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Research Paper

Optimal battery sizing using stochastic programming to consider building load variation and peak demand charge

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ABSTRACT

Demand charges and Time-of-use pricing are fundamental elements of contemporary electricity markets, introducing complexities in the operation of microgrids. Time-of-use pricing incentivizes energy consumption during off-peak hours, while demand charges impose fees based on peak power usage, significantly impacting electricity costs for both residential and commercial users. This research investigates the potential of battery energy storage systems to mitigate these costs by reducing demand charges and facilitating energy arbitrage. A significant challenge in determining optimal battery size lies in the uncertainties associated with building load predictions. Therefore, the study addresses critical uncertainties in load forecasts driven by climate change and occupant behavior. A novel stochastic framework is proposed that integrates these uncertainties into building load forecasts and considers demand charges in the optimization process. By employing the K-medoids clustering method in conjunction with the Bayesian information criterion, the framework achieves a remarkable reduction in computation time of 75.4% to 87.4%, while preserving essential load variability. The stochastic framework results in an overall cost reduction of 5.7%, alongside a 13.3% increase in the optimal battery size. Furthermore, implementing the proposed framework leads to a peak demand reduction of up to 25.8%.

1. Introduction

Demand charges and Time-of-use (TOU) pricing are critical components in the landscape of modern electricity markets. Their combination adds an additional layer of complexity to the operation of microgrids [1]. TOU pricing varies electricity rates based on the time of day, encouraging users to consume energy during off-peak hours when rates are lower [2]. Demand charges, on the other hand, are fees based on the maximum power drawn during a billing period, which can significantly increase electricity costs for both residential and commercial users [3].

The installation of battery energy storage systems (BESS) is anticipated to significantly mitigate these costs by lowering demand charges and leveraging energy arbitrage opportunities [4]. By storing energy during off-peak periods when rates are low and discharging it during peak periods when rates are high, BESS can effectively reduce the peak load that triggers demand charges. BESS enables consumers to engage in energy arbitrage, which involves buying electricity when prices are low and selling or using it when prices are high. This not only enhances cost savings but also contributes to a more stable and resilient energy grid [5].

Determining the optimal size of BESS is essential for maximizing economic benefits. Both undersized and oversized systems can lead to suboptimal outcomes: an undersized BESS may fail to provide the anticipated advantages, while an oversized system incurs unnecessary investment costs, ultimately diminishing overall efficiency and profitability [6]. One significant challenge in optimal BESS sizing is the inherent uncertainties associated with building load predictions [7]. According to the International Energy Agency (IEA), climate and occupant behavior are considered key drivers of building load variations [8]. Therefore, uncertainties stemming from these factors complicate the accurate estimation of energy demands [9].

Once reliable building load variations are predicted, the next challenge is to determine the optimal battery size, considering the associated uncertainties [10]. Stochastic programming emerges as a powerful tool in this context, aiming to identify a feasible policy for all possible scenarios while minimizing the objective cost function under uncertainty [11]. Ideally, this approach involves iterating through all scenarios and making balanced decisions with the option for recourse. However, the presence of high-dimensional and continuous random variables can lead to an overwhelming computational burden. As a result, it becomes necessary to reduce the scenario set to a more manageable size [7].

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Nomenclature

Abbreviations

BESS	Battery energy storage system
BIC	Bayesian information criterion
CRF	capital recovery factor
EAC	Equivalent annual cost
GCMs	Global Climate Models
IEA	International Energy Agency
Obj	objective function
O&M	operation and maintenance
SOC	state of charge
SSPs	Shared Socioeconomic Pathways
TOU	time of use pricing for electricity
XGBoost	Extreme Gradient Boosting

Symbols

m	total number of tree models
n/N	project life set N enumerated by index n
s/S	scenario set S enumerated by index s
t/T	time step set T enumerated by index t

Parameters

C_{DC}	demand charge cost
C_{Elec}	electricity cost
C_{Invest}	investment cost
$C_{O\&M}$	operation and maintenance cost
$Cost_{Bat}$	battery cost coefficient
d	discount rate

Variables

Cap_{Bat}	battery energy storage size
$E_{Bat}^{t,s}$	energy stored in battery
L	loss function
$P_{Bat-ch}^{t,s}$	charging power of battery energy storage system
$P_{Bat-dis}^{t,s}$	discharging power of battery energy storage system
P_{DC}^{s}	peak demand charge values
$P_{Grid-E}^{t,s}$	Exported electricity to grid
$P_{Grid-I}^{t,s}$	Imported electricity to grid
x	first stage variable in two-stage stochastic formulation
y	data vector
y_s	second stage variables in two-stage stochastic formulation
z_i	actual value
$\hat{z}_i$	predicted value

Greek letters

α	operation and maintenance cost coefficient
$\hat{\imath}^{2}$	ratio of exported to imported electricity price
γ	self-discharge coefficient
η	charging and discharging efficiencies
θ	vector of unknown parameters
Ω	regularization factor
τ	storage charging/discharging time

Therefore, there is a need for a study that addresses the load uncertainties caused by occupant behavior and weather conditions for optimizing BESS design. This research is essential for effectively leveraging TOU and demand charge, ultimately maximizing cost savings and optimizing energy management within microgrids.

1.1. Related work

This section provides a comprehensive review of the existing literature on optimizing BESS design under uncertainty. It includes various aspects of battery sizing, including demand charges, time-of-use tariffs, uncertainties in energy systems, and the impact of climate change and human behavior on building load.

1.1.1. Demand charges and time-of-use tariffs

Minimizing annual energy costs is crucial for consumers and utilities, particularly in the context of increasing energy demands and renewable integration. TOU tariffs and demand charges are innovative pricing strategies that encourage energy consumption during off-peak hours. Rashid et al. [12] discuss how integration of BESS can help households reduce energy costs up to 45% compared to traditional energy management methods.

Optimization methods have emerged as vital tools for enhancing the effectiveness of battery management strategies. Sharma et al. [13] presented an optimization problem to minimize annual energy costs while exploring various battery management strategies, finding that using a TOU tariff with demand charges can lead to significant savings and a 35% reduction in peak load on the distribution network. Koolman et al. [14] propose a multi-objective optimization framework that utilizes BESS to perform demand charge management through peak shaving. The study employs genetic algorithms to optimize the sizing of BESS and grid-tie systems, evaluating their effectiveness in reducing demand charges while minimizing charging delays for electric vehicle users. The results demonstrate that appropriate BESS sizing can lead to reducing demand charges by 60–70% in high tariff areas like New York City and by 40–60% in Switzerland, depending on charging delays.

A significant limitation of many optimization frameworks is their reliance on fixed load profiles, which inadequately reflect the dynamic nature of actual energy consumption. Wang et al. [15] underscore the pressing need for comprehensive research to investigate how these uncertainties impact the economic optimization of microgrids. Langenmayr et al. [16] present a central planner-decentral operator approach to schedule local electricity flows and limit peak demand for a residential Photovoltaic (PV)-battery system with an electric vehicle. This study addresses uncertainties associated with load, PV generation, and electric vehicle charging patterns. A two-stage optimization framework is developed to limit the daily peak demand of the decentral operator's system by optimizing the battery schedule. The approach achieved a peak demand reduction of 17% to 52% over a week by optimizing reserve capacity and relaxation factors.

1.1.2. Uncertainties

Optimal design is challenging due to the numerous uncertainties affecting the design problem [17]. These uncertainties include weather conditions, renewable energy generation, market prices, regulatory frameworks, consumer behavior, and technical characteristics. They can be classified into two categories: epistemic and aleatory uncertainties. Epistemic uncertainty arises from a lack of knowledge regarding specific phenomena and mechanisms, while aleatory uncertainty is a result of the inherent variability found in observable data [18]. Ignoring these uncertainties can lead to unrealistic models and inaccurate predictions, ultimately resulting in suboptimal decision-making and increased life-cycle total costs. Therefore, considering uncertainty modeling in the optimization processes is essential to enhance reliability of energy systems. By addressing these uncertainties, energy managers can develop strategies that not only optimize resource allocation and minimize costs but also ensure system resilience, sustainability, and adaptability to changing conditions [17].

