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Multi-objective optimization of campus microgrid system considering electric vehicle charging load integrated to power grid

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ABSTRACT

The increasing use of renewable energy sources and electric vehicles (EVs) has necessitated changes in the design of microgrids. In order to improve the efficiency and stability of renewable energy sources and energy security in microgrids, this paper proposes an optimal campus microgrid design that includes EV charging load prediction and a constant power support strategy from the main grid. The problem of load variation due to changes in the number of EVs connected to the microgrid will occur, and this paper presents a detailed prediction method and effective solutions. The load profile of EVs connected to the microgrid is simulated using the Monte Carlo (MC) method, taking into account EV owners' usage habits, including charging options and dwell time, as well as battery parameters, including state of charge (SOC) and size. The simulation results show that the peak-to-valley difference in grid power after adding EVs is close to 14 times due to the uniformity of travel between staff and students. Based on how long EVs stay in the parking place, a charging and discharging policy for participation in grid dispatch is developed, which has reduced the gap between the peak and the valley. This paper gives precedence here for the main grid to provide constant power support, which would limit the electricity consumption of the campus, reduce the dependence on the main grid and moreover increase the utilization of renewable energy by the microgrid. The ideal solution set for this microgrid system model's best configuration is found using the NSGA-II optimization algorithm. To select the most suitable option, the TOPSIS method is employed. The simulation results show that the microgrid system can operate with EV integration in an economical and stable manner. Additionally, the peak-to-valley value and CO_2 emissions are reasonably reduced, and the income of EV users is increased. At the same time, the microgrid operator's charging fee for EVs can lower operating costs and also suggests that future microgrid electricity sales will be more accessible and transparent.

1. Introduction

Since the Industrial Revolution, greenhouse gas (GHG) emissions on Earth have been steadily increasing (Beerling & Royer, 2011; Ekwurzel et al., 2017). The resulting global warming has led to rising sea levels (Lindsey, 2020; Meehl et al., 2005), frequent extreme weather changes (Škerlak, Sprenger, Pfahl, Tyrlis, & Wernli, 2015), and the potential for a sixth mass extinction event that may be closely related to human activities (Ceballos, García, & Ehrlich, 2010). These issues present unprecedented survival challenges for humanity. In recent years, people have begun to focus on sustainable and renewable energy to reduce greenhouse gas emissions and address these pressing issues. Multiple countries have also signed the Paris Agreement, committing to reducing carbon dioxide emissions (Paris Agreement, 2015). Reports (IRENA, 2021) show that renewable energy has proliferated over the past few years. In 2020, the global installed capacity of renewable energy was increased by around 260 GW. The newly installed capacity of solar photovoltaic power systems was 127 GW, while wind power increased by 111 GW. The global installed capacity of renewable energy has reached 2,799 GW, with hydropower still accounting for the majority of electricity generation (1,211 GW). Meanwhile, in the transportation sector, due to the environmental friendliness of electric vehicles (EVs), the gradual improvement of charging facilities, and government promotion, the development of EVs

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Nomenclature

Introduction and Background

GHG	Greenhouse gas
EVs	Electric vehicles
PV	Photovoltaic
$FCEV2G$	Fuel cell electric vehicle-to-grid
MC	Monte Carlo method
PSO	Particle Swarm Optimization algorithm
$NSGA-II$	Non-dominated Sorting Genetic Algorithm-II

Campus Microgrid System Modeling

$P_{pv}(i)$	Output power of solar system
P_{STC}	Reference conditions power
$I_r(i)$	Solar radiation
K_t	PV temperature coefficient (−0.37%/C°)
T_{cell}	PV cell temperature
T	25°
T_{amb}	Ambient temperature
$P_{constant}$	Average hourly power supply excluding PV power
$Load(i)$	Campus consumption
$P(i)$	Power supply
$P_{grid}(i)$	Constant power pre-purchased from grid
$SOC(i)$	Battery bank state of charge
γ_{inv}	Conversion efficiency
γ_{cha}	Charging efficiency
γ_{dis}	Discharging efficiency
$P_s(i)$	Output of power source

Charge and Discharge Strategy

$S(T)$	Probability of parking time
T	Waiting time

Operational Stability Analysis

$P_{ta}(i)$	Total available electricity power
$EV(i)$	EV charge load
LPS	Loss of power supply
$LPSP$	Loss of power supply probability
LCC	Total cost of life cycle
WE	Waste Energy
K	Variance in power matching

has shown an unstoppable trend (IEA, 2021). Conservatively estimated, by 2040, EVs will account for 11%–28% of the global transportation fleet, which will lead to an additional 11%–20% increase in global electricity consumption (Kapustin & Grushevenko, 2020). The rapid development of renewable energy and EVs presents new challenges for the stability of the power supply system. Microgrids enter the scene in this context as a crucial part of intelligent power supply. They can not only alleviate the pressure on the grid but also provide basic guarantees for the safe operation of the grid. Moreover, microgrids can consume more renewable energy, reduce dependence on external energy supplies, improve energy efficiency, and lower energy costs. After EVs are integrated into the grid, the structure of the power supply system will become more complex. However, microgrids can reduce local complexity, simplify complex situations, and process them in stages to ensure the safety and stability of the main grid. In the paper (Dehghani-Pilehvarani, Markou, Ferrarini, et al., 2019), smart buildings were considered as flexible loads, and a distributed model predictive control method was used. The management and coordination of energy resources in microgrids have been solved. The feasibility of real-time optimization was demonstrated at NTUA in Athens, Greece. With the microgrid system as the carrier, the effective combination of renewable energy and EVs could provide opportunities for stable operation of the power grid and potentially reduce CO_2 emissions, accelerating the achievement of carbon reduction targets (Hannan, Hoque, Mohamed, & Ayob, 2017; He et al., 2023; Kobashi et al., 2020). Although we are about to enter this intelligentization era, the optimized design and construction of microgrids still play a crucial role in the future development of sustainable cities and societies. In the face of uncertain changes in future regions, geopolitics, and socio-economics, the issue of energy security always requires continuous exploration and breakthroughs from researchers.

1.1. Literature review

Article (Haidar, Fakhar, & Helwig, 2020) proposes a mathematical model for adjusting the size of system components to meet the maximum load demand under constantly changing weather conditions and at the lowest possible cost. Different microgrid models are simulated using deterministic and stochastic optimization methods to find the accurate dynamic energy prices for optimal system configuration under uncertain conditions. However, with the changing times, electric vehicles (EVs) will soon be integrated into people's lives. EVs are both loads and mobile power sources, which means they can supply power to the grid during peak demand and use electricity during low demand. When optimizing at the lowest cost, the factor of EVs participating in microgrid operation needs to be considered. Article (Wu et al., 2023) presents an energy-saving and carbon-reducing optimization scheme for the integration of transportation and buildings, but achieving 100% zero emissions for large-scale microgrids is still a tricky problem. Although this paper takes the optimization of campus microgrids as an example, its load characteristics and the entry and exit of EVs are also applicable to large shopping malls or companies. (Due to the geographical characteristics of the Okinawa region, people tend to use private cars for travel, which also results in a large number of vehicles entering and exiting the campus (Huang, Gamil, et al., 2021; Huang, Gamil, Takahashi, & Senjyu, 2020).)

The article (Luo, Liu, Liu, & Liu, 2019) proposes a mixed-integer linear programming model to optimize the structure and operation of distributed energy systems in the islands of the South China Sea. The results show that the application of distributed energy systems reduces the system cost by 3.33%. Combined heat and power (CHP) is essential to improving energy utilization efficiency in microgrid technology (Cheng, Huang, He, Ibrahimi, & Senjyu, 2023). Article (Zhang, Evangelisti, Lettieri, & Papageorgiou, 2015) solves the optimization design problem of microgrids with CHP units by considering environmental and economic sustainability in a multi-objective optimization model. The results show that installing multiple CHP systems in microgrids is more cost-effective and environmentally friendly than installing only one. Article (Jordehi, 2021) studies the impact of the power grid and heat network on microgrid operation and the sensitivity of operating costs to electricity and heat prices. However, these articles do not consider the changes in load structure when electric vehicles are integrated into the grid, nor do they consider scenarios where electric vehicles are used as energy storage to supply power to microgrids.

Standalone microgrid systems are more suitable for remote mountain villages or islands. The article (Kamal, Ashraf, & Fernandez, 2022) is based on the electricity consumption patterns of rural residents in Uttarakhand (India). An integrated model for an isolated microgrid system was developed using solar photovoltaic, micro-hydropower, biogas, batteries, biomass, and wind energy. The system's overall energy cost and size were optimized using differential evolution. This study focuses on the construction of independent microgrids in rural communities. However, the operation of microgrids in urban areas is more complex. For example, during weekends, the electricity consumption of companies or campuses will be significantly lower than on workdays. The amount of renewable energy generated by the microgrid's configuration is sufficient to meet electricity demand and supply power to the main grid. On workdays, power support from the main grid is needed.

Article (Yoshida & Farzaneh, 2020) aimed to minimize costs and used the particle swarm optimization (PSO) algorithm to optimize the design of a standalone microgrid system (PV/wind/battery/diesel). The results showed that the microgrid system's power generation could meet the load requirements of a small residential area in Kasuga City, Fukuoka Prefecture. However, more than single-objective optimization is required to meet the current microgrid construction and development needs. Article (Alshammari & Asumadu, 2020) used Harmony Search (HS), Jaya, and Particle Swarm Optimization (PSO) algorithms to determine the optimal design scale of a standalone hybrid renewable energy system.

Article (Kharrich, Mohammed, Alshammari, & Akherraz, 2021) used three multi-objective optimization algorithms, MOPSO, PESA II, and SPEA2, to design a PV/wind/diesel/battery hybrid system. The three objective functions were the net present value cost, the cost of the emission penalty, and the amount of carbon dioxide released into the atmosphere. System reliability, availability, and renewable portion were used as constraints. However, no specific operational method was provided for selecting the optimal solution for multi-objective optimization.

