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Game-theoretic optimization strategy for maximizing profits to both end-users and suppliers in building rooftop PV-based microgrids

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ABSTRACT

Rooftop photovoltaic (PV) with battery storage offers a promising avenue for enhancing renewable energy integration in buildings. Creating microgrids with backup power from closely spaced solar buildings is widely recognized as an effective strategy. Nevertheless, a notable gap exists between the preferences and priorities of electricity consumers residing in these solar-powered buildings and the interests of microgrid investors. The electricity consumers focus on decreasing the levelized cost of energy, while the microgrid investors focuses on achieving high net profit. This study proposes a novel game theory-based microgrid optimal design approach for designing power generations of the microgrid system and PV installation with battery storage on the building roofs, considering the different requirements and interests of electricity consumers and microgrid investors. The design optimization is framed around the Nash Equilibrium of the Stackelberg game, incorporating a bi-level optimization cycle that addresses the conflict and cooperation of electricity consumers and microgrid investors. A win-win situation can be yielded using the developed optimal design approach compared to conventional optimal design approaches. The results demonstrate a significant improvement, with the microgrid power generation yielding a large net profit (up to 0.08 USD/kWh) and concurrently reducing the levelized cost of energy by approximately 14 %.

Nomenclature

Abbreviations	
COP	Coefficient of Performance
DR	Demand Response
LCOE	Levelized Cost of Energy
PV	Photovoltaic
UG	Utility grid
Notations	
A_{PV}	PV areas (m^2)
C_{ini}	Initial cost (USD)
$C_{mai,sbs}$	Maintenance cost (USD)
C_{opt}	Operating cost (USD)
Cap	Capacity (kW)

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Abbreviations	
E_{tot}	Total electricity consumption (kWh)
P^t	Power purchased at time step *t*
$P_{ele,t}$	Electrical load at time step *t*
Pr	Electricity unit price (USD/kWh)
$Profit_{MG}$	Profit of aggregator
$P_{ren,t}$	Renewable power generation at time step *t*
PL	Partial load
P_{PV}	Power generated from solar radiation (kW)
Rad	Solar radiation per area (kW/m^2)
Δt	Timestep
T_{amb}	Ambient temperature (°C)
UP_{bpg}	Unit price of the backup power generator (USD/kW)

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(*continued*)

Abbreviations	
T_{ref}	PV panels reference temperatures (°C)
Y_k	Total years of its life cycle
Subscripts	
amb	Ambient
bpg	Backup power generation
bat	Battery storage
ec	Electricity consumers
MG	Microgrid
PV	Photovoltaics
rpc	Renewable power generation components
Greek letters	
η_{bpg}	Backup power generator efficiency
η_{PV}	Overall efficiency of PV panels
ε_{ope}	Power generation efficiency

1. Introduction

China has set a commendable goal of achieving carbon neutrality before 2060, and to confront the pressing issue of carbon emissions, a major focus is placed on power generation. Notably, 70 % of China's power generation is attributed to conventional thermal power plants, making it a primary contributor to carbon emissions [1]. Tackling this challenge necessitates urgent attention to two crucial scientific problems: augmenting the penetration of renewable energy in power generation and ensuring a reliable power supply [2]. These challenges have garnered substantial responses from both academic and industrial sectors, signifying a collective commitment to finding viable solutions [3, 4].

As the prospective electrical system, a microgrid consists of distributed power generators, energy storage systems, and interconnected loads [5]. This innovative system holds significant promise in advancing renewable energy penetration for electricity generation, fostering economic benefits, and enhancing system reliability simultaneously [6]. Alfergani et al. [7] employed multi-objective optimization to enhance the power capacity of the microgrid. Zhang et al. [8] has developed a hybrid robust-stochastic multi-objective optimization approach for integrating cooling, heating, hydrogen, and power-based microgrids, achieving a potential reduction in operational costs by up to 15.44 %. Lou et al. [9] developed an optimization approach for the microgrid system based on power load analysis considering the impact of microgrid locations on system performance. Due to the abundant solar energy resources in Lhasa, this approach allowed for a reduction in the area required for solar thermal collectors by more than 50 % compared to Xi'an. The proper optimal design of microgrids proves instrumental in realizing these objectives by leveraging presumed/quantified power generations and electrical loads. The optimization of microgrid power generators and battery storage capacities serves to mitigate carbon emissions from power generation and decrease the operation costs. This optimization process integrates a typical annual load profile and renewable power generation based on typical annual weather data [10, 11]. Jung and Villaran [12] introduced an innovative optimal design method that utilizes a typical daily power-load profile derived by condensing the annual load and power generation data into a 24-h format. This approach enhances economic benefits and minimizes the computational complexity associated with the design process.

To further unlock the potential of microgrids in terms of system economics and environmental friendliness, new technologies, such as demand response (DR) and system flexibility, are actively incorporated into microgrid optimal design [13]. For instance, Tsao et al. [14] developed a microgrid optimal design approach by leveraging blockchain technology to provide demand response programs, where the profitability of the designed microgrid was increased up to 1.68 %. Gamil et al. [15] developed a microgrid optimal design approach considering different percentages of demand response participation. The results showed that the operation cost can effectively be reduced (maximum up to $ 0.1664 million) under 30 % demand response participation. As for the application of the system flexibility, Swaminathan et al. [16] optimized the capacities of the renewable power generator considering the impacts of the building energy flexibility, where savings of initial cost and operational costs can be further realized. Tomin et al. [17] proposed a microgrid design approach considering the impacts of flexible renewable power generation, achieving a potential reduction of up to 40 % in the levelized cost of energy (LCOE).

The literature shows that the developed optimal design approaches can effectively provide environment-friendly and cost-effective solutions for microgrid investors. However, a notable gap exists as these studies commonly assume alignment between the demands and interests of electricity consumers and the overall microgrid system, which diverges from the actual situation. In practice, from the electricity consumers' perspective, electricity consumers solely focus on having a reliable power supply with relatively lower electricity prices [18]. However, to our best knowledge, only a few studies have optimized the microgrid system considering the different requirements and interests of microgrid investors and electricity consumers, respectively.

Addressing these challenges requires a solution that acknowledges the differing needs of microgrid stakeholders, and game theory emerges as a promising tool to achieve this [19]. Game theory provides a theoretical framework for conceiving social situations among competing players and delves into mathematical models of conflict and cooperation between different decision-makers [20]. Currently, game theory has been adopted to conduct energy trading in the smart grid system concerning the grid-building interactions in Refs. [21–27]. For instance, Nwulu and Xia [28] proposed a game-theoretic energy-economic model to decrease the fuel costs for the grid side and offer an incentive to the electricity customers for the demand side to offset the impact of power supply interruption. Dabush et al. [22] developed a game-theoretic model to examine the viability of installing PV systems on rooftops of affordable housing buildings, where the economic benefits of the building electricity consumers and the utility grid are quantified. While many existing game theory-based energy system design works concentrate primarily on proposing design solutions to decrease the operation cost and/or proposing the operation schedule to achieve peak shifting and enhance the reliability of the power grids. Few studies began to focus on the issue of the profit distribution for the power generation investors and electricity consumers when distributed renewable power generation is used in the energy system. This critical aspect represents an evolving area of research that merits further exploration and attention in the broader landscape of game theory applications in the energy sector.

