓	✓	✓	✓

7.1.2 Two-stage coordinated restoration strategy

The flowchart of the proposed two-stage restoration strategy is depicted in Table 7-2. Input data includes grid topology (e.g., fault lines and status of tie-line switches), CLPU and EV charging rebound data for critical nodes, EV arrival status at buildings, DERs resource (e.g., PV generation), and DG information (e.g., remaining energy capacity and rated power). In Stage 1, the primary objective is to accelerate restoration and enhance system resilience by

optimizing the sequence of load restoration. The optimization interval aligns with the restoration timestep, while the optimization horizon covers the entire desired restoration period. Once the optimal load restoration sequence is determined, Stage 2 focuses on jointly optimizing the power output of EV reverse discharge, DGs output, and VSC power dispatching to minimize network losses. To ensure stability in hybrid AC/DC grids, power flows are continuously balanced to maintain that DC voltage deviations remain within acceptable limits. In this stage, the VSC functions as a slack terminal to stabilize the DC bus voltage, employing typical V_{dc}/Q and P/Q control strategies [158].

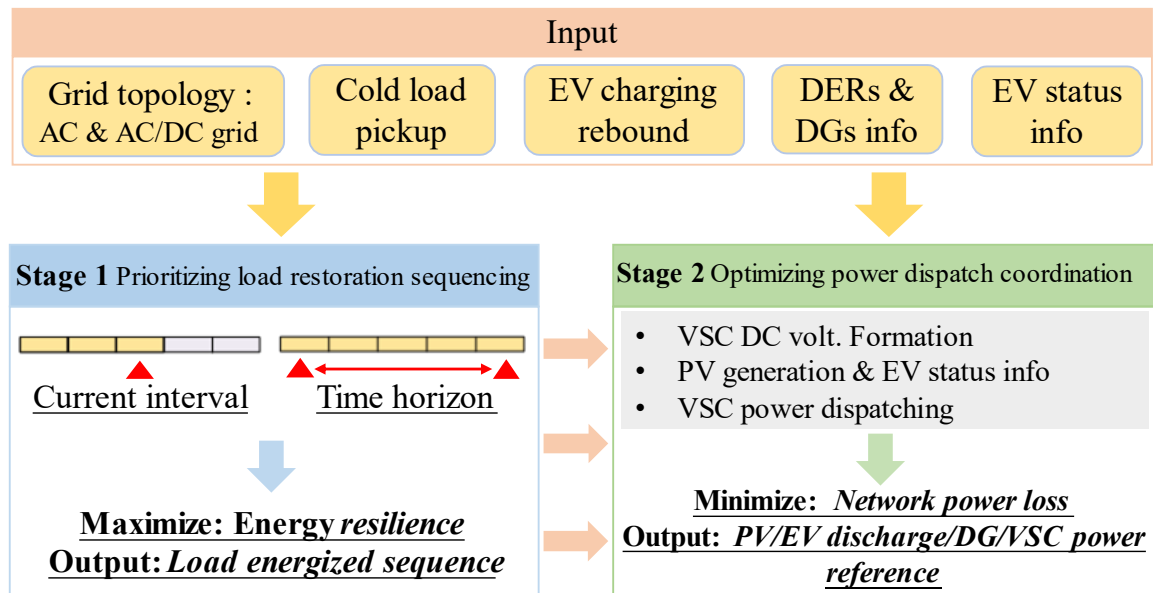


Figure 7-2 The flowchart of the two-stage coordinated restoration strategy

Stage 1: optimize the load restoration sequence

Regarding the resilience curve during extreme disasters, the restoration process typically defines the resilience index as the product of the recovered electrical power and its weighting factors, which represents the system's restoration capability. Enhancing the resilience of distribution grids can be achieved by prioritizing the restoration of essential loads exhibiting higher weighting indexes and increasing the base power support to these loads during the restoration period. Thus, the above-mentioned CLPU would delay the load-energized timeslot

due to the emerging load peak considering the inadequate power supply. Moreover, if the total stored energy from available DGs in the distribution network is insufficient to meet all critical demands, the limited sources should be used to energize the critical loads with a higher priority. In light of this, the resilience index in Eq. (7.1) is represented as the multiplication of the load weighting factors and the recovered base power quantity for the loads.

$$\max f = \sum_{k \in T} \sum_{i \in L} \omega_i S_{i,t} P_{i,t} \quad (7.1)$$

Stage 2: optimize the power flow for network losses reduction.

The former stage generates the load-energized sequence considering the CLPU. During an extreme disaster, when the available power storage is insufficient to meet the whole demand, it is necessary to utilize all available resources to its maximum capacity until finishing all the restoration process. Thus, it is necessary to optimize the overall power flow of grids by arranging DG output and VSC power dispatching properly for resilience enhancement. The optimization function can be expressed as Eq. (7.2).

$$\min f = \sum_{t \in T} \sum_{ij \in \Omega_B} I_{ij}^{sqr,t} R_{ij} + \sum_{k \in T} \sum_{x \in \Omega_{VSC}} P_{VSC_x}^{loss,t} \quad (7.2)$$

7.1.3 Constraints

This problem is subject to a series of technical and operational constraints that ensure the feasibility and safety of the restoration process.

- 1) Sequencing constraints: The load should not be shed after it is restored during the restoration process.

$$S_{i,t+1} \geq S_{i,t} \quad (7.3)$$

- 2) DG ramp rate constraints: The operational constraints of DGs include the capacity limits and ramping-up limits, which should be within the acceptable range. Eq. (7.4) denotes the

power capacity limits. And the ramping-up constraint comprises two consecutive steps, which is described as Eq. (7.5).

$$\begin{cases} 0 \leq P_{DG-i}^t \leq P_{DG-i}^{\max}, i \in G \\ 0 \leq Q_{DG-i}^t \leq Q_{DG-i}^{\max}, i \in G \end{cases} \quad (7.4)$$

$$R_{DG-i}^- \leq P_{DG-i}^{t+1} - P_{DG-i}^t \leq R_{DG-i}^+, i \in G \quad (7.5)$$

- 3) Power flow constraints: The Simplified DistFlow equations have gained widespread usage in radial distribution systems [21]. These equations are based on the assumption that the non-linear terms in the DistFlow equations are significantly smaller than the linear terms and can be disregarded [54]. To incorporate binary restoration variables, the following revised DistFlow equations are formulated:

$$\sum_{j \in \delta(i)} P_{ij}^t - \sum_{j \in \gamma(i)} (P_{ji}^t - R_{ji} I_{ji}^{sqr,t}) = P_{DG-i}^t + P_{VSC-i}^t - s_{i,t} P_{i,t}^{sum} \quad (7.6)$$

$$\sum_{j \in \delta(i)} Q_{ij}^t - \sum_{j \in \gamma(i)} (Q_{ji}^t - X_{ji} I_{ji}^{sqr,t}) = Q_{DG-i}^t + Q_{VSC-i}^t - s_{i,t} Q_{i,t}^{sum} \quad (7.7)$$

$$V_{i,t}^{sqr} - V_{j,t}^{sqr} - 2(R_{ij} P_{ij}^t + X_{ij} Q_{ij}^t) + (R_{ij}^2 + X_{ij}^2) \frac{P_{ij}^t \wedge 2 + Q_{ij}^t \wedge 2}{V_{i,t}^{sqr}} \leq M(1 - z_{ij}) \quad (7.8)$$

$$V_{i,t}^{sqr} - V_{j,t}^{sqr} - 2(R_{ij} P_{ij}^t + X_{ij} Q_{ij}^t) + (R_{ij}^2 + X_{ij}^2) \frac{P_{ij}^t \wedge 2 + Q_{ij}^t \wedge 2}{V_{i,t}^{sqr}} \geq M(z_{ij} - 1) \quad (7.9)$$

$$I_{ij}^{sqr,t} = \frac{P_{ij}^t \wedge 2 + Q_{ij}^t \wedge 2}{V_{i,t}^{sqr}} \quad (7.10)$$

- 4) Eqs. (7.6) - (7.7) describe that the active/reactive power injected into node i equals the power flowing out of the node. The DG, interconnected VSC, and critical load power at node i (if possible) are included in the power balance equation. Equ. (14)-(15) is the voltage drop. Since line fault or topology reconfiguration would lead to a line open state, the corresponding line voltage drop will not be determined by the line power flow in this

condition. The used Big-M method guarantees the constraints would be active when there is no line open state. An analytical method for big M selection is discussed in [70]. As for Eq. (7.11) belonging to the quadratic equation, further convexification is conducted by conic inequality as follows in Eq. (7.11).

$$I_{ij}^{sqr,t} + V_{i,t}^{sqr} \geq \left\| \begin{array}{c} 2P_{ij}^t \\ 2Q_{ij}^t \\ I_{ij}^{sqr,t} - V_{i,t}^{sqr} \end{array} \right\|_2 \quad (7.11)$$

5) Network topological constraints: the distribution grid is supposed to be a radial structure.

In the condition of line fault, the origin grid topology can be switched to another radial topology to minimize load shedding with considering line capacity limits. The virtual power flow-based radial topology description method is always used, which introduces the group of switching status variable z_{ij} as the original network and each no-balance source node is assumed to have a unity load demand 1. The radial topology constraints are illustrated below.

$$\sum_{ij \in \Omega_B} z_{ij} = |\Omega_N| - 1 - |\Omega_N^{Is}| \quad (7.12)$$

$$\begin{cases} \sum_{k \in \delta(j)} F_{jk} - \sum_{i \in \gamma(j)} F_{ij} = -1, & j \in \Omega_N \setminus \Omega_N^{Is}, j \neq 1 \\ \sum_{k \in \delta(i)} F_{jk} - \sum_{i \in \gamma(i)} F_{ij} = 0, & j \in \Omega_N^{Is} \end{cases} \quad (7.13)$$

$$\sum_{k \in \delta(j)} F_{jk} = |\Omega_N| - 1 - |\Omega_N^{Is}|, \quad j = 1 \quad (7.14)$$

$$-M \cdot z_{ij} \leq F_{ij} \leq M \cdot z_{ij} \quad (7.15)$$

$$\begin{cases} z_{ij} = 0, & (i, j) \in \Omega_B^{Fa} \\ z_{ij} = 1, & (i, j) \in \Omega_B^{Ns} \setminus \Omega_B^{Fa} \\ z_{ij} = 0, & (i, j) \in \Omega_B^{Is} \end{cases} \quad (7.16)$$

Eq. (7.13) restricts the virtual line power balance in a grid topology; For an islanded topology, this line is not energized; Eq. (7.14) illustrates the balance between virtual power flow and nodes. Eq. (7.15) represents the bus flow constraint with the big-M method; Eq. (7.16) means the state of the fault lines/no switch lines/islanded lines.

6) Voltage limit: node voltage should remain within the maximum and minimum boundary.

$$(V^{\min})^2 \leq V_{i,t}^{sqr} \leq (V^{\max})^2 \quad (7.17)$$

7) Bus capacity constraint: the power flow on bus lines should be constrained, taking into account the thermal capacities.

$$P_{ij}^t \wedge 2 + Q_{ij}^t \wedge 2 \leq z_{ij} \overline{S}_{ij}^2 \quad (7.18)$$

When both sides are divided by $V_{i,k}^{sqr}$, the transformed Eq. (7.19) is shown below.

$$I_{ij}^{sqr,t} \leq z_{ij} \overline{I}_{ij}^2 \quad (7.20)$$

8) EV charging and discharging constraints

The SOC of EVs must remain within safe operating bounds to prevent overcharging or deep discharging, as expressed in Eq. (7.21). EV charging and discharging power must also comply with specified limits, as depicted in Eqs. (7.22) - (7.23).

$$SOC_{ev}^{\min} \leq SOC_{ev}^t \leq SOC_{ev}^{\max} \quad (7.21)$$

$$P_{ev,ch}^{\min} \leq P_{ev,ch}^t \leq P_{ev,ch}^{\max} \quad (7.22)$$

$$P_{ev,dis}^{\min} \leq P_{ev,dis}^t \leq P_{ev,dis}^{\max} \quad (7.23)$$

9) VSC operation constraints

To realize the DC interconnection, multiple VSCs are deployed in some grid nodes. The transfer power capacity is limited by the VSC rated power boundary, which is expressed as Eq. (27). It can be seen that this equation presents a circular constraint. For quadratic constraint linearization, a common method is to adopt several square constraints to approximate the circular constraint. As shown in Figure 7-3, two square constraints are used to replace Eq. (7.24), providing enough precision for engineering use. The colored region means the data selection area, the green square means the constructed area by the former two equations of Eq. (7.25), and the orange square means the constructed area by the last two equations of Eq. (7.25). In general, more square constraints would enhance the accuracy of the approximation.

$$P_{VSC_x}^t{}^2 + Q_{VSC_x}^t{}^2 \leq \overline{S_{VSC_x}}^2 \quad (7.24)$$

$$\begin{cases} -\overline{S_{VSC_x}} \leq P_{VSC_x}^t \leq \overline{S_{VSC_x}} \\ -\overline{S_{VSC_x}} \leq Q_{VSC_x}^t \leq \overline{S_{VSC_x}} \\ -\sqrt{2}\overline{S_{VSC_x}} \leq P_{VSC_x}^t + Q_{VSC_x}^t \leq \sqrt{2}\overline{S_{VSC_x}} \\ -\sqrt{2}\overline{S_{VSC_x}} \leq P_{VSC_x}^t - Q_{VSC_x}^t \leq \sqrt{2}\overline{S_{VSC_x}} \end{cases} \quad (7.25)$$

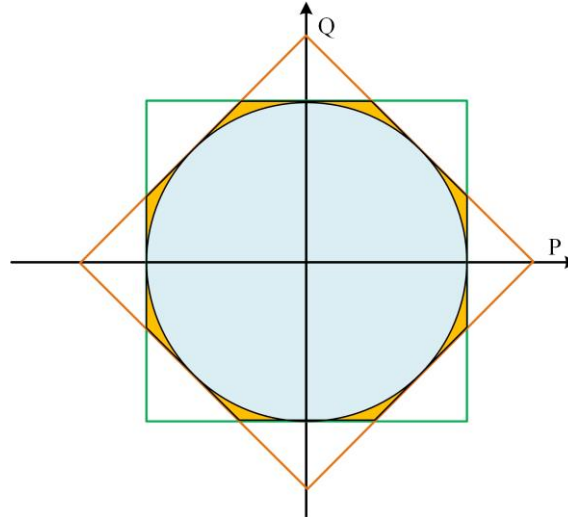


Figure 7-3 Circular constraint linearization method

10) VSC loss constraint

VSC power loss model is expressed as Eq. (7.26). Since this equation belongs to nonlinear quadratic constraints, which could be further relaxed to the below second-order cone constraint, as depicted in Eq. (7.27).

$$P_{VSC_x}^{loss,t} = A_m \sqrt{P_{VSC_x}^t{}^2 + Q_{VSC_x}^t{}^2}, \quad x \in \Omega_{VSC} \quad (7.26)$$

$$\left\| \begin{array}{c} P_{VSC_x}^t \\ Q_{VSC_x}^t \end{array} \right\|_2 \leq \frac{P_{VSC_x}^{loss,t}}{A_m} \quad (7.27)$$

7.2 Demand side load rebound profiles

After a power outage, electricity demand surges sharply as CLPU and EV charging rebound, causing significant stress on the grid. Therefore, accurately modeling these demand-side rebound effects is crucial for understanding their impact on system stability and developing strategies to mitigate potential overloading during the restoration phase.

7.2.1 Building cold load pickup (CLPU)

The CLPU phenomenon arises due to the loss of load diversity, which refers to the proportion of process-controlled loads exhibiting random and independent switching cycles relative to the total load population. Under normal conditions, the switching actions of these loads are distributed evenly, maintaining their internal states independently around set points. However, following a power outage, the divergence in internal states causes simultaneous switching operations when feeders are re-energized, leading to an unusually high power demand. Various modeling methods, including physical-based and exponential models, have been developed to characterize CLPU properties [23, 24]. The evolution of CLPU can be approximated using a delayed exponential function, with parameters determined through physical or data-driven approaches [159]. Figure 7-4 (a) illustrates a standard delayed exponential CLPU curve for an extended outage, depicting temporal evolution across four states: Normal supply, Extended

outage, Peak duration, and Decay duration. Following an outage occurrence at t_0 , all TCLs across different nodes undergo a gradual loss of diversity. Upon restoration at t_1 , a continuous increase in demand ensues, maintaining a peak value A_i^U for a specific duration due to concurrent switching actions of TCLs. As the first TCL reaches its preset temperatures at t_3 , the total load begins an exponential decline until it returns to pre-utage levels A_i^D at t_7 . This restored power level, known as the base power, signifies normal power consumption to maintain the operation of buildings. The decline is influenced by the thermal characteristics of buildings and devices. In describing this curve, it is assumed to be equally sampled during the CLPU condition, with the sample interval Δt equivalent to the restoration timestep. Therefore, the CLPU value of the i^{th} load deviation between the k^{th} timeslot and the $k-1^{\text{th}}$ timeslot is expressed as Eq. (7.28).

$$\Delta L_i^t = \begin{cases} 0 & k=1 \\ L_i^t - L_i^{t-1} & 1 < k < n \end{cases} \quad (7.28)$$

Then, L_i^k is calculated as Eqs. (7.29)-(7.31), which effectively characterize the CLPU curves encompassing the peak stage and decay stage.

$$L_i^t = (A_i^D + (A_i^U - A_i^D) \cdot e^{-\alpha \cdot C_i^t}) \cdot u(C_i^k) + A_i^U \cdot (1 - u(C_i^t)), \quad 1 \leq k \leq n \quad (7.29)$$

$$C_i^t = (k-1)\Delta t - D_i \quad (7.30)$$

$$u(j) = \begin{cases} 1, & j > 0 \\ 0, & j \leq 0 \end{cases} \quad (7.31)$$

The style of the CLPU curve is intricately linked to the timeslot at which corresponding loads are restored. Therefore, the load energization symbol $e_{i,k}$ is defined in Eq. (7.32), where $e_{i,k} = 1$ signifies the i^{th} load being restored at timeslot k , while $e_{i,k}$ equals 0 otherwise.

$$e_{i,t} = \begin{cases} s_{i,t}, & k=1 \\ s_{i,t} - s_{i,t-1}, & 1 < k \leq n \end{cases} \quad (7.32)$$

Assuming a total restoration period from t_1 to t_n spans n timeslots Δt , each load could potentially be restored at any timeslot within the range of $\{t_1, t_2, t_3, \dots, t_n\}$. Consequently, n CLPU curves are generated for restoration, each corresponding to one of the n timeslots. This arrangement forms an $n \times n$ matrix L_i to represent the CLPU curve, as elaborated in Eq. (7.33).

$$L_i = \begin{bmatrix} L_i^{1,1} & L_i^{1,2} & L_i^{1,3} & \dots & L_i^{1,n-1} & L_i^{1,n} \\ 0 & L_i^{2,2} & L_i^{2,3} & \dots & L_i^{2,n-2} & L_i^{2,n} \\ \dots & \dots & \dots & \dots & \dots & \dots \\ 0 & 0 & 0 & 0 & 0 & L_i^{n,n} \end{bmatrix} \quad (7.33)$$

Within matrix M , the j th row signifies the CLPU curve of the i^{th} load, which is energized at j^{th} timeslot. Considering the building side load including the non-TCLs and TCLs, the overall load demand P_i^{sum} is described as Eq. (7.34).

$$P_i^{\text{sum}} = e_{i,t} \cdot L_i^{\text{fix}} + e_{i,t} \cdot L_i \quad (7.34)$$

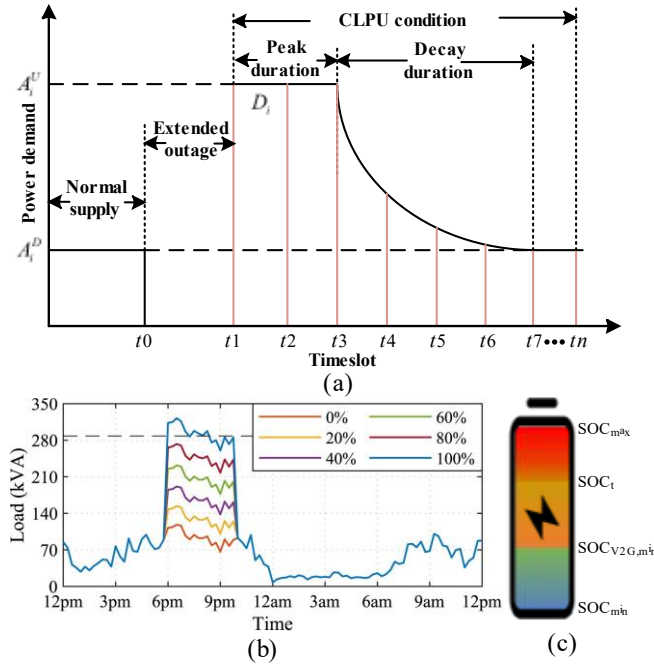


Figure 7-4 Load rebound model of demand-side load: (a). Delayed exponential model of CLPU; (b). EV charging load rebound; (c). Four typical states of EV SOC

7.2.2 EV charging load

The surge in EV charging load upon power restoration, known as "EV charging load rebound," poses a significant challenge [160, 161]. When power is restored after an outage, the EV charging system is designed to reconnect simultaneously to the utility grid, resulting in a sudden surge in charging load, as depicted in Figure 7-4 (b). This rebound is inevitable, as EV users must recharge their vehicles to meet forthcoming travel requirements. Therefore, coordinating the restoration of critical load nodes while considering EV charging dynamics is essential for power system restoration. Efficient allocation of demand-side load supply across all nodes are crucial for ensuring a smooth transition during the restoration process.