The Normal Boundary Intersection (NBI) method is a multi-objective optimization method based on merging multiple single-objective optimization problems into one multi-objective optimization problem and then using constraint methods to solve the multi-objective optimization problem. Article (Khaloie, Anvari-Moghaddam, Hatziargyriou, & Contreras, 2021) used this method. However, the NBI method is sensitive to constraint conditions, easily falls into local optima, and the computational complexity increases exponentially with the number of objective functions. Article (Khaloie, Vallée, Lai, Toubeau, & Hatziargyriou, 2021) used the ϵ-constraint method, which first identifies a primary objective, sets this objective as a constraint, searches for a series of Pareto policies, and then generates the optimal scheduling mode based on the out-of-sample evaluation posterior method. This method increases the workload of evaluation and verification and uses the TOPSIS method to calculate the Pareto optimal solution directly. Both VIKOR and TOPSIS are commonly used to solve multi-attribute decision-making problems (Eren & Katanalp, 2022; Wu, Zhang, Xu, & Li, 2018), and are effective methods for evaluating the performance of sustainable cities and communities (Suganthi, 2018; Watrobski, Baczkiewicz, Ziemba, & Saabun, 2022). The VIKOR method has a higher decision mechanism coefficient compared to the TOPSIS method, which allows decision-makers to make more aggressive or conservative decisions. The TOPSIS method's process does not incorporate any subjective factors and is more suitable for decision environments that require completely objective results. However, the TOPSIS method can only obtain a unique optimal solution because its process is entirely objective.

Al-Ghussain, Samu, Taylan, and Fahrioglu (2020) suggests that by integrating energy storage systems (ESS) with renewable energy systems (RES), the reliability of RES can be improved, and the difference between energy output and consumption trends can be reduced. The results of Guo, Nojavan, Lei, and Liang (2021) indicate that with the combination of electric vehicles and demand response in microgrids, the total operational cost can be reduced by 9.97%, emissions can be reduced by 12.34%, and renewable energy generation can be reduced by 8.49%. Since the EVs market will have substantial energy storage potential and colossal energy consumption demand in the future and can improve energy utilization efficiency and save operating costs, it is wise to incorporate EVs into the microgrid. Meanwhile, in real-life scenarios, EV charging is highly unstable in terms of time and space, with numerous factors affecting it. The paper (Zhang, Yan, Liu, Zhang, & Lv, 2020) demonstrates an improved probability model based on social and demographic factors, such as gender, age, education level, location, date type, charging preferences, and electricity consumption, to provide an accurate daily overview of EVs charging consumption. However, the charging scene on campus is often much more straightforward, with the time of entering and exiting campus being the most critical factor. Other factors that need to be considered include the number of vehicles, battery capacity, charging power selection, start time, and end time. Therefore, this paper uses the Monte Carlo (MC) idea, based on the distribution of vehicles entering and leaving the campus (Su et al., 2018; Su, Li, & Gao, 2017), to simulate a one-year electricity load. More details will be introduced in Section 2.1.

Numerous articles (Datta, Saiprasad, Kalam, Shi, & Zayegh, 2019; Gamil, Senjyu, Masrur, Takahashi, & Lotfy, 2022; He et al., 2021; Hsu et al., 2017; Masrur, Shafie-Khah, Hossain, & Senjyu, 2022; Salvatti, Carati, Cardoso, da Costa, & Stein, 2020) also discussed the use of V2G and V2H, but centralized charging will be a phenomenon because people's work and rest habits are so similar. This presents the power grid with an enormous and intolerable challenge. For example, García-Vázquez, Espinoza-Ortega, Llorens-Iborra, and Fernández-Ramírez (2022) looks into the viability of a V2H option as a backup for a hybrid renewable energy system (HRES) with battery for a household without considering the dynamics of charging/discharging of EVs and taking them only as electrical loads. Although article (Guo et al., 2021) investigated the economic-environmental performance of the microgrid, seasonal performances are overlooked. Article (Nasiri, Zeynali, & Ravadanegh, 2022) focuses on transactive energy trading of EV-equipped microgrids in electric distribution networks, ignoring the impact of environmental and constant grid support. Those articles did not mention the high power consumption peak caused by unregulated charging during the day. Therefore, a systematic strategy for charging and discharging electric vehicles needs to be developed to reduce peak power usage. This is crucial for a microgrid and irreplaceable in sustainable cities and societies. Especially the EV charging scenario during the day has been rarely studied. In the face of research gaps in this area, this will be introduced in more detail in Section 3.

The paper (Samy, Almamlook, Elkhouly, & Barakat, 2022) presents a unique approach to the optimization problem for a hybrid, off-grid Photovoltaic (PV)-wind energy system using a variety of optimization techniques and an Artificial Neural Network (ANN)-based decision-making mechanism. Both papers tackle optimization problems in renewable energy systems, but we focus on different aspects. This paper focuses on a campus microgrid with EV integration, aiming to balance the load and improve energy efficiency. In contrast, the comparison paper targets an off-grid PV-wind hybrid system, with a focus on selecting the optimal energy storage system. The manuscript (Mohammadi, Shakouri, & Kazemi, 2022) proposes an intelligent supply and demand management system for a micro smart grid (MSG) that includes diverse electricity production and consumption sources and battery storage. The MSG, equipped with a solar cell, wind turbine, and diesel generator, can trade energy with a smart grid. It utilizes intelligent fuzzy controllers optimized by the NSGA-II algorithm, aiming for multiple objectives such as user comfort, renewable energy usage, cost efficiency, and power supply reliability. While both manuscript (Mohammadi et al., 2022) and this paper aim for microgrid optimization to balance supply and demand, increase efficiency, and harness renewable energy, they differ in components, optimization goals, and application of the same optimization algorithm.

Furthermore, the rapid deployment of solar power systems has led to the 'duck curve' problem, increasing the electricity supply during the day. As sunlight weakens, this can result in a steep drop in power supply (Hou et al., 2019; Howlader, Furukakoi, Matayoshi, & Senjyu, 2017; Howlader, Sediqi, Ibrahimi, & Senjyu, 2018; Olczak, Jaśko, Kryzia, Matuszewska, Fyk, & Dyczko, 2021). Nevertheless, the majority of vehicles are parked for 20 h per day (Kempton & Tomić, 2005; Kempton et al.,

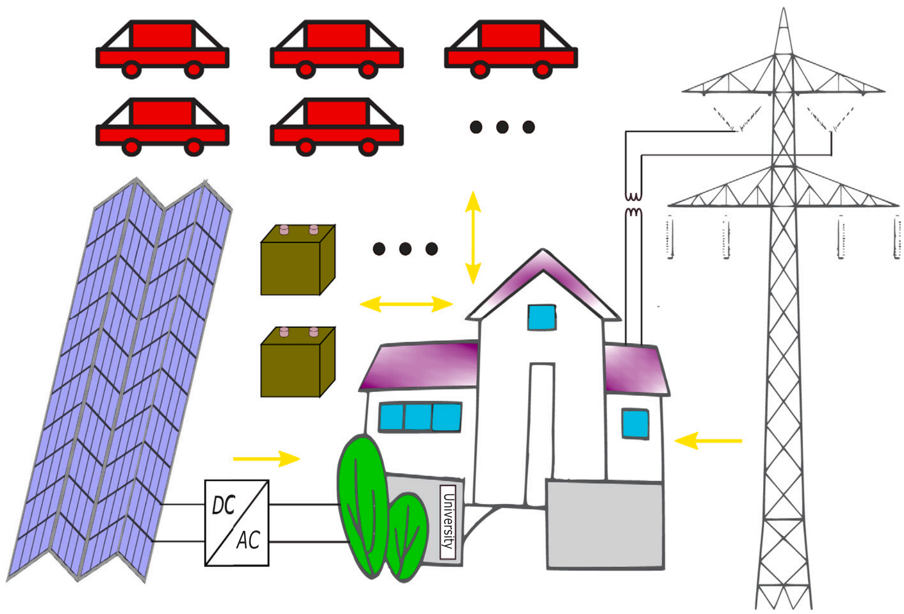


Fig. 1. Proposed campus microgrid system model.

2008; Lund & Kempton, 2008), demonstrating the enormous potential of EVs as distributed energy storage components. Thus, flexible use of the energy storage characteristics of electric vehicles is a crucial point in solving the 'duck curve' problem. The 'duck head' height, which represents the peak pressure on the power grid between 18–21 h, can be significantly reduced if EVs can still provide some power to households after returning home. In order for EVs to have sufficient energy storage to perform V2H or V2G operations, it is essential to ensure that electric vehicles have enough power before nightfall (before the end of work). Moreover, use M-shape to increase PV power generation in the morning and evening, and delay the emergence of the 'duck curve', which will be mentioned in Section 2.2.

1.2. Contribution

Although campus microgrid design is not a mainstream topic, it also has research value (Alrashed, 2020; Huang, Gamil, et al., 2020; Huang, Masrur, et al., 2021; Husein & Chung, 2018; Talei et al., 2015), which is an indispensable part of realizing sustainable cities and society. Fig. 1 shows the schematic diagram of the campus microgrid system in this study. This paper proposes the idea of a constant power supply, which is almost nonexistent in the real world, to limit the microgrid's dependence on the main grid significantly. Then, using the Monte Carlo method to consider specific details (charging power selection, charging willingness, waiting time, battery size), a detailed plan for predicting the power consumption of EVs is provided. Finally, a microgrid accessory combination best fits the campus area is designed based on the new power load. The problem is turned into a mathematical model, and the NSGA-II optimization algorithm is used to find the best solutions. TOPSIS is then used to choose the best solution that does not cause any interference. Moreover, a method is proposed to enable EVs to participate in microgrid power dispatch based on their waiting time, so as to earn income and calculate costs when there is a large gap between peak and off-peak electricity prices during the research process. A charging recommendation for EVs is made based on their parking time, and the charging costs or the fees for supplying electricity from EVs to the grid are calculated according to their contributions to the grid. The characteristics of the power consumption in microgrids (such as those in campuses, companies, and shopping malls) are fully considered to create the optimal configuration of the microgrid system and the operational strategy for EVs. The results show that optimizing the microgrid design by considering movable energy storage devices for microgrid dispatch can not only adjust the peak-to-valley ratio of the microgrid after the EVs are connected but also improve the stability of the microgrid and benefit both vehicle owners and microgrid operators. This research provides references and suggestions for the innovation of microgrids in the new era of the power grid. The highlights of this paper are as follows:

- Various electric vehicle charging loads are simulated using the MC method.
- A novel idea of constant power supply for the microgrid is proposed and verified.
- A suitable EVs charging strategy has been formulated for the campus.
- The TOPSIS method is used to select the optimal solution in the NSGA-II solution set.
- The free trade of electricity in the microgrid can reduce its own operating costs.