Li et al. [18] present a planning optimization method for hybrid renewable energy systems (HRES) designed for remote rural and island regions, where data scarcity poses significant challenges. This paper considers both epistemic and aleatory uncertainties and utilizes credibility theory to generate planning scenarios based on limited available information. The approach involves developing scenario generation models to create typical and extreme scenarios for renewable energy and load demands. The results indicate that incorporating both types of uncertainties leads to better reliability and lower costs compared to traditional methods. The paper reduces the levelized cost of energy by 33% compared to the deterministic method.

Among different uncertainty sources, the fluctuations in energy prices and the carbon footprint of energy grids are heavily influenced by political and economic factors [19], which are beyond the scope of this study. These uncertainties are typically addressed using sensitivity analysis methods, which are essential for understanding how they affect the performance and optimization of energy systems [20].

Throughout the entire life cycle, building loads keep changing. Le et al. [21] reveal significant uncertainties in building energy demand, with peak loads showing a 24% relative deviation and average loads exhibiting a more pronounced 75% deviation across 1040 scenarios. To effectively account for uncertainties in building load profiles, Zhou et al. [22] and Yang et al. [23] have employed the Normal and Bivariate normal probability distribution functions, respectively. However, determining the probability distribution of uncertain parameters remains a challenge [23]. The main limitation of relevant studies is the reliance on historical data for scenario generation, which may not capture all potential future uncertainties, potentially affecting the robustness of the optimization results.

1.1.3. Climate-human driven load uncertainties

The concern about climate change leads to study the impact of climate change on building energy performance. Jiang et al. [24] and Chan [25] focus on generating future weather data that is crucial for predicting building energy loads under climate change scenarios. By using the morphing method, they adjust current weather data to reflect projected future conditions, based on four IPCC greenhouse gas emission scenarios. The findings highlight the necessity of adapting building designs and energy strategies to mitigate the effects of future climate conditions.

Occupancy behavior is also a major contributor to the uncertainty of building load. Jeksen et al. [26] show that varying building operational patterns can result in up to a 60% increase in building electric demand, renewable energy capacity, and capital costs of the systems. The data-driven analysis of actual buildings showed even larger spreads in electric demand compared to the simulated scenarios, highlighting the challenge of predicting building performance using limited data. The variability in electric demand directly translated to large differences in the techno-economic performance of the PV systems, with up to 60 % differences in the present value of nets between different occupancy profiles.

Hu and Xiao [27] also introduced a survey-based method to quantify uncertainty in the aggregate energy flexibility of residential building clusters. It features a data-driven stochastic occupancy model, which captures diverse occupancy patterns influenced by factors such as household size and day of the week. An aggregation analysis quantifies energy flexibility across different building archetypes and occupancy scenarios. The authors propose performance indices for assessing energy flexibility using Monte Carlo sampling. Notably, while energy flexibility remained stable at approximately 12.40% as cluster size increased, weekly uncertainty significantly decreased from 19.12% for 8 households to just 0.74% for 5,120 households. Considering uncertainties related to weather conditions is essential for achieving accurate and reliable load variation predictions.

Wu and Zhong [28] examine uncertainties in community energy supply and demand due to variable climate conditions and human behaviors. It models these uncertainties separately, generating 20 climate scenarios paired with various human behavior scenarios for different community sizes. Future climate conditions are synthesized using temperature weight coefficients from regional climate models to create datasets for typical, extreme warm, and extreme cold years. Human behavior uncertainty is addressed by sampling from probability distributions based on urban statistical data. This approach reveals that cities like Toronto may experience a 5.82% increase in annual energy demand under a 3.5 °C climate period, while the hybrid solar-wind strategy can achieve 10–20% higher energy self-production rates.

Xue et al. [29] also address uncertainties related to weather and occupant behavior by identifying key parameters that influence building loads, including outdoor dry bulb temperature, relative humidity, and indoor heat gains from occupants, equipment, and lighting. The study employs actual meteorological data to capture the variability in weather conditions and assumes that indoor heat gain and solar heat gain coefficients follow a normal distribution. By integrating these uncertainties into a stochastic optimization framework, the research facilitates the selection of scenarios with load guarantee rates ranging from 70 % to 90 %, ensuring that the energy system configuration effectively addresses the impacts of these uncertainties on heating and cooling demands.

Perera et al. [9] introduced a computational platform that combines climate models, building simulations, Generative Adversarial Networks (GANs), and energy system models to quantify the compound impact of future climate variations and human behavior on energy demand in the building sector. The results reveal that the uncertainties brought by climate significantly influence building cooling and heating demand, and the compound impacts increase the net present value of the energy system by 28 % and the levelized costs up to 12 %. The study emphasizes the importance of considering both climate and human system uncertainties during the energy system design process to improve the climate resilience of cities.

1.1.4. Stochastic optimization

Stochastic optimization involves the use of probabilistic models to account for uncertainty. This method allows for the incorporation of various scenarios based on the likelihood of different outcomes. One prominent approach is the use of two-stage stochastic programming, which allows for the incorporation of uncertainties in energy carrier prices, demand profiles, and renewable generation patterns. The first stage optimizes the investment portfolio and design of the energy system, while the second stage minimizes operational costs amidst uncertainties [30].

Zheng et al. [7] developed a two-stage stochastic programming model aimed at optimizing the design and operation of residential PV-battery systems. It addresses uncertainties related to load demand and PV production, proposing an integrated framework that combines investment sizing and operational strategies. The model incorporates a multi-year financial analysis to evaluate cash flows and net benefits, considering factors such as battery aging and varying electricity tariffs. The effectiveness of the framework is validated through simulations based on realistic data. The study relies on some specific scenarios for addressing uncertainties of demand and PV production, which may not capture all real-world variations.

Bagheri et al. [31] also proposed a two-stage stochastic programming model for the design and operation of a microgrid including PV-battery system. The paper employs GANs to generate scenarios for uncertain parameters and uses the k-medoids method for scenario reduction to manage computational complexity. The findings indicate that the optimized microgrid configuration achieves a remarkable reduction in operational costs of approximately 82.5%, highlighting the benefits of integrating PV and battery systems.

Zhang et al. [10] utilize a combination of Monte Carlo methods and probability techniques to characterize uncertainties in building load forecasts, which include variations in heating, cooling, and electricity demands. By generating multiple load scenarios that reflect these uncertainties, the study aims to enhance the robustness of energy system designs. Previous studies have not addressed the effects of scenario reduction on the objective function, optimal battery capacity, and computation time, which are crucial factors for achieving efficient energy system design.

Perera et al. [9] address the uncertainties in energy planning caused by climate change and human behavior. This study also involves using GANs to create various energy demand scenarios from climate data, which are then applied in a stochastic optimization model for better energy system design. The study stresses the need to integrate climate and human uncertainties to enhance the resilience and efficiency of urban energy systems, advocating for comprehensive approaches in energy planning to adapt to future changes. However, in this study, the exclusion of demand charges may result in a significant underestimation of the actual cost of energy consumption.

1.2. Research gap

The existing literature reveals significant gaps that this research aims to address:

- There is a notable gap in addressing the complexities of building load predictions that account for the effects of climate change and occupant behavior patterns. Most current literature fails to incorporate these critical factors into a comprehensive model and heavily relies on historical data for optimizing battery size.
- The implications of peak demand charges on battery sizing are overlooked, leading to sub-optimal energy storage solutions.