During restoration, EV users decide whether to charge their vehicles based on impending travel needs. Beyond travel needs, EVs can provide ancillary services and act as reserve resources through V2G technology, enabling bidirectional energy flow. Thus, EVs serve dual roles in the power system: as energy consumers during charging and as energy providers during discharging. However, the decision to charge or discharge depends on the EV's current SOC (SOC_t) and the minimum SOC required for upcoming travel ($SOC_{V2G,min}$), as illustrated in Figure 7-4 (c). If SOC_t exceeds $SOC_{V2G,min}$, the EV can discharge power to the grid via V2G, supporting critical load restoration. Conversely, if SOC_t is below $SOC_{V2G,min}$, the EV must charge to meet future travel demands. To evaluate rigid charging load rebound accurately, this study proposes a systematic three-step methodology, building on prior research and incorporating advanced statistical modeling for spatiotemporal precision. The steps are as follows:

Step 1: Spatiotemporal distribution of EVs using Monte Carlo Markov Chain (MCMC) method

The first step leverages the MCMC method, as developed in Section 3.3.3, to estimate the spatiotemporal distribution of EVs among buildings types—including residential, office,

commercial, and other buildings—across different time periods. Given the association between each journey and its preceding destination, the current departure $D_{i,t}$ and subsequent destination $D_{i,t+1}$ are modeled using a Markov transition matrix, as described in Eqs (7.35) - (7.36). This approach probabilistically simulates EV movements and occupancy patterns, capturing heterogeneity in EV usage and charging.

$$P_{ij,T} = P(D_{i,t} \rightarrow D_{j,t+1}) = P(D_{j,t+1} | D_{i,t}) \quad (7.35)$$

$$P_{T_k} = \begin{pmatrix} D_{11}^{T_k} & D_{12}^{T_k} & D_{13}^{T_k} & D_{14}^{T_k} \\ D_{21}^{T_k} & D_{22}^{T_k} & D_{23}^{T_k} & D_{24}^{T_k} \\ D_{31}^{T_k} & D_{32}^{T_k} & D_{33}^{T_k} & D_{34}^{T_k} \\ D_{41}^{T_k} & D_{42}^{T_k} & D_{43}^{T_k} & D_{44}^{T_k} \end{pmatrix} \quad (7.36)$$

Step 2: Aggregation of SOC distributions upon EV arrival

This step aggregates the SOC distributions of EVs upon arrival at different buildings, representing the energy status before charging begins. Building upon the framework in Ref. [162], the model ensures that SOC distributions reflect real-world diversity in individual EV charging requirements and usage patterns. To capture the variability in EV operations, probability density function (PDF) is used to model stochastic factors such as driving behavior, travel distance, and prior charging events. Statistical processing of household vehicle usage and population census data supports this probabilistic approach, ensuring a realistic representation of EV arrival SOC [135, 162].

Step 3: Calculation of rigid charging load rebound and flexible discharge power

The final step quantifies the rigid charging load rebound and flexible discharge power of EVs within building communities across all nodes. During rigid charging, EVs begin charging upon arrival at the building community based on their current SOC. The charging process continues until the SOC reaches the predefined threshold, $SOC_{V2G,min}$, ensuring sufficient energy for

upcoming travel. Conversely, discharging ceases once SOC drops to $SOC_{V2G,min}$ to preserve travel needs. The charging and discharging statuses are formulated by Eqs. (7.37) - (7.40). Specifically, the number of EVs with SOC values below or above the threshold ($SOC_{V2G,min}$) is identified, and their respective charging or discharging power is determined by multiplying the count by the rated charging or discharging power. It is worth noting that $SOC_{V2G,min}$ is typically a time-varying parameter influenced by expected mileage requirements [163]. However, since the focus of this study is not on designing a novel V2G discharging strategy, $SOC_{V2G,min}$ is treated as a constant value (0.35) in this study. This simplification focuses the analysis on rigid charging load rebound and flexible discharge power of EVs rather than the optimization of dynamic V2G strategies.

$$SOC(t) = \frac{E_{EV}(t)}{E_{EV,N}} \times 100\% \quad (7.37)$$

$$SOC(t+1) = SOC(t) + \xi(t) \frac{P_{EV,ch}(t) \cdot \Delta t \cdot \eta_{ch}}{E_{EV}} - (1 - \xi(t)) \frac{P_{EV,dis}(t) \cdot \Delta t}{E_{EV} \cdot \eta_{dis}} \quad (7.38)$$

$$P_{EV,ch}^{rebound} = \sum_{n \in N} n \cdot P_{ch,i} \quad (7.39)$$

$$P_{EV,dis} = \sum_{n \in N} (N - n) \cdot P_{dis,i} \quad (7.40)$$

7.3 Case study

This section presents the detailed implementation process for evaluating the proposed two-stage coordinated restoration strategy. The test environment integrates standard IEEE distribution grids, realistic building and transportation load modeling, and a comprehensive set of operational scenarios to thoroughly assess the effectiveness and robustness of the restoration strategy under various outage conditions.

7.3.1 Test system

The case study employs an integrated distribution network combining the IEEE 33-node and IEEE 13-node standard test systems, as illustrated in Figure 7-5. The conventional restoration strategy relies on a typical AC distribution grid architecture, shown in Figure 7-5 (a). In contrast, the proposed restoration strategy introduces a reconstructed hybrid AC/DC grid architecture, depicted in Figure 7-5 (b). Additionally, Figure 7-5 (c) outlines the connectivity between EV charging stations and grid nodes. To address power outage issue, three black-start-capable DGs—DG-1, DG-2, and DG-3—are strategically deployed at nodes 27, 33, and 35, respectively. The interconnection switch between nodes 17 and 32 remains normally open but can be closed during topology reconfiguration to ensure continuous power supply. Initially, the 33-node grid and the 13-node grid operate independently. Subsequently, enhancements are made to the DC lines extending from node 32 to 35 and from node 24 to 35. Following a disaster scenario where the primary grid resources are offline, line faults occur between nodes 3 and 4, as well as nodes 5 and 25, resulting in the formation of three distinct subgrids. These subgrids, labeled Subgrid 1, Subgrid 2, and Subgrid 3, correspond to different building communities: residential, public, and office building communities.

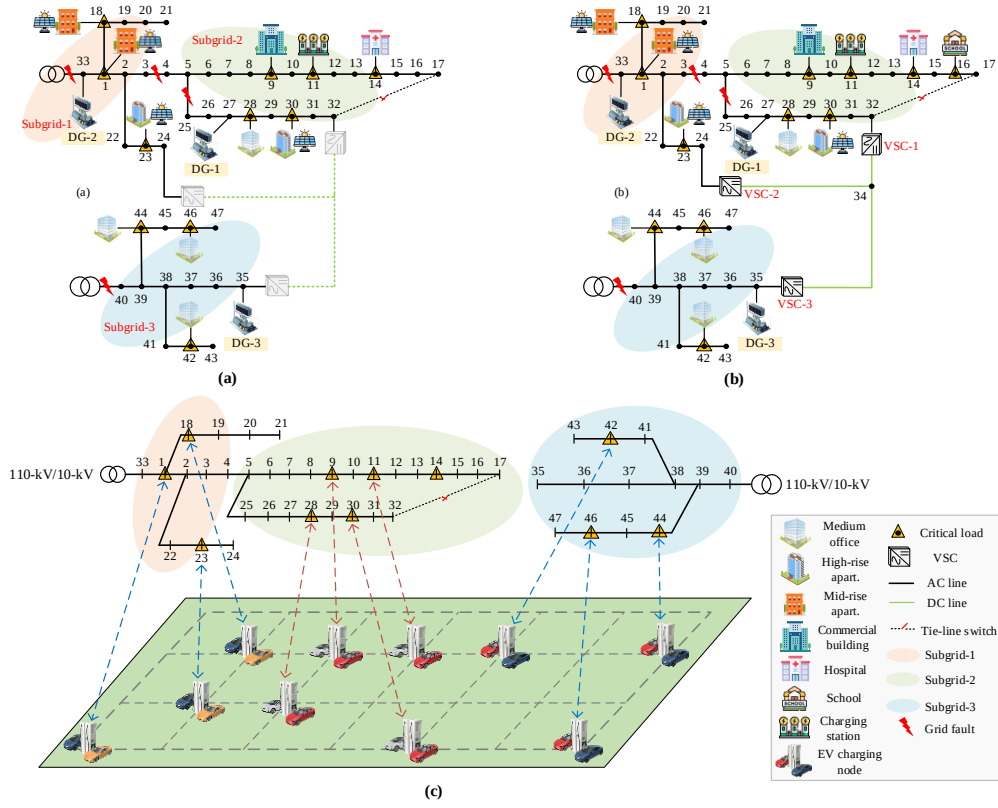


Figure 7-5 Grid network featuring emergency DGs, distributed energy resource, and crucial demand-side (building and transportation) loads: (a) Traditional AC distribution grid architecture; (b) Hybrid AC/DC distribution grid architecture; (c) Distribution of nodes for transportation

7.3.2 Load restoration scenarios

To accurately capture real-world variability in demand-side recovery, the study models both CLPU and EV charging load rebound phenomena. Building CLPU is simulated using TRNSYS 18, taking into account building envelope characteristics, operational schedules, and local climate conditions (based on TMY data) [164]. The process of building CLPU modeling is illustrated in Figure 7-6 (a). Each building assumes an equal penetration level of TCLs at 50%, with a setpoint temperature of 24°C [165]. Subsequently, building consumption and CLPU profiles for various building types are generated. Furthermore, the EV charging load rebound is simulated utilizing the MCMC method through a systematic three-step approach detailed in Section 7.2.2 and depicted in Figure 7-6 (b). The combined demand-side rebound model is used to generate load profiles under four different outage start times: 02:00, 09:00, 14:00, and

19:00, representing diverse temporal conditions. Thus, the model evaluates four temporal scenarios (02:00, 09:00, 14:00, and 19:00), representing different outage initiation times. Furthermore, Table 7-2 specifies the restoration priority weights assigned to different load nodes across scenarios. The assignment of these weights follows the principle that essential loads serving critical community functions should be restored preferentially during emergency conditions. Specifically, loads associated with hospitals and healthcare facilities are assigned the highest priority weights due to their life-safety implications, followed by schools and public service buildings that serve vulnerable populations. Commercial and office buildings are assigned moderate priority weights, while non-essential and deferrable loads receive lower weights. These restoration priority weights directly influence the optimisation objective function, guiding the load restoration sequence to maximise weighted load recovery under resource constraints. This prioritisation mechanism ensures that limited generation and storage resources are allocated first to loads with the greatest societal importance, thereby enhancing overall community resilience and welfare during grid disturbance events.

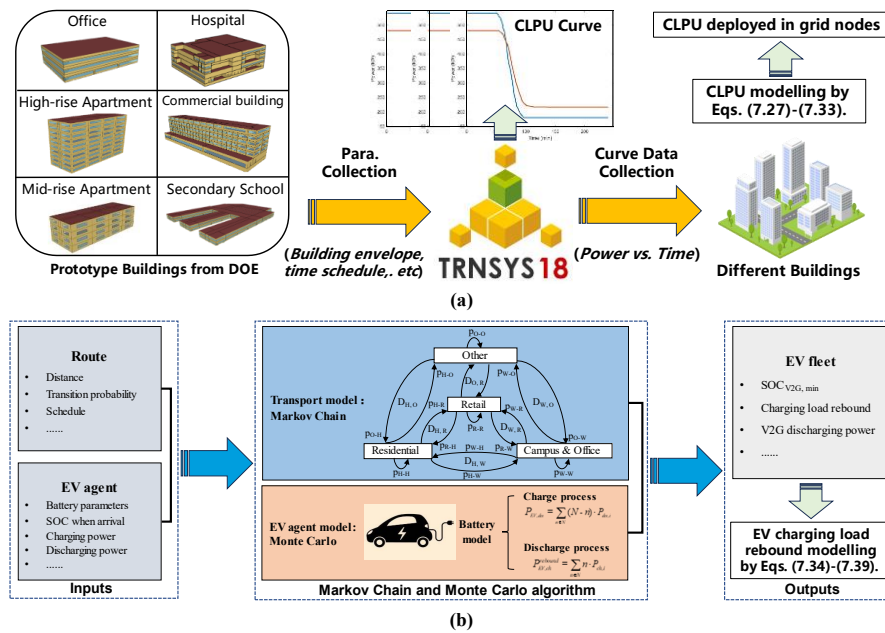


Figure 7-6 Schematic diagram of the demand-side load rebound modelling: (a) Building CLPU modelling; (b) EV charging load rebound modelling

Table 7-2 Restoration weights of load nodes in different scenarios

Node	Building type	Weight value			
		Scenario 1 (02:00)	Scenario 2 (09:00)	Scenario 3 (14:00)	Scenario 4 (19:00)
Node 1	Residential	1.5	1.1	1	1.5
Node 9	Commercial	0.8	1.2	1.2	1.2
Node 11	Centralized EV charging station	0.8	1.3	0.9	1.2
Node 14	Hospital	1.6	1.6	1.6	1.6
Node 16	School	1	1.6	1.6	1
Node 18	Residential	1.5	1.1	1	1.5
Node 23	Residential	1.5	1.1	1	1.5
Node 28	Office	0.9	1.4	1.3	1
Node 30	Residential	1.5	1.1	1	1.5
Node 42	Office	0.9	1.4	1.3	0.8
Node 44	Office	0.9	1.4	1.3	0.8
Node 46	Office	0.9	1.4	1.3	0.8

7.3.3 Case definitions

A total of 14 distinct cases are designed to comprehensively evaluate the restoration strategy's performance under multiple operational and architectural configurations. These cases consider variations in grid architecture (traditional AC versus hybrid AC/DC), the presence or absence of distributed PV generation, and the integration of EV reverse discharging capabilities. Details of all scenarios and their definitions are summarized in Table 7-3. Key parameters for DGs and VSCs are listed in Table 7-4.

All simulations are performed on the MATLAB 2023a platform, with a 5-minute restoration timestep over a total of 36 timeslots. The restoration problem is formulated as a Mixed Integer Linear Programming (MILP) model and solved using Gurobi on an Intel Core i7-10700 workstation. The simulation outputs include optimized load restoration sequences and real-time power dispatch results, which are then used to evaluate the effectiveness of the proposed coordinated restoration strategy across all defined cases.

Table 7-3 Detailed information about rebound scenarios and cases

Rebound scenario	Description for scenario	Case information on DERs/flexible sources utilization & distribution grids
Scenario 1: 02:00	A scenario in which both the building cooling load and EV charging load rebounds are minimal.	Case 1: WithoutPV-EV + noAC/DC
		Case 2: WithoutPV-EV + AC/DC
Scenario 2: 09:00	A scenario where the building cooling load is minimal, while the EV charging load is significant.	Case 3: WithoutPV-EV + noAC/DC
		Case 4: WithoutPV-EV + AC/DC
		Case 5: WithPV-EV + noAC/DC
		Case 6: WithPV-EV + AC/DC
Scenario 3: 14:00	A scenario where the building cooling load rebounds significantly, while the EV charging load rebounds moderately.	Case 7: WithoutPV-EV + noAC/DC
		Case 8: WithoutPV-EV + AC/DC
		Case 9: WithPV-EV + noAC/DC
		Case 10: WithPV-EV + AC/DC
Scenario 4: 19:00	A scenario where the building's cooling load is moderate, while the EV charging load is significant.	Case 11: WithoutPV-EV + noAC/DC
		Case 12: WithoutPV-EV + AC/DC
		Case 13: WithPV-EV + noAC/DC
		Case 14: WithPV-EV + AC/DC

Note: Without PV-EV indicates the absence of PV power generation and reverse discharge of electric vehicles. With PV-EV implies the presence of PV power generation and reverse discharge of electric vehicles. AC/DC denotes a hybrid AC/DC distribution grid architecture, while noAC/DC signifies a conventional AC distribution grid architecture.

Table 7-4 Parameter of grid components

Symbol	Value	Symbol	Value
S_{VSC}	1 MVA	R_{DG-2}^+/R_{DG-2}^-	0.6/-0.6 MW/5min
$P_{DG-1}^{max}/P_{DG-2}^{max}$	1.5 MW	R_{DG-3}^+/R_{DG-3}^-	0.4/-0.4 MW/5min
P_{DG-3}^{max}	1 MW	C_{DG-1}/C_{DG-2}	4 MWh
R_{DG-1}^+/R_{DG-1}^-	0.6/-0.6 MW/5min	C_{DG-3}	3 MWh

7.4 Results and discussion

The section is categorized into five subsections, i.e., demand-side load rebound profile under different scenarios, restoration sequence of load nodes, DGs power output, VSCs power dispatching, and average node voltage.

7.4.1 Load rebound profiles under different scenarios

Figure 7-7 - Figure 7-10 illustrates the demand-side load rebound profiles, encompassing the CLPU of building and EV charging load across various buildings and twelve nodes in four

distinct scenarios. In Scenario 1 (02:00), both building energy consumption and EV charging loads are minimal, resulting in negligible demand-side load rebound. The power consumption across load nodes remains stable with minor fluctuations over the 36 timeslots (Figure 7-7). In contrast, Scenario 2 (09:00) exhibits a significant increase in demand-side load rebound, primarily driven by a surge in EV charging load. EV charging load escalates from approximately 18 kW in Scenario 1 to 500 kW (residential buildings) and 650 kW (office buildings), as depicted in Figure 7-8. Additionally, building CLPU exhibits a slight upward trend due to increased HVAC operation in response to rising outdoor temperatures. Scenario 3 (14:00) demonstrates the most pronounced rebound effect, with building CLPU reaching nearly peak levels of around 1000 kW, while EV charging loads decrease to a moderate level of 300 kW, as illustrated in Figure 7-9. Notably, the CLPU values for all three building types are nearly identical, despite differences in thermal capacities and resistances based on the DOE building prototype model. However, the demand-side load rebound in Scenario 4 (19:00) presents another extreme situation, as shown in Figure 7-10. In this scenario, EV charging load rebound reaches its peak level, hitting 1000 kW (commercial buildings) and 800 kW (residential buildings), reflecting the peak charging period. In contrast, building CLPU decreases to approximately 240 kW due to lower outdoor temperatures and reduced solar radiation compared to Scenario 3.