In the future energy systems, an increasing number of electricity customers are expected to adopt distributed power generators, such as PV systems on building roofs [29]. This shift will usher in a new mode where the microgrid's power generation and the utility grid's power supply collaborate to ensure a reliable power source. The effect of optimizing distributed power generation capacity for electricity consumers on the microgrid backup power generation capacity, crucial for microgrid investors, cannot be overlooked. It is imperative to address the optimal design concerning their different requirements and interests of the power generation investors and electricity consumers. Developing reasonable design schemes has become critical, necessitating a prior understanding of the diverse needs of multiple stakeholders.

To address these research gaps, this study proposes a game theory-based microgrid optimal design approach, aiming to effectively consider the practical optimization objectives from two different roles (i.e., electricity consumers and microgrid investors). The main objective of this study is to effectively consider the multiple requirements of different stakeholders (i.e., investors of the microgrid power system with equipped backup power generation and demand-side electricity consumers with the voluntary installation of renewable energy generation) in the microgrid system, where the former focus on achieving high net profit and the latter aims to decrease the LCOE and ensure a reliable power supply. The main contributions and innovations of this study are outlined as follows:

- A bi-level design optimization is developed based on the Nash Equilibrium of the Stackelberg game concerning the conflict and cooperation of electricity consumers and microgrid investors.
- Diverse requirements and interests of electricity consumers and microgrid investors are methodically quantified and considered throughout the optimal design process.
- A design solution is proposed to create a win-win scenario by harmonizing the requirements and interests of both electricity consumers and microgrid investors within the optimal design framework.

The proposed innovative game theory-based microgrid optimal design approach contributes strategically to navigating the intricate landscape of stakeholder needs, effectively accommodating the diverse objectives of electricity consumers and microgrid investors in the microgrid system.

2. Structure of microgrid systems and their requirements and interests

2.1. Typical microgrid system

Due to the limited impact of individual building on the utility grid, a microgrid system is developed as an aggregator within a specific area encompassing closely spaced spatially distributed electricity consumers. This system, depicted in Fig. 1, serves to ensure a reliable power supply by incorporating backup power generators. In the shown setup, the adopted microgrid system equipped with backup power generation is proposed to cope with the risk of power outage due to the uncertainties of the dynamic electrical load and the intermittent and uncontrollable renewable power generations. As the major electricity consumers on the demand side, the buildings are anticipated to install PV modules equipped with the battery storage system to decrease the burden of the utility grid and the electricity consumption operation cost.

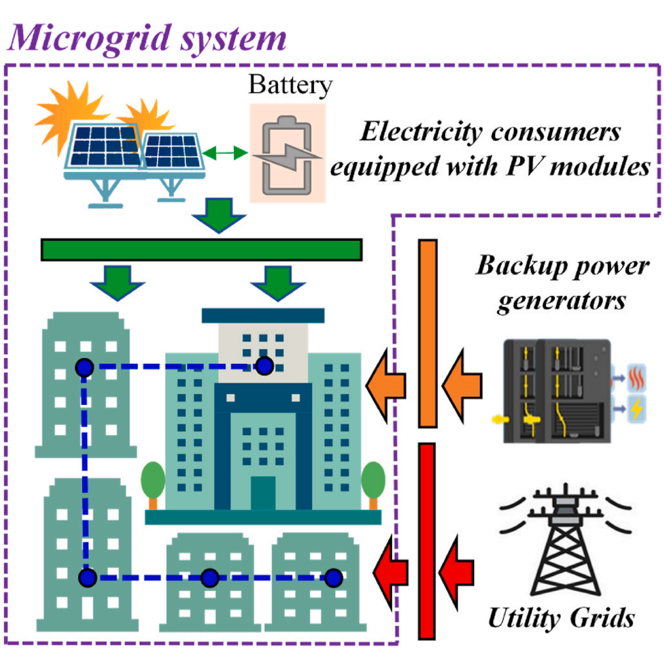

Fig. 1. Components of a simple microgrid system.

2.2. Requirements and interests of electricity consumers

Electricity consumers require a stable power supply and decreased LCOE. The LCOE, as a quantitative electricity utilization indicator, is used to calculate the power utilization cost of traditional energy projects such as thermal power, hydropower, and gas power, and later expanded to the renewable energy field. It is quantified as shown in Eq. (1), which consists of the initial cost ($C_{ini,ec}$), the operating cost ($C_{opt,ec}$), and the maintenance cost ($C_{mai,ec}$) and E_{tot}, which is the total of electricity consumption.

The initial cost as shown in Eq. (2) is the average annual initial cost that electricity consumers must pay for renewable power generators, battery storage, and renewable power components. The initial costs of the renewable power generation components as shown in Eq. (3) include the hardware cost of the system controller and soft cost (e.g., engineering, construction, commissioning, and regulatory costs), as well as the additional electric infrastructure costs [30,31]. Where, $C_{PV,ec}$, and $C_{Bat,ec}$ are the initial cost of PV panels and battery storage. Y_k represents the total years of its life cycle, and P_{PV} represents the power generation from PV panels.

The operational cost as shown in Eq. (4) is the sum of electricity purchased from the microgrid system and the utility grid. Where, P_{MG}^t is the power purchased from the microgrid, and P_{UG}^t is the power purchased from the utility grid. Pr_{MG} and Pr_{UG} are the electricity unit price of the microgrid and utility grid, respectively.