This research aims to bridge these identified gaps by developing a novel stochastic framework.

1.3. Scope and objectives

The primary objective of this investigation is to develop a comprehensive framework for determining the optimal BESS capacity under uncertainty. This study integrates the impacts of climate change and occupant behavior patterns into building load predictions. Furthermore, it considers the demand charges in the optimization process, ensuring that the resulting battery storage solutions are not only technically efficient but also economically beneficial. The research also examines the influences of battery costs, demand charges, and scenario reduction on the overall optimization framework. In summary, this paper makes the following key contributions:

- Building load prediction: It investigates the various factors that influence energy load profiles in buildings, including weather patterns and occupant behaviors.
- Stochastic optimization: A stochastic optimization model to minimize total annual cost is developed that accommodates uncertainties in energy demand and identifies the optimal battery size.
- Demand Charges: The study analyzes the effects of peak demand charges on battery design and energy management strategies, highlighting their significance in the economic assessment of energy storage solutions.

2. Method

The overall methodology of this paper is illustrated in Fig. 1. The first step involves characterizing the uncertainties related to weather conditions and occupant behavior, which is essential for generating the scenarios needed for stochastic optimization. In the second step, a load forecasting model is developed using historical data. Finally, the last step entails the development of a stochastic optimization model aimed at identifying the optimal design, operational strategies, and associated costs.

Fig. 2 provides a detailed explanation of the method for generating uncertain load scenarios in steps 1 and 2. The scenarios produced in the first step serve as inputs to the load prediction model, facilitating the generation of load variations that reflect fluctuations in both weather conditions over the project's lifetime and occupant behavior. While existing literature typically employs daily representative periods for load scenarios [32], this study adopts a monthly approach to more effectively account for demand charges and to capture all hourly variations within each month. To enhance computational efficiency, the optimal number of scenarios that can represent the entire scenario set is determined. The Bayesian information criterion (BIC) is utilized to identify this optimal number, while K-Medoids is employed for scenario reduction. This reduction process ensures that the model remains manageable while preserving essential information. The resulting reduced scenarios each possess distinct probabilities and are subsequently integrated into the stochastic optimization model.

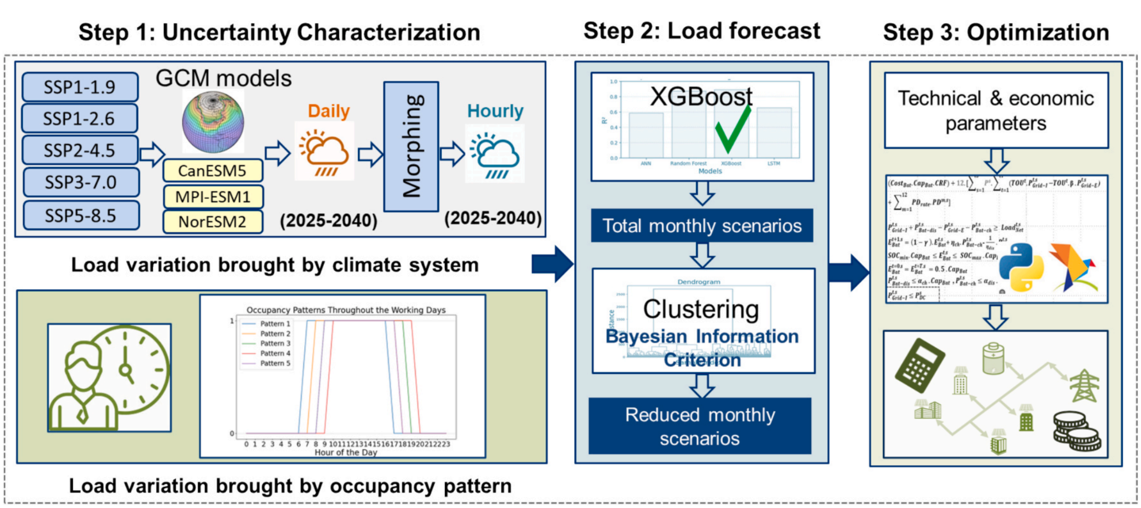

Fig. 1. Illustration of the overall methodology employed in the current study. 1) Uncertainties related to weather conditions and occupant behavior are characterized by generating scenarios for stochastic optimization. 2) A load forecasting model is developed using historical data, which incorporates these scenarios to produce monthly load variations. The scenarios are reduced for computational efficiency using the Bayesian information criterion. 3) A stochastic optimization model is created to identify the optimal design, operational strategies, and associated costs for the energy system as well as computation time.

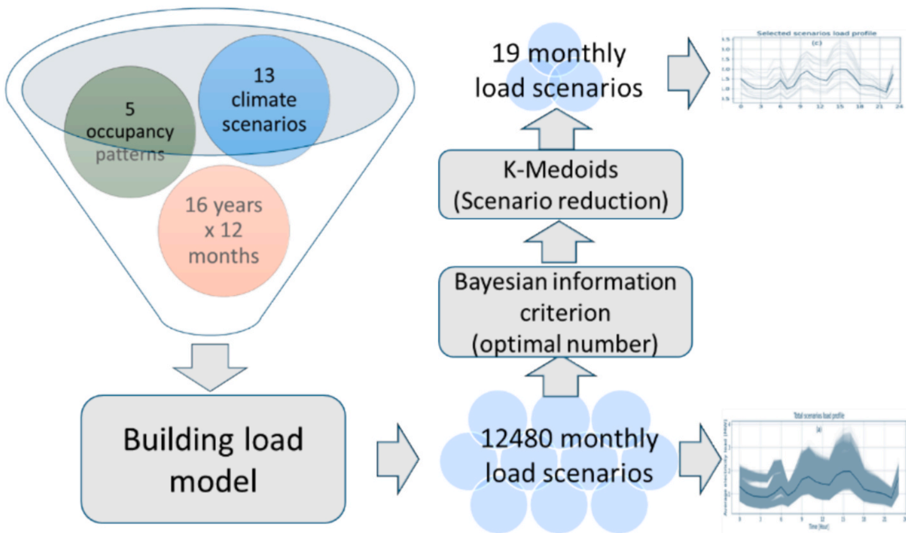

Fig. 2. Method for generating uncertain load scenarios, utilizing a monthly approach to effectively capture hourly variations and demand charges. The optimal number of scenarios is identified using the bayesian information criterion, while K-Medoids is employed for scenario reduction.

2.1. Step 1: Uncertainty characterization

Characterizing uncertainties is essential for predicting building loads. The constantly changing weather conditions and occupant behaviors are the two major sources for the uncertainties of building load [9], which are discussed in detail below.

2.1.1. Climate-driven uncertainty

As illustrated in Fig. 1, this study characterizes weather condition uncertainty by utilizing multiple future climate projections sourced from database [33] for the period of 2025 to 2040. This open-source database predicts future climate conditions by analysing outputs from three distinct global climate models (GCMs), each based on different input assumptions. GCMs are sophisticated mathematical representations of planetary atmospheres and oceans, designed to simulate the impacts of climate change, and are categorized by their country of origin, grid resolution, and carbon emission scenarios [24].

The coupled model intercomparison project phase 6 (CMIP6) [33] introduces future climate change scenarios that integrate shared socio-economic pathways (SSPs) [34] and representative concentration pathways (RCPs) [35]. This project forecasts future climate conditions across diverse scenarios, utilizing multiple GCMs [36]. Further details about these climate scenarios can be found in Appendix A.