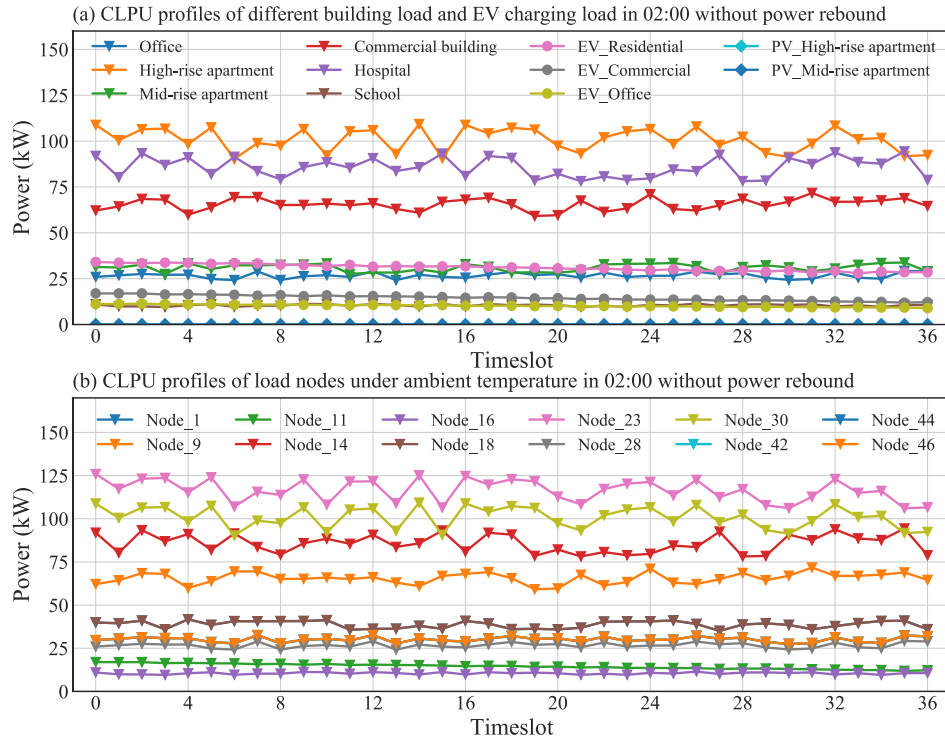


Figure 7-7 Demand-side load rebound profile for building and load nodes in Scenario 1

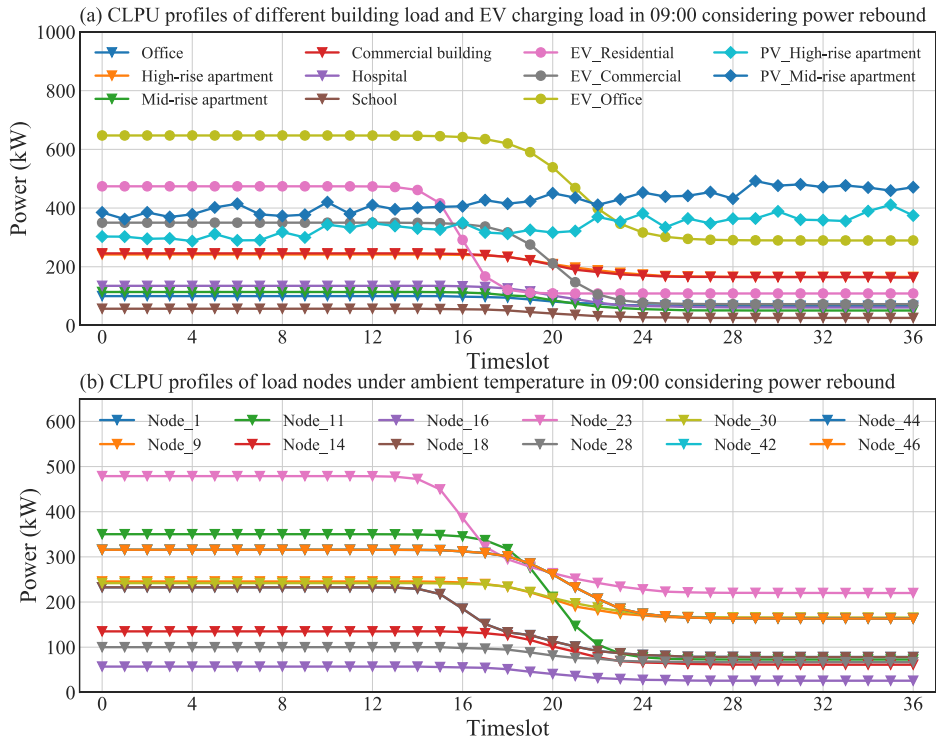


Figure 7-8 Demand-side load rebound profile for building and load nodes in Scenario 2

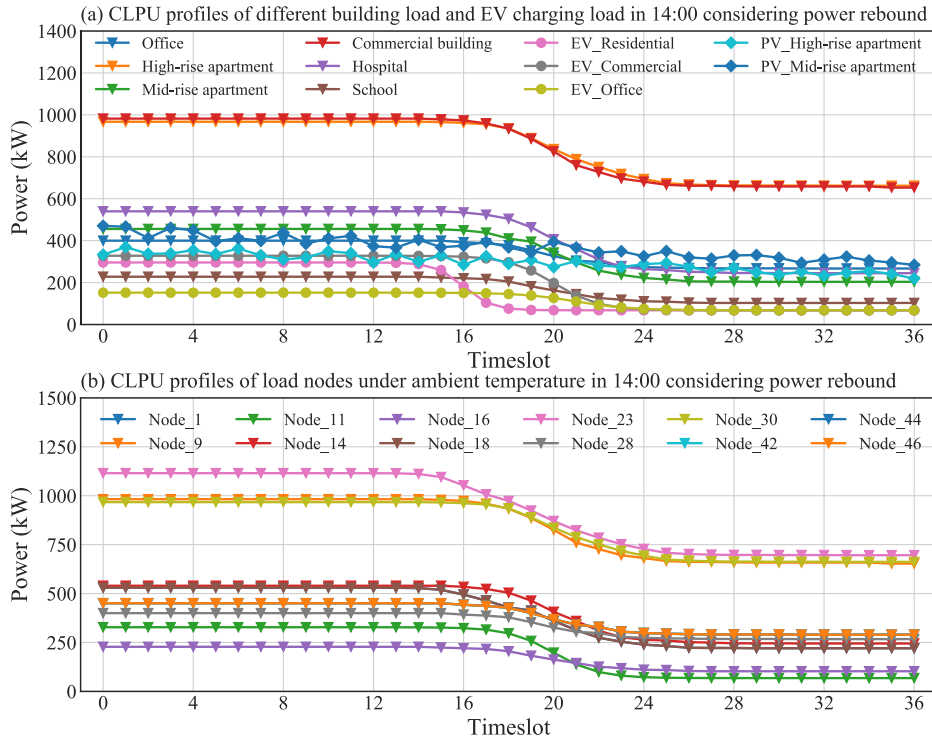


Figure 7-9 Demand-side load rebound profile for building and load nodes in Scenario 3

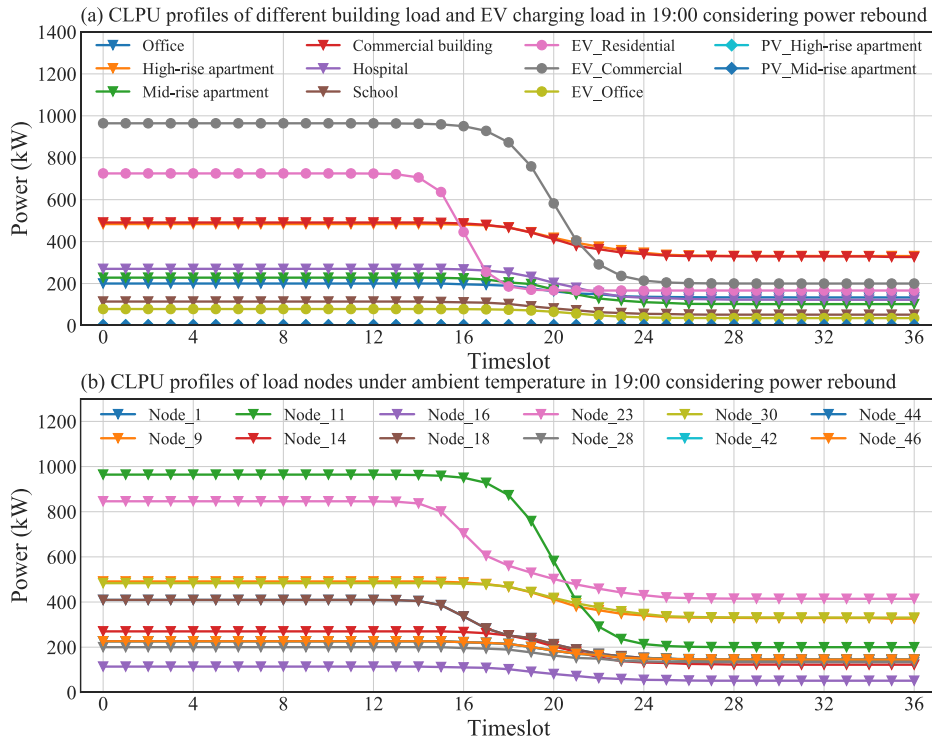


Figure 7-10 Demand-side load rebound profile for building and load nodes in Scenario 4

7.4.2 Restoration sequence of load nodes

Figure 7-11 - Figure 7-14 depict the restoration sequences of load nodes under two grid architectures and energy management strategies across the four scenarios. Colored bars represent restoration sequences in subgrids with different building types: yellow for residential buildings (Subgrid 1 with node 1, node 18, and node 23), green for commercial buildings (Subgrid 2 with node 9, node 11, node 14, node 16, node 28, and node 30), and blue for office buildings (Subgrid 3 with node 42, node 44, and node 46). In Scenario 1 (02:00), where the demand-side load and load rebound are minimal, nearly all load nodes are restored simultaneously within one timeslot (5 minutes) after power restoration begins, as shown in Figure 7-11. Conversely, in Scenario 2 (09:00), as the demand-side load and load demand slightly increase, all load nodes can be restored within three timeslots (15 minutes). There is a distinction in the starting restoration sequence under different distribution grid architectures (Figure 7-12 (a), Figure 7-12 (b) for the conventional AC grid architecture and Figure 7-12 (c), Figure 7-12 (d) for the hybrid AC/DC grid architecture). Notably, the hybrid AC/DC grid architecture completes load restoration in one timeslot (5 minutes), compared to three timeslots (15 minutes) for the conventional AC grid. Scenario 3 (14:00), characterized by the highest demand-side load rebound, exhibits significant differences in load node restoration sequences depending on the utilization of DERs and flexible sources. Specifically, when power recovery relies solely on DGs without leveraging rooftop PV and V2G reverse discharge (Cases 7 and 8 in Figure 7-13 (a) and Figure 7-13 (b)), certain load nodes fail to restore within the 3-hour period, significantly impairing the energy system's resilience to recover swiftly from outages. In contrast, when DGs, rooftop PV, and V2G reverse discharge are concurrently utilized as power restoration sources (Cases 9 and 10 in Figure 7-13 (c) and Figure 7-13 (d)), nearly all load nodes are restored within the entire restoration period. The load node with the slowest restoration sequence is node 11 in Case 9, which begins restoration in the 31st time slot. Notably, while the distribution grid architectures have minimal impact on the overall starting

time for load node restoration, the hybrid AC/DC distribution grid significantly accelerates the restoration of load nodes with higher restoration weight values compared to the traditional AC distribution grid. This improvement is primarily attributed to the internal power exchange facilitated by VSCs. In Scenario 4 (19:00), characterized by the peak EV charging load, individual load nodes associated with EV charging exhibit the highest load rebound characteristics, particularly node 11. The load restoration sequence is significantly influenced by the adoption of DERs and flexible source, as well as the type of distribution grid architectures implemented. For instance, in Case 11 (Without PV-EV + noAC/DC) under the traditional AC grid architecture without utilizing rooftop PV and the V2G discharge strategy, most load nodes can be restored within four timeslots (20 minutes), as depicted in Figure 7-14 (a). However, the centralized charging station (Node 11) within the commercial complex buildings, which bears the highest EV charging load rebound, fails to restore within the entire restoration period due to the power ramp limit of DGs output. Conversely, under the hybrid AC/DC distribution grid architecture, inter-subgrid power exchange enables the supply of remaining DG power from subgrid 1 and subgrid 3 to subgrid 2, ensuring that Node 11 achieves load restoration by the 22nd timeslot, as depicted in Figure 7-14 (b). Furthermore, leveraging rooftop PV and V2G discharge accelerates load restoration under the conventional AC distribution grid architecture (Case 13: With PV-EV + noAC/DC), with all nodes restored within 21 timeslots, as shown in Figure 7-14 (c). Similarly, employing PV and the V2G discharge under the hybrid AC/DC distribution grid architecture (Case 14: With PV-EV + AC/DC) further hasten subgrids load restoration, enabling all load nodes to achieve load restoration within 15 timeslots, as depicted in Figure 7-14 (d).

This analysis underscores the critical role of distribution grid architecture, DERs, and energy management strategy in optimizing load restoration across various scenarios. Key factors such as demand-side load rebound variations, utilization of DERs and flexible resources, and

distribution grid architectures significantly influence the speed of load restoration. The findings indicate that in scenarios with stable demand-side load and slight load rebound, rapid recovery of load nodes is achievable. However, as demand-side load rebound intensifies, leveraging DERs and flexible sources like rooftop PV and V2G discharge becomes essential to ensure timely restoration of all load nodes. The comparison between the conventional AC grid architecture and the hybrid AC/DC grid architecture highlights the significant influence of internal power exchange mechanisms facilitated by VSCs in accelerating the restoration sequence of critical load nodes. These insights emphasize the importance of advanced grid architectures and diversified energy resources in enhancing system resilience and operational efficiency during outage events. Additionally, the impact of EV charging load dynamics on load restoration sequences highlights the need for tailored approaches that consider the unique characteristics of load nodes associated with high load rebound, such as centralized charging stations. By integrating DERs and advanced energy management techniques like V2G discharge, the efficiency of load restoration can be significantly improved, ensuring rapid recovery of all load nodes within the restoration period.

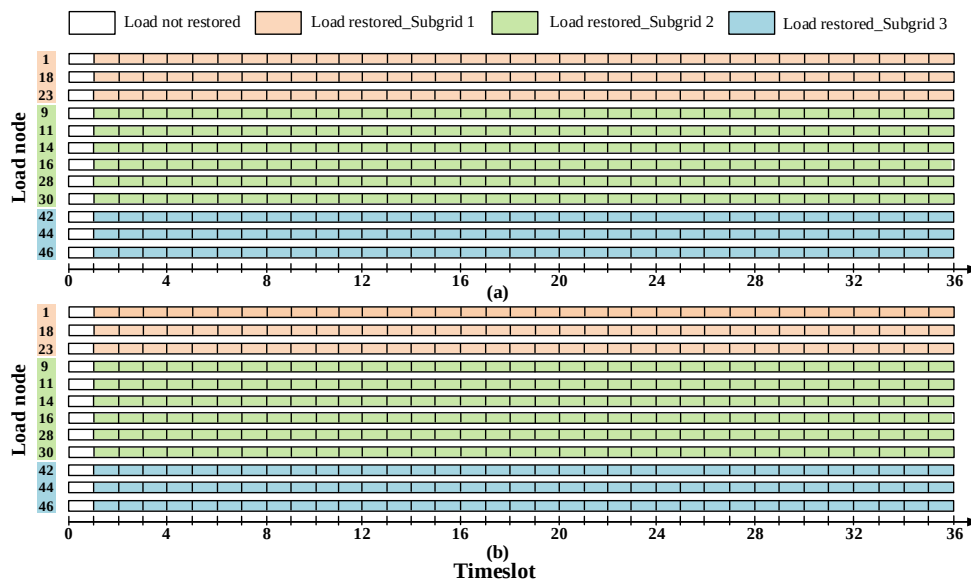


Figure 7-11 Distribution of load nodes starting restoration sequence under different distribution grid architectures in scenario 1 (02:00): (a) Case 1: Without PV-EV + noAC/DC; (b) Case 2: Without PV-EV + AC/DC

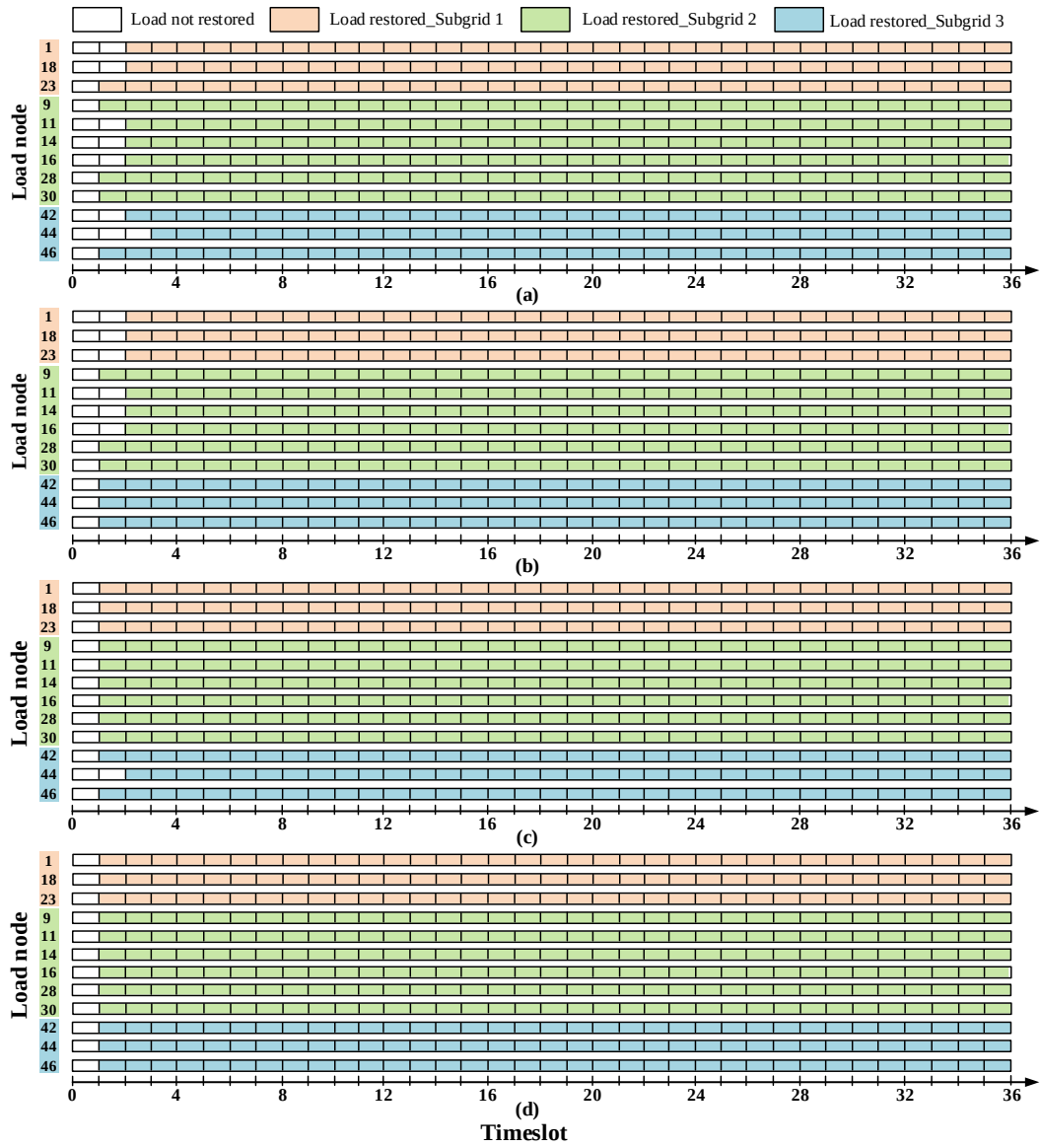


Figure 7-12 Distribution of load nodes starting restoration sequence under different distribution grid architectures in scenario 2 (09:00): (a) Case 3: Without PV-EV + noAC/DC; (b) Case 4: Without PV-EV + AC/DC; (c) Case 5: With PV-EV + noAC/DC; (d) Case 6: With PV-EV + AC/DC

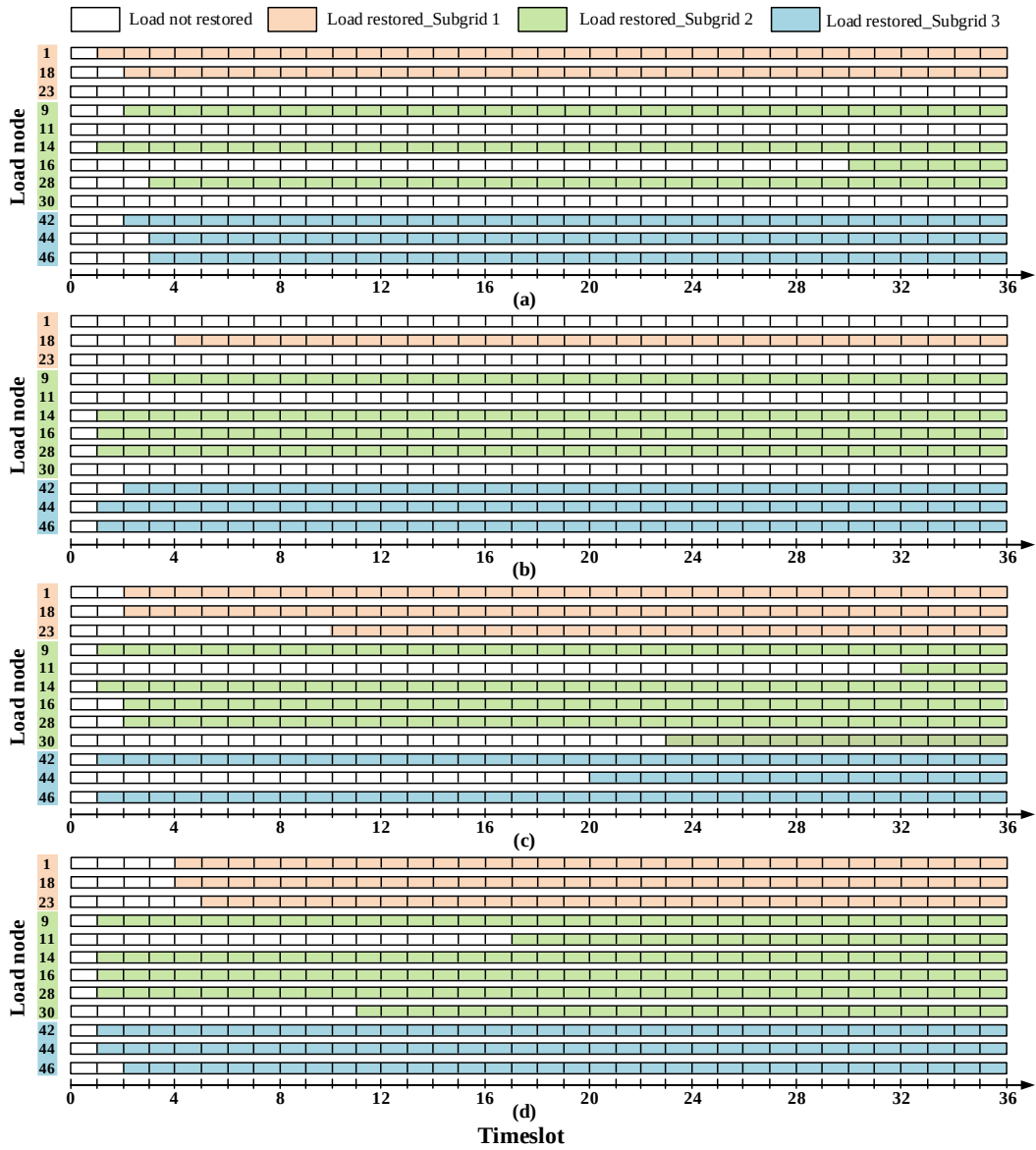


Figure 7-13 Distribution of load nodes starting restoration sequence under different distribution grid architectures in scenario 3 (14:00): (a) Case 7: Without PV-EV + noAC/DC; (b) Case 8: Without PV-EV + AC/DC; (c) Case 9: With PV-EV + noAC/DC; (d) Case 10: With PV-EV + AC/DC