The annual maintenance cost is assumed to be 1 % of the total average annual initial cost as shown in Eq. (5) based on [32], which investors have to pay per year to provide maintenance for the major facilities of the system per year.

$$LCOE_{ec} = \left(C_{ini,ec} + C_{opt,ec} + C_{mai,ec}\right) / E_{tot} \tag{1}$$

$$C_{ini,sbs} = \left(C_{PV,ec} + C_{Bat,ec}\right) \times 1 / Y_k + C_{rpc,ec} \tag{2}$$

$$C_{rpc,ec} = max(P_{PV}) \times 50 + 1900 \tag{3}$$

$$C_{opt,ec} = \left(\sum_{t=1}^{8760} P_{MG}^t\right) \times \Delta t \times Pr_{MG} + \left(\sum_{t=1}^{8760} P_{UG}^t\right) \times \Delta t \times Pr_{UG} \tag{4}$$

$$C_{mai,ec} = 1\% \times \sum \left(C_{fac,k} \times 1 / Y_k\right) \tag{5}$$

2.3. Requirements and interests of the microgrid investors

Regarding investor requirements, the microgrid needs to ensure the power supply to the electricity consumers and decrease electricity purchases from the utility grid. Microgrid investors primarily focus on maximizing their net profit derived from microgrid power generation. This net profit is calculated by deducting the relevant power generation costs from the revenue generated by selling electricity to consumers, as quantified in Eq. (6) [19]. The power generation costs encompass the initial costs of backup power generators and the operation cost of power generation, as quantified in Eq. (7) and in Eq. (8) respectively.

$$Profit_{MG} = \left(\sum_{t=1}^{8760} P_{MG}^t\right) \times \Delta t \times Pr_{MG} - C_{ini,MG} - C_{bpg,MG} \tag{6}$$

$$C_{ini,MG} = C_{MG,bpg} \times 1 / Y_{bpg} \tag{7}$$

$$C_{bpg,MG} = \left(\sum_{t=1}^{8760} \left(P_{MG}^t / \eta_{bpg}\right)\right) \times \Delta t \tag{8}$$

3. Game theory-based optimal design of the microgrid-building system

3.1. Establishment of the stackelberg game between the electricity consumers and microgrid investors

In the game theory approach, each player aims to maximize their own welfare in a game by adopting effective measures, even though there may be partial conflicts among players. In this established Stackelberg game, three key elements are included (i.e., $ESG = \{\sigma, S, U\}$), i.e., players, their design solutions, and their benefits. Each player i ($i \in \sigma$) determines their design solution s_i ($s_i \in S$) to maximize the benefit u_i ($u_i \in U$). The final solution is obtained when the game is in the Stackelberg Nash Equilibrium, which is shown in Eq. (9). The obtained design solution s^* is a Nash equilibrium when each player cannot increase one's own expected payoff by changing the design solutions while the other players keep theirs unchanged [33].

$$U(s^*) \geq U(s_i, s^*_{-i}) \tag{9}$$

Fig. 2 illustrates a schematic diagram of the proposed game-theoretic optimal design for microgrid power generation and solar building systems. In this game-theoretic optimization, two different requirements for the two different interested parties are considered. This first party is microgrid power generation system, where the objective is to maximize the net profit of the microgrid. The second party is solar building system, where they prefer to decrease the levelized cost of the energy. Due to this, it consists of two optimizations, i.e., microgrid power generation optimization and solar building system optimization. The former, acting as the leader, aims to design the power generator capacity to pursue the maximum net profits as one type of power supply. It should be used in the second optimization. The latter, functioning as a follower, aims to design the PV area and battery storage capacity to decrease the LCOE according to the capacity of the microgrid power generators. Subsequently, based on the optimal design solution from the latter optimization, the power generation requirements are communicated to the former optimization to calculate the real net profits.

As for the difference of the mentioned two optimizations, the Optimization A is a Nash equilibrium of leads and the Optimization B is a Nash equilibrium of followers. In other words, the system optimization is begun in the Optimization A and the optimal design for the solar building system in Optimization B is conducted based on the optimization results of the Optimization A. Then, the optimization results are tested in Optimization A whether the optimal design in optimization A can be regarded as the global optimal results. If not, the optimal process is repeated. This method can effectively avoid the local optimizations of two players and a win-win situation for two players with different requirements can be achieved.

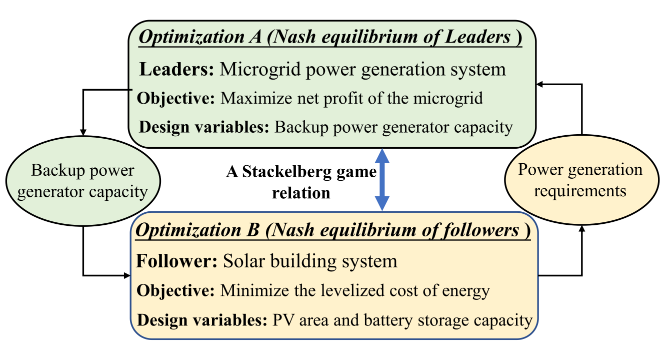

Fig. 2. Schematic diagram of proposed game-theoretic optimal design for the microgrid power generation and solar building systems.

3.2. Basic scheme for identification of nash equilibrium

3.2.1. Nash equilibrium of leader – optimization of microgrid power generator capacity

Fig. 3 outlines detailed steps of Optimization A, specifically the method for designing the optimal microgrid power generator capacity. The capacity of the microgrid power generator is optimized within its designated search range, guided by the power generation requirements. The power generation system is directed based on these requirements. Concerning the dynamic efficiency of the power generation, the operation cost for the power generation is calculated in the microgrid power generation model. These factors are incorporated into the objective function to calculate the net profit of the microgrid. Then, the obtained net profit of the microgrid power generation is used in the optimizer to judge whether the design solution is the best choice. The optimization process will be repeated until the optimal design solution (i.e., microgrid power generator capacity) is found.

3.2.2. Nash equilibrium of followers – optimization of PV areas and battery storage capacity

Fig. 4 shows detailed steps of Optimization B (mentioned in Fig. 2), that is, the optimal design method of PV areas and battery storage capacity for the solar building system. The PV area and the battery storage capacity are determined via optimization within their search ranges. The weather data is fed into the solar building model, and the electrical loads are quantified according to the thermal comfort requirements and usage profiles. The power generation from the PV modules is quantified based on the design PV area and weather data. Considering the power balance, the electricity purchase from the microgrid and utility grid is calculated according to electrical loads and renewable power generations. Based on the power generation capacity of the microgrid, the electricity purchased from the microgrid's power generation system and utility grid are quantified, respectively. This partial cost, as operation cost, is considered in the objective function. In the end, the optimizer aims to minimize the LCOE, and the iterative optimization process will be repeated until the optimal design solutions (i.e., PV areas and battery storage capacity) are determined.

3.3. Objective functions and their constraints in the game theory-based optimizations

According to the above optimal design methods of the solar building system and microgrid power generation system in this Stackelberg game, the objective functions aligned with their interests (as stated in Section 2.2 and Section 2.3) are formulated respectively, which are shown in Eq. (10) and Eq. (11) respectively. Where, A_{PV} and Cap_{bat} are the PV area and capacity of the battery storage. Constraints are set within the lower and upper limits according to practical limits in the optimization processes, as shown in Eqs. 12–14.

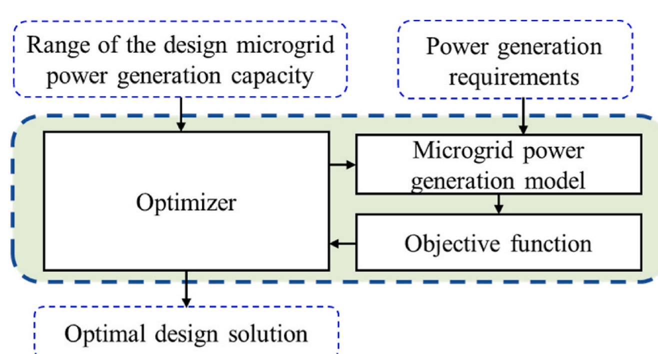

Fig. 3. Optimal design method of microgrid power generator capacity (Optimization A).