This study considers weather profiles derived from 13 available future climate change scenarios of CMIP6 over a 16-year period, covering the time horizon from 2025 to 2040. This results in a total of 2496 monthly weather scenarios. The weather projections including ambient temperature and precipitation are available at a daily temporal resolution. To convert these daily values into hourly-resolved time series, morphing technique is employed based on [37], which adjusts the daily data to reflect hourly variations based on historical patterns [38].

The morphing method [39] transforms daily weather data into hourly data using historical data as a reference. This technique combines present-day observations with future projections to create time series that reflect future climate conditions while maintaining realistic weather sequences. Historical hourly weather data for 2024 [38] is analyzed to calculate mean hourly temperatures and their ratios. These ratios are applied to adjust daily weather scenarios, ensuring realistic variations in hourly temperatures. This adjustment ensures that the resulting hourly temperatures maintain the realistic variations observed in historical weather patterns.

In summary, quantifying climate-driven uncertainty involves analyzing the variations in temperature and precipitation predicted by different GCMs and climate scenarios. This assessment is essential for understanding the potential building load scenarios in the future.

2.1.2. Occupancy-driven uncertainty

Occupant behaviors are inherently uncertain and can change over time, significantly impacting building energy demand. To enhance the prediction of energy consumption and evaluate energy management strategies, occupancy models are created and integrated with building energy modeling tools. These models are categorized into three types based on the level of occupancy including occupancy status, the number of occupants and tracking the location of occupants [27]. By analyzing the data provided by the industry partner and utilizing the method proposed by Hu and Xiao [27], occupancy pattern scenarios are identified. Due to the similarities among the occupancy scenarios, these patterns were consolidated to create a more manageable number of scenarios and integrated into the load prediction model. Consequently, a total of 12,480 monthly load scenarios are generated for analysis based on 2496 monthly weather scenarios in combination with 5 occupant behavior scenarios.

2.2. Step 2: Load forecast

In order to generate building load scenarios, it is essential to develop a model that takes into account inputs such as weather conditions, occupancy schedules, hour of the day, day of the week, and month of the year. Extreme gradient boosting (XGBoost) is a highly regarded machine learning algorithm celebrated for its efficiency and predictive accuracy. As an ensemble method, XGBoost combines multiple weak learners, primarily decision trees, to create a robust predictive model through the process of gradient boosting. This technique sequentially trains models, focusing on correcting the errors of previous ones, which enhances overall performance. XGBoost includes regularization techniques to mitigate overfitting, ensuring high accuracy across various tasks, including regression and classification. It is widely utilized for both building-scale and city-scale load forecasting [1]. In XGBoost, a new learner, specifically a decision tree, is generated to fit the residual of the preceding trees through a process of continuous iteration. The final result is obtained by summing these learners, as illustrated below:

$$\hat{z}_i^{(m)} = \sum_{k=1}^{m} f_k(x_i) = \hat{z}_i^{(m-1)} + f_m(x_i) \tag{1}$$

Here, $\hat{z}_i^{(m)}$ represents the final tree model, while $\hat{z}_i^{(m-1)}$ denotes the previously generated tree model. The term $f_m(x_i)$ refers to the newly generated tree model, and m indicates the total number of base tree models.

In accordance with the principles of XGBoost, each new tree is specifically designed to reduce prediction error, which typically results in enhanced prediction performance. Consequently, the challenge of identifying the optimal algorithm transforms into the task of finding a new learner capable of minimizing the loss function, as illustrated in Eq. (2).

$$Obj^{(m)} = \sum_{i=1}^{m} L\left(z_i, \widehat{z}_i^{(m)}\right) + \sum_{i=1}^{m} \Omega(f_i) \tag{2}$$

In this context, z_i represents the actual value, while $\widehat{z}_i^{(m)}$ denotes the predicted value. The term $L\left(z_i, \widehat{z}_i^{(m)}\right)$ refers to the loss function, and $\Omega(f_i)$ is the regularization term, which serves to prevent overfitting and enhance the accuracy of model predictions. The XGBoost algorithm can accept both continuous and discrete variables as input; however, the output variable must be discrete, including binary variables [40]. The dataset was divided into training and testing sets, with 80% of the data designated for training and 20 % reserved for testing. The model demonstrated impressive predictive performance, achieving an R^2 value of 0.89. The features utilized in this algorithm are detailed in Table 1.

2.2.1. Clustering for scenario reduction

The objective of clustering is to identify typical scenarios to be used in stochastic programming to accelerate computing. K-Medoids approach is employed to identify representative months and their probabilities from the dataset of monthly load profiles. The number of typical scenarios is obtained using BIC. The K-Medoids algorithm minimizes the sum of dissimilarities between the data points and their corresponding medoids, defined mathematically as:

$$\sum_{g_m \in g_d} min_{g_n \notin g_d} D(g_m, g_n) \tag{3}$$

Here, (g_m) and (g_n) are two scenarios from a larger set (G), while (g_d) represents a reduced set containing (k) scenarios. The distance $(D(g_m, g_n))$ measures how similar or different these scenarios are. Medoids are the most representative points in the scenario set, chosen for their low average dissimilarity to other scenarios. Each scenario is assigned to the nearest medoid cluster. During the process, a non-medoid scenario is evaluated as a potential replacement for an existing medoid, and the associated costs are calculated. This iterative approach continues until the most representative medoids are identified for each cluster [31].

2.2.2. Optimal number of clusters

The BIC is a widely utilized metric for identifying the optimal model and determining the optimal number of clusters in a dataset. When comparing models with varying numbers of clusters, the model that exhibits the minimum BIC value is considered the optimal choice. Conversely, in cases where the BIC values are negative, the model with the maximum BIC value is considered optimal [41]. Let $p(y|\theta_k)$ represent the probability density function, also known as the likelihood function, of the data vector (y). In this context, (θ_k) denotes the vector of all unknown parameters associated with the k th candidate model. The BIC score for a model of order k is given as [42]:

$$BIC(k) = -2\ln p(y|\widehat{\theta}_k) + k.lnN \tag{4}$$

where $k.lnN$ is the penalty term, which compensates for over parameterization. In this research, the BIC method is employed to significantly reduce the number of scenarios, enhancing the feasibility of the problem.

Table 1
Hyperparameter and feature configuration of XGboost algorithm.

Parameter	Value
Covariates	Temperature, Precipitation, Hour of the day, Day of the month, Month of the year, Day of the week
epochs	100
Learning rate	0.3
Minimum child weight	1
maximum depth	6
gamma	0
subsample	1
colsample bytree	1
regularization alpha	0

2.3. Step 3: Stochastic optimization model

The developed stochastic optimization framework is presented in this section, which returns optimal sizing of BESS and hourly energy flows considering different scenarios. This framework aims to minimize the total equivalent annual cost of the system while satisfying uncertain load profiles. The input data of the framework includes hourly load profiles of reduced monthly scenarios as well as techno-economic information. Techno-economic data is assumed to be constant throughout the lifetime of the system. The general two-stage stochastic programming model is described as follows [43]:

$$MinObj = c^T.x + \sum_{s \in S} p_s.q_s^T.y_s \tag{5}$$

$$A.x = b \tag{6}$$

$$W_s.y_s + D_s x \le h_s, \forall s \in S \tag{7}$$

$$x \in X, y_s \in Y \tag{8}$$

where X and Y are used to denote first stage (system design and sizing) and second stage (system operation) variables in the two-stage stochastic formulation, respectively. Moreover, p_s represents the probability of each scenario s. The following is a detailed explanation of the optimization framework based on [44] in terms of input data, decision variables, constraints, objective functions, and implemented approach for multi-objective optimization.