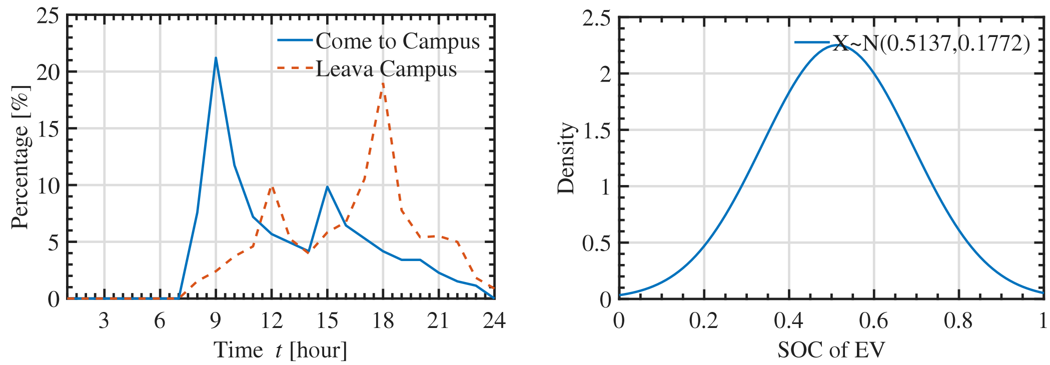
1.3. Organization

The paper is arranged as follows: In Section 2, the mathematical model components of the microgrid are given. These include the load requirements of EVs, the PV power generation model, the constant power required by the microgrid in different time periods, and the battery energy storage model. In Section 3, the charging and discharging of EVs in the microgrid are discussed. Adopt the strategy of giving priority to emergency charging of EVs and delaying the charging of other EVs by one hour to adjust the load of the microgrid, reduce the difference between peaks and valleys, and improve the load structure. In Section 4, four evaluation systems for this microgrid are described to ensure safe, reliable and economic microgrid operation.

In Section 5, the process of setting up NSGA-II and the use of TOPSIS are shown. The rationality of Pareto solution set selection is guaranteed. In Section 6, the results of the simulation and optimization are discussed. A summary of this paper is done in the last section.

2. Campus microgrid system modeling

This section will discuss the EVs' load and available power supply units in the microgrid under study. University of the Ryukyus, based in Okinawa, Japan is chosen for modeling the campus microgrid.



(a) Percentage of vehicles enter and leave (b) Distribution of EVs SOC

Fig. 2. Electric vehicles load analysis.

Table 1
Percentage of all vehicles entering and leaving the campus at each time.

Time of day	1	2	3	4	5	6	7	8	9	10	11	12
Enter [%]	0	0	0	0	0	0	0	7.58	21.21	11.74	7.20	5.68
Leave [%]	0	0	0	0	0	0	0	1.53	2.41	3.72	4.59	10.06
Time of day	13	14	15	16	17	18	19	20	21	22	23	24
Enter [%]	4.92	4.17	9.85	6.44	5.30	4.17	3.41	3.41	2.30	1.52	1.14	0
Leave [%]	5.25	3.97	5.83	6.74	10.54	18.99	7.77	5.40	5.51	4.99	1.82	0.87

2.1. Electric vehicles load

When the charging load of EVs is added to a campus microgrid, a significant peak-to-valley difference is expected due to the consistent times students or lecturers enter and exit the campus. This affects the regular operation of the power grid and can cause severe damage to the quality of electricity and underlying distribution infrastructure. Therefore, it is necessary to simulate and model the charging load of campus EVs to understand how the demand changes in the distribution system at different times of the day (this also applies to shopping malls or office buildings where there is a large parking aggregation during the day). The charging load of EVs is influenced by multiple factors, such as charging methods, number of users, battery characteristics, and individual user behavior, all of which have uncertainties. However, randomness often contains inevitability, as reflected in the idea of the Law of Large Numbers, where the repetition of random events often exhibits an almost unavoidable pattern. Based on this, the Monte Carlo (MC) method can be considered for predicting EV charging loads (Domínguez-Navarro, Dufo-López, Yusta-Loyo, Artal-Sevil, & Bernal-Agustín, 2019; Hu, Li, & Bu, 2019; Zhang, Chen, Yu, Zhu, & Shi, 2018). This is a numerical calculation method based on probability statistical theory and methods. It connects the problem to be solved with a certain probability model and uses computer statistical simulation or sampling to obtain an approximate solution to the problem.

For this study, the frequency distribution data of vehicle entry and exit from the university campus, as shown in Table 1 and Fig. 2(a), were obtained using Su et al. (2017). The normal distribution of EVs battery State of Charge (SOC) is given by the following Formula (1) (Huang, Gamil, et al., 2021). Fig. 2(b) displays the probability distribution of SOC for different EVs.

$$X \sim \mathcal{N}(\mu, \sigma^2) \tag{1}$$

Where $\mu = 0.5137$, $\sigma = 0.1772$.

The simulation steps and flowchart Fig. 3 of MC are shown as follows:

- First, generate an EV according to Table 1 and select the charging start time for entering the park time for charging.

Table 2
Monte Carlo simulation of EVs charging parameters.

Battery size	Chance of selection	Charging power
20 [kWh]	20%	1–5 KW
30 [kWh]	30%	10–20 KW
35 [kWh]	30%	25–35 KW
40 [kWh]	20%	40–60 KW

- Next, select the battery size and charging power according to the probability in Table 2.
- Then, calculate the time required for charging. If it exceeds 20 h, repeat the First step when regenerating a new EV.
- Finally, calculate the number of EVs and charged power that has been charged in each period.

From the flowchart Fig. 3, a simulation result is obtained showing the electrical load generated by 2500 EVs arriving on campus, as Fig. 4(a). The parameter settings are shown in Table 2. The electrical load is displayed on Fig. 4(a) left, and the number of vehicles entering the campus is visible on Fig. 4(a) right. The total electricity use for a campus working day, including the load from EV charging, is shown in Fig. 4(b). The highest power consumption occurs when the load is 14 times higher than it is at the lowest. It is impossible to guarantee the grid's operational efficiency if such a sizable load gap is not optimized.

2.2. Photovoltaic M-shape power generation model

The M-shaped solar panel array system increases the number of solar panels within a given area, thereby increasing the power output of the PV system (Huang, Shigenobu, et al., 2020). In the northern hemisphere, PV panels are installed facing east and west instead of the traditional south-facing solar panels, as shown in Fig. 5. (In the southern hemisphere, solar panels face north.) This system has the advantage of increasing solar power output in the morning and nightfall and improving land use efficiency. The power output of the M-shaped PV system is more suitable for charging EVs, as evidenced by the distribution of university vehicle traffic peaks shown in Fig. 4, which occur in

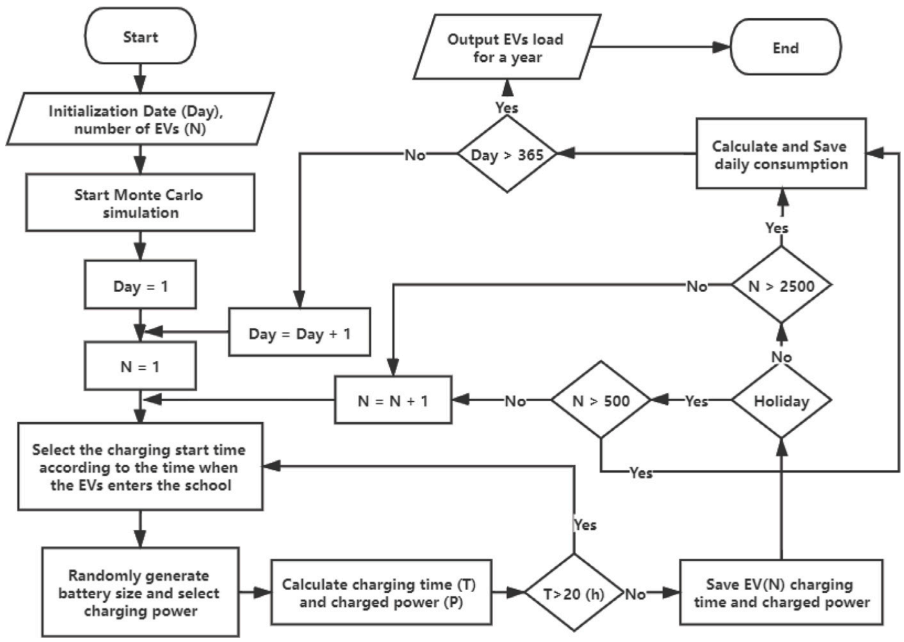
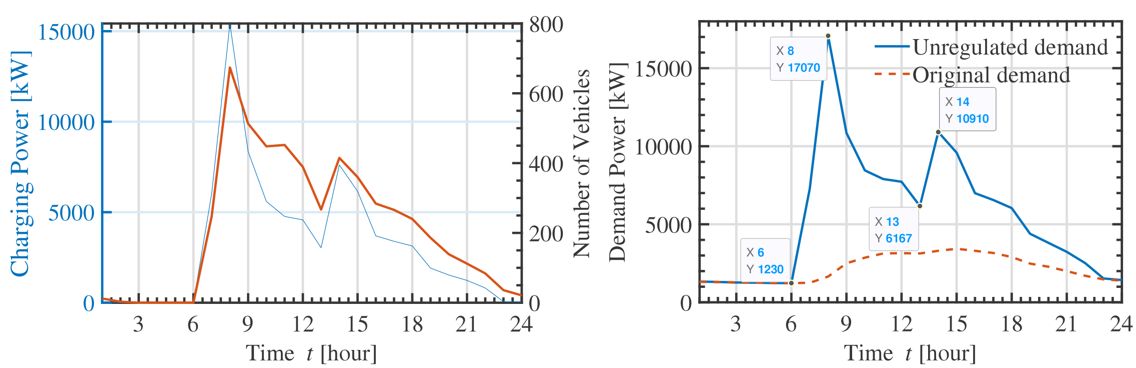


Fig. 3. Flowchart for generating Monte Carlo simulations of EVs loads. Initialize the charging time, and calculate the charging time and required power according to randomly selected battery parameters. When entering the loop, distinguish between holidays and weekdays, and add a probability function to calculate the charging load for one year.