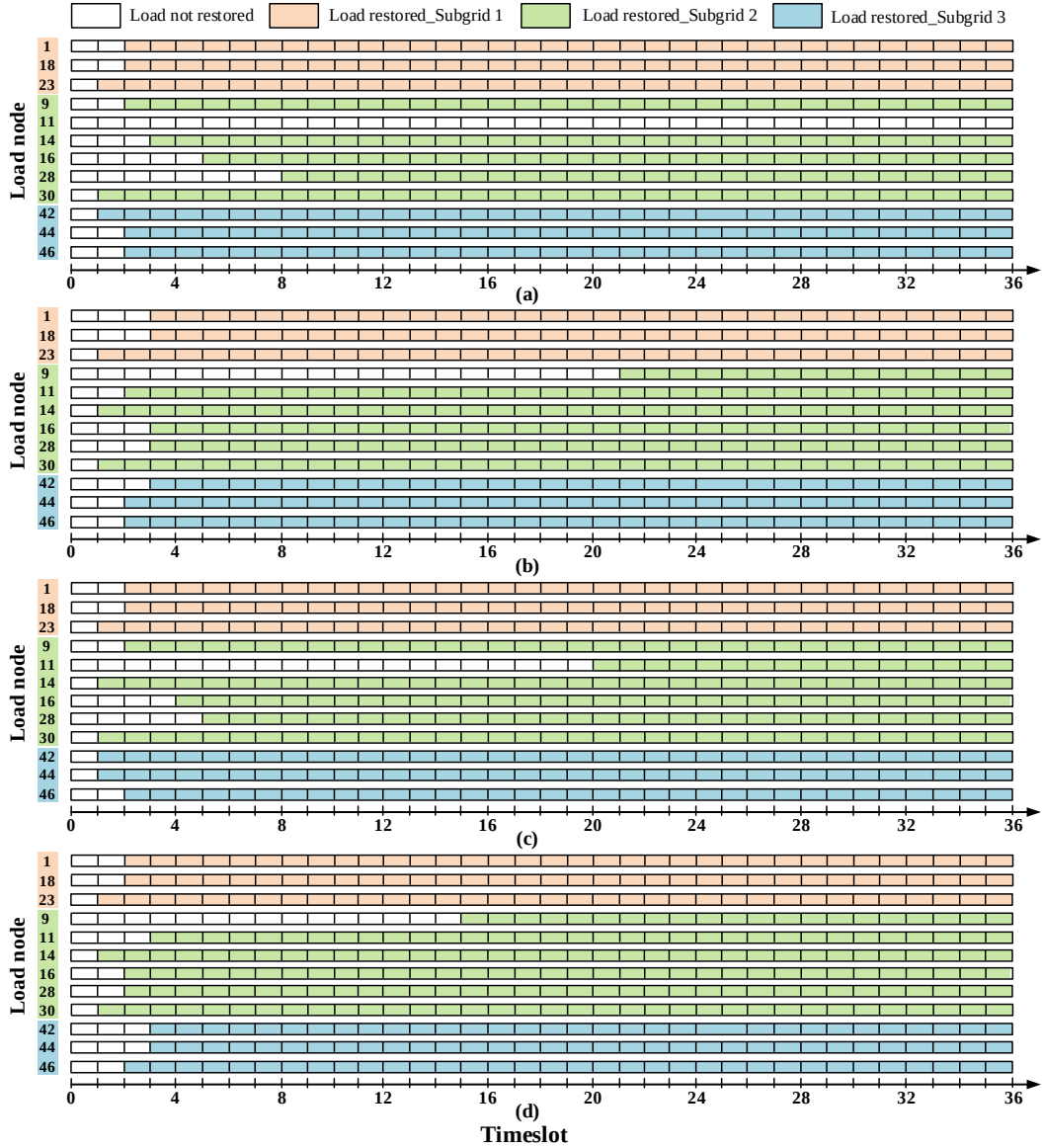


Figure 7-14 Distribution of load nodes starting restoration sequence under different distribution grid architectures in scenario 4 (19:00): (a) Case 11: Without PV-EV + noAC/DC; (b) Case 12: Without PV-EV + AC/DC; (c) Case 13: With PV-EV + noAC/DC; (d) Case 14: With PV-EV + AC/DC

7.4.3 Distributed power generations

Figure 7-15 illustrates the average power output of DGs (DG1, DG2, and DG3) across four scenarios, comparing cases with and without the adoption of rooftop PV and V2G discharge under different distribution grid architectures. In scenarios where rooftop PV and V2G discharge are not employed, the power output primarily depends on the DGs, leading to all

DGs operating at high power levels. This is particularly evident in Scenario 3 (14:00) and Scenario 4 (19:00), where peak demand-side building CLPU and EV charging load rebound occur. In these cases, DG1, DG2, and DG3 operate near the maximum capacity to ensure the rapid restoration of critical load nodes. By contrast, the incorporation of rooftop PV and V2G discharge proves to be effective in reducing the reliance on DGs during the power restoration period, resulting in a moderate decrease in the output of DGs. Furthermore, the hybrid AC/DC distribution grid architecture demonstrates a slight increase in DG output compared to the conventional AC grid, attributed to inter-subgrid power exchange facilitated by VSCs. Hence, Thus, compared to the conventional distribution grid architecture, the hybrid AC/DC distribution grid architecture ensures faster restoration of critical load nodes within each subgrid.

Figure 7-16 illustrates the percentage distribution of power output across energy resources across four scenarios, emphasizing the influence of flexible resources and grid architectures on power allocation. In Scenario 1 (02:00), for Case 1 and Case 2, where both demand load and load rebound are minimal, the power supply during restoration is predominantly provided by DGs, accounting for 99.8% and 100%, irrespective of whether a traditional AC grid or hybrid AC/DC grid architecture is employed. In Scenario 2 (09:00), demand load and load rebound increase compared to Scenario 1. For Case 3 and Case 4, which exclude rooftop PV and V2G discharge, DGs remain the primary power supply during restoration, contributing 99.1% and 99.3%, respectively. Conversely, in Case 5 and Case 6, which incorporate rooftop PV and V2G discharge, PV generation supplies the largest share of power during restoration (66.6%), while V2G discharge contributes significantly at 21.1% and 19.1%, respectively. DGs contribute only 12.3% and 14.4% in these cases. The hybrid AC/DC grid architecture facilitates power dispatch between subgrids, slightly increasing the total DG power output. In Scenario 3 (14:00), characterized by maximum load rebound (BLUP), DGs in subgrids cannot meet demand loads

under rated power operation. For Case 7 and Case 8, which exclude rooftop PV and V2G discharge, DGs contribute 49.2% and 62.7% of the restoration power, respectively. However, due to the absence of alternative power sources, the proportions of unrestored load are 50.8% and 37.3%, respectively. In contrast, for Case 9 and Case 10, which incorporate rooftop PV and V2G discharge, DG contributions remain substantial at 49.2% and 52.4%, respectively, while PV generation accounts for 35.4% and V2G discharge adds 15.4% and 12.2% to restoration power, respectively. In Scenario 4 (19:00), although the load rebound decreases compared to Scenario 3, the EV charging load rebound is most significant across scenarios, preventing some subgrid DGs from meeting demand loads under rated operation. For Case 11 and Case 12, which exclude rooftop PV and V2G discharge, DGs contribute 81.7% and 93.9%, respectively, with unrestored load proportions of 18.3% and 6.1%. In contrast, for Case 13 and Case 14, which adopt rooftop PV and V2G discharge, DG contributions remain high at 81.7% and 91.3%, respectively. Although PV generation contributes minimally due to low solar radiation, V2G discharge compensates for DG shortages, accounting for 18.3% and 8.7% of restoration power, ensuring complete load restoration in these cases. The results underscore the critical role of DG, rooftop PV, and V2G discharge in ensuring effective power restoration across scenarios. In low-demand conditions (Scenario 1), DGs dominate power supply, but as demand and load rebound increase (Scenarios 2–4), the integration of rooftop PV and V2G discharge significantly enhances restoration capabilities, reducing DG dependency and unrestored load proportions. The hybrid AC/DC grid architecture, where VSCs facilitate inter-subgrid power dispatch, further improves power dispatch efficiency between subgrids, particularly under high load rebound conditions, thereby increasing the total proportion of DGs power output during restoration. However, the effectiveness of rooftop PV is limited during low solar radiation periods (Scenario 4), emphasizing V2G discharge as a critical complementary resource for achieving full load restoration.

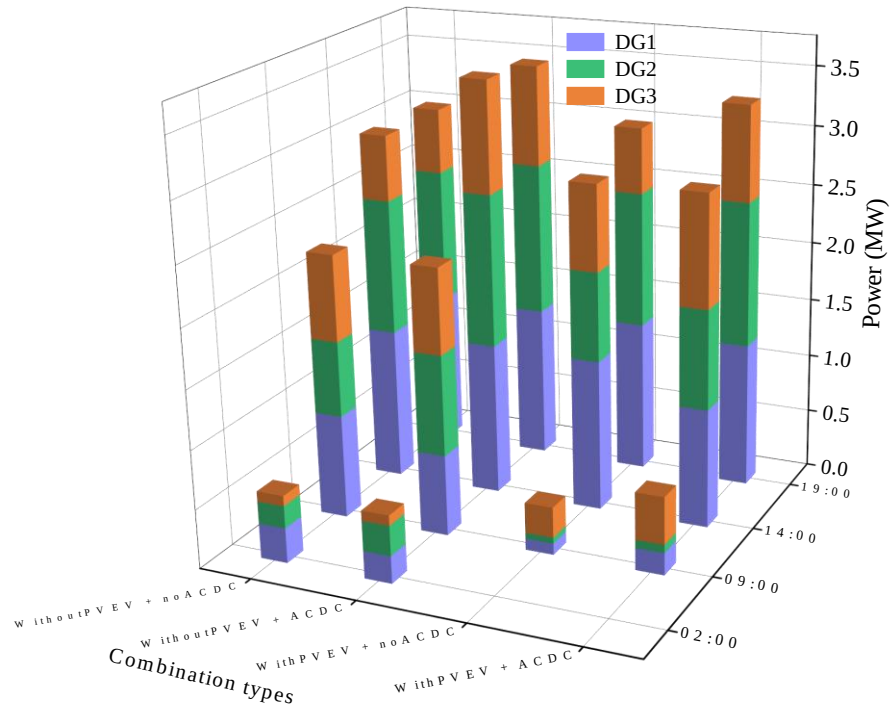


Figure 7-15 Distribution of average DG power output across four scenarios, with or without adopting distributed energy resources and distribution grid architectures

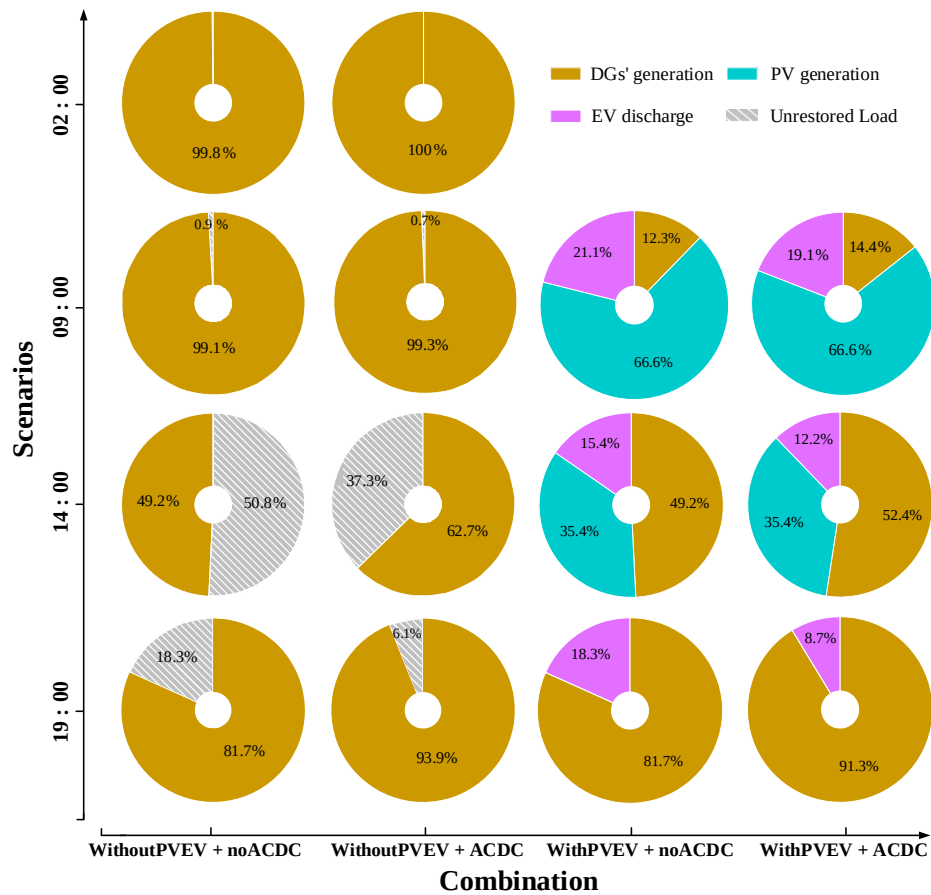


Figure 7-16 Distribution in power output across different power resources in four scenarios, with or without adopting distributed energy resources and distribution grid architectures

7.4.4 Power dispatch among voltage source converters

Figure 7-17 illustrates the average power exchange between subgrids via VSCs in the hybrid AC/DC distribution grid, with and without DERs and the V2G discharge. A positive VSC power output indicates power injection into other subgrids to support restoration and operation, while a negative output signifies power imported from other subgrids. As depicted in Figure 7-17, the VSCs exhibit a significant power exchange without rooftop PV and the V2G discharge, with VSC-1 and VSC-2 averaging approximately 0.28 MW and -0.32 MW, respectively. In contrast, when rooftop PV and the V2G discharge are employed, the power exchange through VSCs decreases markedly, with VSC-1 and VSC-2 maintaining average powers of around 0.006 MW and -0.006 MW, respectively. These results underscore the substantial influence of integrating DERs and the flexible resources, along with the adoption of the proposed two-stage coordinated restoration strategy for hybrid AC/DC distribution grids. This strategy plays a pivotal role in diversifying and stabilizing power restoration sources across subgrids, enabling a more balanced power exchange through VSCs and reducing reliance solely on DGs within individual subgrids for effective power restoration.

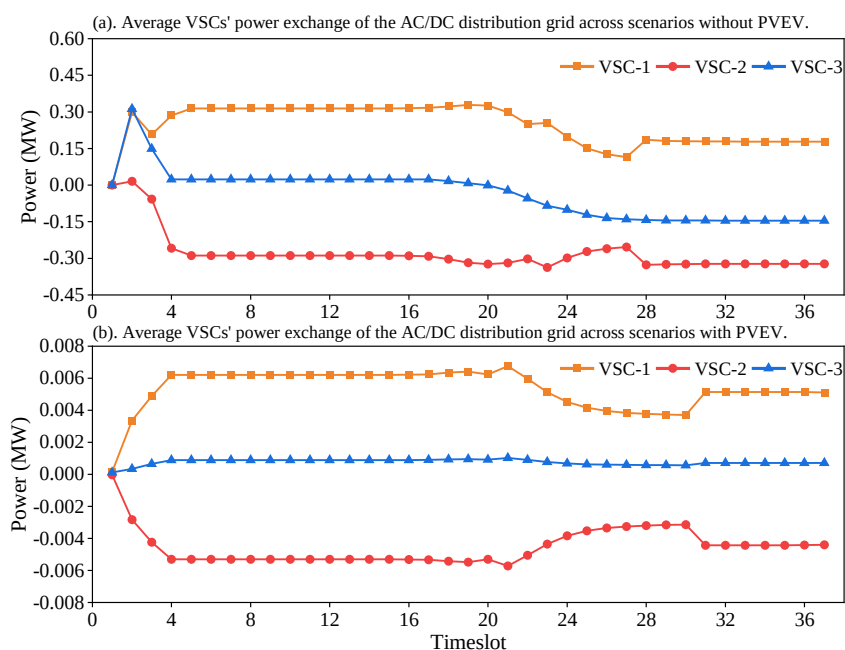


Figure 7-17 VSCs' power exchange distribution of the AC/DC distribution grid architecture across scenarios, with or without adopting DERs and V2G discharge

7.4.5 Node voltage stability

Figure 7-18 illustrates the average node voltage distribution during restoration, with and without rooftop PV and V2G discharge under different grid architectures. All node voltages remain within the permissible 7% fluctuation limit [166]. Regardless of the grid architecture or the use of DERs and the V2G discharge strategy, the node voltage at each timeslot stays within the allowable range. However, voltage distribution across different nodes exhibits relatively large fluctuations due to variations in load rebound and node locations. For instance, nodes 4 and 5, situated at the terminal of subgrid-2, are more susceptible to significant voltage drops. In the conventional AC grid architecture without PV and V2G discharge, node 5 experiences the lowest system average voltage, reaching 0.942 p.u. during timeslots 3 to 22. Additionally, the type of distribution grid architecture and the adoption of rooftop PV and the V2G discharge significantly influence the overall node voltage distribution. Compared to the conventional AC grid architecture, the hybrid AC/DC grid architecture slightly improves the overall node voltage. For example, the minimum voltage value at node 5 increases to 0.951 p.u. during timeslots 3 to 22 and further approaches 1 p.u. during timeslots 32 to 36. More significantly, the adoption of the rooftop PV and the V2G discharge markedly enhance the minimum node voltage at local nodes while reducing voltage differences and fluctuations across all nodes. When the rooftop PV and the V2G discharge are utilized, the minimum node voltage increases to at least 1 p.u. for all nodes. This analysis demonstrates that the proposed coordinated restoration strategy effectively enhances voltage stability and mitigates fluctuations during the restoration process. This approach facilitates the dynamic coordination of DERs, diverse energy resource, and DGs output during the power restoration, ensuring voltage levels remain within acceptable boundaries across all nodes. Furthermore, the coordinated restoration strategy contributes to improving the reliability and resilience of hybrid AC/DC grid

architecture, particularly in scenarios involving high renewable energy integration and complex load rebound dynamics.

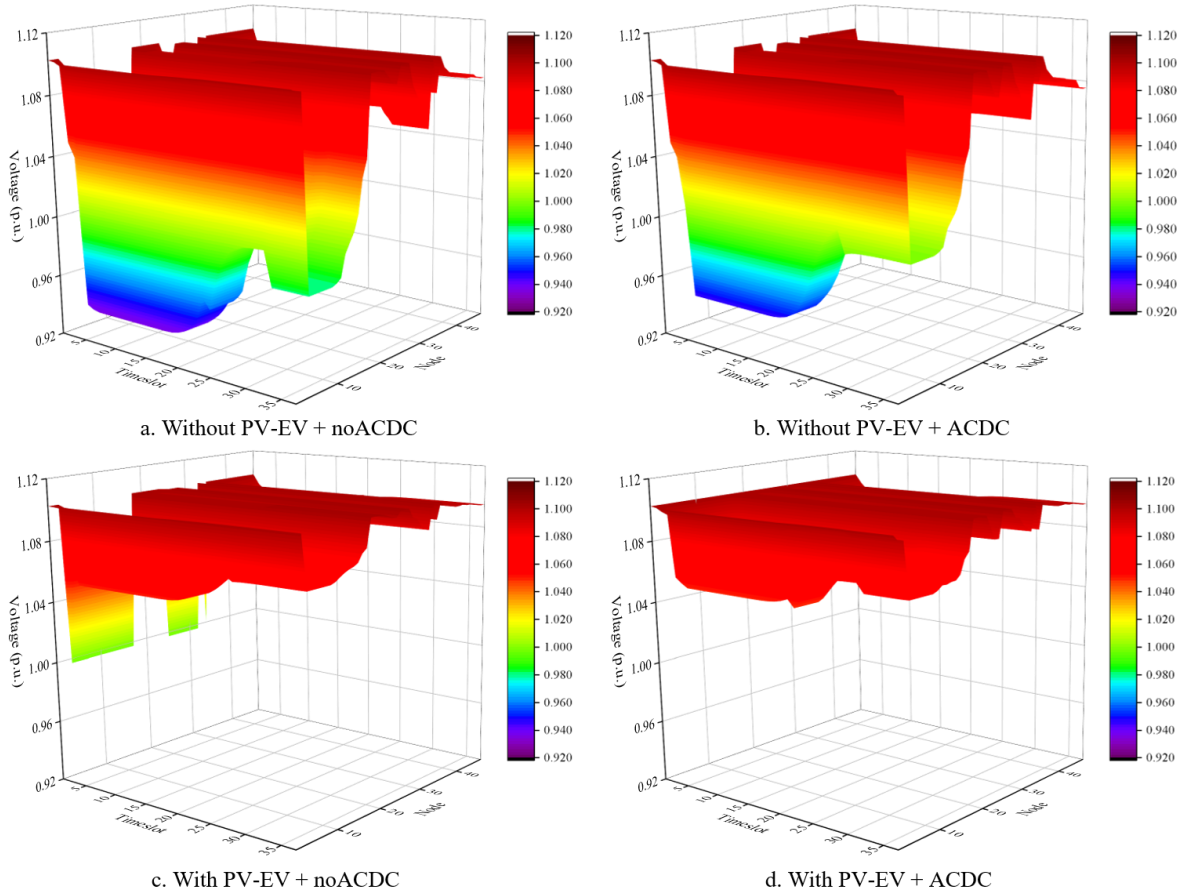


Figure 7-18 Voltage distribution of 47 nodes: (a). Without considering PV and V2G

discharge in the conventional AC grid; (b) Without considering PV and V2G discharge in the hybrid AC/DC grid; (c). With considering PV and V2G discharge in the conventional AC grid; (d) With considering PV and V2G discharge in the hybrid AC/DC grid

7.5 Summary

This chapter investigates a coordinated restoration strategy for modern distribution grids, focusing on the complex dynamics of demand-side load rebound, including building cold load pick-up (CLPU) and electric vehicle (EV) charging loads, alongside the integration of diverse energy resources such as distributed energy resources (DERs) and vehicle-to-grid (V2G)

discharge. The findings underscore the critical role of distribution grid architecture, DERs, and energy management strategies in optimizing power restoration and enhancing grid resilience.

