Optimization on Photovoltaics and Energy Storage Integrated Flexible Direct Current Distribution Systems of Buildings Considering Load Uncertainty Using Scenario Generation Method

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Abstract

This study explores the intricate challenge of energy demand uncertainty in the design of Photovoltaics and Energy Storage integrated Flexible Direct Current Distribution (PEDF) systems. Our objective is to examine the impact of different scenario generation methods on PEDF system optimization. We compare four approaches, including probabilistic techniques based on Monte Carlo simulation, Latin Hypercube Sampling for base scenario sampling, and a simulation-based method using building performance modeling.

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We evaluate these approaches using the Independent Scenario Optimization (ISO) and Two-Stage Stochastic Programming (TSSP) models, aiming to minimize the annual total cost within PEDF systems while addressing uncertainties. Our findings shed light on the optimal PEDF design under uncertainty, offering valuable insights for future decision-making in dynamic energy systems.

Keywords: Stochastic programming, scenario generation method, independent scenario optimization, energy flexibility, energy storage.

1 Introduction

As energy resources become scarce and environmental concerns escalate, renewable energy has emerged as a popular research direction within the energy field due to its clean and sustainable nature [1]. The Photovoltaics and Energy Storage integrated Flexible Direct Current Distribution (PEDF) system, as a fusion of photovoltaic generation, energy storage, and flexible load management, is considered a crucial component of future energy systems [2]. However, the design and optimization of such systems face challenges stemming from the uncertainty in energy demand, making performance analysis and decision-making more intricate.

The uncertainty in energy demand arises from various factors, including climate change, energy price fluctuations, changes in user behavior, and the interplay of these factors makes accurate predictions of future energy demand highly challenging [3]. Hence, to ensure the reliability and cost-effectiveness of PEDF systems under different scenarios, detailed description and analysis of these scenarios are essential [4, 5]. It is in response to this need that scenario generation methods have become an effective approach to address energy demand uncertainty.

Numerous scholars have proposed various scenario generation methods and achieved successful applications in different fields. In the domain of energy system optimization, Monte Carlo simulation is often employed to generate probabilistic distribution scenarios, effectively considering various sources of uncertainty [6, 7]. The Latin Hypercube method, on the other hand, provides better coverage of the entire possibility space with relatively fewer scenario samples. Furthermore, building performance simulation methods can more realistically model system performance in different scenarios, offering a more precise foundation for system optimization.

To delve into the practical effects of these scenario generation methods, this study adopts two optimization models: independent scenario optimization and two-stage stochastic programming, aiming to minimize the annual total cost of the PEDF system [8]. By comparing the optimization results of four different scenario generation methods under these two models, we can uncover the impact of different methods on system design and performance, providing more decision support for system design [9].

The paper's research motivation is to address the challenge of energy demand uncertainty in the design of PEDF systems. This is important because the intermittency and uncertainty of renewable energy sources pose challenges to stable operation and optimization of these systems. The objective is to examine the impact of different scenario generation methods on PEDF system optimization, with the goal of minimizing annual total costs while addressing uncertainties. The research aims to provide valuable insights for future decision-making in dynamic energy systems.

The paper makes significant contributions in multiple dimensions, bringing forth novel insights and advancements to the field. Firstly, a groundbreaking Two-Stage Stochastic Programming (TSSP) model is introduced, revolutionizing the analytical approach to optimizing PEDF systems. This innovative model allows for a thorough exploration of the intricacies involved in optimizing PEDF systems under the challenging conditions of load uncertainty.

Secondly, the paper stands out through its meticulous and comprehensive comparative analysis. It critically evaluates the impact of four distinct uncertainty research methods on the optimization outcomes of a specific PEDF system. This exhaustive examination not only sheds light on the performance characteristics of these methodologies but also provides a deeper understanding of their implications within the broader context of energy system design.

Furthermore, the study delves into a detailed examination of the anti-risk capabilities exhibited by diverse equipment components within the PEDF system when subjected to load uncertainty. This aspect of the research uncovers discernible trends and strategic guidelines, offering invaluable insights for effective system configuration. The findings are particularly tailored to managing various types of load uncertainty risks, thereby enhancing the overall resilience and reliability of PEDF systems.

In summary, these noteworthy contributions collectively propel the understanding of optimal PEDF design under uncertainty to new heights.

The research not only fills gaps in existing knowledge but also provides substantial guidance for informed decision-making in the dynamic realm of energy systems. The incorporation of the TSSP model, the in-depth comparative analysis, and the exploration of anti-risk capabilities contribute significantly to the advancement of the field, making this paper a key reference for researchers and practitioners alike.