2.3.1. Decision variables

The values of the following decision variables are the outputs of optimization problem:

1) The size of the energy storage system (Cap_{Bat})
2) The charging and discharging power of energy storage system $(P^{t,s}_{Bat-ch}, P^{t,s}_{Bat-dis})$
3) The energy stored in battery system $(E^{t,s}_{Bat})$
4) The imported and exported electricity $(P^{t,s}_{Grid-I}, P^{t,s}_{Grid-E})$
5) The peak demand charge values (P^{s}_{DC})

2.3.2. Objective function

The objective function of the developed optimization framework is the equivalent annual cost (EAC) of the system, given by the investment cost (C_{Invest}), electricity cost (C_{Elec}), operation and maintenance cost $(C_{O\&M})$ and demand charge cost (C_{DC}). The demand charge term is included in the utility bill and is calculated using a fixed marginal rate applied to the maximum power consumption during the billing cycle. The EAC is expressed as:

$$minTotalcost : EAC = C_{Invest} + C_{Elec} + C_{O\&M} + C_{DC} \tag{9}$$

$$C_{Invest} = Cost_{Bat}.Cap_{Bat}.CRF \tag{10}$$

$$C_{Elec} = 12.\left(\sum_{s=1}^{S} P^s.\sum_{t=1}^{T}\left(TOU^t.P_{Grid-I}^{t,s} - TOU^t.\beta\ .P_{Grid-E}^{t,s}\right)\right) \quad (11)$$

$$C_{O\&M} = \alpha_{O\&M}.(Cost_{Bat}.Cap_{Bat}.CRF) \quad (12)$$

$$C_{DC} = 12.\left(\sum_{s=1}^{S} P^s.PD_{rate}.P_{DC}^s\right) \quad (13)$$

$$CRF = \frac{d.(1+d)^n}{(1+d)^n - 1} \quad (14)$$

where $Cost_{Bat}$ represents the cost coefficient, while CRF denotes the capital recovery factor. d and n correspond to the discount rate and project lifetime, respectively. P^s signifies the probability of each scenario s, while S indicates the total number of scenarios. The term TOU^t refers to the time-of-use pricing for electricity and β indicates the ratio of exported to imported electricity price. The operation-maintenance cost coefficient is represented by $\alpha_{O\&M}$. PD_{rate} denotes the peak demand charge rate. Additionally, t represents the time step, while T indicates the total number of time steps within a monthly scenario.

2.3.3. Optimization constraints

Optimization constraints can be categorized into two main types. The first category includes energy balance equations, which are fundamental to ensuring the system's overall energy integrity. The second category includes constraints that pertain to the performance of BESS. These constraints are crucial for accurately modeling and optimizing the energy system.

Eq. (15) ensures energy balance by stipulating that the energy supplied must meet the energy demand across various time-steps and scenarios. Furthermore, Eq. (16) addresses the peak demand charge constraint by ensuring that the amount of imported electricity at each hourly time step remains below a specified maximum during each billing cycle.

$$P_{Grid-I}^{t,s} + P_{Bat-dis}^{t,s} - P_{Grid-E}^{t,s} - P_{Bat-ch}^{t,s} \geq Load_{Net}^{t,s} \quad (15)$$

$$P_{Grid-I}^{t,s} \leq P_{DC}^{s} \quad (16)$$

The details of the second category are explained as follows. Eq. (17) incorporates the battery model, which regulates the behavior and performance of the BESS. Eq. (18) establishes limits on energy storage, defining both the lower and upper bounds, while Eq. (19) ensures that the battery's storage level at the initial time step is equal to its storage level at the final time step. Finally, Eqs. (20) and (21) set upper limits on the charging and discharging rates of the battery.

$$E_{Bat}^{t+1,s} = (1-\gamma).E_{Bat}^{t,s} + \eta_{ch}.P_{Bat-ch}^{t,s} - \frac{1}{\eta_{dis}}.P_{Bat-ch}^{t,s} \quad (17)$$

$$SOC_{min}.Cap_{Bat} \leq E_{Bat}^{t,s} \leq SOC_{max}.Cap_{Bat} \quad (18)$$

$$E_{Bat}^{t=0,s} = E_{Bat}^{t=T,s} = 0.5.Cap_{Bat} \quad (19)$$

$$P_{Bat-dis}^{t,s} \leq \frac{Cap_{Bat}}{\tau} \quad (20)$$

$$P_{Bat-ch}^{t,s} \leq \frac{Cap_{Bat}}{\tau} \quad (21)$$

where γ represents the self-discharge parameter, and η_{ch} and η_{dis} denote the charging and discharging efficiencies, respectively. Additionally, τ indicates the time required to fully charge or discharge the BESS.

3. Results

This section is structured into four parts. Section 3.1 provides an overview of the case study. Section 3.2 presents the monthly load scenarios derived from uncertainty characterization, along with the results of the scenario reduction process. In Section 3.3, the outcomes of design and operation optimization are discussed. Finally, Section 3.4 analyzes the impact of demand charges and battery price on the optimization results.

3.1. Case study

The developed methodology has been implemented to effectively address the electricity demand of an industrial park center located in Changsha, China. The microgrid under investigation is depicted in Fig. 3. As illustrated in Fig. 4, the hourly load profile for this industrial center in 2024 provides a comprehensive overview of electricity consumption patterns throughout the year. The load data for 2024 serves as the baseline for both load prediction and the subsequent analysis of the stochastic solution results. The total annual heating load is estimated to be approximately 12.41 GWh, indicating the significant energy demand of the facility. The hourly weather data for the same year is obtained from [38]. This data was further enhanced by incorporating hourly, weekly, and monthly patterns, which were integrated into the input dataset. Table 2 presents a detailed list of the technology-related parameters utilized within the optimization framework, along with their corresponding sources. Table 3 illustrates the diverse occupancy patterns extracted from historical data on occupant presence times during working days within the industrial center.

3.2. Load prediction

Fig. 5(a) illustrates the average hourly load profiles of each monthly scenario, highlighting the variability in these profiles. In this study, the average load varies from 1.2 MW to 1.5 MW, resulting in a deviation of 16.6%. In contrast, the peak load ranges from 3.4 MW to 5.5 MW, leading to a more significant deviation of 38.5%. Given the substantial computational demands associated with integrating 12,480 monthly scenarios into the optimization model, the K-medoids clustering method is employed to effectively reduce the scenario set. To ascertain the optimal number of reduced scenarios, the BIC method is utilized. As indicated in Fig. 5(b), the analysis demonstrates that the optimal number of clusters for scenario reduction is 19, as this configuration yields the lowest BIC score. Furthermore, Fig. 5(c) presents the average hourly load profiles of selected scenarios identified through this analytical process.

3.3. Optimization results

In this section, the results obtained from the stochastic optimization approach are presented utilizing 19 monthly scenarios with different probabilities, as detailed in Table 4. The analysis reveals that the optimal battery size is 14.15 MWh, accompanied by an optimal annual cost of 9.84 million CNY, with a computational runtime of 118.3 seconds. Notably, there is a 13.29% increase in the BESS size and a 5.66% decrease in the equivalent annual cost compared to the optimal results obtained from the deterministic solution based on 2024 load data shown in Fig. 4. This is achieved through improved energy management and reduced peak demand charges. Achieving a lower annual cost with a larger battery size demonstrates the advantages of using stochastic models in energy storage optimization, allowing for strategic resource allocation without the need for costly hardware upgrades, such as replacing chillers. These findings indicate that the proposed method not only yields a robust and lower-cost solution but also achieves a significant reduction in computational time through the application of scenario reduction techniques.