- In scenarios with minimal demand-side load rebound, rapid restoration of load nodes is achievable, with nearly all nodes restored within one timeslot (5 minutes). However, as demand-side load rebound increases, the integration of rooftop PV and V2G discharge becomes essential. For instance, in Scenario 3, the CLPU of buildings surge to nearly 1000 kW, while EV charging load rebound reach 300 kW. Without DERs, certain load nodes, such as Node 11, cannot be restored within the 3-hour restoration interval. In contrast, leveraging DERs and V2G discharge ensures complete restoration within 31 timeslots, highlighting the importance of dispatching flexible energy resources in high-load rebound scenarios.
- The restoration sequence of load nodes reveal the advantages of the hybrid AC/DC distribution grid architecture over conventional AC grid architecture. The hybrid AC/DC grid's ability to facilitate inter-subgrid power exchange via voltage source converters (VSCs) significantly improves the restoration speed of critical load nodes, especially under high-demand scenarios. For instance, in Scenario 4, the hybrid AC/DC grid ensures the restoration of centralized EV charging stations, which exhibits the highest load rebound, within a shorter timeframe compared to the conventional AC grid. This underscores the importance of advanced grid architectures in enhancing power system resilience.
- The analysis of DG power output further demonstrates the critical role of DERs in reducing dependency on DGs during the restoration process. The incorporation of rooftop PV and V2G discharge not only alleviates the burden on DGs but also enhances the overall efficiency of power restoration. Scenarios with high load rebound (e.g.,

Scenario 3) particularly benefite from the power provided by DERs, leading to reduced proportions of unrestored load and improved stability in power supply. However, the effectiveness of rooftop PV is limited during periods of low solar radiation, emphasizing the complementary role of V2G discharge in ensuring complete load restoration.

- The coordinated dispatch of VSCs in the hybrid AC/DC grid architecture further optimizes power exchange between subgrids, minimizing reliance on DGs within individual subgrids. By balancing power across subgrids, the hybrid architecture demonstrates improved resilience and operational flexibility, particularly when DERs are employed. Similarly, the analysis of average node voltage distribution indicates that adopting rooftop PV and V2G discharge significantly enhances voltage stability, reduces fluctuations, and ensures all node voltages remained within permissible limits under high-demand scenarios.

In summary, the findings of this chapter underscore the necessity of advanced grid architectures and flexible energy resource integration for resilient and efficient power system restoration under complex demand-side dynamics.

CHAPTER 8 INTEGRATED ENERGY SYSTEM CAPACITY PLANNING CONSIDERING BUILDING- TRANSPORTATION ELECTRIFICATION IN LONG- TERM DECARBONIZATION ROADMAPS

This chapter focuses on distributed energy system capacity planning for community energy systems in the context of building and transportation electrification, aligning with long-term decarbonization roadmaps. Building upon the system modeling, optimization approaches, and case study foundation established in Chapter 4, this chapter extends the analysis to address strategic planning over extended time horizons. The chapter begins with an overview of decarbonization pathways, highlighting the progressive electrification of both buildings and transportation, the development of diverse carbon emission scenarios, and the methodology adopted for long-term system planning. A detailed case study is conducted using a diverse building district in Japan, previously introduced as a representative test system. Comprehensive, hourly load data—including electricity, heating, cooling, and domestic hot water—are utilized to construct realistic demand profiles under varying electrification and decarbonization scenarios, ensuring the evaluation reflects practical system conditions. The optimal DER capacity planning process is then analyzed, including the assessment of supply-demand balance, operational performance across typical days, and a comprehensive evaluation of the system's ability to achieve electrification and decarbonization targets. The potential for further electrification within the district is also explored, along with its implications for future system design and flexibility.

8.1 Decarbonization roadmaps overview

Decarbonization roadmaps are strategic frameworks that outline pathways toward significant reductions in greenhouse gas emissions across various sectors of the economy. These roadmaps serve as guiding documents for policymakers, researchers, and industry stakeholders, charting the course towards a low-carbon or carbon-neutral future. In the context of integrated energy systems, decarbonization roadmaps are particularly vital as they provide a structured approach to balancing the increasing demands for electrification in buildings and transportation with the imperative of reducing carbon emissions. By mapping out target milestones, technological interventions, and policy measures over specific time frames, these roadmaps allow for the systematic assessment and comparison of different decarbonization scenarios. This section provides a comprehensive overview of the electrification and carbon emission scenarios adopted in this study, and presents the long-term planning methodology employed for capacity optimization and performance assessment of integrated energy systems under these roadmaps.

8.1.1 Electrification roadmaps for buildings and transportation

The electrification of buildings and transportation is a central pillar of contemporary decarbonization strategies. Electrification roadmaps outline the process of transitioning energy end-uses—traditionally reliant on fossil fuels—to electricity, ideally sourced from low-carbon or renewable generation. In the building sector, electrification entails the widespread adoption of electric heating, cooling, and cooking technologies, such as heat pumps and induction stoves, replacing conventional gas or oil-fired systems. For the transportation sector, electrification primarily focuses on the deployment of EVs, as well as the development of supporting charging infrastructure and grid integration solutions.

These roadmaps typically involve incremental targets, such as achieving a certain percentage of electrification by 2030, 2040, and 2050, and are informed by both technological readiness and policy feasibility. For instance, moderate scenarios might envision 50-75% electrification of building loads and a gradual increase in EV market share, whereas deep decarbonization

scenarios aim for near-complete electrification of both sectors by 2050. The interplay between building and transportation electrification introduces new dynamics to energy systems, such as increased peak loads, the need for flexible demand management, and opportunities for sector coupling (e.g., V2G technologies). The electrification roadmaps adopted in this study reflect these trends, incorporating progressive targets for both sectors in alignment with international best practices and national policy ambitions.

8.1.2 Design of carbon emission scenarios

To effectively evaluate long-term decarbonization pathways, this study employs a scenario-based approach for carbon emissions, drawing inspiration from methodologies used by the *International Energy Agency (IEA)* in its flagship publications such as the *World Energy Outlook (WEO)* [167] and *Energy Technology Perspectives (ETP)* [168]. The scenarios are constructed using the *Global Energy and Climate (GEC) Model*, which integrates a range of assumptions about technology adoption, policy implementation, and energy demand evolution. Following a similar approach, this study adopts five distinct carbon emission scenarios to evaluate long-term decarbonization pathways: the 2010 baseline scenario, the 2030 moderate decarbonization scenario (2030 MD scenario), the 2030 deep decarbonization scenario (2030 DD scenario), the 2050 moderate decarbonization scenario (2050 MD scenario), and the 2050 deep decarbonization scenario (2050 DD scenario), as depicted in Table 8-1.

1. **2010 Baseline Scenario:** Utilizes actual measurement data from 2010 as a reference point, capturing the status quo of electricity, heating, and cooling loads in a diverse building community.
2. **2030 Moderate Decarbonization (2030 MD) Scenario:** Targets moderate emission reductions and a 75% electrification level compared to the deep decarbonization scenario by 2030.

3. **2030 Deep Decarbonization (2030 DD) Scenario:** Sets more ambitious goals for substantial emissions reduction and higher electrification rates by 2030.
4. **2050 Moderate Decarbonization (2050 MD) Scenario:** Builds upon the progress of the 2030 MD scenario, seeking further improvements in emissions reduction and electrification by 2050.
5. **2050 Deep Decarbonization (2050 DD) Scenario:** Represents the most aggressive pathway, aiming for near-complete decarbonization and electrification by 2050, in line with global carbon neutrality objectives.

Each scenario is characterized by its own set of input assumptions regarding energy demand, fuel mix, technology penetration, and policy measures. The moderate decarbonization scenarios typically assume that 75% of the electrification levels achieved in the deep decarbonization scenarios are met, providing a practical yet ambitious pathway. The deep decarbonization scenarios, by contrast, envision transformative changes across all sectors, requiring substantial investments in clean technologies and innovative policy support. By systematically comparing these scenarios, the study seeks to reveal the implications of different decarbonization trajectories for integrated energy system design and operation.

Table 8-1 Definitions of carbon emission scenarios

Emission scenario	Electrification level
2010 benchmark scenario	A scenario is treated as a reference point utilized in the analysis of future energy trends
2030 moderate decarbonization (2030 MD scenario)	13% cooking load and 18% light-vehicle need to be electrified.
2030 deep decarbonization (2030 DD scenario)	17% cooking load and 24% light-vehicle need to be electrified. [8, 169]
2050 moderate decarbonization (2050 MD scenario)	71% cooking load and 47% light-vehicle need to be electrified.
2050 deep decarbonization (2050 DD scenario)	94% cooking load and 63% light-vehicle need to be electrified. [170, 171]

8.1.3 Long-term capacity planning methodology

The long-term planning methodology adopted in this study is designed to facilitate a comprehensive capacity optimization and performance assessment of integrated energy systems, with a particular focus on the electrification of buildings and transportation under various decarbonization scenarios. This methodology synthesizes the demand-side electrification scenarios defined in Sections 8.1.1 and 8.1.2 with the advanced multi-objective optimization approach detailed in Section 4.3.

At its core, the methodology involves developing a mathematical optimization model that seeks to balance multiple objectives—such as minimizing total system cost, reducing carbon emissions, and maximizing energy efficiency—over a multi-decade planning horizon. The model incorporates detailed representations of supply-side resources (renewable and conventional generation, storage systems), demand-side electrification profiles (buildings and EVs), and system constraints (network capacity, reliability, and flexibility requirements). Scenario-specific parameters, such as target electrification rates and emission reduction goals, are input into the model to simulate the evolution of the energy system under each roadmap.

The optimization process employs techniques such as mixed-integer linear programming (MILP) or evolutionary algorithms to identify optimal infrastructure investments and operational strategies. Sensitivity analyses are conducted to account for uncertainties in technology costs, policy developments, and demand growth. The performance of each scenario is assessed using a suite of technical, economic, and environmental indicators, including system reliability, renewable integration levels, cost-effectiveness, and emissions abatement.

This study proposes an optimization framework for multi-objective capacity planning of IES across five carbon emission scenarios. The framework, depicted in Figure 8-1, consists of four key steps: data input, multi-scenario equipment capacity optimization, multi-scenario system

operation, and techno-economic-environmental assessment. Initially, the data input incorporates energy consumption data collected from diverse building communities (campus, residential, and commercial), along with the simulated electrified loads of EVs and cooking appliances across various carbon emission scenarios. Subsequently, NSGA III (Non-dominated Sorting Genetic Algorithm III) and TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) are utilized to optimize equipment capacity. The system's performance under different scenarios, accounting for demand variations and renewable energy availability, is simulated and analyzed based on the optimized capacity. Finally, a comprehensive assessment is conducted, considering aspects such as electricity self-sufficiency, investment outlays, carbon emissions, and grid stability. By integrating scenario-based electrification and emissions projections with rigorous optimization techniques, this long-term planning methodology enables stakeholders to evaluate trade-offs between different pathways and supports evidence-based decision-making for the sustainable transformation of integrated energy systems in the face of evolving climate and energy objectives.

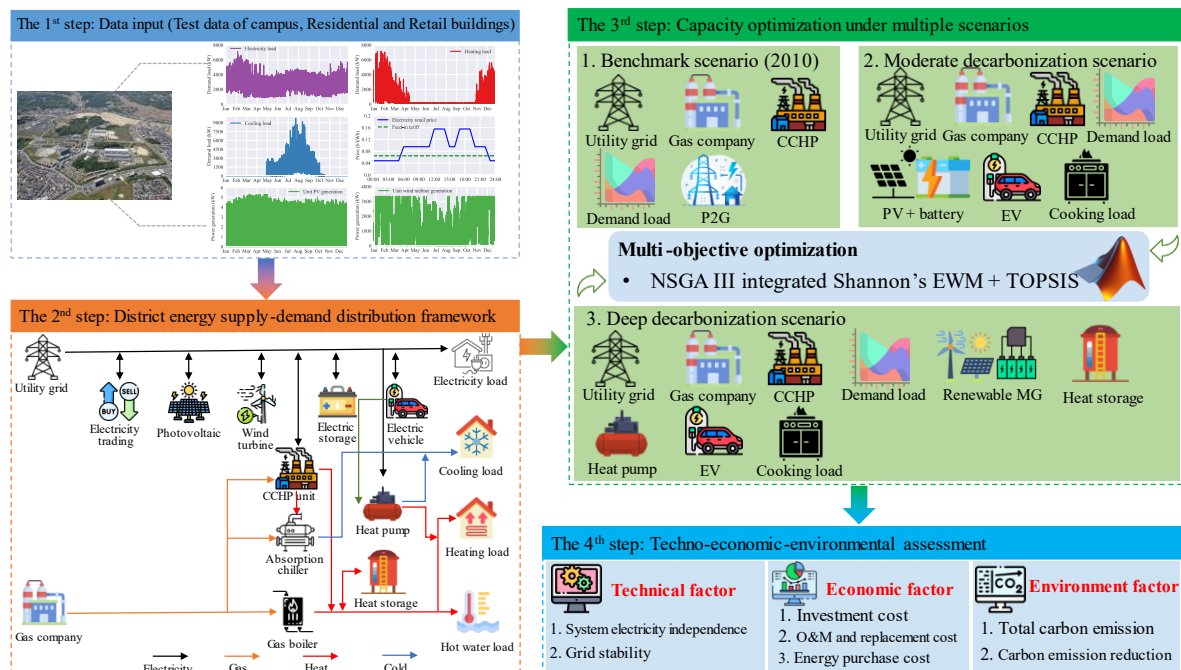


Figure 8-1 Research framework for capacity planning optimization of the IES with distributed energy resources under diverse emission scenarios

8.2 Case study

This section presents a case study based on a diverse building district in Japan, incorporating campus, residential, and commercial communities. The analysis focuses on evaluating electrification demand profiles and energy system planning under different decarbonization scenarios.

8.2.1 Diverse building communities

The diverse building district examined in this section is the same as that introduced in Section 3.6.2, which is based on our previous work involving a representative district in Japan [172]. This district features a mix of campus, residential, and commercial communities, each contributing unique energy demand characteristics. Detailed testing data for this diverse building community were collected, including hourly measurements of electricity load, space cooling load, space heating load, and domestic hot water demand throughout the entire year. These comprehensive datasets provide a solid foundation for analyzing the energy consumption patterns and system requirements of the district. By leveraging the measured hourly load profiles, the case study is able to realistically capture the temporal variations and diverse needs of different building types within the community, enabling a robust evaluation of distributed energy resource planning and electrification strategies under various decarbonization scenarios.

8.2.2 Demand load profiles

A central aspect of this study is the assessment of the electrification demand load profiles, with a particular focus on EV charging and the use of electric cooking devices. Figure 8-2 illustrates the electrification load distribution for both EVs and cooking devices under the 2030 DD scenario and the 2050 DD scenario. These two end-uses are expected to experience significant growth as part of broader decarbonization efforts in the coming decades. The analysis considers two key scenarios: the 2030 DD scenario and the 2050 DD scenario. In the 2030 DD scenario,

the electrification load remains moderate, with EV charging peaking at 1600 kW and electric cooking devices peaking at 170 kW. This reflects an early stage of electrification adoption, where the impacts on the overall energy system are manageable within existing infrastructure capacities.

By contrast, the 2050 NZE scenario represents a more ambitious pathway aligned with long-term carbon neutrality goals. Under this scenario, the electrification load increases significantly as a result of higher penetration rates of EVs and the widespread replacement of traditional cooking fuels with electric alternatives. The peak demand for EV charging rises sharply to 5300 kW, while the cooking electrification load reaches 700 kW. This dramatic increase underscores the necessity for robust capacity planning and highlights the challenges associated with managing higher and more variable electricity demand profiles under deep decarbonization policies.

The demand profiles for both EV charging and cooking devices also reveal notable patterns of daily and weekly variation. The cooking load, for instance, is closely tied to the occupants' dining habits, resulting in pronounced peaks during meal times and observable differences between weekdays and weekends. Such patterns are important for energy system operators, as they introduce temporal variability that must be accommodated through flexible supply and demand management strategies. Similarly, the EV charging load is shaped by the mobility patterns of residents and employees, with charging events often concentrated in the evenings and at times of high vehicle turnover. Understanding these behavioral influences is critical for designing demand response programs and optimizing distributed energy resources to meet electrification goals.

The comprehensive demand load dataset used in this study comprises 8,760 hours of electricity, heating, and cooling load records for the year 2010, representing the aggregated energy

requirements of the campus, residential, and commercial communities. These hourly data form the baseline against which future electrification and decarbonization scenarios are assessed. Figure 8-3 illustrates the annual distribution of electricity, heating, and cooling loads under different carbon emission scenarios, providing valuable insights into the evolving energy demand landscape of complex urban communities. Analyzing these load profiles facilitates the identification of critical periods of peak demand, informs system flexibility requirements, and supports the development of optimal energy resource allocation strategies for future community energy systems.