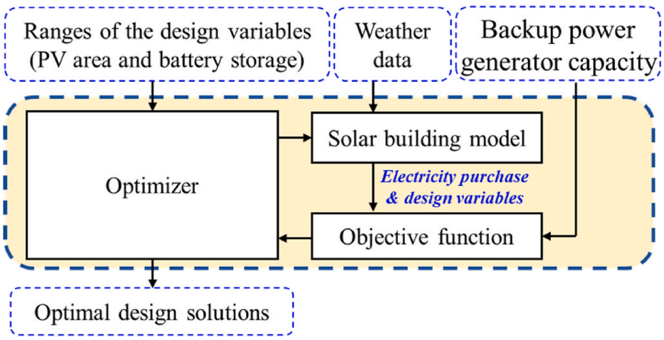

Fig. 4. Optimal design method of PV areas and battery storage capacity for the solar building system (Optimization B).

$$max\ Obj_{MG} = F_{MG}\left(Cap_{bpg}\right) \tag{10}$$

$$min\ Obj_{sbs} = F_{sbs}(A_{PV}, Cap_{bat}) \tag{11}$$

$$Cap_{bpg,min} \le Cap_{bpg} \le Cap_{bpg,max} \tag{12}$$

$$A_{PV,min} \le A_{PV} \le A_{PV,max} \tag{13}$$

$$Cap_{bat,min} \le Cap_{bat} \le Cap_{bat,max} \tag{14}$$

4. Basic information and model developments of proposed systems

4.1. Basic information about the microgrid system

To verify the performance of the proposed game theory-based optimal design, a microgrid comprising four hotel buildings equipped with PV and battery storage is selected as the case study. These four buildings are homestay hotels with three stories, and the PV panels can be equipped on the roofs of the four buildings. The ceiling height of each building is 2.5 m, and the area per floor is about 210 m^2 with dimensions of 15 m × 14 m. Their building envelopes are similar; the details are shown in Table 1.

The microgrid is located in Sanya, Hainan Province, China, and the exact location (a red star) is shown in Fig. 5. In this location, abundant solar resources can be exploited for power generation to provide a sustainable power supply, where the annual average solar radiation is 600 W/m^2, and the maximum value is about 3600 W/m^2.

4.2. Cost data of the solar homestay hotel buildings and microgrid power generation system

Table 2 shows the detailed cost data of the solar homestay hotel buildings. The renewable power generation system involves two key parameters (i.e., PV panes and battery storage). Their initial cost and lifetime are considered since they significantly impact the overall cost of the solar homestay hotel buildings. As for the electricity prices, they are different based on the different electricity retailers. The electricity price of the utility grid is determined according to the current price [35,36]. Since there is no electricity price for the microgrid system, 90 % of the electricity price of the utility grid is used to promote power generation from the microgrid system and can also effectively decrease the utility grid's burden simultaneously.

Table 1
Main parameters of the considered four buildings [34].

Name	Parameter	Value
Dimmable lighting	Lighting density	10 W/m^2
Other electrical equipment	Equipment load density	15 W/m^2
Fresh air Ventilation	Ventilation rate	15 L/h × $person^{-1}$
Cooling load	Load density	153 W/m^2
Infiltration rate	–	0.2 air changes per hour

As for the microgrid generation system, the unit price of the backup power generator (UP_{bpg}) decreases with the capacity increase. It has been calculated as shown in Eq. (15) based on the capacities (Cap_{bap}) referring to Ref. [37].

$$UP_{gas} = 3711.78 - 280.47 \times \ln\left(Cap_{gas}\right) \tag{15}$$

4.3. Development of the power generation models

4.3.1. Rooftop PV generation model for the homestay hotel buildings

PV model: The PV generation model is developed to quantify the power generation from the PV panels (P_{PV}), according to Daud and Ismail [38]. It is calculated as below:

$$P_{PV} = Rad \times A_{PV} \times \left(1 + K_{PV}\left(T_{PV} - T_{ref}\right)\right) \times \eta_{pv} \tag{22}$$

$$T_{PV} = T_{amb} + 0.0256 \times Rad \tag{23}$$

$$0 \le P_{PV,t} \le P_{PV}^{Max}, \forall t \in [1, 8760] \tag{24}$$

where, solar power generation considers the solar radiation (Rad), PV areas (A_{PV}), the overall efficiency of PV panels (η_{pv}), PV cell temperature (T_{PV}), and ambient temperature (T_{amb}). The PV cell temperature is determined by solar radiation and ambient temperature, as shown in Eq. (23). K_{PV} is set as -3.7×10^{-3}, and the reference temperature T_{ref} is 25 °C referring to Refs. [6,35]. Besides, the overall efficiency of PV panels is 11–25 % [39]. This work uses a constant value (20 %) to simplify the calculation.

Battery storage model: Battery storage is widely used to overcome uncertainties and intermittent renewable power generation. The overall charge and discharge efficiencies are set as 0.85 based on [40]. Besides, the maximum charging rate ($R_{batch,max}$) and discharging rate ($R_{batdch,max}$) are set as 20 % of the battery capacity and 50 % of the battery capacity, respectively, in the constraints shown in Eqs. (19) and (20) respectively. To ensure the battery storage works within a safety range, the minimum ($Cap_{bat,min}$) and maximum ($Cap_{bat,max}$) limits of the battery capacity are set as 20 % and 80 %, respectively (as shown in Eq. (21)).

$$0 \le R_{batch} \le R_{batch,max} \tag{19}$$

$$0 \le R_{batdch} \le R_{batdch,max} \tag{20}$$

$$Cap_{bat,min} \le Cap_{bat} \le Cap_{bat,max} \tag{21}$$

4.3.2. Power generation model for the microgrid systems

The selected power generators of the microgrid power generation system are driven by natural gas since natural gas is a clean-burning, efficient fuel [41]. The operation power generation efficiency of the gas generator ($\varepsilon_{ope,gas}$) is quantified based on the standard power generation efficiency ($\varepsilon_{std,gas}$) and its operational partial load ratio (PL_{gas}), as shown in Eq. (22) referring to Refs. [42,43]. The standard power generation efficiency is sensitive to the change of capacity, calculated by Eq. (23) referring to Refs. [44,45]. The partial load ratio is calculated in Eq. (24). Where, ele_{gas} is the requirement of the electricity generation for power generation.

$$\varepsilon_{ope,gas} = \varepsilon_{std,gas} \times \left(0.715 + 0.478 \times PL_{gas} - 0.190 \times \left(PL_{gas}\right)^2\right) \tag{22a}$$

$$\varepsilon_{std,gas} = 0.01 \times \left(4.236 \times \ln\left(Cap_{gas}\right) + 70.3\right) \tag{23a}$$

$$PL_{gas} = ele_{gas} \Big/ Cap_{gas} \tag{24a}$$

Fig. 5. Overview of the microgrid system location.