(a) Charging demand and charging EVs

(b) Unregulated demand in microgrid

Fig. 4. Electric vehicles charging load analysis.

the morning and afternoon, coinciding with the peak electricity generation periods of the solar panels. In addition, in tropical or subtropical regions where rainfall is frequent, such as Okinawa, where typhoons are common, rainwater containing salt can accelerate vehicle rusting. Raising the M-shape mounting columns can serve as rain shelters for parking lots, prolonging the lifespan of EVs and reducing maintenance costs. Although beyond the scope of this article, the utilization of the M-shape system is worth considering. Furthermore, although the wind energy resources in Okinawa are abundant, they are challenging to develop. Therefore, this study chose M-shape PV systems as the renewable energy source for research. The following simple Formula (2) can be used to calculate the PV power generation (Borhanazad, Mekhilef, Ganapathy, Modiri-Delshad, & Mirtaheri, 2014; Hlal et al., 2019):

$$P_{pv}(i) = N_s \times P_{STC} \times I_r(i) \times [1 + K_t \times (T_{cell} - T)] \tag{2}$$

$$T_{cell} = T_{amb} + (0.0256 \times I_r) \tag{3}$$

Where P_{pv} is the output power of the solar system, N_s is the number of solar panel modules, P_{STC} is the reference power at the standard test conditions, I_r is solar radiation, K_t is PV temperature coefficient (−0.37%/C°), T_{cell} is PV cell temperature, T is 25 C°, and T_{amb} is ambient temperature.

2.3. Constant power supply from grid

Given the cost-effectiveness constraints, it is still difficult to rely on a completely independent PV system to provide all the campus energy. As a result, it is necessary to obtain energy from the grid. During peak periods, real-time electricity prices, time-of-use (TOU) electricity prices, or other demand-response mechanisms are frequently used to adjust the pressure on the power grid. It cannot, however, address the issue of people's ever-increasing power demand Huang, Gamil, et al. (2020), Huang, Masrur, et al. (2021). This article suggests limiting how much electricity is used. It reduces the campus's constant power supply cycle to 12 h, with peak power consumption during the day and low power consumption at night. The aim is also to limit power consumption while at the same time increasing the level of comfort associated with electricity consumption. Formula (4) calculates the average hourly power supply required in a constant period (12 h).

$$P_{constant} = \frac{\sum_{i=1}^{12}(Load(i) - P_{pv}(i))}{12} \tag{4}$$

Where $P_{constant}$ is the average power supply from the grid over a 12-hour period.

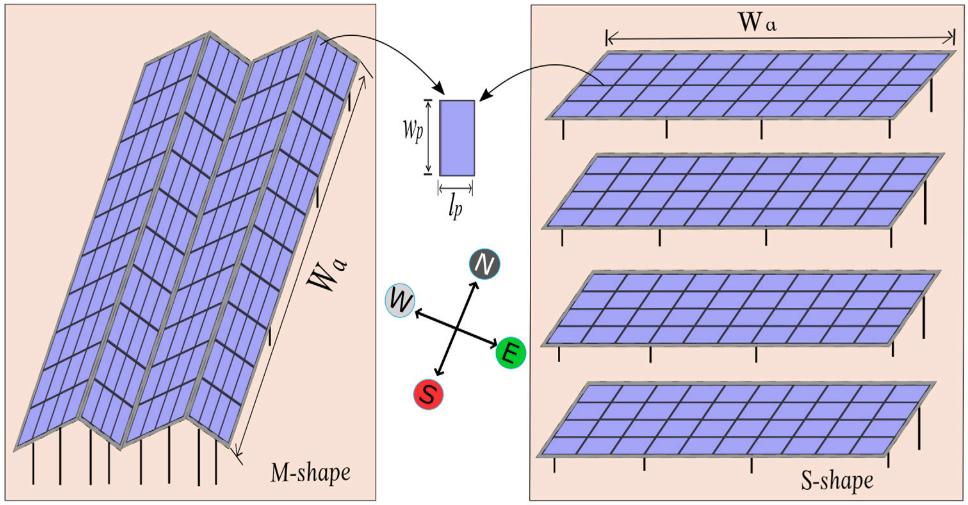


Fig. 5. The difference between M-shape and S-shape. The left side is M-shape, facing the east and west, and the right side is S-shape, facing the south.

2.4. Energy storage modeling

The output power of renewable energy systems is unstable due to weather variability. If this power is integrated into the grid, it may affect the quality of the distribution network. Thus, PV systems often need to operate with batteries. Also, local consumption is a better choice for a solar power system (Huang, Yona, et al., 2021). This study used EVs to receive electricity from solar energy in a microgrid. Moreover, optimizing the battery size has a direct impact on initial cost and grid operation efficiency. Therefore, it is essential to establish a battery model. When the system's power generation exceeds the consumption, the battery stores power, and when the power generation is lower than the consumption, it recharges its power. The following Formulas describe the battery's operation.

$$P_s(i) = P_{pv}(i) + P_{grid}(i) \tag{5}$$

$$SOC(i) = \left[P_s(i) - \frac{Load(i)}{\gamma_{inv}}\right] \times \gamma_{cha} + SOC(i-1) \tag{6}$$

$$SOC(i) = \left[\frac{P_s(i)}{\gamma_{dis}} - \frac{Load(i)}{\gamma_{inv}}\right] + SOC(i-1), \tag{7}$$

$$SOC_{min} < SOC(i) < SOC_{max} \tag{8}$$

Where $P_s(i)$ is a power source, the constant electricity pre-purchased is denoted by $P_{grid}(i)$. γ_{inv}, γ_{cha} and γ_{dis} are conversion efficiency, charging efficiency and discharging efficiency, respectively.

3. Electric vehicle charging and discharging strategy

3.1. Electric vehicle charging scheme design (G2V)

From the previous discussion, it can be concluded that the peak load of the campus power grid is 14 times that of the trough load. Suppose there are no restrictions to meet the charging needs of EV users. In that case, the hidden dangers of safe power grid operation will increase, the operation efficiency will decrease, and the difficulty of optimization and control will increase. Therefore, when studying grid-connected EVs, it is not only necessary to consider the prediction of their charging load, it is needed to rationally adjust the increased power load, reduce the grid's peak load, and ensure the safe operation of the microgrid. To deal with intermittent problems in renewable energy production, it is necessary to design a reasonable charging scheme and coordinate the charging and discharging of EV batteries (Nguyen, Zhang, & Mahmud, 2015).

By knowing the waiting time of the EVs, it can be decided whether to enable fast charging or slow charging. Therefore, this parameter is essential for analysis, and the following equation describes the probability of waiting time.

$$S(T) = 21.88\ e^{-0.2046\ T} \tag{9}$$

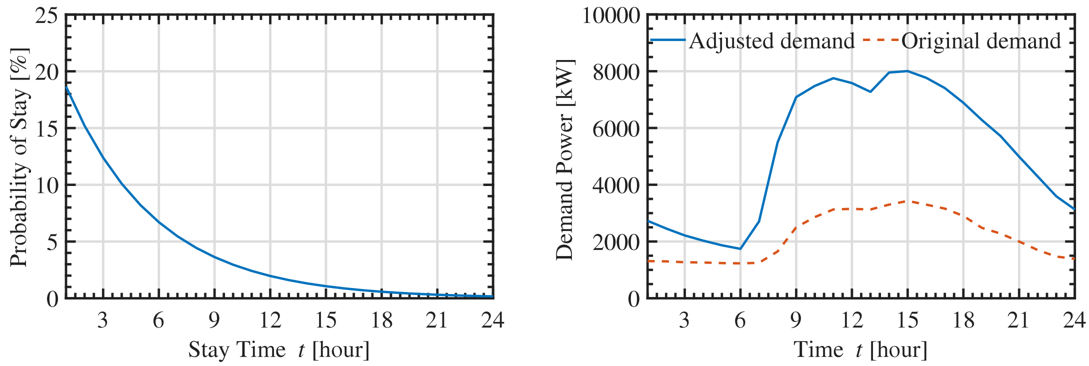
Where, $S(T)$ is probability of parking time, and T is waiting times (Yunna, Fang, Chuanbo, Chao, & Xu Ruhang (Google Translate), 2018).

Fig. 6 shows the probability distribution of waiting times. Half of the EVs do not stay for more than 4 h. Also, the amount of remaining power will lead to the choice of charging type. From the residence time distribution in Fig. 6(a), it can be seen that the probability distribution of EV staying for one hour is about 19%. According to the user's visit time and the user's needs, the charging mechanism is divided into two categories. If the user stays for one hour only, he can charge it immediately. If he stays long, he can postpone the charge for one hour or choose a low-speed charge. Adopting a mechanism that encourages extending the stay time of EVs is the best option to participate in the dispatch of the microgrid effectively. Usually, when the EVs leave the school, it is required to calculate the parking and charging fee and the income from the sale of electricity. According to the length of stay, the charging fees for EVs are expected to be reduced, or the electricity sold to the grid will be increased. From Monte Carlo thinking, the charging load in Fig. 6(b) can be obtained. The calculation process is as follows:

- According to Table 1, the number of EVs entering the campus is calculated for the corresponding time period.
- Using Formula (9), the number of EVs entering the campus in the corresponding time period can be obtained according to the length of stay time.
- EVs that stay for more than one hour in each time period are delayed for one hour to connect to the microgrid.
- According to Formula (1) and Table 2, calculate the charging load after re-planning and add them up.

3.2. Electric vehicles available power range (V2G)

EVs can be used as controllable load and energy storage components. EV batteries achieve flexible and fast-response discharging and charging in Vehicles-to-Grid strategies. According to the grid demand and user response, selecting the peak discharge can better optimize



(a) Waiting time distribution

(b) Regulated microgrid loads

Fig. 6. Waiting time distribution and regulated microgrid loads.

and coordinate the charging and discharging process, balance the relationship between supply and demand, and improve the stability of the grid (Ahmad, Alam, & Asaad, 2017). Compared to the battery's natural wear, the increased wear of V2G can have a minimal impact on vehicle battery life (Wang, Coignard, Zeng, Zhang, & Saxena, 2016). EVs are being gathered in vast numbers, and the longer they stay in school, the more noticeable the energy storage effect of EVs grows. Although the number of connected cars in the campus microgrid is limited, the power demand tends to be consistent. Despite the different departure times of EVs, the number of EVs connected to the grid within a certain period and their potential power can be calculated. Here, we assumed that the user's response level is 0, 10%, 20% and 30% so that four different EVs' response power can be considered.

4. Operational stability analysis

4.1. Loss of Power Supply Probability (LPSP)

Although the micro-grid system is powered by a constant value of grid power, due to the intermittent nature of solar energy and the uncertainty of loads, it cannot be guaranteed that electricity consumption will always receive sufficient energy supply. Here, to ensure better reliability, the time when the power supply is below 90% of the load demand is called Loss of Power (LPS) time. Therefore, judging the continuous reliability is expressed by power failure probability (LPSP). LPSP is defined in many articles (Ayop, Isa, & Tan, 2018; Heydari & Askarzadeh, 2016; Huang, Masrur, et al., 2021), and is expressed by the following.

$$P_{ta}(i) = EV(i) + P_s(i) + SOC(i) \tag{10}$$

$$LPS(i) = \begin{cases} 0 & P_{ta}(i) \geq Load(i) \times 90\% \\ 1 & P_{ta}(i) < Load(i) \times 90\% \end{cases} \tag{11}$$

$$LPSP = \frac{\sum_{i=1}^{N} LPS(i)}{N} \tag{12}$$

Where P_{ta} is total energy support available, N is one year hours.