Fig. 6 illustrates the operational decision variables for the first day of each scenario. Notably, between 6:00 pm and 10:00 pm, the electricity price reaches its peak, during which there is no charging or grid import observed. Instead, the system discharges energy from the battery and

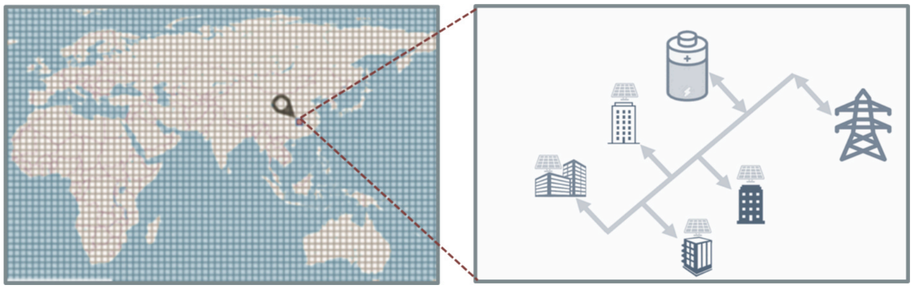

Fig. 3. Schematic representation of the investigated energy system located in Changsha, China.

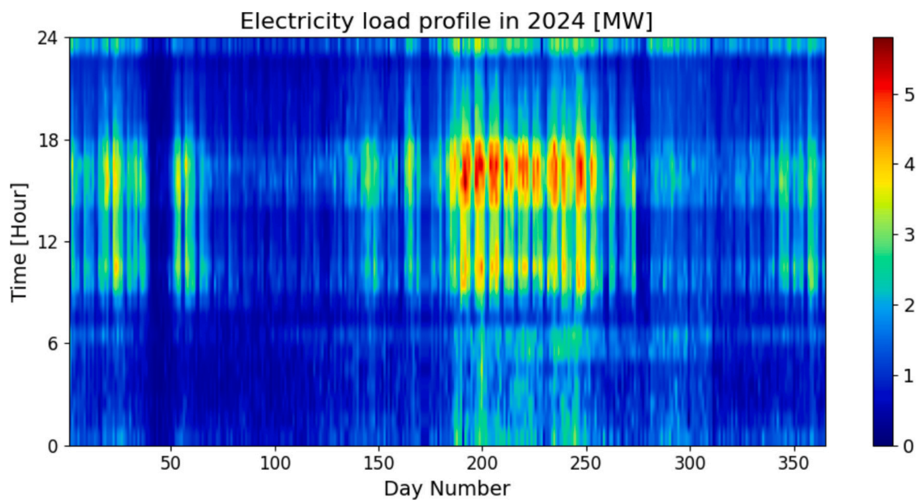

Fig. 4. Electricity demand of an industrial park center located in Changsha, China.

Table 2
Technical and economic parameters used in the optimization framework.

Parameter	Explanation	Unit	Value
SOC_{min}	Minimum state of charge	%	20
SOC_{max}	Maximum state of charge	%	80
$Cost_{Bat}$	Battery cost	CNY/kWh	890
η_{ch}/η_{dis}	Charging/Discharging efficiency	%	90
γ	Battery self-discharge	%	0.54
τ	Time required to fully charge or discharge the storage	hour	4
N	Project lifetime	years	15
î²	Selling/buying electricity price ratio	%	60
PD_{rate}	Peak demand charge rate	CNY/kW	33.8
d	Discount rate	%	10

Table 3
Different occupancy patterns of the industrial park center during working days based on historical data.

Occupancy patterns	Working time in weekdays
Pattern 1	7:00–17:00
Pattern 2	8:00–18:00
Pattern 3	9:00–19:00
Pattern 4	10:00–20:00
Pattern 5	9:00–18:00

exports it to the grid. Conversely, from 1:00 am to 7:00 am, when electricity prices are at their lowest, the system engages in charging the battery and importing energy from the grid. This strategy results in the highest state of charge for the battery during this period.

3.4. Demand charge analysis

In this section, the optimization results are analyzed regarding the peak demand charge rate. Fig. 7(a) indicates a clear correlation between the peak demand charge rate and optimal annual costs; specifically, as the peak demand charge increases, the optimal annual costs also rise. The relationship between peak demand charges and battery capacity is more nuanced. Notably, when the peak demand charge is below 20 CNY/kW, an increase in this charge leads to a higher optimal battery capacity. This is because, at lower charge rates, discharging energy from the battery becomes more economical than purchasing electricity from the grid. Conversely, when the peak demand charge exceeds 20 CNY/kW, the optimal battery capacity begins to decrease with increasing charges. This decline occurs because the higher charges limit the amount of electricity that can be effectively stored in the battery, making it less advantageous to maintain a larger capacity. Fig. 7(b) illustrates the reduction in peak imported electricity across various scenarios, reflecting the impact of different demand charge rates. Initially, an increase in the peak demand charge rate leads to a sharp decline in electricity consumption. However, beyond a rate of 20 CNY/kW, the reduction in consumption becomes more gradual.

3.5. Battery cost analysis

In this section, the optimization outputs are analyzed based on changes in battery price. Fig. 8 indicates a clear correlation between the battery price, optimal annual costs, and battery capacity; specifically, as the battery cost increases, the optimal annual cost also rises while the battery capacity decreases. A 10% drop in battery costs leads to a 15.73% rise in battery capacity, showing that lower prices boost energy storage potential. In contrast, a 10% increase in costs results in a 10.40%

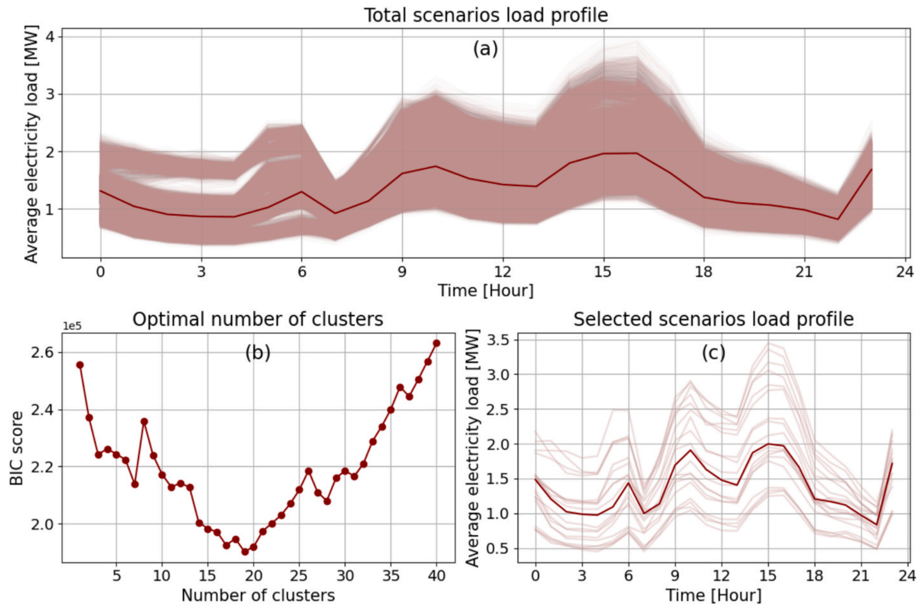

Fig. 5. Presentation of load scenarios obtained through the uncertainty characterization method. a) The average hourly load profiles for each monthly scenario are shown, while the red line shows the median of the scenarios. b) The optimal number of reduced scenarios determined using the BIC is 19. c) The average hourly load profiles of the selected scenarios, while each scenario has a different probability. The red line shows the median of scenarios.

Table 4
Design optimization results.

Optimal results	Developed method (Stochastic)	Base results (2024 data)
Battery size	14.15 MWh	12.49 MWh
Annual cost	9.84 million CNY	10.43 million CNY
Computation time	118.3 s	44 s

decrease in capacity.

4. Discussion

In this section, the effects of clustering on optimal battery capacity and costs are examined in section 4.1. Additionally, the significance of the proposed approach in presenting a linear demand charge formulation for stochastic design optimization problems is explained in section 4.2.