Table 2
Cost data of the solar homestay hotel buildings.

Name	Items	Value
Renewable power generation system	Initial cost of PV panels	288 $/m^2$
	Lifetime of PV panels	20 years
	Initial cost of battery	255.6 $/kWh
	Lifetime cost of battery	15 years
Name	Electricity retailer	Value
Unit price of electricity from different electricity retailers	Utility grid	0.2 $/kWh
	Microgrid system	0.2 × 90 % $/kWh

4.4. Energy simulation

The electrical loads of the solar homestay hotel buildings consist of the cooling, lighting, and plug loads, considering their location (i.e., typical tropical region). They are simulated via TRNSYS based on the pre-set values of the load densities. TRNSYS is a modular-based simulation software specifically designed for modelling and optimizing energy systems. The load densities, including the lighting density, equipment load density, and cooling load density, are fed into the "TYPE 56" of the TRNSYS. Type 56 stands out for its capability in multi-zone building energy analysis. Type 56 allows for precise simulation of solar radiation and heat transfer through windows of complex building geometries and configurations. it also supports a wide range of heating, cooling, and ventilation systems, providing detailed outputs on system variables and energy consumption. Then, according to the weather conditions, the electrical load profiles of these buildings can be calculated. As for the coefficient of performance (COP) of the chillers, a constant value is set as four in the cooling load calculation for these four solar homestay hotel buildings.

4.5. Electricity usage priority and control mechanism

To decrease the operation cost of the electricity consumers and increase the utilization of renewable power generation, the priority of the power supply is listed in Table 3. The renewable power generation is used as the first option. It can significantly lower the rate of renewable energy generation that goes to waste. Battery storage can store the redundant renewable generated power and used as the second opinion. The mentioned first two power supplies are free and they can be prioritized while the other two are used to ensure the reliability of the power supply. Thus, the control mechanism can effectively ensure a reliable power supply to the electricity consumers and achieve the economic operation of the system. Two typical operational modes (i.e., islanded mode and grid-connected mode) of the microgrid system are considered and adopted in the control mechanism.

Fig. 6 illustrates the detailed control mechanism of operational modes selection for the microgrid energy system. The islanded mode is adopted when the microgrid can adequately fulfil the demand. In other words, if the power output from the first three power supply options is sufficient to meet the demand, the operational mode defaults to the islanded mode. Conversely, when the demand is higher than the power output of the microgrid, the grid-connected mode is adopted. In this mode, the utility grid serves as an additional power supply to meet the demand and ensure system's reliability.

Table 3
Priority of the power supply.

Option	Power supply type
Option 1	Renewable power generation
Option 2	Battery storage discharging
Option 3	Microgrid backup power generation
Option 4	Supports of the utility grid

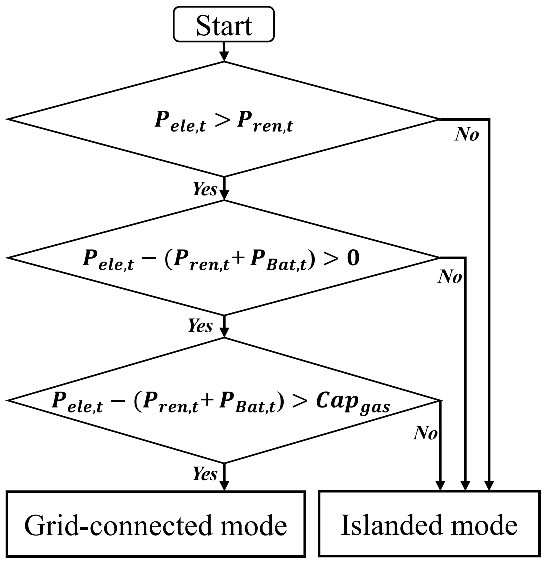

Fig. 6. Control mechanism of operational modes selection for the microgrid energy system.

5. Results and discussions

5.1. Descriptions of the reference for microgrid optimal design methods

Microgrid optimal design methods to face the different requirements and interests of microgrid investors and electricity consumers have been investigated in academia and industry. According to the different orders of the optimizations, three conventional microgrid optimal design methods are presented, that is, Supply-to-Demand Optimal Design method, Demand-to-Supply Optimal Design method, and Decentralized Optimal Design method. Detailed information on these three optimal design methods is introduced below.

- **Supply-to-Demand Optimal Design method**: In this approach, the capacity of the microgrid power generators is initially optimized for the microgrid investors by using the electrical load profile without consideration of the renewable power generation impacts. Then, according to the determined microgrid power generator capacity and different electricity prices of the different power generations, the PV panels' area and the battery storage capacity are optimized for electricity consumers.
- **Demand-to-Supply Optimal Design method**: This method conducted the design optimization by using the opposite optimization direction compared with the Supply-to-Demand Optimal Design method. The area of the PV panels and the battery capacity are optimized firstly for electricity consumers. Then, the capacity of the microgrid power generator is optimized for microgrid investors according to the electrical load profile with consideration of the renewable power generation impacts.
- **Decentralized Optimal Design method**: This optimal design method conducted the design optimizations of the power generator capacity for microgrid investors, the PV panels' area, and the capacity of the battery storage for electricity consumers, respectively. In the process of optimization, the impacts of the microgrid power generator capacity on the optimization of the area of the PV panels and the capacity of the battery storage are ignored. Besides, the impacts of the determined area of the PV panels and the battery storage capacity on optimizing the microgrid power generator capacity are also ignored.

5.2. Results of optimal design solutions for microgrid and solar hotel building systems

5.2.1. Game-theory-based optimal design solutions for microgrid and solar hotel building systems

Fig. 7 shows the results of the game theory-based optimal design under the different capacities of the microgrid power generators. The green curve is according to the game theory-based optimization curve. It presents the net profits of microgrid investors when the PV area and the battery storage are optimized to obtain the minimum LCOE of electricity consumers under designed microgrid power generator capacities. Besides, the net profit under different microgrid power generator capacities consists of two boundaries (i.e., upper and lower boundaries of the microgrid net profits) since the different portfolios of the PV areas and battery storages are involved. The largest difference between the upper and lower boundaries is up to 90.9 % of the largest net profits. Thus, the portfolios of the PV area and battery storage for the electricity consumers have significant impacts on achieving large net profits. They have to be considered in the microgrid power generation system design.