4.2. Life cycle cost (LCC)

The total cost of the life cycle is an essential factor for measuring the project's feasibility and it is an essential objective function for system configuration optimization. The life cycle cost formula is described in the following equations. Here, the cost of purchasing electricity from EVs and the income from selling electricity to EVs are also considered. The calculation parameters are given in Table 3. The system's lifetime is considered to be 20 years. Annual maintenance and battery replacement every 5 years.

$$LCC = C_{unit} + C_{OM} + C_{rep} + C_{grid} + C_{EV} - P_{EV} \tag{13}$$

$$C_{unit} = C_{pv} + C_{bat} \tag{14}$$

$$C_{OM} = C_{pv} \times \sum_{j=1}^{19} \left(\frac{1+u}{1+v}\right)^j \tag{15}$$

$$C_{rep} = C_{bat} \times \sum_{j=5,10,15} \left(\frac{1+u}{1+v}\right)^j \tag{16}$$

$$C_{grid} = \begin{cases} 15 \times P_{grid}, & 0 < P_{grid} \leq 1000 \\ 15000 + 20 \times (P_{grid} - 1000), & 1000 < P_{grid} \leq 2000 \\ 35000 + 25 \times (P_{grid} - 2000), & 2000 < P_{grid} \leq 3000 \\ \dots & \dots \\ 230000 + 50 \times (P_{grid} - 7000), & 7000 < P_{grid} \leq 8000 \end{cases} \tag{17}$$

Where LCC is the total cost of the system. C_{unit} is every unit cost. C_{OM} is the PV system operating and maintenance cost. The cost of replacing a battery is denoted by the variable C_{rep}. C_{grid} is main grid electricity bill. C_{EV} is the money spent on electricity support from EVs, P_{EV} is the income from selling power to EVs.

Formula (17) is the calculation of electricity consumption and the step tariff. As power consumption increases, the unit price of electricity increases. Whenever the electricity consumption increases by 1000 [kWh], the price of the increased portion will be increased by 5 [JPY] on top of the original tariff of electricity. Here, the coefficient of carbon emission from the main grid is 0.769 kg/kWh (*A public table of basic emission coefficients, adjusted emission coefficients of the electric company in Heisei 30*, 2021).

4.3. Waste of energy (WE)

Because of the weather's inherent qualities, it is not easy to ensure stable and reasonable power generation. At the same time, the microgrid load, which takes into account the EVs charging power consumption, also has great uncertainty. Establishing an objective function for evaluating the amount of energy waste can improve overall energy utilization.

$$WE(i) = \begin{cases} 0 & P_{ta}(i) \leq Load(i) \\ P_{ta}(i) - Load(i) & P_{ta}(i) > Load(i) \end{cases} \tag{18}$$

$$WE = \sum_{i=1}^{N} WE(i) \tag{19}$$

The calculations reflect the total amount of electricity consumed per hour when the power supply exceeds the load.

Table 3
Price of units.

Index	PV[Module]	Battery [kWh]	Tariff [kWh]	EV Discharge [kWh]	EV Charging [kWh]
Unit Price [JPY]	10000	15000	Formula (17)	25	20

4.4. Energy matching variance

For microgrid systems, in order to get full use of the renewable energy source, the optimized configuration of the power supply system should have an output power curve close to the consumption curve. This will help in reducing the power difference between the power generation system and the load, reducing the energy matching variance of the system, and improving the overall operating efficiency. The power generation units in this study are a solar power generation array and a constant amount of purchased power from the grid; the power consumption is the campus load demand. Solar power can only be generated during the day hours, and the peak load period of the campus is also during the day. Therefore, it is necessary to consider the degree of match between power generation and power consumption. This can not only improve the system's quality of the power supply but also reduce the number of batteries charging and discharging times, which effectively extends the battery life and reduces costs. The Energy Matching Variance is also an effective indicator to measure the rationality of microgrids. The following formula describes the proposed objective (Liao, Chang, & Cheng, 2021; Shi, Sun, Yao, Ni, & Bazargan, 2014).

$$K = \sqrt{\frac{\sum_{i=1}^{N}\left[P_{pv}(i) + P_{grid}(i) - Load(i)\right]^2}{N}} \tag{20}$$

$$Objectives = \min(LSPS, WE, LCC, K)$$
$$s.t. \quad \begin{cases} 10000 \le Pan_{mun} \le 20000 \\ 500 \le Bat_{size} \le 5000 \\ 0.6 \times P_{constant} \le P_{grid} \le 1.2 \times P_{constant} \end{cases} \tag{21}$$

5. Non-dominated sorting genetic algorithm II (NSGA-II) and technique for order of preference by similarity to ideal solution (TOPSIS)

5.1. NSGA-II optimization

NSGA-II is a popular multi-objective non-dominated sorting algorithm (Deb, Pratap, Agarwal, & Meyarivan, 2002). It reduces the computational complexity, has an elite strategy, and does not need to specify parameters manually. Fig. 7 shows the flowchart of the NSGA-II algorithm. The overall structure of the optimization mechanism follows the steps below.

- First, input the data and build a microgrid model (Section 2).
- Next, establish the objective function and specify the range value of the solution (Section 4).
- Then, use the NSGA-II algorithm to generate random solutions within the specified range and perform iterative evolution as required (Fig. 7).
- Finally, find the best solution according to TOPSIS (Section 5.2).

5.2. Technique for order preference by similarity to ideal solution (TOPSIS)

TOPSIS is a widely utilized comprehensive assessment method (Yoon & Hwang, 1995). Its results accurately reflect the evaluation fitness because it can fully use the information from the original data. The basic procedure begins with the use of a normalized original data matrix, followed by the calculation of the distance between each evaluation fitness and the optimal and worst solutions, and finally the calculation of the relative closeness of each evaluation to the optimal solution, which is used to assess the benefits and drawbacks. The data distribution is unrestricted in any way, and the calculation is simple and straightforward. TOPSIS is always used in the result selection of NSGA-II in order to avoid the influence of people's subjective factors (Lin, Chang, Yeng, & Huang, 2019; Sen, Hussain, Mia, Mandal, & Mondal, 2019; Xu, Ke, Li, Chu, & Wu, 2020).

The TOPSIS process is carried out as follows:

Step 1: Select the index attributes that are homogenized and positive. The TOPSIS method introduces the optimal solution and the worst solution. The distance scale is used to measure the gap between the sample and the ideal sample. The index attributes need to be processed in the same direction. Because if the data of one dimension is larger, the better, and the data of the other dimension is smaller, the better, which will cause scale confusion.

Minimal indicators: the smallest expected value.

$$x' = \begin{cases} \frac{1}{x} \quad (x > 0) \\ \quad or \\ M - x \end{cases} \tag{22}$$

Where M is the maximum possible value of index x.

Intermediate indicators: It is expected that the index value should not be too large or too small. It is better to choose an intermediate value appropriately.

$$x' = \begin{cases} 2\frac{x - m}{M - m}, & m \le x \le \frac{1}{2}(M + m) \\ 2\frac{M - x}{M - m}, & \frac{1}{2}(M + m) \le x \le M \end{cases} \tag{23}$$

Where m is the minimum possible value of index x.

Interval indicators: The value of the expected index should fall within a certain interval.

$$x' = \begin{cases} 1 - \frac{a - x}{a - A}, & x < a \\ 1 & a \le x \le b \\ 1 - \frac{x - b}{B - b}, & x \ge b \end{cases} \tag{24}$$

The best stable interval of index x is [a, b], whereas the greatest tolerance interval is [A, B].

Step 2: Make a normalized initial matrix. If there are p items to assess and each object includes m indications, the original data matrix looks like this:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{p1} & x_{p2} & \cdots & x_{pm} \end{bmatrix} \tag{25}$$

Normalize the properties using a weighted normalization matrix. The element of each column is divided by the current column vector's norm (cosine distance metric).

$$y_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{p} x_{ij}^2}}, \quad i = 1, 2, \ldots, p, \quad j = 1, 2, \ldots, m. \tag{26}$$

Thus, the normalized matrix Y after normalization is obtained.

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1m} \\ y_{21} & y_{22} & \cdots & y_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ y_{p1} & y_{p2} & \cdots & y_{pm} \end{bmatrix} \tag{27}$$

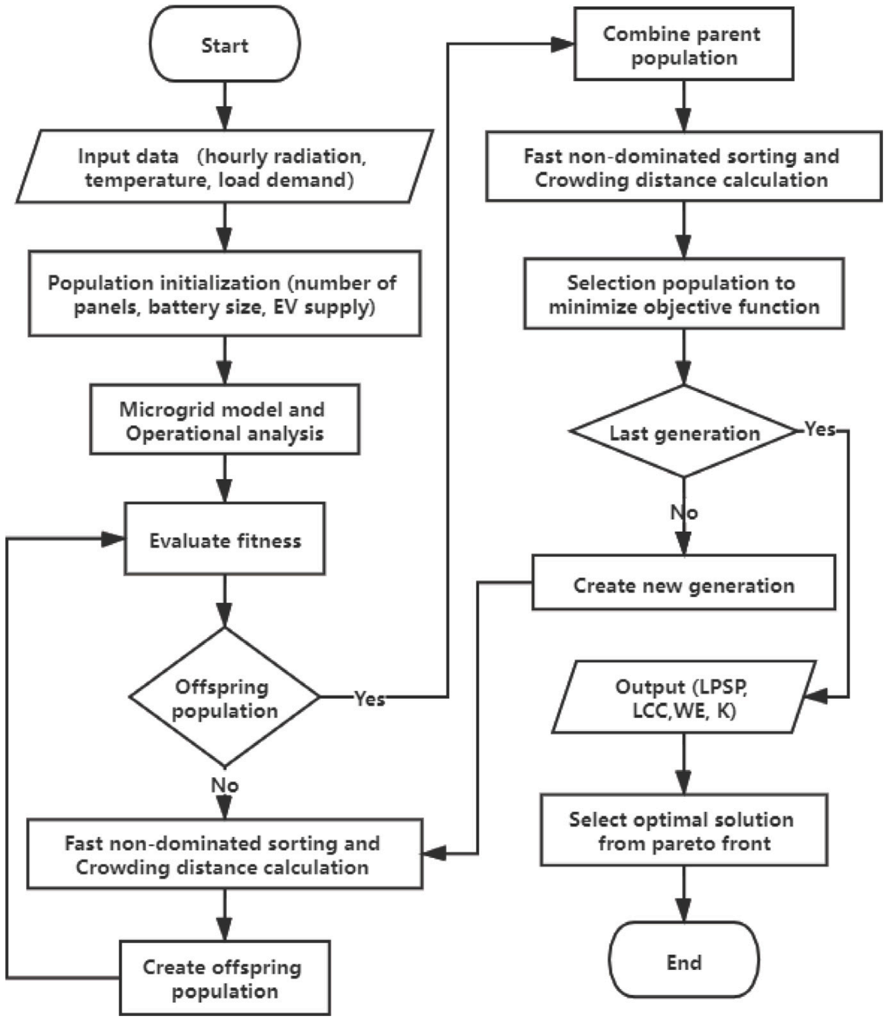


Fig. 7. NSGA-II flowchart for campus microgrid system. Input the initialization data into the microgrid model, generate the first generation, and calculate the fitness function. Enter genetic optimization, and perform non-dominated sorting, selection, crossover, and mutation to generate offspring solution sets. Iterative evolution outputs the optimal solution sets.