4.1. Cluster number analysis

Fig. 9 illustrates the significant impact of scenario reduction on the optimal results achieved in the analysis. When examining the problem on a smaller scale with 128 scenarios, the findings reveal that reducing the number of scenarios can lead to a substantial decrease in computation time. For example, when the scenarios are reduced from 128 to 64, there is an impressive 87.43% reduction in computation time, while the annual cost only decreases by 3.33% and the battery capacity is reduced by 1.33%. Furthermore, as the number of scenarios continues to decrease from 64 to 8, the computation time decreases significantly, ranging from 75.43% to 86.11%. However, this reduction comes with trade-offs: the optimal battery size changes between 1.33% and 4.98%. Notably, reducing the scenarios to 8 results in a concerning increase in optimal battery capacity by 20.93%.

This highlights the importance of selecting the number of clusters optimally, as excessive scenario reduction can alter the fundamental nature of the problem. Such alterations may lead to a markedly different objective function and design variables, potentially undermining the effectiveness of the solution. Therefore, it is essential to adopt a balanced approach that ensures computational efficiency while preserving the integrity of the results.

4.2. Comparative analysis

In this study, the peak load varies between 3.38 MW and 5.50 MW, resulting in a significant deviation of 38.5% between the minimum and maximum peak load values. Moreover, the related variation noted in reference [21] is 24%. These substantial fluctuations underscore the importance of accounting for demand charges. Typically, demand charges are integrated into operational strategies, such as model predictive control studies [1] and energy management studies [45]. However, they are often overlooked in design problems and are frequently modeled as non-linear functions, even in operational studies like [13]. Brandt et al. [46] reached 3%-20% peak shaving while this paper does not consider uncertainties.

Therefore, it is important to propose a linear formulation that ensures both uncertainties and global optimality. On the other hand, existing studies like [19] mostly focus on addressing uncertainties and overlook demand charges. This underscores the importance of this study in presenting a linear-based demand charge formulation within the context of stochastic design optimization problems. The findings indicate that in this study the peak load is reduced by 25.8%.

4.3. Contribution and limitations

This research highlights the crucial role of BESS in optimizing energy management and minimizing costs within microgrids, particularly in the context of TOU pricing and demand charge tariffs. The study presents an innovative stochastic design model that effectively incorporates the impacts of climate change and occupant behavior patterns into building load predictions. By employing a combination of BIC and K-medoids clustering, the developed framework significantly enhances computational efficiency while preserving essential variability in load profiles. Furthermore, the study achieves a notable reduction in peak load, demonstrating the effectiveness of the proposed methodology.

For future work, the integration of diverse renewable energy sources, such as solar and wind, within the existing BESS framework is proposed. This integration has the potential to provide valuable insights into how these combinations can further enhance the overall efficiency and

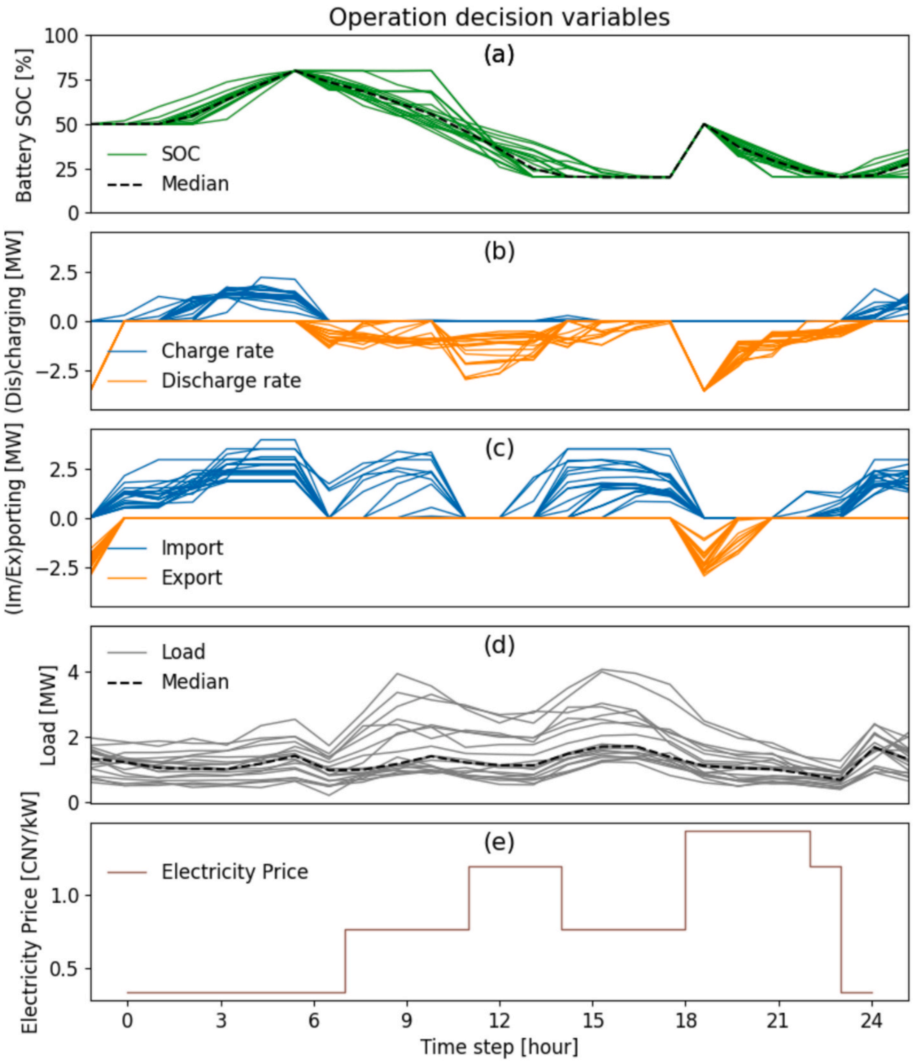

Fig. 6. Hourly operational decision variables for the first day of each scenario: a) State of Charge (SOC) of the battery across various scenarios and time steps; b) Battery charge and discharge rates for different scenarios and time steps; c) Electricity imported and exported from the grid in various scenarios and time steps; d) Load profiles across different scenarios and time steps e) Electricity price across different time steps.