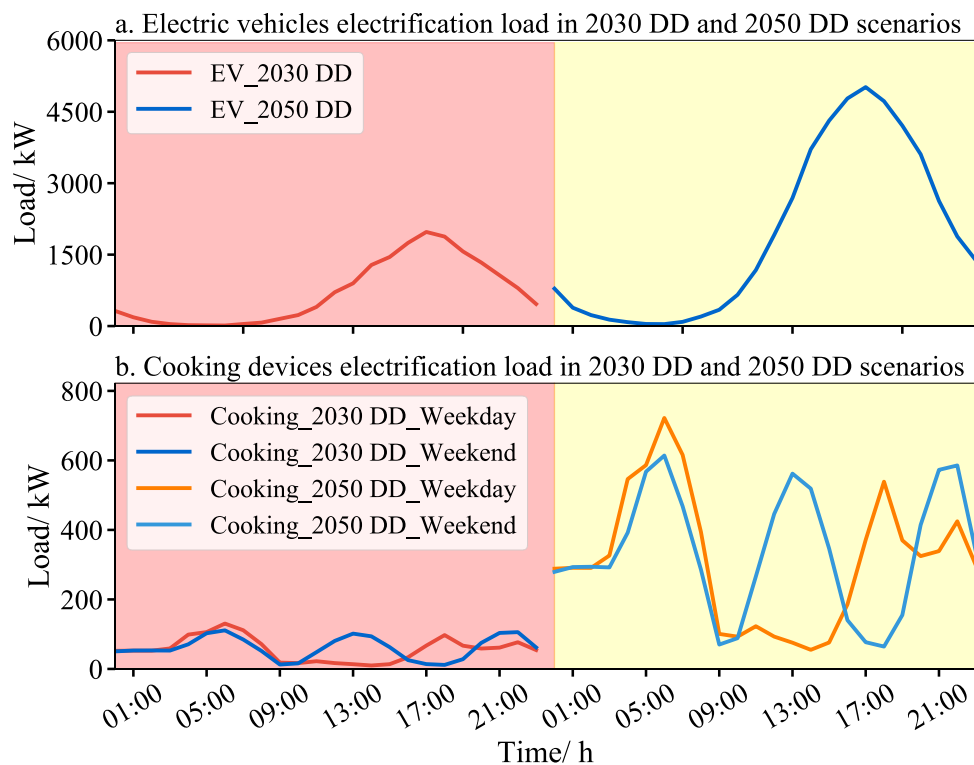


Figure 8-2 Electrification load of EVs and cooking devices in 2030 and 2050, a. Electric vehicle electrification load; b. Cooking devices electrification load

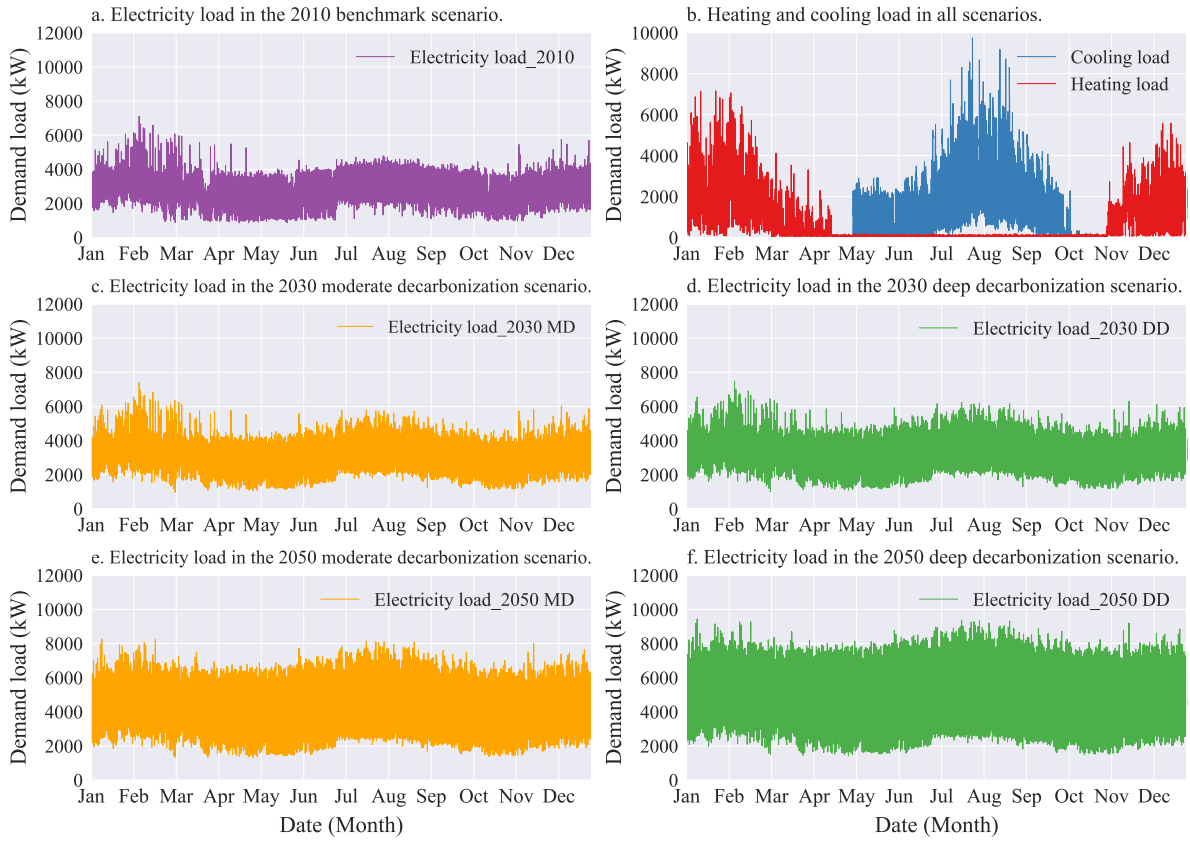


Figure 8-3 Demand load of complex communities under carbon emission scenarios

8.3 Results and analysis

The section is categorized into five subsections, i.e., optimal capacity planning results, supply-demand balance assessment, operational analysis across typical days, overall performance evaluation, and electrification potential assessment.

8.3.1 Optimal capacity planning results

The Pareto front, derived by applying the NSGA-III algorithm to solve the optimization model (Eq. (4.2)), is visualized in Figure 8-4, illustrating the trade-offs among the three objectives—ATC, SEI, and ACE—under the 2010 benchmark, 2030 MD scenario, 2030 DD scenario, 2050 MD scenario, and 2050 DD scenario. This three-dimensional curve represents 122, 105, 110, 109, and 116 alternative design schemes for the respective scenarios, highlighting the inherent trade-offs among the objectives. The negative correlation between the three objective functions

necessitates an effective decision-making method to select the optimal solution. This study employs the TOPSIS method to rank and identify the best configurations. The optimization results combining NSGA-III and TOPSIS are presented in Table 8-2.

Figure 8-5 presents the capacity distribution trends of various equipment types in different years and scenarios. The equipment categories include renewable energy units (e.g., PV and WT), fuel-based units (e.g., CCHP, AC, and GB), heat pumps, and energy storage units (e.g., BAT and HST). Renewable energy units show a significant increase in capacity as electrification advances, while fuel-based units experience a decline. Heat pumps and energy storage units also exhibit growth, albeit at a more modest scale. The effect is most notable for renewable energy units, with the DD scenario showing an average 43.4% higher capacity compared to the MD scenario. Conversely, the optimal capacity of fuel-based units under the DD scenario is approximately 17.3% lower than that under the MD scenario.

Table 8-2 Optimal capacity planning of IES under different carbon emission scenarios

Scenarios	PV (kW)	WT (kW)	CCHP (kW)	AC (kW)	HP (kW)	GB (kW)	BAT (kWh)	HST (kWh)	ATC (\$)	SEI (%)	ACE (tCO ₂)
2010	360	630	8400	5390	50	4360	90	350	23,318,934	90.4	108,151
2030 MD	1380	1850	3620	3140	860	3080	410	270	13,163,780	55.2	82,905
2030 DD	1720	2260	3090	2890	950	2940	500	260	9,778,729	43.5	74,490
2050 MD	4870	5250	1380	890	2420	1820	1120	210	7,353,499	29.6	45,713
2050 DD	6370	6790	600	390	2680	1540	1460	190	3,362,140	14.4	30,103

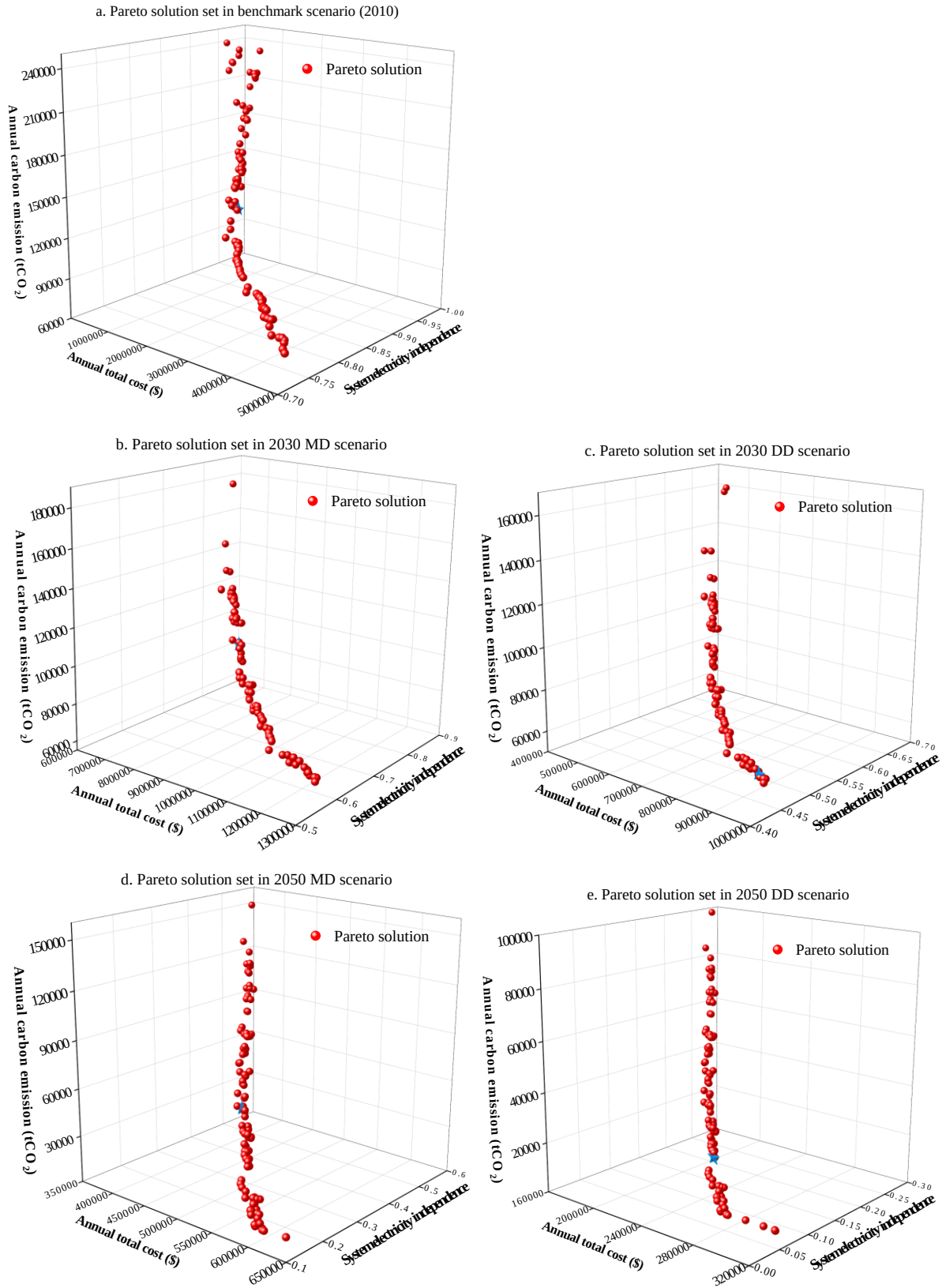


Figure 8-4 The obtained Pareto frontier under different carbon emission scenarios by NSGA

III algorithm

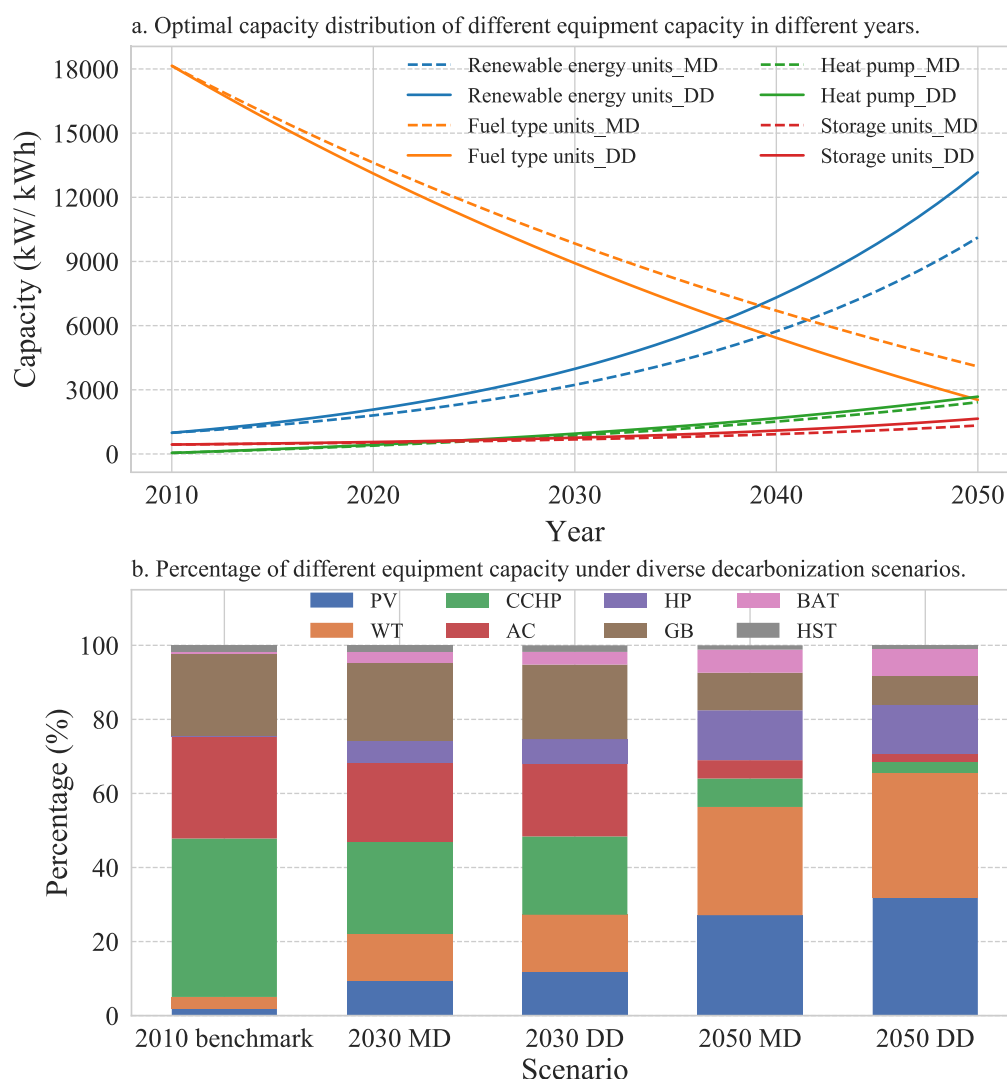


Figure 8-5 Capacity distribution trends of different types of equipment in different years and scenarios, a. Optimal capacity distribution of different equipment in different years; b. Percentage of different equipment capacity under diverse decarbonization scenarios

8.3.2 Supply-demand balance assessment

In this sections, the energy system's performance under varying optimal capacities across different years is analyzed, focusing on the deep decarbonization (DD) trajectory as a representative pathway. To enhance clarity and conciseness in visualization, we select the 2010 benchmark, 2030 DD, and 2050 DD scenarios for detailed analysis, as the differences between the moderate and deep decarbonization scenarios in 2030 and 2050 follow similar trends. The

energy supply-demand distribution under 2010 benchmark, 2030 DD, and 2050 DD is illustrated in Figure 8-6.

In the 2010 benchmark scenario, with no specific focus on carbon emission reduction, the energy system relies heavily on primary energy consumption. CCHP equipment plays a central role, supplying electricity, cooling, and heating loads. Specifically, 62.7% of the electricity load is met by the utility grid, while CCHP contributes 31.8%, and PV and WT generation account for only 5.4%. The absorption chiller, utilizing waste heat from CCHP, covers 97.8% of the cooling load, with the remainder supplied by electricity-driven heat pumps. For heating, gas boilers and CCHP meet 59.8% and 35.2% of the load, respectively, with heat storage equipment addressing the residual demand. This configuration reflects the limited adoption of renewable and electrified technologies at that time, as well as a reliance on established fossil-based infrastructure. The predominance of CCHP and gas boilers is reasonable given the policy and technological context of 2010, where cost, efficiency, and reliability favored these solutions.

Transitioning to the 2030 DD scenario, the energy system undergoes significant structural changes due to increased emphasis on carbon emission reduction and electrification. The reliance on gas decreases substantially, while electricity imports from the utility grid rise slightly. Renewable energy sources, particularly PV and WT, contribute 35.4% of the electricity load. Although the proportion of directly imported electricity decreases to 53%, total grid electricity input increases due to electrification in the building and transportation sectors. CCHP and battery storage contribute 8.5% and 3.1% of the electricity supply, respectively. For cooling, heat pumps and absorption chillers meet 53.6% and 46.4% of the load, respectively. For heating, gas boilers remain dominant at 58.9%, while heat pumps and CCHP provide 25.5% and 12% of the load, respectively. These changes are reasonable and expected as policy drivers and technological advancements promote renewable energy deployment and electrification.

The increased share of PV and WT generation directly responds to decarbonization targets, while the growth in electricity demand reflects broader electrification trends in end-use sectors. The co-existence of multiple supply technologies (e.g., heat pumps, chillers, storage) demonstrates both the transitional character of 2030 and the need for flexibility as the system adapts to variable renewable generation and shifting demand patterns.

In the 2050 DD scenario, the energy system further reduces its dependence on primary energy, with renewable sources dominating the supply. PV and WT generation, along with battery storage, contribute 76.5% and 6.1% of the electricity load, respectively, while the utility grid supplies only 16.2%. Heat pumps become the primary source for cooling, meeting 94.9% of the cooling load. For heating, gas boilers and heat pumps cover 45.5% and 36.5% of the load, respectively, while CCHP and heat storage devices account for the remaining 18%. The dramatic increase in the share of renewables and electrified end-uses is consistent with a deeply decarbonized future, where technological maturity, supportive policy frameworks, and cost reductions make renewables and electrification the most viable energy solutions. The sharp decline in grid dependence and fossil fuel use reflects anticipated improvements in distributed energy integration and storage technologies. The high penetration of heat pumps and storage for both heating and cooling highlights the system's shift toward maximizing renewable utilization and minimizing emissions. These results not only demonstrate technical feasibility but also align with global decarbonization pathways as outlined by leading energy transition roadmaps.

In summary, the evolution of energy supply and demand balance across these scenarios is both logical and justified by the underlying drivers of decarbonization, technological progress, and policy intervention. The observed trends underscore the increasing role of renewables and electrification, the gradual phasing out of fossil-based technologies, and the growing importance of flexibility and integration in the future energy system.

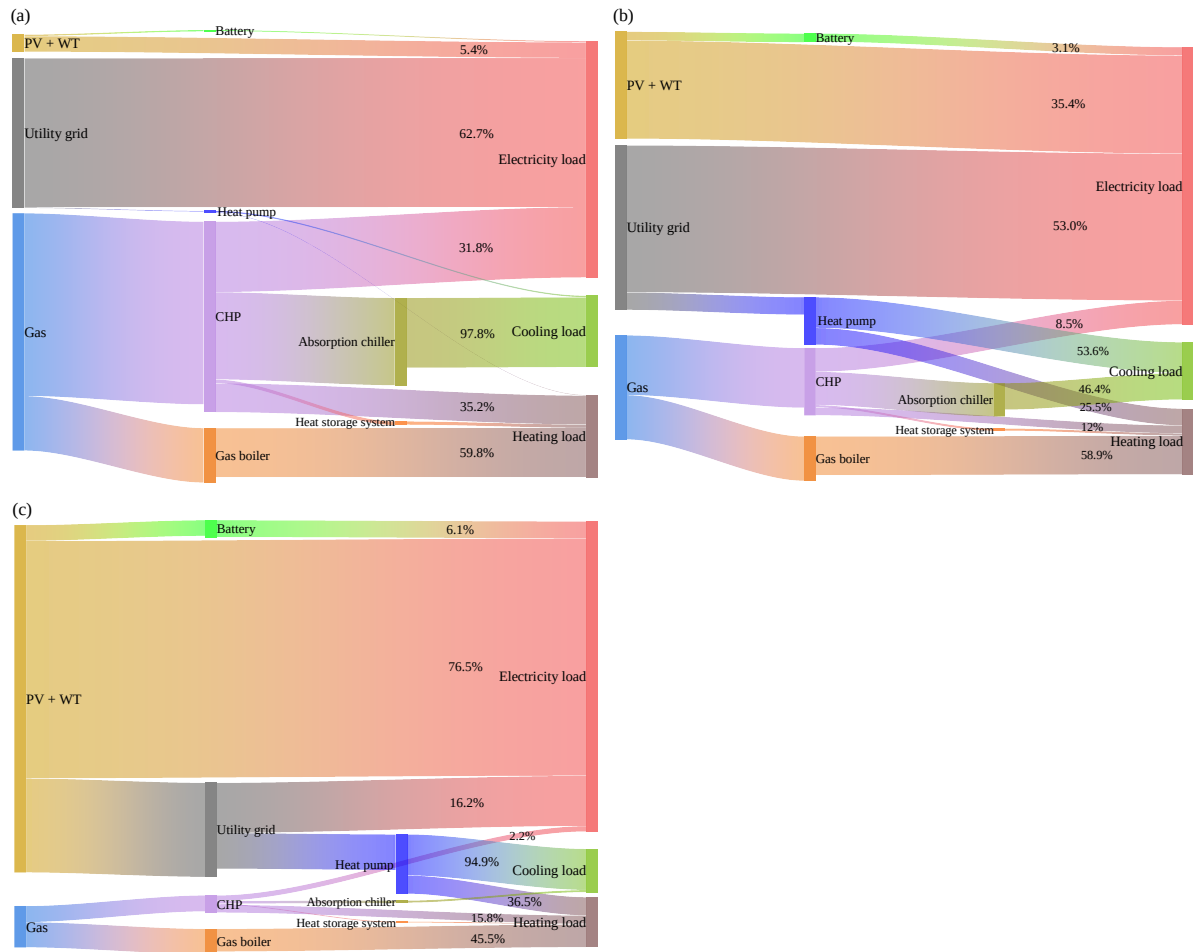


Figure 8-6 Supply-demand energy distribution under different carbon emission scenarios, a. 2010 benchmark scenario; b. 2030 DD scenario; c. 2050 DD scenario

8.3.3 Operation analysis across typical days

To ensure clarity and avoid redundancy, the assessment of the optimal energy system structure and capacity design under the deep decarbonization trajectory focuses on the 2010 benchmark, 2030 DD, and 2050 DD scenarios, as the moderate and deep decarbonization scenarios in 2030 and 2050 reveal similar trends. Representative days from different seasons with varying electricity, cooling, and heating load demands are selected, and the operational outcomes of the IES under optimal design are analyzed to validate equipment efficiency and identify operational changes over time.