The green line is inconsistent with the upper boundary of the microgrid net profits, which means the interests of the microgrid investors and electricity consumers are inconsistent. The green line is also inconsistent with the lower boundary of the microgrid net profits, which means the interests of the microgrid investors and electricity consumers are not completely opposed. The maximum value appears at the red point, representing the optimized design microgrid power generator capacity (i.e., 70 kW). The largest net profits can be achieved when this capacity of the microgrid power generator is selected, considering the impacts of different portfolios of the PV area and battery storage.

The net profits under determined different capacities of the power generator are not always positive. It means that the economic risk due to increasing the capacity of the power generator exists, and the net profit is negative. The reasons include the high initial costs and maintenance costs of the power generators and the relatively low efficiency of the power generation. The negative net profit may appear above the 110 kW capacity of the power generators or 180 kW capacity of the power generators, considering different portfolios of the PV area and battery storage.

Then, according to the determined capacity of the microgrid power generators (i.e., 70 kW), the PV area and battery storage capacity are optimized to decrease the overall cost of electricity consumers, as shown in a 3-D graph (Fig. 8). The impacts of the combination between PV areas and battery storage capacity on the economics are presented. The overall cost can increase sharply with the PV area increasing under determined battery storage capacity. Increasing the battery storage capacity solely impacts the overall cost when the PV area is constant. The minimum overall cost is obtained considering the portfolios of these two

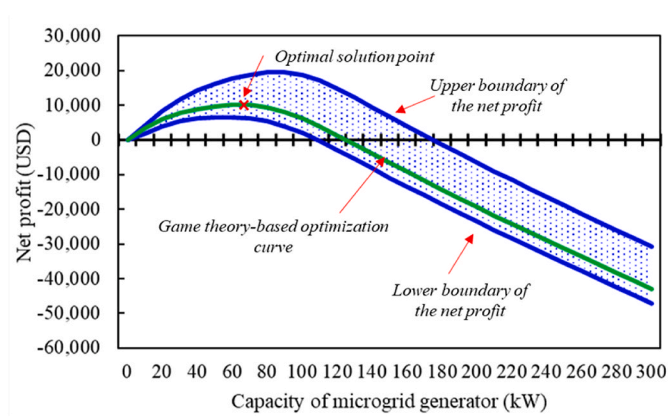

Fig. 7. Results of the game-theory-based optimal design under the different capacities of the microgrid power generators.

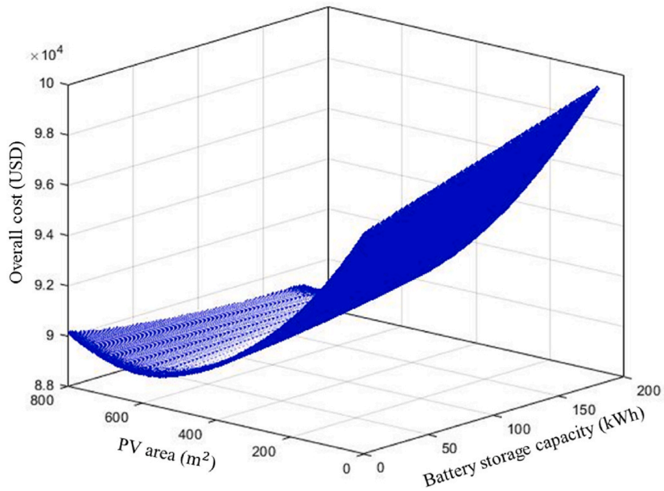

Fig. 8. Optimal design results of the PV area and battery storage capacity under determined microgrid power generator capacity.

renewable power generation facilities (i.e., PV area as 680 m^2 and battery storage capacity as 75 kWh).

5.2.2. Design solutions among the different optimization cases

Table 4 shows the design solutions among the different optimization cases. The design solution of the Game-Theory-Based Optimization Case is obtained, and the other three design solutions are obtained based on the introduced optimization cases in Section 5.1.

5.3. Economic analysis concerning the different optimal design methods

5.3.1. Net profit analysis from microgrid investors' perspective

Increasing the net profit is the major objective for microgrid investors. Fig. 9 shows comparison results for the net profit of the microgrid power generation per unit. If the net profit value is positive, power generation can obtain the cost revenue from power generation. The proposed Game-Theory-Based Optimization Case has the best performance among these four optimization cases. In this case, the net profit of the microgrid power generation is up to 0.08 USD/kWh. As for the Demand-to-Supply Optimization Case, the optimal design on the demand side is considered before the power generation optimization of the supply side. However, without considering the interaction between the supply and demand sides, and even under giving up the dominance of the supply side for microgrid power generation, the net profit of the microgrid power generation in the Demand-to-Supply Optimization Case only reaches a quarter of the power generation net profit per unit compared to the Game-Theory-Based Optimization Case. Suppose the impacts of the PV panels and battery storage installations from the electricity consumers on the optimal design of the microgrid power generation capacity are ignored. In that case, the optimization design results cannot achieve the expected results and even cause high additional expenses in power generation such as Supply-to-Demand

Table 4
Design solutions among the different optimization cases.

Case	Natural gas generator capacity (kW)	PV area (m^2)	Battery storage (kWh)
Game-Theory-Based Optimization Case	70	680	75
Supply-to-Demand Optimization Case	100	667	67
Demand-to-Supply Optimization Case	50	816	200
Decentralized Optimization Case	100	816	200

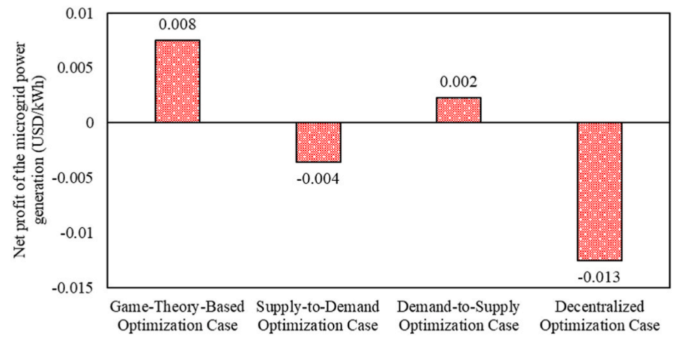

Fig. 9. Net profit of the microgrid power generation per unit among these four cases.

Optimization Case and Decentralized optimization Case. The net profits of the microgrid power generation per unit are both negative.

5.3.2. LCOE analysis from electricity consumers' perspective

Decreasing LCOE is the major objective for electricity consumers. Fig. 10 shows the LCOE of the electricity consumers and the comparison results of the LCOE among these four cases. The PV installation of building roofs for electricity consumers effectively reduces the LCOE (at least up to 12.7 %). The design solution in the proposed Game-Theory-Based Optimization Case is regarded as the best adoption considering the interests of the microgrid investors and the interests of electricity consumers since the reduction of the LCOE is about 14 %. Moreover, although the lower values of the LCOE appear in other cases, the net profit of the microgrid power (as shown in Fig. 9) is negative. It means that the optimization case cannot be accepts for power suppliers in the microgrid power generation system. The different interests and requirements for power suppliers and consumers should be considered together. The detailed reasons are further analyzed below.