Step 3: Compare and contrast the best and worst options. The best and worst solutions are Y^+ and Y^-, respectively. The maximum and minimum values of each column's element in Y.

$$Y^+ = max(y_{11}, y_{1i}, \ldots, y_{1m}) \quad = (Y_1^+, Y_i^+, \ldots, Y_m^+)$$
$$and \tag{28}$$
$$Y^- = min(y_{11}, y_{1i}, \ldots, y_{1m}) \quad = (Y_1^-, Y_i^-, \ldots, Y_m^-)$$

Step 4: Calculate the distance between each evaluation item and the best and worst plans.

$$D_j^+ = \sqrt{\sum_{j=1}^{m} w_j (Y_j^+ - z_{ij})^2}, \quad D_{(j)}^- = \sqrt{\sum_{j=1}^{m} w_j (Y_j^- - z_{ij})^2} \tag{29}$$

Step 5: Determine how near each evaluation item is to the best plan.

$$C_i = \frac{D_i^-}{D_i^+ + D_i^-} \tag{30}$$

Step 6: Sort according to the size of C_i and give the evaluation result.

6. Results and discussion

6.1. Comparison of 4 different responses

Figs. 8 to 11 shows the Pareto Front for each level of EVs' response. The points in the Figures are the best solutions selected using the TOPSIS method. The gradual process of color from blue to yellow in the Figures corresponds to different Energy Matching Variance K. In Fig. 8, there is no response from EVs. The $LPSP$ is 0.02%, which means 2 h out of the 8760 h in the whole year when the power supply falls short of 90% of the required power. The total cost for 20 years is 5.73×10^9 [JPY]. There are 7.21×10^5 [kWh] energy unused. In Fig. 9, there are 10% responses from EVs. The $LPSP$ is 0.07%, which means there are 6 h out of the 8760 h a year when the power supply falls short of 90% of the required power. The total cost for 20 years is 5.20×10^9 [JPY]. There are 6.55×10^5 [kWh] energy unused. In Fig. 10, there are 20% responses from EVs. The $LPSP$ is 0.09%, meaning that there are 8 h out of the 8760 h a year when the power supply falls short of 90% of the required power. The total cost for 20 years is 4.91×10^9 [JPY]. There are 3.05×10^5 [kWh] energy unused. In Fig. 11, there is a 30% response from EVs. The $LPSP$ is 0.11%, which means that there are 10 h out of the 8760 h in a year when the power supply falls short of 90% of the required power. The total cost for 20 years is 4.88×10^9 [JPY]. There are 1.86×10^5 [kWh] energy unused.

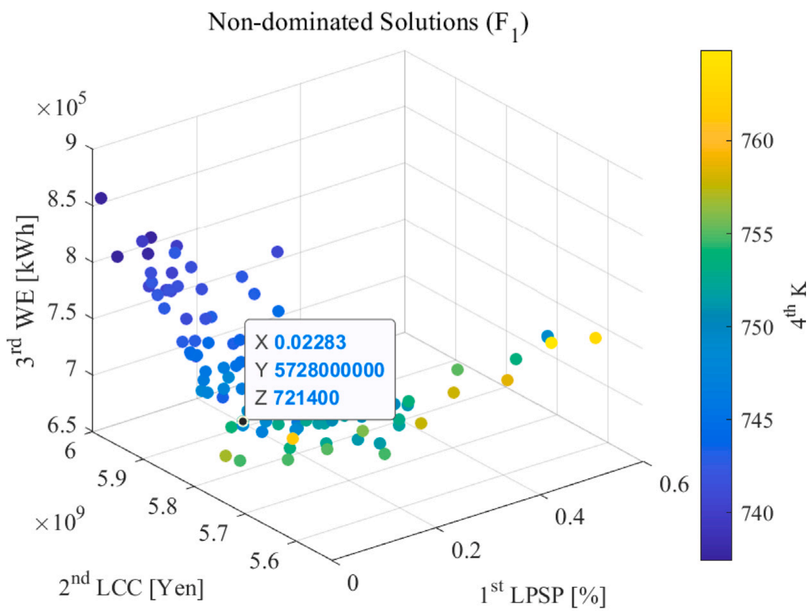


Figure 8: No EVs response.

Fig. 8. No EVs response.

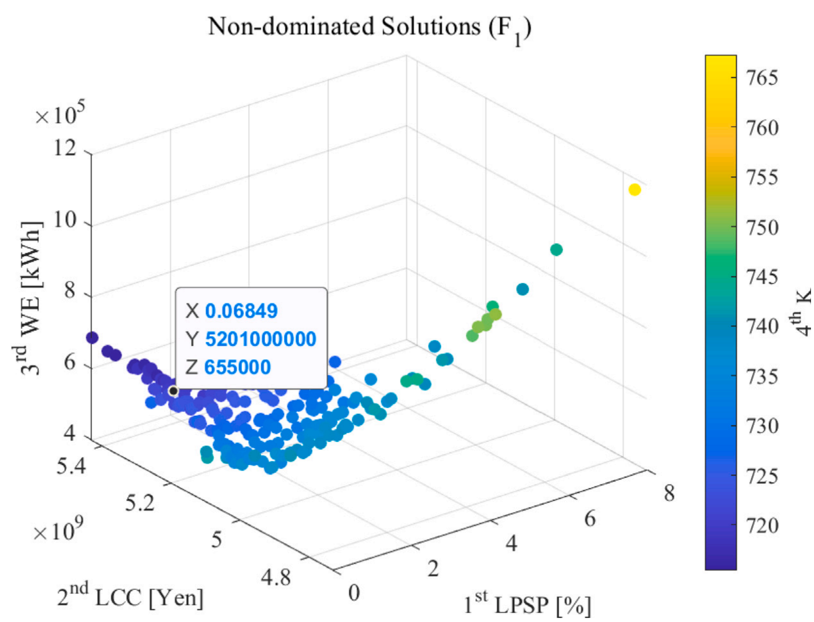


Fig. 9. 10% EVs response.

The numerical indicators of each lever show that the microgrid can guarantee power supply and has considerable economic benefits. Since the annual campus electricity bill is about 1.5×10^8 [JPY], 20 years will be 3.0×10^9 [JPY]. It can be seen from the simulation that adding EVs to the microgrid will significantly increase campus electricity usage. However, using this plan only increases the operating cost by 20 years by 50%. In terms of energy utilization, the WE of the 4 response levers respectively account for 19.02%, 17.37%, 7.98%, and 4.90% of solar power generation, which is 2.49%, 2.38%, 1.22%, and 0.78% of the total energy (P_s). Specific values can be compared using Table 5. In addition, comparing the 4 Figures also displays that $LPSP$ increases with EVs response from the numerical range of the coordinate axes. Furthermore, LCC decreases and WE decreases as well. This is because as the electric power delivered by EVs to the microgrid increases, it first reduces the electrical load of EVs, which reduces the constant power supply pre-purchased from the main grid. This also increases $LPSP$ and reduces WE. The main reason for this phenomenon is that constant power support requires a high level of stability for the load and a large difference between load peaks and valleys will make it challenging to order constant power in advance. Another way this also indirectly shows that the constant power support strategy may lead people not to have arbitrary electricity use, otherwise $LPSP$ will be higher.

Table 4 shows details of the best solutions results. As EV responsiveness increases, $LPSP$ increases, LCC decreases, WE decreases, and K is not easy to observe a significant change. CO_2 emissions are decreased, and EVs revenue is positively correlated with the increase in responsiveness. In order to quickly compare the changing relationship

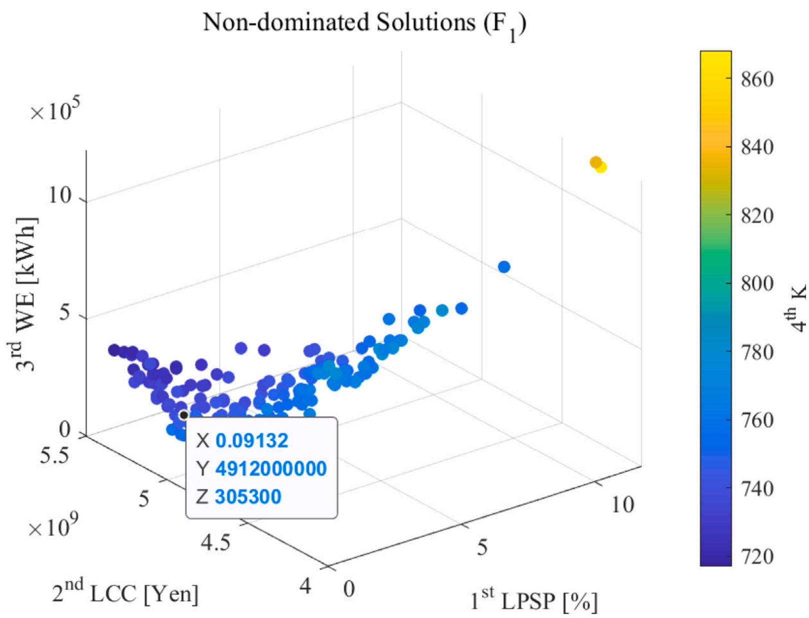


Fig. 10. 20% EVs response.