In the 2010 benchmark scenario, as illustrated in Figure 8-7, the IES operates based on a strategy that prioritizes renewable energy utilization, with determining heat by cooling and

determining electricity by heat. This strategy creates a strong link between cooling, heating, and electricity within the system. During the summer day, minimal cooling demand from 00:00 to 08:00 results in low CCHP operation, with up to 70% of electricity supplied by the grid. As cooling demand increases from 09:00 to 23:00, CCHP ramps up, meeting 60% of electricity demand and reducing grid reliance. The absorption chiller, utilizing CCHP waste heat, covers the cooling load, while CCHP handles heating with minimal hot water demand. During the winter day, gas boilers meet most heating needs during low-demand periods, while CCHP operates during peak demand (08:00–11:00 and 16:00), providing heating and reducing grid electricity purchases. Deactivating CCHP during low heating periods increases grid reliance. During the mid-season day, with moderate cooling and heating demands, CCHP operates primarily during peak electricity pricing periods, reducing grid dependence and enhancing economic efficiency. Renewable energy sources (PV and WT) meet minor electricity needs, with limited battery storage utilization. Additional electricity demands are met through CCHP generation or grid imports.

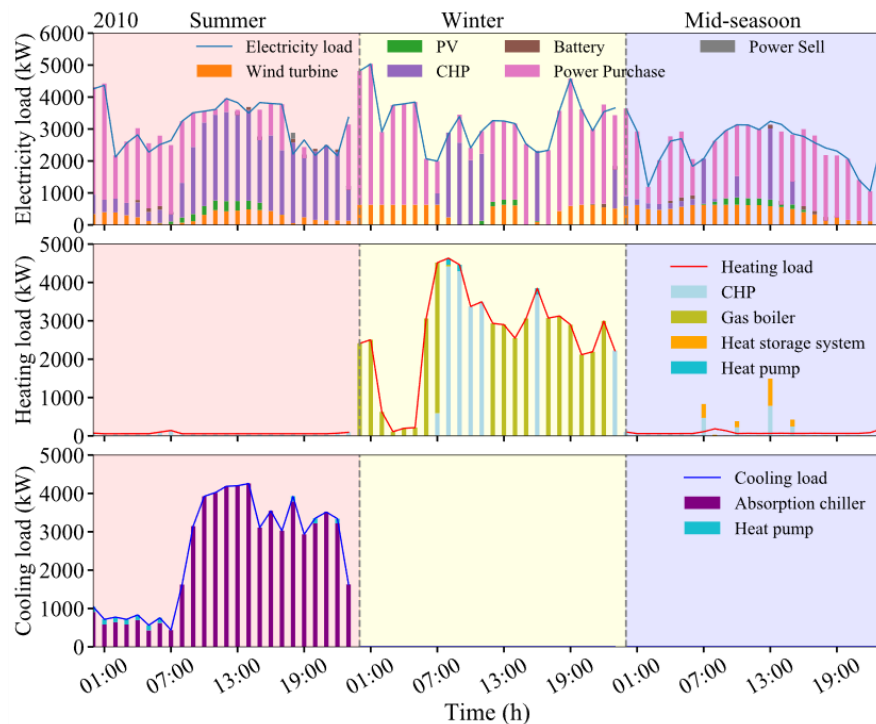


Figure 8-7 Electricity, heating and cooling loads on different season typical days under the optimal capacity of the energy system in 2010 benchmark scenario

In the 2030 DD scenario, driven by carbon emission reduction mandates, the energy system is redesigned for optimal performance. The operational results of the energy system in 2030, following the optimal design blueprint, are illustrated in Figure 8-8. During the summer day, the heat pump handles cooling demand from 08:00 to 23:00, while the absorption chiller operates only during peak hours when the heat pump, even at full capacity, cannot fully meet the cooling load requirements. Increased renewable energy capacity (PV and WT) reduces grid reliance by approximately 40% compared to 2010. Expanded battery capacity enables demand response during peak pricing hours (13:00–14:00 and 18:00–19:00). During the winter day, CCHP operates during high heating demand periods (07:00–09:00 and 11:00), with limited electricity contribution due to reduced capacity. Gas boilers and heat pumps are activated based on electricity prices. Renewable energy, particularly WT, generates more electricity than in summer, further reducing grid imports. During the mid-season day, CCHP operates selectively during peak pricing periods, managing electricity and storing excess heat. Reduced total electricity demand and surplus renewable generation (08:00–13:00) minimize grid reliance. Battery discharge during peak hours (13:00–15:00 and 18:00–19:00) further reduces grid electricity imports. Despite increased renewable capacity, the system prioritizes self-consumption, with minimal electricity exported to the grid.

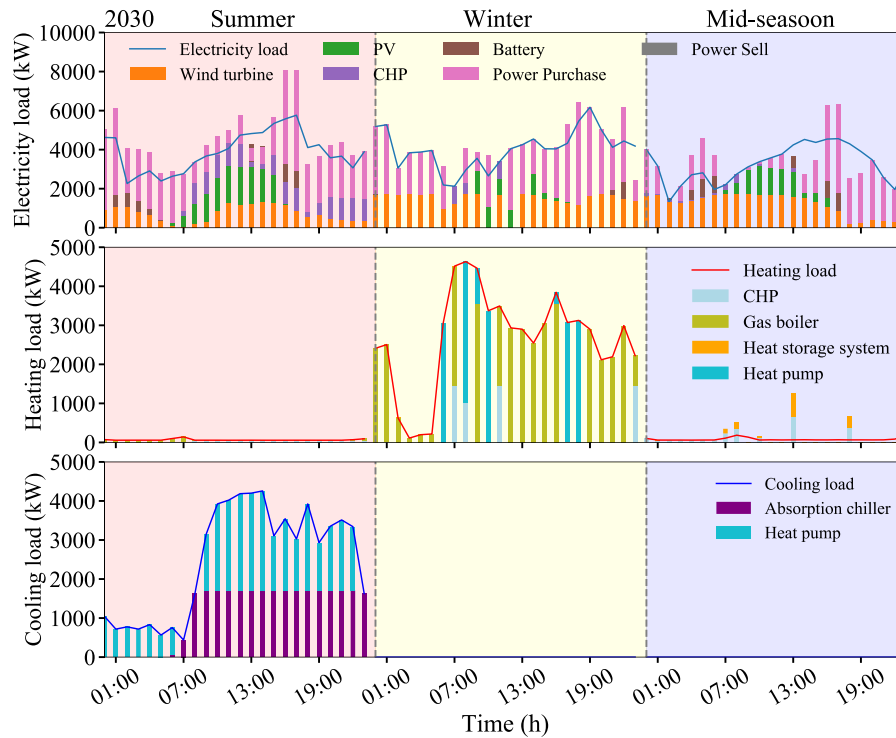


Figure 8-8 Electricity, heating and cooling loads on different season typical days under the optimal capacity of the energy system in 2030 DD scenario

In the 2050 DD scenario, achieving near-zero carbon emissions, the energy system shifts toward distributed generation and energy-efficient devices. The operational results of the energy system under the optimal capacity in 2050 are outlined in Figure 8-9. During the summer day, renewable energy generation (PV and WT) nearly matches electricity demand, with surplus electricity exported to the grid during periods of high generation. Minimal grid electricity is imported from 16:00 to 23:00. CCHP operates only during the electricity procurement window of 16:00 to 23:00, contributing a small fraction of electricity due to its limited capacity. Heat pumps handle most cooling loads, with minimal support from absorption chillers, especially at night. During the winter day, electricity operations resemble the summer day, but heat pump efficiency decreases in colder temperatures, making gas boilers the primary heating source initially. Heat pumps supplement heating when gas boilers are insufficient. During the mid-season day, electricity operations align with the operation in the summer day. During low generation periods (16:00–23:00), electricity is sourced from the grid. Batteries

shift consumption from peak (18:00–20:00) to off-peak hours (16:00–17:00), reducing grid imports during peak periods.

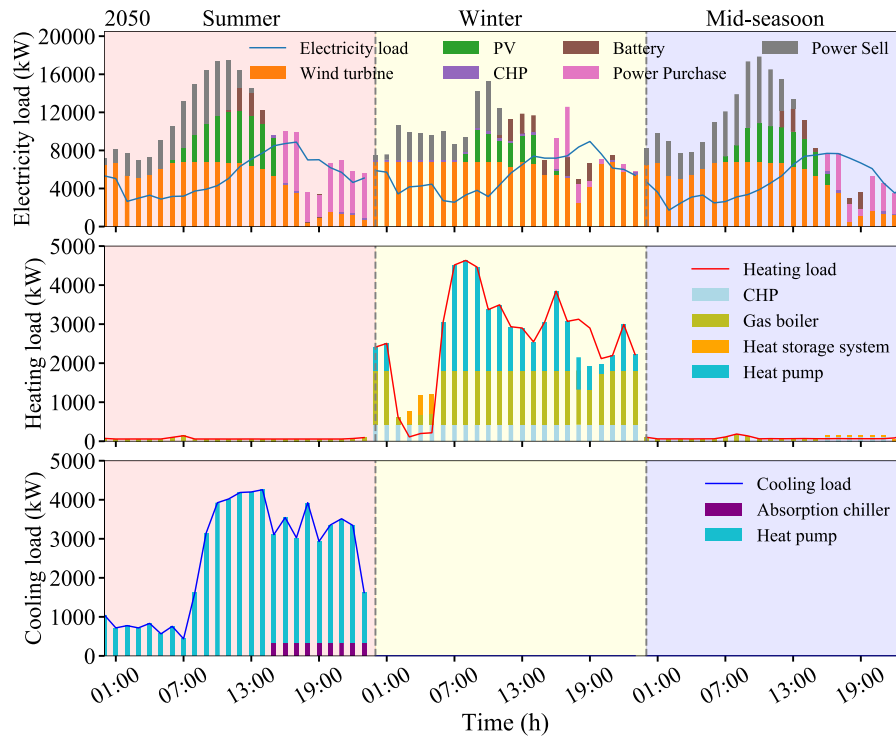


Figure 8-9 Electricity, heating and cooling loads on different season typical days under the optimal capacity of the energy system in 2050 DD scenario

8.3.4 Overall performance evaluation

To further compare the performance variations of the energy system under the deep decarbonization trajectory (2010 benchmark, 2030 DD, and 2050 DD scenarios), a comparative analysis of techno-economic-environmental indicators was conducted. Figure 8-10 illustrates these indicators for the three scenarios. In the 2010 benchmark scenario, which lacks a carbon emission strategy and is characterized by high costs of renewable energy equipment, key indicators such as primary energy consumption, total investment and operational costs, system electricity reliance, and CO₂ emissions reaches their highest levels. This highlights the system's limited autonomy, cost-effectiveness, and sustainability, constraining its ability to enhance energy adaptability and durability.

In the 2030 DD scenario, governmental interventions aimed at reducing carbon emissions led to significant advancements in the renewable energy system compared to 2010. Although renewable energy equipment costs remain slightly higher than traditional equipment, the capacity of high-emission CCHP equipment decreased by up to 60%. Renewable energy capacity increases gradually, accompanied by a modest rise in electricity imports from the utility grid due to partial electrification of the transportation sector and reduced CCHP capacity. Despite increased electricity imports driven by higher overall demand from building and transportation electrification, the system's reliance on the grid decreases overall, as evidenced by the reduction in the SEI index from 0.904 in 2010 to 0.435 in 2030. Primary energy utilization declined slightly, while total investment and operational costs, as well as gas consumption, see significant reductions. Carbon dioxide emissions during system operation decreased by approximately 31.1% compared to 2010.

In the 2050 DD scenario, higher electrification levels in the building and transportation sectors enable a self-sufficient energy system powered by distributed renewable energy generation and storage. As a result, electricity procurement from the utility grid, gas consumption, and primary energy utilization are substantially reduced. The system's reliance on the grid decreases significantly, with the SEI index dropping to 0.144. Carbon emissions during operation are further reduced to only 27.8% of 2010 levels. Improved production technologies by 2050 also lead to considerable reductions in the investment costs of distributed energy equipment, further lowering total investment and operational expenses. Overall, the optimized layout and capacity planning of the energy system in 2050, leveraging distributed resources effectively, significantly enhances its flexibility and resilience. This progress supports future technological advancements and the sustainable evolution of the power system, particularly in the context of extensive electrification.

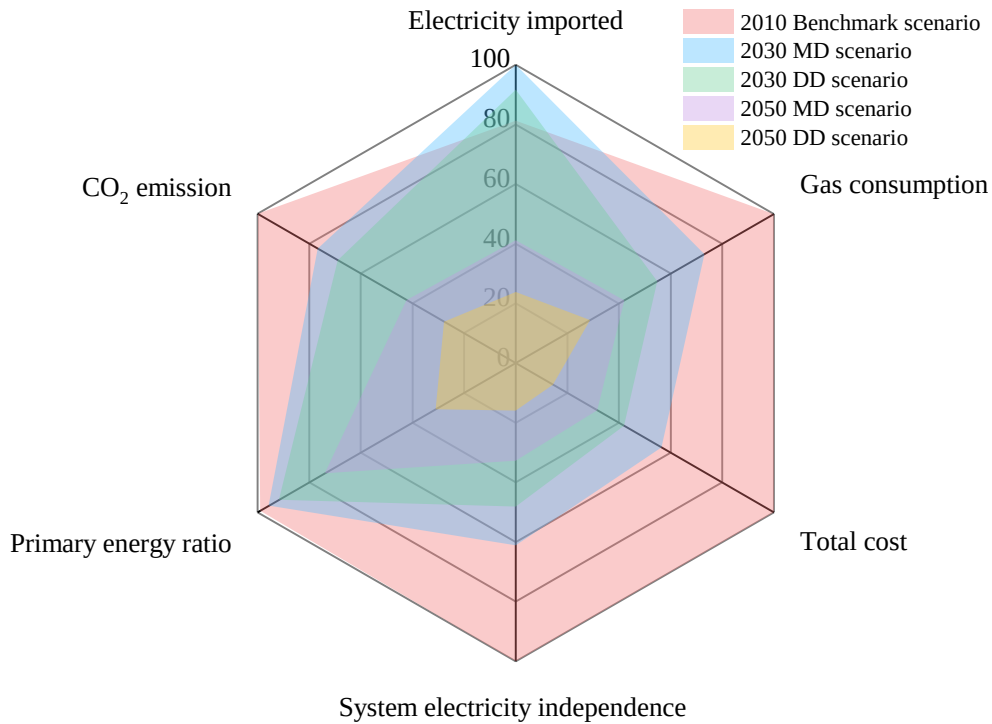


Figure 8-10 Comparison of technical, economic and environmental indicators under the deep decarbonization trajectory (2010 benchmark, 2030 DD, and 2050 DD)

8.3.5 Electrification potential assessment

The design of future energy systems is critical for achieving sustainable and reliable energy provision. This section examines the permissible range of demand-side electrification under the optimal equipment capacity configuration of the IES across the deep decarbonization trajectory (2010 benchmark, 2030 DD, and 2050 DD scenarios). Figure 8-11 illustrates the distribution of the minimum and maximum electrification ranges within the energy system.

The minimum demand-side electrification level refers to the surplus electricity generated by renewable energy systems (PV and WT) and CCHP systems, beyond meeting regional self-consumption and optimal energy storage capacity, which is fed back to the grid for economic returns. The maximum demand-side electrification level involves storing all surplus electricity generated by renewable energy and CCHP systems beyond regional self-consumption, ensuring complete storage to meet future demands and maximizing the potential for demand-side electrification under 100% self-consumption of the energy system's electricity generation.

Variations in optimal energy system planning schemes across scenarios result in different levels of demand-side electrification. In the 2010 benchmark scenario, the energy system's electrification level is relatively low, ranging from 5% to 8% on the demand side, due to the prevalent use of conventional fossil fuels and limited renewable energy integration. However, with increasing demand for sustainable energy and technological advancements, the energy system has transitioned toward higher electrification. Significant changes in electrification scope are expected in the coming decades. In the 2030 DD scenario, the energy system's electrification level increases compared to 2010, with the minimum demand-side electrification level at approximately 20% and the maximum at around 28%. By the 2050 DD scenario, the energy system achieves its peak electrification level, with demand-side electrification further enhanced to a minimum of 53% and a maximum of about 77%.

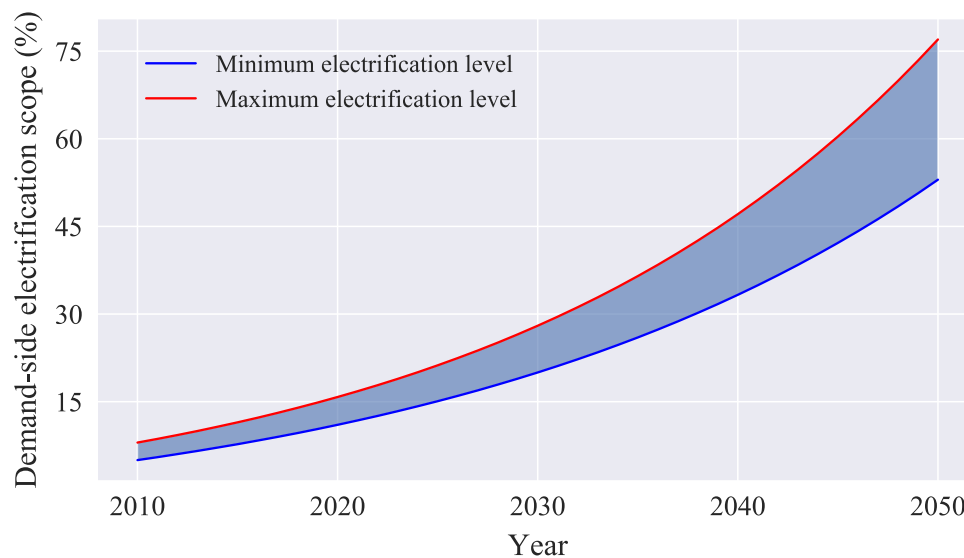


Figure 8-11 Distribution of demand-side electrification scope under the long-term energy system planning

8.4 Summary

This chapter proposes a multi-objective optimization framework for configuring the capacity of an Integrated Energy System (IES) with distributed energy resources (DERs) under multiple

carbon emission scenarios, including the 2010 benchmark scenario, moderate and deep decarbonization scenarios in 2030 (2030 MD and 2030 DD), and moderate and deep decarbonization scenarios in 2050 (2050 MD and 2050 DD). The framework incorporates carbon emission scenarios and energy system operation to enhance performance and facilitate the electrification transformation in a complex community (including campus, residential buildings, and commercial buildings). By evaluating the techno-economic-environmental aspects of electrification—such as energy consumption patterns, system reliability, operational costs, and carbon emissions—a comprehensive understanding of the system's evolution is achieved. The key findings are summarized as follows:

- Increasing emphasis on carbon emissions drives a shift from primary energy consumption to renewable sources, such as PV and WT power generation. As electrification advances, heat pumps play a critical role in electrifying cooling and heating load demands. Meanwhile, the role of CCHP systems diminishes from a significant contributor in 2010 to a minor role in 2030 and 2050, as renewables and electrification dominate. This transition is marked by the gradual phase-out of gas-powered equipment and the replacement of CCHP with heat pumps, paving the way for a sustainable, low-carbon energy landscape.
- The study highlights the influence of electrification growth on equipment capacities under deep decarbonization (DD) and moderate decarbonization (MD) scenarios. Renewable energy units experience a 43.4% capacity increase under the DD scenario with higher electrification, while fuel-based units see a 17.3% decline in optimal capacity. These findings underscore the significant impact of electrification levels on equipment capacities, particularly the sensitivity of renewable energy units to varying electrification degrees.

- The optimal design scheme demonstrates its effectiveness through the analysis of the energy system's typical daily operation under the deep decarbonization trajectory (2010 benchmark, 2030 DD, and 2050 DD scenarios). Results reveal a transition toward increased renewable energy utilization, improved energy efficiency, and reduced reliance on the utility grid. From 2010 to 2050, the system evolves from 70% grid dependence during peak demand in 2010 to 40% in 2030 with greater renewable integration, achieving self-sufficiency and even exporting excess electricity by 2050.
- The analysis of demand-side electrification under various carbon emission scenarios demonstrates that the primary driver for advancing the electrification level of the energy system in the future lies in the expansion of renewable energy systems' capacity (PV and WT). The electrification scope ranges from 5% to 8% in 2010, increases to approximately 20% to 28% in 2030, and reaches a high of 53% to 77% in 2050. These figures emphasize the importance of sustainable energy and have policy implications for future planning and development in integrated building and transportation scenario.

CHAPTER 9 CONCLUSIONS AND FUTURE WORK

This chapter presents the concluding remarks and outlines the future directions for research based on the findings and contributions of this study. This chapter is divided into three sections, each addressing different aspects of the research conducted. Section 9.1 highlights the main contributions of this study. Section 9.2 presents the conclusions drawn from the analysis and interpretation of the research outcomes. Section 9.3 focuses on recommendations for future work based on the research conducted.