As for the Demand-to-supply Optimization Case, the PV area and battery storage are optimized before optimizing the microgrid power generator capacity. The optimal design solution of the microgrid power generator capacity is smaller due to the consideration of the renewable power generation impacts. The amount of electricity from the microgrid power generation system decreases due to the selected smaller capacity of the microgrid power generator. Thus, the LCOE cannot decrease at the lowest value in this optimization case. As for the Supply-to-Demand Optimization Case and Decentralized Optimization Case, the larger capacity of the microgrid power generator is selected. However, the net profit of the microgrid power generation is negative, which cannot be adopted by the microgrid investors in practice.

5.4. Energy efficiency analysis concerning the different optimal design methods

From the microgrid investors' perspective, high power generation efficiency can effectively decrease the operation cost for power generation and increase the net profit of the microgrid power generation. Fig. 11 shows the annual power generation efficiency profile under dynamic electricity consumption among these four cases. The selected larger capacity of the power generator in the Supply-to-Demand Optimization Case (Fig. 11b) and Decentralized Optimization case (Fig. 11d) can achieve higher efficiency during summer (from 2150 h to 6570 h). However, during the winter and some periods with relatively lower electricity consumption, the power generation efficiencies (mostly below 75 %) in these two cases are lower than the other two cases with selected relatively smaller capacity of the power generators. As for these two cases, when selecting the smaller capacity of the power generators, the determined capacity of the power generators in the Demand-to-Supply Optimization Case is smaller compared to the design results in the Game-Theory-Based Optimization Case. The maximum efficiency in

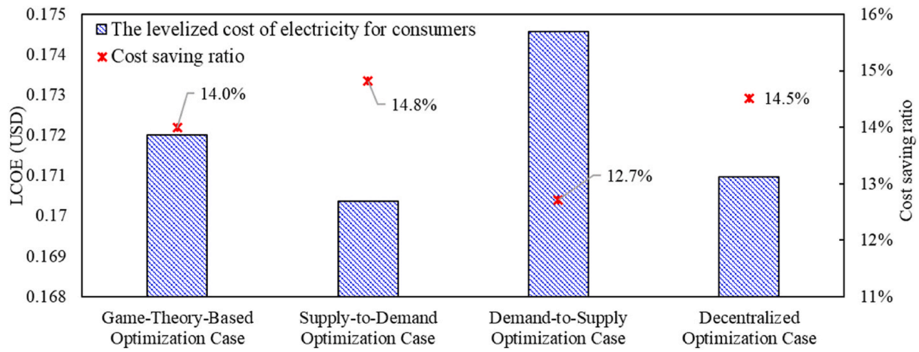

Fig. 10. LCOE of the electricity consumers among these four cases.

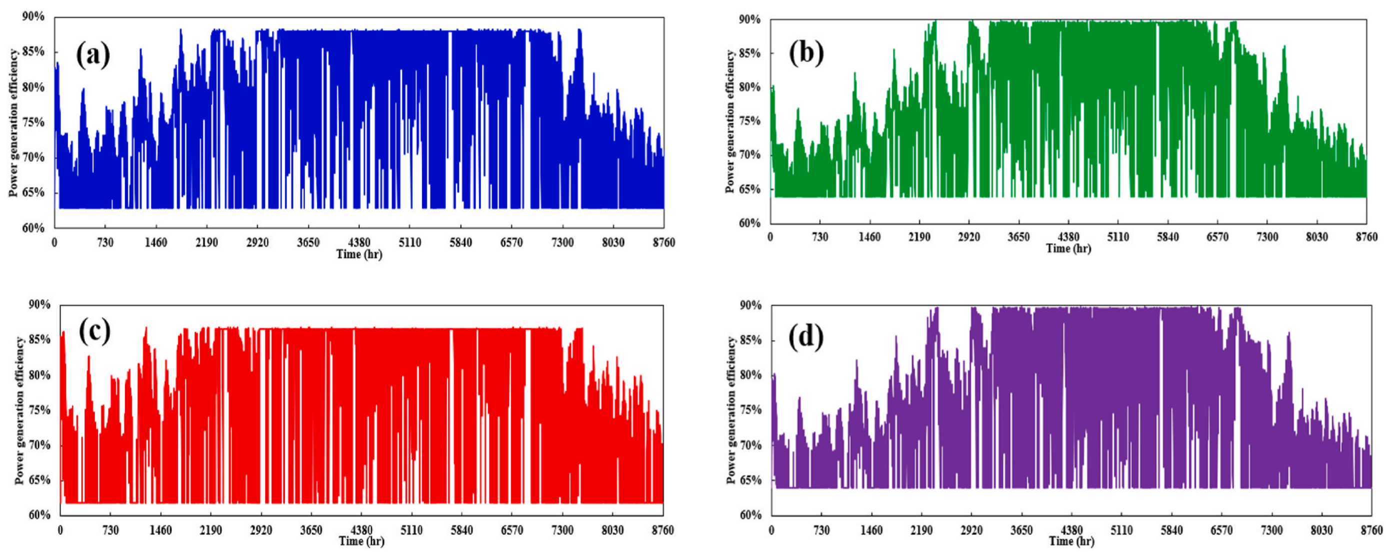

Fig. 11. Annual power generation efficiency profile among four cases: Game-Theory-Based Optimization Case (a), Supply-to-Demand Optimization Case (b), Demand-to-Supply Optimization Case (c), and Decentralized Optimization case (d).

the Game-Theory-Based Optimization Case is up to 88 %, while the maximum efficiency in the Demand-to-Supply Optimization Case is about 86 %. Table 5 shows the annual average power generation efficiency among these four cases, where the best power generation efficiency is in the Game-Theory-Based Optimization Case, and the maximum gap of the average power generation efficiency reaches 2.1 % compared to Game-Theory-Based Optimization Case with the other three cases.

5.5. Discussions

5.5.1. Advantages of the developed optimization methods

Microgrid systems that include multiple closely spatially distributed electricity consumers have been developed to decrease the utility grid's burden further and enhance the power supply's reliability. If the mentioned power supply duties are achieved, and the net profit is positive for microgrid investors, microgrid development will be accepted by the markets. On the other hand, electricity consumers seek to find effective measures to decrease the LCOE as much as possible. Thus, distributed renewable energy generations (especially PV installations on building roofs) have begun to promote and accelerate installation since renewable power generation has a promising potential to decrease the operation cost by decreasing the amount of purchased electricity [46].