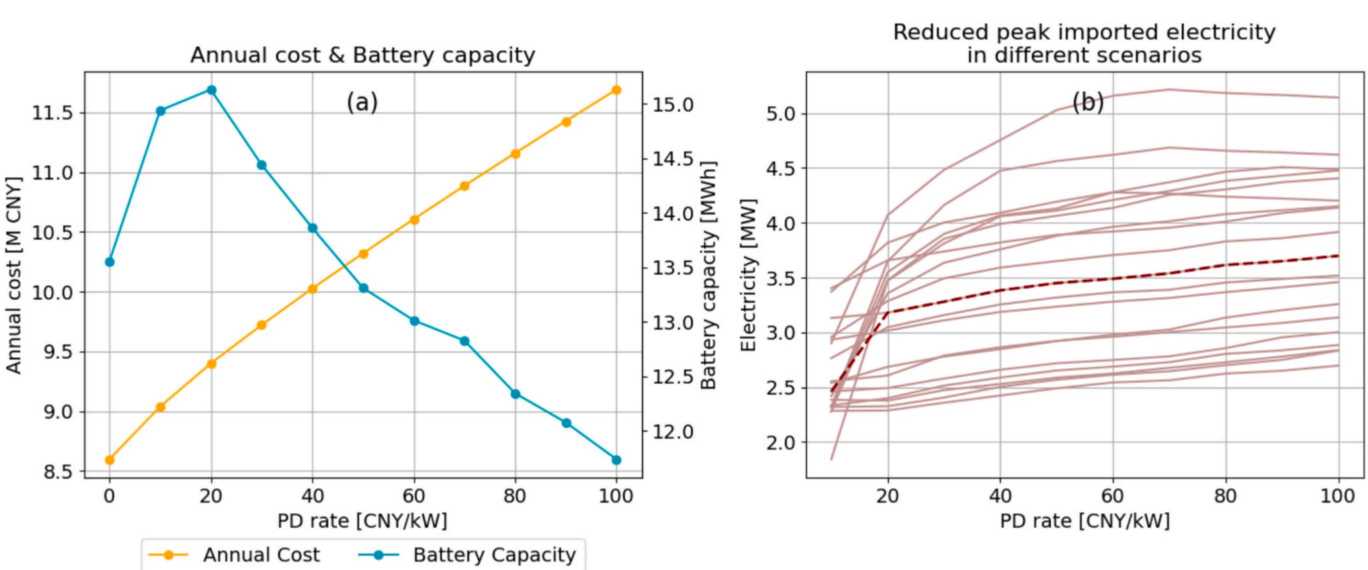

Fig. 7. Demand charge sensitivity analysis: a) Correlation between the peak demand charge rate, optimal annual cost, and optimal battery capacity; b) Reduction in peak imported electricity across various scenarios, highlighting the effects of different demand charge rates.

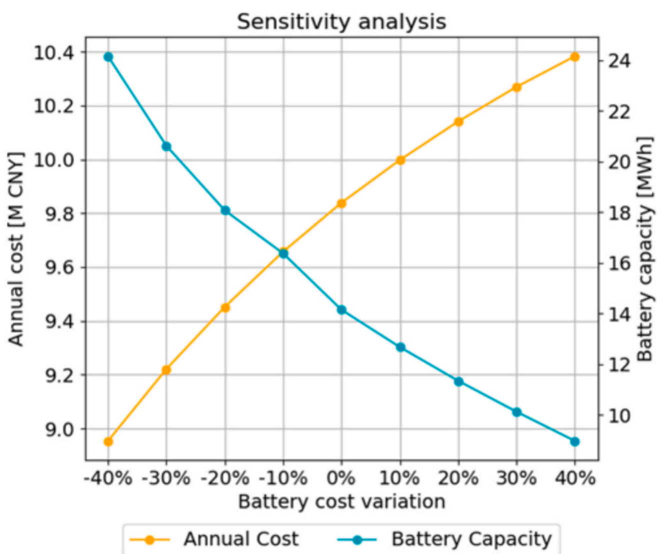

Fig. 8. Battery price sensitivity analysis to find the correlation between the battery price, optimal annual cost, and optimal battery capacity.

sustainability of microgrids. While this study adopts an occupancy-based approach to address occupant-driven uncertainties, there is an opportunity for the development of more sophisticated methodologies that capture the complexities of human behavior. Additionally, future investigations will focus on the geographic variability in climate and energy consumption patterns to better understand how these factors influence the optimal design and sizing of BESS across different regions.

5. Conclusion

The contribution of this work is twofold. First, this research demonstrates the significant potential of BESS on optimizing energy management within microgrids and reducing the utility bills, particularly in the context of demand charges and TOU pricing. Second, a stochastic programming-based solution is proposed to effectively address the uncertainties associated with building load predictions driven by climate change and occupant behavior. The key findings of this research are summarized as follows:

- By effectively addressing the uncertainties associated with climate change and occupant behavior, the proposed stochastic programming-based battery sizing is able to reduce the life-cycle cost by 5.7%, along with a 13.3% increase in optimal battery size.
- The developed framework achieved peak demand reduction by 25.8%. Furthermore, sensitivity analysis indicates a clear correlation between demand charges and optimal annual costs; as the peak demand charge increases, the optimal annual costs rise correspondingly. Specifically, when the peak demand charge exceeds 20 CNY/kW, the optimal battery capacity begins to decrease, highlighting the nuanced relationship between demand charges and battery design.
- Moreover, the study highlights the crucial role of scenario management in the optimization process. By utilizing the K-medoids clustering method in combination with Bayesian information criterion, the scenario set was effectively condensed from an extensive pool of 12,480 scenarios to just 19 representative monthly scenarios. Sensitivity analysis demonstrates that this approach results in a significant reduction in computation time, ranging from 75.4% to 87.4%, while preserving essential load variability. However, it is important to note that excessive reduction may alter the fundamental nature of the problem, leading to a different objective function and design variables, which could negatively impact the effectiveness of the solution.

CRediT authorship contribution statement

Parastoo Mohebi: Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Ziqi Hu:** Software, Data curation. **Lunlong Li:** Investigation, Data curation. **Farzin Golzar:** Writing – review & editing, Supervision. **Zhe Wang:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

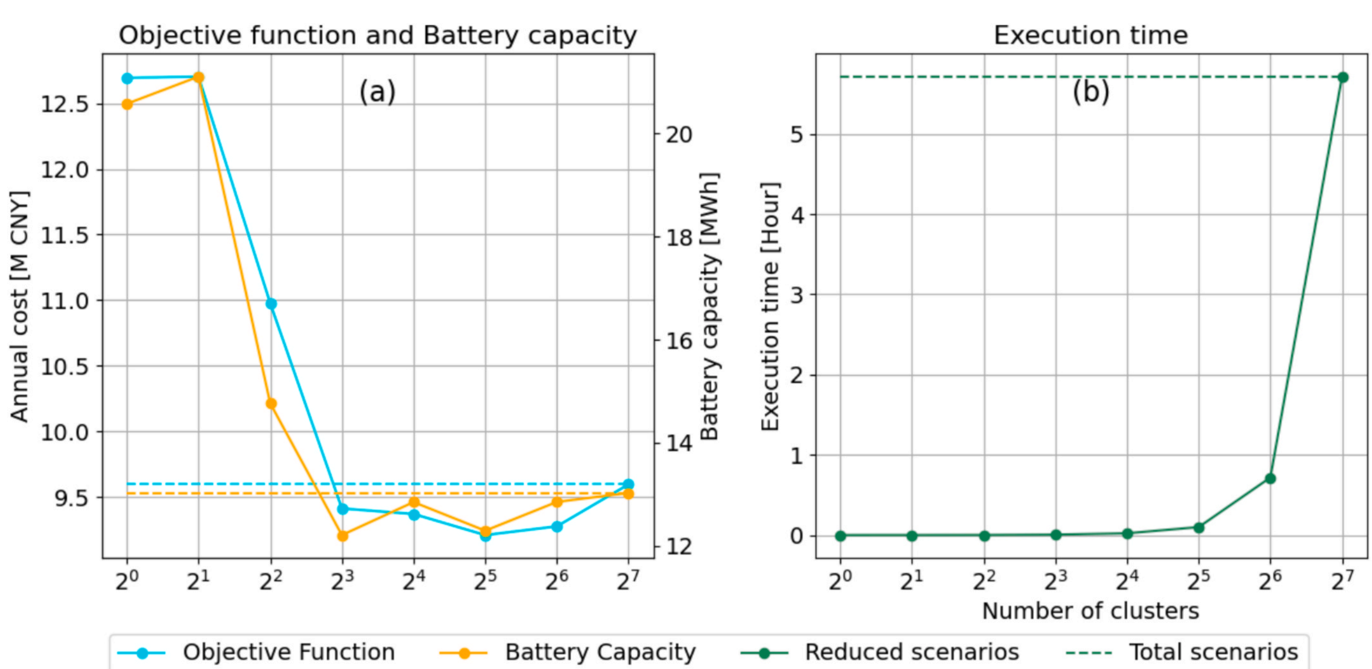

Fig. 9. The impact of scenario reduction on the optimal results a) Objective function and battery capacity b) Computation time.

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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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.enconman.2025.120794.

Data availability

Data will be made available on request.

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