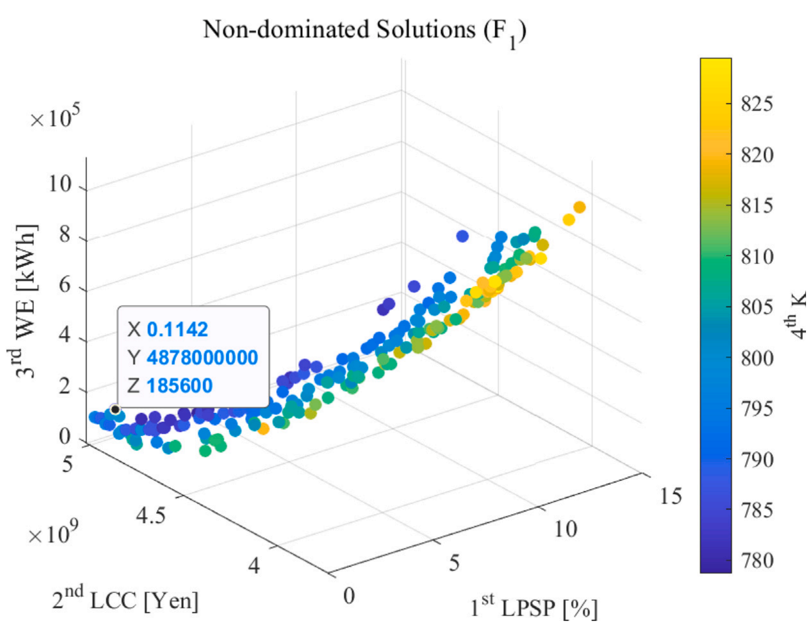


Fig. 11. 30% EVs response.

Table 4
Comparison and difference of 4 responses.

Responses	0	10%	20%	30%
$LPSP$ [%]	0.02	0.07	0.09	0.11
LCC [JPY]	5.73×10^9	5.20×10^9	4.91×10^9	4.88×10^9
WE [kWh]	7.21×10^5	6.55×10^5	3.05×10^5	1.86×10^5
K	7.52×10^2	7.21×10^2	7.38×10^2	7.84×10^2
CO_2 [tCO$_2$]	3.88×10^8	3.65×10^8	3.34×10^8	3.07×10^8
EV [JPY]	0	6.24×10^8	1.45×10^9	2.26×10^9

between the results, the proportional relationship between the corresponding variables was made. Figs. 12 and 13 show the relationship between each indicator and 4 responses level of EVs participation in the microgrid mobilization. Among the 6 indicators, $LPSP$, EVs revenue, and WE have the most apparent changes. From the grid power supply given in Table 5, it can be found that the constant power decreases as the response level of EVs increases. Therefore, it will lead to an increase in $LPSP$, and at the same time, WE is also decreasing. Another reason for the WE decrease can be seen in Table 5 that the capacity of the battery is increasing. The reason for the extra EV revenues and EV responses is that as the number of response EVs increases, less electricity will be drawn from the grid at peak power levels. Because the peak power consumption of the microgrid is mainly brought by EVs, as EVs support the rise of the microgrid level, it can not only avoid purchasing more power from the main grid but also reduce the peak-to-valley gap of the microgrid. It can be seen from Formula (17) that the more electricity ordered, the higher the price will be. At this time, the optimization algorithm tends to purchase more electricity from EVs. Significant improvements in wasted electricity could also increase storage across the grid due to an increase in the number of EVs. The number of EVs on campus reflects the number of people on campus and,

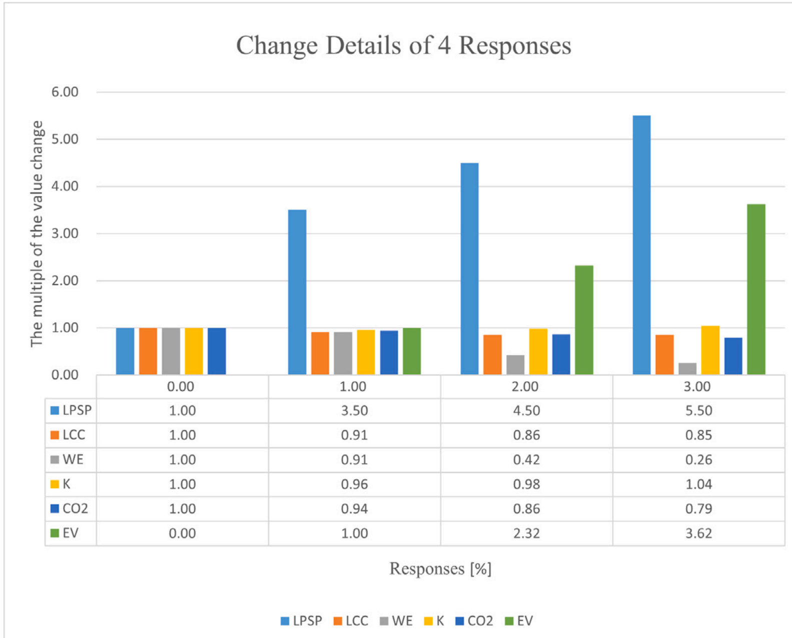


Fig. 12. Change extent details of 4 responses.

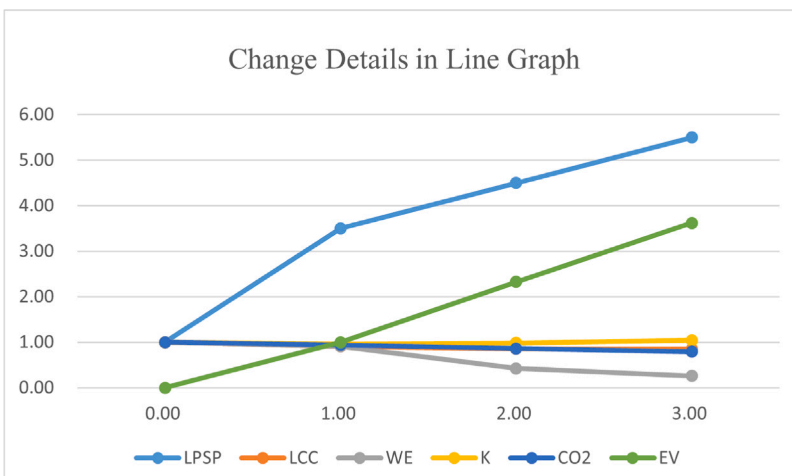


Fig. 13. Change extent details of 4 responses in the graph.

thus, the electricity consumption. The price Formula (17) is designed to allow people to conserve electricity when electricity consumption and unit price increase, thus limiting electricity consumption. As the degree of EVs responses increases, electricity consumption decreases. The electricity tariff for EVs discharging is lower than the grid tariff at peak times so a significant cost reduction can happen with V2G schemes. At the same time, EV owners can be paid a reasonable amount. The grid power consumption is the main source of CO_2 emissions in this study, and the EVs responses make the microgrid less dependent on the grid, as seen from the drop in CO_2.

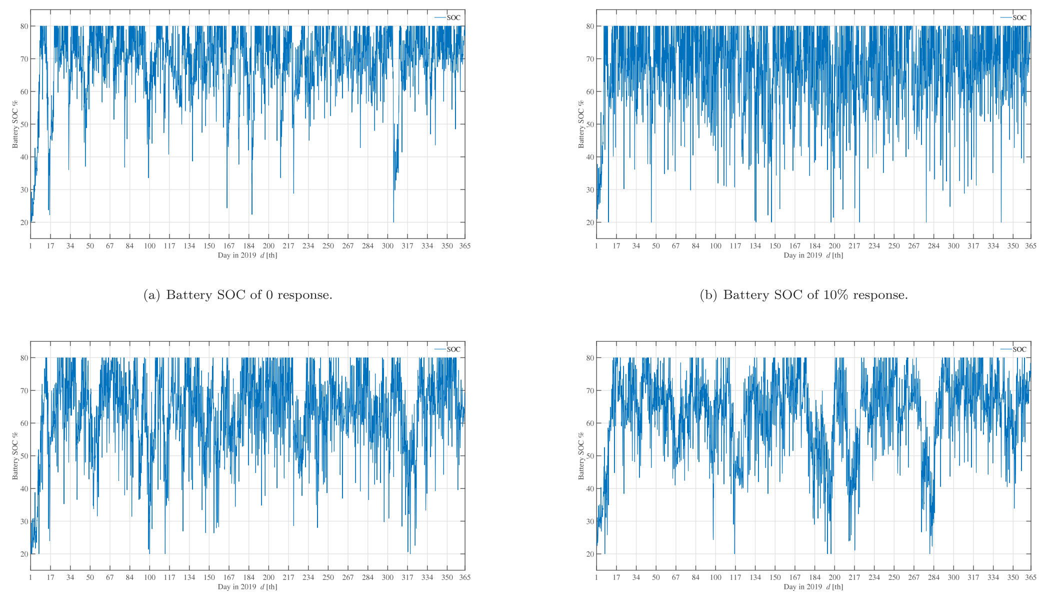
Table 5 shows the best solution for this simulation: PV capacity, battery size, and purchasing power from the grid. By comparing WE and battery size, it can be found that there is a high correlation between them. As the size of the battery increases, WE decreases. However, the 4 response levels have little correlation with PV capacity shown in Fig. 13. The two lines of LCC and CO_2 emissions basically coincide, indicating that the total cost strongly correlates with the electricity purchased from the grid.

6.2. Running simulations for 4 different responses

Fig. 14 illustrates the annual state of charge (SOC) of four different responses. To facilitate the discussion of SOC, we divide the range from 80% to 60% into a phase of sufficient power, the range from 60% to 40% into an available phase, and the range from 40% to 20% into a deficient phase. Comparing the 70% to 80% range in Fig. 14(a)(b) with Fig. 14(c)(d), it can be observed that there is a larger white area in Fig. 14(c)(d), indicating that Fig. 14(c)(d) discharge depth is deeper, while Fig. 14(a)(b) remains in the phase of sufficient power for a longer time, resulting in low utilization efficiency. This result is also reflected in Table 5, where Fig. 14(a)(b) battery size is smaller, but it purchases more electricity from the grid. As the response of EVs increases, Fig. 14(c)(d) battery spends more time in the available phase, indicating an increase in battery usage frequency. With the response of EVs, energy utilization efficiency can be improved and operating costs reduced. Table 4 shows the benefits that EVs revenue receives from the grid, highlighting the importance of encouraging EVs to respond to microgrids.

Table 5
Solution of EVs' response.