9.1 Main contributions of this study

This thesis presents a systematic and comprehensive investigation into the optimal capacity design, electricity trading mechanisms, and operational strategies for community energy systems, with a particular emphasis on building and transportation electrification under long-term decarbonization roadmaps. The main contributions can be summarized as follows:

- i. Integrated multi-energy system modeling: A robust modeling framework was established for community-scale integrated energy systems, fully capturing the interactions among electricity, heating, cooling, and domestic hot water demands within diverse building communities, as well as the coupling with electric vehicle charging.
- ii. Advanced optimization methodologies: Novel capacity optimization approaches were developed, including the application of the golden section method for preliminary sizing and a multi-objective optimization framework employing NSGA-III, Shannon entropy-based weighting, and TOPSIS for exploring trade-offs among techno-economic and environmental objectives.

- iii. Innovative energy trading paradigms: The dissertation proposed and evaluated both rule-based and advanced peer-to-peer electricity trading strategies, notably a hybrid game theory-based peer-to-peer model integrating cooperative and non-cooperative games for intra- and inter-microgrid optimization, respectively.
- iv. Demand response and flexible resource integration: The PhD study incorporated demand-side management strategies, dynamic dispatch of distributed energy resources, and vehicle-to-grid capabilities to enhance grid resilience, energy autonomy, and system flexibility.
- v. Short-term coordinated restoration scheme and rebound modeling: A novel two-stage coordinated restoration scheme was developed, integrating high-resolution, real-world data and detailed modeling of demand-side load rebound—including building cold load pickup and EV charging—enabling scenario-based analyses and supporting practical strategies for resilient power system restoration with flexible energy resources.
- vi. Long-term capacity planning considering demand-side electrification under decarbonization roadmaps: A comprehensive methodology was developed to integrate real-world, high-resolution load data and electrification trends into long-term distributed energy resource capacity planning, enabling scenario-based evaluation of decarbonization pathways and ensuring robust supply-demand balance under increasing building and transportation electrification.

Overall, this research provides a holistic methodological foundation for the design, operation, and transformation of future-ready community energy systems under the dual imperatives of electrification and decarbonization.

9.2 Conclusions

This thesis systematically addressed the challenges and opportunities in optimizing community energy systems amid the accelerating trends of building and transportation electrification. Key conclusions drawn from the research are as follows:

- i. Capacity planning under decarbonization: The multi-objective optimization framework developed in this study enables the identification of optimal DER configurations, balancing cost, reliability, and environmental impact. As decarbonization targets become more stringent, there is a clear transition from fossil-based systems, such as CCHP and gas boilers, towards high shares of renewables and electrified technologies—especially heat pumps and PV/wind generation.
- ii. Electricity trading and management: Advanced P2P trading paradigms, particularly those based on hybrid game theory, significantly improve system efficiency, cost-effectiveness, and flexibility compared to traditional rule-based or time-of-use strategies. These strategies also foster fairer and more efficient electricity transactions among heterogeneous building communities, while reducing reliance on the central utility grid.
- iii. Demand-side flexibility and grid resilience: Integrating demand response, distributed resources, and flexible architectures (e.g., hybrid AC/DC grids and V2G) is essential for mitigating load rebound, enabling rapid restoration after outages, and maintaining voltage stability under high electrification scenarios.
- iv. Impact of electrification: The electrification of both building end-uses and transportation substantially increases the complexity and variability of energy demand profiles. However, with proper planning and optimization, these challenges can be

transformed into opportunities for enhancing renewable integration, reducing carbon emissions, and advancing towards energy self-sufficiency at the community level.

- v. Policy and practical implications: The findings underscore the necessity of coordinated planning, advanced operational strategies, and flexible trading mechanisms to achieve a resilient, low-carbon, and economically viable community energy future. The developed frameworks and insights serve as valuable references for policymakers, planners, and practitioners engaged in the sustainable transformation of urban energy systems.

9.3 Recommendations for future work

This PhD study lays a solid foundation for the continued development of smart, sustainable, and resilient community energy systems. Ongoing efforts in technology integration, market innovation, and holistic planning will be essential to meet the ambitious goals of deep decarbonization and electrification in the coming decades. Building upon the findings of this thesis, several key avenues for future research are recommended:

- i. Real-world demonstration and pilot projects: Future work should focus on implementing the proposed optimization and trading frameworks in real community energy systems, enabling validation under practical operational conditions and capturing real-world uncertainties.
- ii. Expanded modeling of sector coupling: Further research is needed to extend the modeling framework to include other sectors, such as water, waste, and industrial processes, for a more comprehensive assessment of multi-vector energy systems and their interdependencies.

- iii. Integration of emerging technologies: The impact of next-generation energy storage, advanced heat pumps, hydrogen production, and smart charging/discharging of EVs should be systematically explored, as these technologies may significantly enhance system flexibility and decarbonization potential.
- iv. Spatio-temporal energy flexibility: Future research could explore the spatio-temporal characteristics of demand-side energy flexibility arising from building-transportation coupling. This would involve investigating how coordinated scheduling of building loads and EV charging across multiple locations and time periods could enhance system flexibility and improve renewable energy utilisation.
- v. Market and regulatory design: Future studies should investigate the design of electricity markets, pricing mechanisms, and regulatory frameworks that can effectively support peer-to-peer trading, demand response, and the large-scale adoption of DERs in diverse communities.
- vi. Socio-economic and behavioral considerations: It is vital to incorporate user behaviors, acceptance of new technologies, and equity considerations into future models to ensure that transition pathways are not only technically and economically optimal but also socially robust and inclusive.
- vii. Central grid interaction and scalability: As peer-to-peer and distributed paradigms expand, their implications for the central grid's stability, ramping requirements, and overall system control must be further analyzed, ensuring seamless integration and scalability.

APPENDIX

Appendix I Game theory model

According to the mechanism of game theory, the necessity of building a cooperative alliance and the two basic conditions of cooperative games are [93]: (1) For an alliance, the overall benefits are greater than the sum of the benefits of its members. (2) There should be allocation rules with Pareto improvement properties within the alliance, that is, each member can receive no less than the income of the alliance.

The game participants jointly form a binding agreement. We hope that all parties can make certain concessions and compromises through cooperation to increase social benefits. For the increased cooperation surplus, participants make allocation decisions between each other based on their power and skills. For a game with n collaborators, any 2 or more participants use their predetermined strategies to combine the alliance and redistribute the total remaining cooperative payments obtained at the end of the game. For an alliance, the overall income is greater than the total income of each member. In addition, there is an allocation rule with Pareto improvement properties, where each member can receive no less than the income of the alliance. Therefore, multiple participants can build collaborative alliances before the game begins.

A. Cooperative game

In a game with n players, we set $N=\{1,..., n\}$ as the set of all players, and $v(s)$ refers to the characteristic functions of all subsets of N , i.e., the coalition S . In short, $v(s)$ represents the maximum benefit that members in coalition S can obtain through full negotiation. If i is a dummy player, that is, for every $S \subset N$, $v(S \cup i) - v(S) = 0$, then $v(i) = 0$. It characterizes that the overall cooperation gain obtained by all players in S through cooperation can satisfy Eqs. (A1) - (A2), then $\Gamma = (N, v)$ is called an n -person cooperative coalition game.

$$v(\phi) = 0 \quad (A1)$$

$$v(N) \geq \sum_{i \in N} v(\{i\}) \quad (A2)$$

B. The core of the coalition

The allocation in the game should revolve around the benefits $v(N)$ generated by cooperation. Assuming the payoffs allocation for each participant is: $U = \{u_1, \dots, u_n\}$, where u_i is the allocation of cooperation for participant i . For the payoff $U \in R_n$, satisfying Eqs. (B1) – (B2), U is considered a allocation of the cooperative coalition game $\Gamma = (N, v)$.

$$\sum_{i \in N} u_i = v(N) \quad (B1)$$

$$u_i \geq v(i), \forall i \in N \quad (B2)$$

The set of all allocations is denoted as $I(v)$. For this set, if there is an allocation $C(v)$ that cannot be broken by any individual or coalition, then this allocation is called a 'core'. The core Games $C(v)$ of the game $\Gamma = (N, v)$ is the following set.

$$C(v) = \{U \in I(v)\} \quad (B3)$$

The core is generally believed to be the solution of a cooperative game, which is reasonable and stable. According to the cooperative game theory and its solutions introduced above, the successful cooperation between microgrids is closely related to two aspects: firstly, whether the cooperation means between microgrids can obtain additional economic profits. The second is whether there is a reasonable mechanism for benefit allocation to coordinate the interests of participants in the power supply chain alliance.

The following is a description of the Nash bargaining solution in cooperative games, which is the coordination strategy used in this study. Nash bargaining is one of the cooperative game

theories that can drive decision-makers to achieve fair Pareto optimal benefit distribution. It revolves around the difficulty of having entangled interests among users who has interactive properties and can better balance the interests of participants. Assuming that N users use price communication to investigate the best handling method in a global scenario. The set of payment utility functions for these users is denoted as $U = \{u_1, \dots, u_n\}$, and the set of their negotiation breakdown points is $B = \{b_1, \dots, b_n\}$. Then, the standard Nash bargaining description is as follows.

$$\begin{aligned} & \max \prod_{i=1}^N (u_n - b_n) \\ & \text{s.t. } u_n \geq b_n \end{aligned} \quad (\text{B4})$$

To ensure that participants have sufficient willingness to collaborate and communicate, a feasible solution for Nash bargaining must ensure that the payment utility of users exceeds the negotiation breakdown point. The above problems can be further equivalently transformed as follows.

$$\begin{aligned} & \max \sum_{i=1}^N \ln(u_n - b_n) \\ & \text{s.t. } u_n - b_n \end{aligned} \quad (\text{B5})$$

The optimal solution obtained by solving Eq. (B5) is the equilibrium solution of this Nash bargaining. It can reasonably ensure that there are incentives for cooperation among game participants and the fixation of such cooperative relationships. It is also used to achieve the best balance between Nash fairness and Nash efficiency.

C. Non-cooperative game

In a given non-cooperative game, consider n players, each with a set of available strategies. We denote the strategy sets of each player as $S_1, S_2, \dots, S_n$, where S_i represents the strategy set of the i -th player. For each player i , let $s_{-i} \in S_i$ represent their chosen strategy, and let s_{-i} denote

the strategy profile of all other players. The utility function of player i is denoted as $u_i(s_i, s_{-i})$, where s_i represents the strategy chosen by player i , and s_{-i} represents the combination of strategies chosen by all other players.

In the Nash equilibrium, the strategy chosen by each player is a best response, meaning that given the strategies chosen by other players, no player has a better alternative strategy to improve their own payoff. Mathematically, this can be expressed as Eq. (C1):

$$u_i(s_i, s_{-i}) \geq u_i(s'_i, s_{-i}) \quad (C1)$$

For all $s'_i \in S_i$, and this inequality indicates that the strategy s_i chosen by player i is a best response, and no higher payoff can be achieved by selecting any other strategy.

D. Nash equilibrium

In a game $G = \{S_1, \dots, S_n; u_1, \dots, u_n\}$, if a strategy combination $(s_1^*, \dots, s_n^*)$ consisting of one strategy from each player is such that for any player i , their strategy s_i^* is the best response to the combination of strategies $(s_1^*, \dots, s_{i-1}^*, s_{i+1}^*, \dots, s_n^*)$, i.e., $u_i(s_1^*, \dots, s_{i-1}^*, s_i^*, s_{i+1}^*, \dots, s_n^*) \geq u_i(s_1^*, \dots, s_{i-1}^*, s_{ij}, s_{i+1}^*, \dots, s_n^*)$ holds for any $s_{ij} \in S_i$, then $(s_1^*, \dots, s_n^*)$ is called a Nash equilibrium of G .

In the Nash equilibrium, the strategy combination $(s_1, s_2, \dots, s_n)$ chosen by all players is a best response, meaning that each player's strategy is the optimal response to the strategies chosen by others. In this situation, the game reaches a stable state where no player has an incentive to unilaterally change their strategy because doing so would not lead to better outcomes.

Appendix II Non-convex optimization problem formulation and its solution

For Eq. (6.14), it is evident that the model has a nonlinear non-convex optimization problem with two optimization variables: trading electricity quantity P_{ij}^t and trading electricity price q_{ij}^t .

The following solution method is used to solve the problem. Firstly, the model can be divided into two sub models, and the optimal solution of the entire problem can be found through sequential optimization and calculation. The two sub problems obtained through decomposition are: system cost minimization problem and multi microgrid joint payment bargaining problem.

E. Multi-microgrid system cost-minimum problem

According to the arithmetic-geometric mean inequality, the optimal solution of Eq. (6.14) must comply with "one positive, two definite, and three equal". Eq. (6.14) has constraint conditions and must meet the requirement of 'one positive'. If the sum of each term is constant, then it also satisfies the 'two definite' condition. Due to $\sum_{i=1}^M C_i^{N,0}$ is a constant, if $\sum_{i=1}^M C_i^C$ is also a constant, then it satisfies the condition of "two qualitative". Meanwhile, the smaller the value of $\sum_{i=1}^M C_i^C$, the larger the value of the objective function to be solved. The minimum value of $\sum_{i=1}^M C_i^C$ can be set to $\sum_{i=1}^M C_i^{C,0}$, which means that when the comprehensive operating cost of a multi-microgrid system is fixed to the minimum value, the objective function of Eq. (6.14) obtains a larger value. According to the "three equal" law, when the value in Eq. (6.14) is equal, the maximum value can be obtained, which conforms to Eq. (6.14).

$$C_i^{N,0} - C_i^{C,0} = \frac{1}{M} \sum_{i=1}^M (C_i^{N,0} - C_i^{C,0}) \text{ where, } C_i^{C,0} \text{ refers to the}$$

optimal cost for MG_i to engage in bargaining transactions. From $P_{ij}^t = -P_{ji}^t$, it can be seen that the transaction cost C_{ij}^m between MG_i and other microgrids offsets each other during the cumulative summation process. Let $U_i^C = C_i^N + C_{ij}^{net}$, Eq. (E1) can be expanded to Eq. (E2):

$$C_i^{N,0} - C_i^{C,0} = \frac{1}{M} \sum_{i=1}^M (C_i^{N,0} - U_i^{C,0}) \quad (\text{E2})$$

where, $U_i^{C,0}$ is the optimal solution when the cost U_i^C is optimal. Substitute Eq. (E2) into Eq. (6.14) above to obtain Eq. (E3).

$$\max \left[\frac{1}{M} \sum_{i=1}^M (C_i^{N,0} - C_i^{C,0}) \right]^M \quad (E3)$$

Since $C_i^{C,0}$ is a fixed value, when the sum of U_i^C has a minimum value, Eq. (E3) has a maximum value, which is further transformed into Eq. (E4)

$$\min \sum_{i=1}^M U_i^C \quad (E4)$$

Eq. (E4) transforms the initial objective function Eq. (6.14) into a problem of minimizing the overall comprehensive operating cost of multi-microgrid alliances, which is also a problem of minimizing social costs during transactions between microgrids. Therefore, a standard convex problem can be solved using distributed optimization algorithms to obtain the optimal operation scheduling strategy and transaction scheme for different microgrid costs.

F. Payment's revenue maximum sub-problem

The optimization solution obtained from the previous subproblem, which minimizes the system operating cost, is the scheduling and trading power strategy $P_{i,t}^{C*}$, $P_{i,t}^{d*}$, $l_{i,t}^*$, $P_{i,t}^{buyG*}$, $P_{i,t}^{sellG*}$, P_{ij}^{t*} of the microgrid, which is substituted into Eq. (6.14) to obtain Eq. (F1). By converting multiplication calculation into addition calculation through logarithmic operation, the optimization objective function is transformed into Eq. (F2), which is also a convex problem. Similarly, its solution can be calculated using distributed optimization algorithms to obtain the most suitable price for electricity trading between microgrids, thereby maximizing the benefits of MG_i. Eqs. (F1) - (F2) are as follows.

$$\max \prod_{i=1}^M (C_i^{N,0} - U_i^{N,0} - C_{ij}^m (P_{ij}^{t*} - q_{ij}^t)) \quad (F1)$$

$$\min \sum_{i=1}^M -\ln \left(C_i^{N,0} - U_i^{C,0} - C_{ij}^m \left(P_{ij}^{t*} - q_{ij}^t \right) \right) \quad (F2)$$

Based on the above calculation, the optimal solution of Eq. (6.14) is decomposed into sequential optimal solutions of two subproblems: minimizing social costs and maximizing payment benefits. Subsequently, the alternating direction multiplier method (ADMM) algorithm can be used to solve the above two subproblems. The processing and calculation steps for solving these two subproblems using the ADMM are introduced as follows:

G. Alternating direction multiplier method (ADMM)

The convergence of the ADMM for solving convex optimization has been proven multiple times and has been widely applied in engineering practice [173]. The specific iterative calculation process for the two subproblems using this algorithm in this study is as follows.

For the calculation of subproblem 1, the social cost of multi microgrid system U_i^C is minimized, where the bargaining power P_{ij}^t is a coupled variable and the constraint $P_{ij}^t = -P_{ji}^t$ needs to be met. The incremental Lagrangian function of MG_i around problem 1 is represented as (G1).

$$L_{i,1} \left(P_{ij}^t, P_{ji}^t, \lambda_{ij}^t \right) = U_i^C + \sum_t \sum_{j \in M/i} \left[\frac{\rho_1}{2} P_{ij}^t + P_{ji}^t P_2^2 + \lambda_{ij}^t \left(P_{ij}^t + P_{ji}^t \right) \right] \quad (G1)$$

where, ρ_1 is the penalty factor for subproblem 1, λ_{ij}^t The Lagrange multiplier for subproblem 1. Assuming that the energy management system of MG_i continuously cycles through the link in Eq. (G2) and stops when Eq. (G3) is satisfied.

Assuming $s_{i,1}$ represents the convergence state of MG_i around subproblem 1. A value of 1 indicates convergence, and a value of 0 indicates non-convergence. When solving subproblem 2, subproblem 1 should achieve global convergence. The optimization of multi-microgrid involved in Nash bargaining transactions converges around sub problem 1, as shown in Eq. (G4).

$$\begin{cases} P_{ij}^t(k+1) = \arg \min_{P_{ij}^t} L_{i,1}(P_{ij}^t, P_{ji}^t(k), \lambda_{ij}^t(k)) \\ P_{ji}^t(k+1) = \arg \min_{P_{ji}^t} L_{j,1}(P_{ij}^t, P_{ji}^t(k+1), \lambda_{ij}^t(k)) \\ \lambda_{ij}^t(k+1) = \lambda_{ij}^t(k) + \rho_1(P_{ij}^t(k+1) + P_{ji}^t(k+1)) \end{cases} \quad (G2)$$

$$\begin{cases} \sum_t \sum_{j \in M/i} P P_{ij}^t(k) + P_{ji}^t(k) P_2 \leq \varepsilon_1 \\ \sum_t \sum_{j \in M/i} P P_{ij}^t(k+1) + P_{ji}^t(k) P_2 \leq \lambda_1 \end{cases} \quad (G3)$$

$$S_{i,1} \prod_{j \in M/i} S_{j,1} = 1 \quad (G4)$$

In the objective function of subproblem 2, the transaction price q_{ij}^t is a coupled variable. The transaction electricity price between two microgrids needs to meet the constraint $q_{ij}^t = -q_{ji}^t$. Therefore, the incremental Lagrangian function of the MG_i can be set as:

$$L_{i,2}(q_{ij}^t, q_{ji}^t, \xi_{ij}^t) = -\ln(C_i^{N,0} - U_i^{C,0} - C_{ij}^m(P_{ij}^{t*} - q_{ij}^t)) + \sum_t \sum_{j \in M/i} \left[\frac{\rho_2}{2} P q_{ij}^t + q_{ji}^t P_2^2 + \xi_{ij}^t (q_{ij}^t + q_{ji}^t) \right] \quad (G5)$$

where, ρ_2 is the penalty factor for problem 2. ξ_{ij}^t is the Lagrange multiplier in subproblem 2.

Keeping looping the process in Eq. (G6) until the requirements of Eq. (G7) can be met.

$$\begin{cases} q_{ij}^t(r+1) = \arg \min_{q_{ij}^t} L_{i,2}(q_{ij}^t, q_{ji}^t(r), \xi_{ij}^t(r)) \\ q_{ji}^t(k+1) = \arg \min_{q_{ji}^t} L_{j,2}(q_{ij}^t, q_{ji}^t(k+1), \xi_{ij}^t(r)) \\ \xi_{ij}^t(r+1) = \xi_{ij}^t(r) + \rho_2(q_{ij}^t(r+1) + q_{ji}^t(r+1)) \end{cases} \quad (G6)$$

$$\begin{cases} \sum_t \sum_{j \in M/i} P q_{ij}^t(r) + q_{ji}^t(r) P_2 \leq \varepsilon_2 \\ \sum_t \sum_{j \in M/i} P q_{ij}^t(r+1) + q_{ji}^t(r) P_2 \leq \lambda_2 \end{cases} \quad (G7)$$

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