Conventional optimizations of the microgrid design commonly consist of two categories (Fig. 12) concerning the requirements and interests of microgrid investors and electricity consumers. The former (Fig. 12a) commonly focused on providing optimal design solutions to meet the interests of microgrid power generations solely for microgrid investors. In contrast, the interests of the electricity consumers are ignored. In the optimal design, all different types of power generations are considered for microgrid investors. Good optimization results can be obtained but are only sometimes consistent with practical conditions and may reduce the motivation of PV installations for electricity consumers. To face the different requirements and interests of microgrid investors and electricity consumers, the latter tries to provide some solutions, where three typical optimal design approaches are shown in Fig. 12b-①, Fig. 12b-②, and Fig. 12b-③. The details of these three optimal design approaches are introduced in Section 5.1, which are listed as the reference cases in this study. According to the tested results, the proposed game theory-based optimal design approach performs better than these three cases.

Table 5
The annual average power generation efficiency among these four cases.

Case Name	Average power generation efficiency
Game-Theory-Based Optimization Case	77.5 %
Supply-to-Demand Optimization Case	76.1 %
Demand-to-Supply Optimization Case	76.7 %
Decentralized Optimization case	75.4 %

5.5.2. Limitations of the developed optimization methods

As demonstrated in this study, the two pivotal limitations cannot be

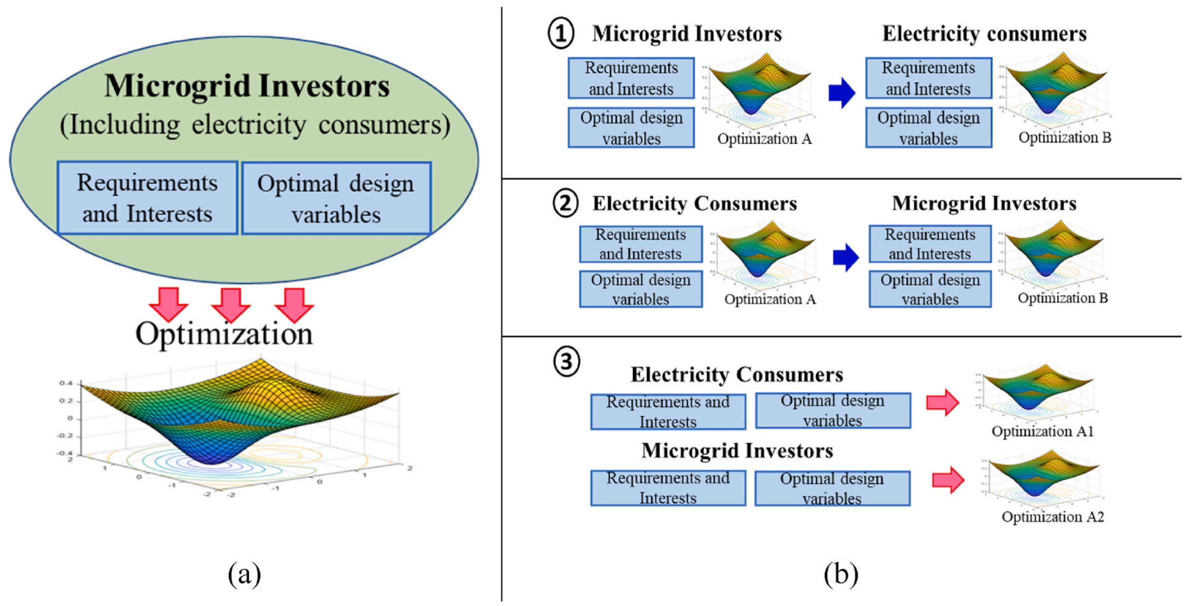

Fig. 12. Schematics of the conventional microgrid optimal design approaches.

overlooked when assessing the practicality and scalability of the proposed optimization method.

- Firstly, while the developed optimization technique has proven to be a successful case in simulations, it is crucial to conduct rigorous experimental validations to ensure its economics before it can be widely applied in practical scenarios. This step is indispensable for bridging the gap between theoretical models and real-world applications.
- Secondly, when confronted with the complexities of practical conditions, the optimization method becomes significantly intricate. It necessitates seamless collaboration among all stakeholders, including building owners, energy providers, and regulatory bodies, each with their unique requirements, interests, and constraints. This requirement poses a substantial engineering challenge, as collecting comprehensive and accurate information from these diverse stakeholders is often difficult and time-consuming. Moreover, coordinating their efforts to align with the optimization objectives can be a daunting task, further complicating the implementation process.

6. Conclusions and future studies

This study proposes a novel game theory-based microgrid optimal design approach for planning microgrid power generators and PV installations with battery storage on the building roofs of electricity consumers, considering the diverse requirements and interests of both electricity suppliers and consumers. The analysis of microgrid investors' and electricity consumers' requirements and interests is approached from different perspectives. The main conclusions can be summarized as follows.

- The proposed game theory-based microgrid optimal design approach, functioning as an interaction design strategy, effectively mitigates the negative effects of decentralized optimization in conventional optimal design methods. It comprehensively addresses the varied requirements and interests of all stakeholders, leading to improved benefits for both microgrid investors and electricity consumers compared to conventional design optimizations.
- From the standpoint of microgrid power generation, the approach achieves high net profit coupled with enhanced high power generation efficiency. The net profit of the microgrid power generation reaches up to 0.08 USD/kWh. Furthermore, under the premise of realizing the positive net profit, the generated electricity per unit is four times higher than that of the second-best optimization case. Considering the impacts of PV installations with battery storage equipment in the building roof for electricity consumers, the highest average power generation efficiency is achieved, reaching up to 77.5 %.
- From the viewpoint of electricity consumers, the proposed game theory-based microgrid optimal design approach leads to a substantial reduction in the LOCE. Under the practical premise of feasibility (positive net profit of the microgrid power generation), the LCOE is reduced by approximately 14 %.

In the pursuit of advancing sustainable energy solutions, several avenues for future research emerge from the findings of this study. One crucial area of exploration lies in the scalability and adaptability of the proposed game theory-based microgrid optimization design approach. Examining its efficacy across a spectrum of microgrid scenarios and diverse geographical locations can offer valuable insights into its broader applicability and potential modifications required for varying contexts. Moreover, delving into the long-term implications of widespread adoption of this optimization approach is imperative. Future studies should aim to unravel the economic and environmental impacts over extended periods, considering factors such as technology evolution, energy market dynamics, and evolving consumer behaviours.

CRediT authorship contribution statement

Jianing Luo: Writing – original draft, Software, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Karthik Panchabikesan:** Writing – original draft, Methodology, Investigation. **Kee-hung Lai:** Writing – original draft, Methodology, Investigation. **Timothy O. Olawumi:** Writing – original draft, Methodology, Investigation. **Modupe Cecilia Mewomo:** Writing – original draft, Methodology, Investigation. **Zhengxuan Liu:** Writing – review & editing, Writing – original draft, Supervision, Software, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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