Response	Battery [kWh]	PV [Module]	Grid [kWh]	PV [kWh]	Energy Efficiency
0	1441	17341	2.52×10^7	3.79×10^6	97.51%
10%	1535	17270	2.37×10^7	3.77×10^6	97.62%
20%	2242	17505	2.12×10^7	3.82×10^6	98.78%
30%	2908	17350	2.01×10^7	3.79×10^6	99.22%



(a) Battery SOC of 0 response.

(b) Battery SOC of 10% response.

(c) Battery SOC of 20% response.

(d) Battery SOC of 30% response.

Fig. 14. Battery SOC of 4 type responses.

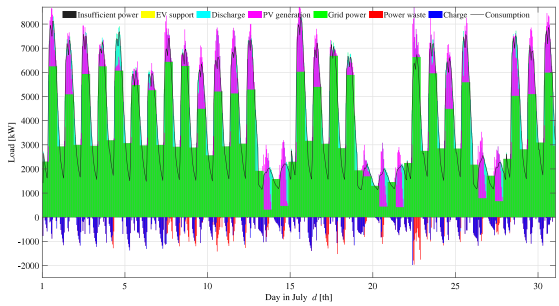
Fig. 15, showing 4 corresponding simulation situations in July. Black represents insufficient power, yellow is the discharge power by the EV, aqua is the power provided by the battery, magenta is the power supply from the PV, green is the constant power support from the main grid, red is the unused power, and blue is stored in battery power. Taking the 5th day as an example, the PV generation was very low on this day. Fig. 15(a) illustrates the strategy of using the energy stored in the battery to support daytime electricity consumption without the battery receiving any supply. In Fig. 15(b), the microgrid purchased a large amount of electricity from the main grid, and both the battery and EVs began to supply electricity to the microgrid, resulting in electricity waste. In Fig. 15(c), the amount of electricity supplied by EVs to the microgrid increased compared to Fig. 15(b), and the amount of electricity purchased from the main grid decreased, with no electricity waste observed. In Fig. 15(d), the EVs provided even more support, and no electricity was wasted. From the comparison of the 4 Figures, the red area was significantly reduced, and EV support gradually increased. However, on the 23rd day in Fig. 15(a), it is worth noting that the purchased electricity significantly exceeded the required load. The reason was that the optimization algorithm failed to give the optimal solution for that day. This also shows that predicting the daily electricity load and how much electricity to purchase is a crucial issue. It can be seen from the simulation situation that the electricity will be purchased from the grid and stored in the battery (blue part) during the low electricity consumption period of the campus and then supplied to the campus grid when the PV power supply is insufficient during the peak electricity consumption period. At the same time, when the PV power generation exceeds the consumption, the excess can be stored in the battery. In addition, the Figures also show that the electricity during peak electricity consumption is supplemented by PV. This also shows that microgrids (campuses, factories, and companies) with peak power consumption during the day are suitable for installing PV power generation systems. Moreover, as the responsiveness of EVs increases, so does the amount of electricity provided by EVs during peak campus electricity consumption periods (yellow part). This can also relieve stress during peak electricity usage.

Although the weather and consumption have significant uncertainties, from the simulation situation of one year, the proposed design can well integrate EVs and the campus microgrid and improve the utilization rate of renewable energy.

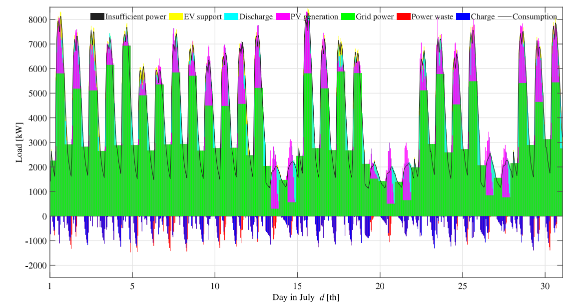
6.3. Limitations and future work

Despite the innovative proposals and findings presented in this paper, there are several limitations that should be considered:

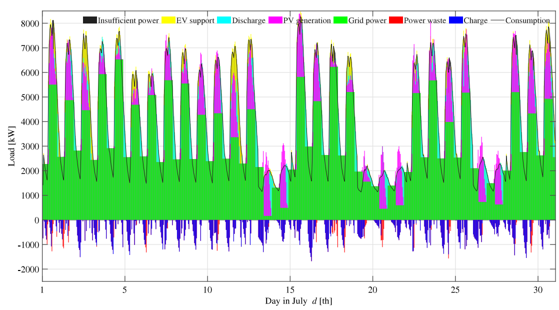
- Assumption-Based Simulations: The load profile of Electric Vehicles (EVs) is simulated using the Monte Carlo method, which is heavily dependent on the input data and assumptions made. The results obtained might not accurately reflect real-world conditions, as they are based on specific assumptions about EV usage habits, battery parameters, and other factors that might vary greatly in different settings.
- Optimization Limitations: The paper uses the NSGA-II optimization algorithm and TOPSIS method to find the best configuration for the microgrid system. While these are sophisticated methods, they have their own limitations and assumptions that may not always hold true, which could impact the validity of the results.
- Constant Power Supply Assumption: The paper proposes a constant power support strategy from the main grid. This might not be practical in real-world scenarios where power supply from the main grid can be intermittent or variable.
- Economic Viability: While the paper proposes an economical and stable operation of the microgrid with EV integration, it does not



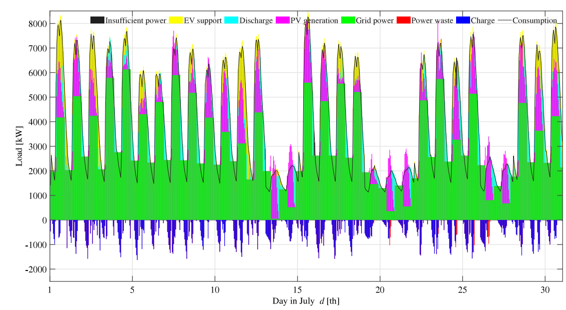
(a) July performance when the response is 0.



(b) July performance when the response is 10%.



(c) July performance when the response is 20%.



(d) July performance when the response is 30%.

Fig. 15. July performance of 4 responses.

fully discuss the initial investment and infrastructure costs that would be required to implement such a system.

- Change in Behavior and Technology: The study assumes a uniform pattern of travel between staff and students, which might change over time. Moreover, advancements in EV technology and changes in charging habits of users could render some of the paper's assumptions and results obsolete.
- Resilience and Security: The paper does not elaborate on the potential risks or threats to the system, such as cybersecurity or system resilience during extreme weather conditions.

To address the limitations identified in the study, the following suggestions could be considered for future work:

- Improved Simulations: Develop more refined simulations that incorporate a wider range of real-world data and scenarios. This could involve integrating more diverse parameters into the Monte Carlo simulations, for instance, variability in EV usage habits, different battery technologies, and diverse user behaviors.
- Expanding Optimization Techniques: Explore and compare the performance of different optimization algorithms. This could help identify the most effective method for the specific challenges of microgrid design and management.
- Real-world Power Supply Conditions: Consider the variability and intermittency of the main grid power supply in the model and investigate how these fluctuations might impact the proposed system.
- Detailed Economic Analysis: Perform a comprehensive economic feasibility study. This should account for not only the operational costs but also the upfront investment required, the payback period, and long-term financial sustainability.
- Adaptation to Behavior and Technological Changes: The model should be designed to adapt to changes in user behavior and technological advancements. Regular updates and recalibration of the model based on observed changes in these factors can help maintain its accuracy and relevance.
- Policy and Regulatory Considerations: Include a thorough examination of potential policy and regulatory hurdles. Understanding these challenges ahead of time can guide the design and implementation of the system to ensure it complies with existing regulations and is prepared for potential policy changes.
- Comprehensive Environmental Impact Assessment: Expand the environmental impact analysis to include not only CO2 emissions but also other environmental aspects related to battery production, disposal, and recycling, among others.
- Resilience and Security Measures: Incorporate resilience measures into the system design to prepare for potential risks or threats. This could include strategies for cybersecurity as well as strategies for maintaining system stability during extreme weather events or other potential disruptions.

7. Conclusion

This article suggests an optimized microgrid design for the university campus, which includes EV charging load prediction and constant power support strategies from the main grid. A detailed prediction method and an effective solution are provided to address the problem of load variation caused by EVs. Solar power generation is simulated using environmental data from Okinawa, and the power consumption and vehicle conditions at the University of the Ryukyus are analyzed. A Monte Carlo method is used to simulate the power consumption of 2500 EVs over a year, considering the probability distribution of EVs entering and exiting from the campus on workdays and holidays. A proposed solution prioritizes charging short-stay EVs based on the distribution probability of vehicle stationary time to address the problem of large peak-to-valley differences in the simulated EV load. The NSGA-II optimization algorithm is used to find the Pareto solution set for 4 annual operational scenarios with different EV response levels, and TOPSIS is used to determine the optimal combination.

The simulation results demonstrate that the proposed approach can reduce peak-to-valley values and CO_2 emissions, increase the income of EV users, and lower the operating costs of microgrid operators. The

LPSP is found to be 0.02% at response level 0, while the overall energy utilization rate is 97.51%. Although the operating cost for 20 years appears to have increased, results indicate that the charging price for EVs is cheaper, which is designed to accommodate flexible pricing for the users. Furthermore, as the level of EVs participation in microgrid response increases, except for the $LPSP$, which rises to 0.11%, other performance indicators are better. The overall energy utilization rate has increased to 99.22% with the operating cost 850 million [JPY], and EVs revenue has increased to 226 million [JPY]. This design is suitable for communities where people have regular schedules, work, study, and commute daily (sunrise work and sunset rest). This study contributes to the development of clean and efficient microgrids in sustainable cities and society and indicates that future microgrid electricity sales will be more convenient and transparent.

Since each region's situation is different, it also has some limitations that should be considered. Firstly, the study only focuses on one campus microgrid, and the findings may not directly apply to other microgrids with different characteristics. Additionally, the proposed constant power supply strategy may be difficult in some microgrid systems with limited renewable energy availability, and its effectiveness in reducing dependence on the main grid may vary depending on the specific context. Moreover, while the simulation results demonstrate the economic and steady operation of the microgrid system with EV integration, there may be practical challenges in implementing the proposed solutions in real-world scenarios, for example, the prediction accuracy of electric load. This paper provides insights when designing microgrids for integrating renewable energy sources and EVs. However, further research is needed to validate the proposed solutions in different contexts and address potential limitations. One interesting extension of this work would be how the EV-equipped campus microgrid would provide ancillary services to the grid if it participated in the electricity market. Additionally, various demand response techniques may be applied to the current model to reduce consumer electricity costs and gain other advantages.

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.

Data availability

Data will be made available on request.

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