2 Model Formulation

As shown in Figure 1, the target system consists of four primary energy components: energy storage systems, photovoltaic systems, flexible loads, and other loads. These four components collaborate to make the entire energy system more efficient, flexible, and sustainable. The role of the energy storage system is to release stored electrical energy during periods of insufficient sunlight or peak electricity demand, ensuring the stable operation of the system. The photovoltaic power generation system converts solar energy into direct current electricity through solar panels, providing renewable energy to the entire system. The flexible load can adjust real-time power demand based on the grid's condition, helping to balance power supply and demand and improve the stability of the power system. Other loads include traditional power loads such as household appliances and factory equipment. Through the optimized configuration and coordinated operation of these four components, the target system can maximize the utilization of renewable energy, reduce dependence on fossil fuels, decrease environmental pollution, and promote energy transition and sustainable development. The primary objective of the PEDF system pertains to the determination of optimal energy device capacities with the aim of minimizing the annual total cost of the energy

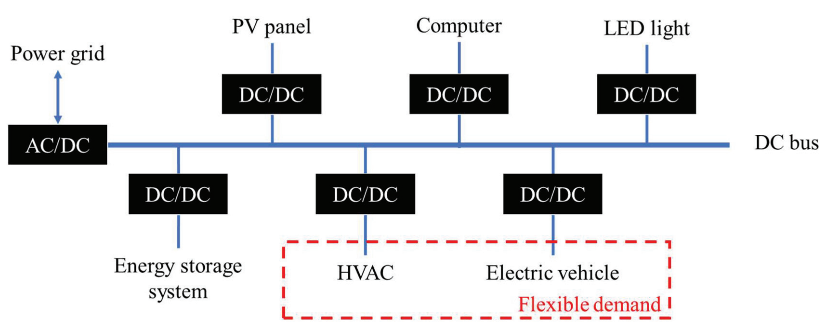

Figure 1 A PEDF system.

system [10, 11]. In contrast to many existing PEDF optimization frameworks that incorporate multi-objective functions, encompassing objectives such as carbon emissions reduction, this study adopts a more focused approach by considering solely economic indicators within the optimization model's objective function. This selective focus is motivated by factors such as the need for enhanced model generality and computational efficiency, particularly relevant when dealing with intricate and large-scale energy systems. It should be recognized that the exclusion of broader environmental and energy efficiency indicators in this specific analysis is a deliberate choice intended to streamline the investigation and ensure practicality, but it does not encompass the full spectrum of sustainability considerations. Future research endeavors should carefully address these dimensions to provide a more comprehensive view of PEDF system optimization.

When it comes to the optimization of PEDF system, the accurate construction and effective solution of the model are crucial to address the challenges posed by energy demand uncertainty. This study incorporates the Independent Scenario Optimization (ISO) model and the Two-Stage Stochastic Programming (TSSP) model as integral methodologies aimed at minimizing the annual total cost within the PEDF energy system [12]. A comprehensive exposition of these models follows, elucidating their structural frameworks, methodological underpinnings, and their specific utility in addressing the intricate challenges arising from uncertain factors within the PEDF system [13]. The detailed examination of the principles and capabilities of ISO and TSSP serves to contribute not only to the complexities of PEDF system design but also to the broader discourse on robust decision-making in dynamic energy systems amidst uncertainty. Through this rigorous analysis, our study facilitates a deeper understanding of these models, enhancing their applicability and guiding decision-makers in navigating the intricacies of dynamic energy system optimization under uncertain conditions.

2.1 ISO Model

A deterministic optimization model is a particular instance within the broader framework of stochastic models, characterized by a scenario that comprises a single scenario with a probability of 1 [14]. In this study, we introduce the term "Independent Scenario Optimization" to underscore the salient distinction arising from the discrepancy in scenario quantity as compared to traditional stochastic models. Within the context of Independent Scenario

Optimization, each scenario effectively represents a deterministic scenario, thereby aligning with the principles of deterministic optimization. Consequently, the Independent Scenario Optimization approach can be construed as a specific manifestation of deterministic optimization, wherein the objective function is formulated as a composite sum of investment and operational costs, denoted as Equation ((1)). This elucidation serves to enhance our comprehension of the nuanced interplay between deterministic and stochastic optimization, thereby providing a robust foundation for analytical investigation and decision-making in the realm of the PEDF energy system optimization.

$$\min f^{ISO} = Invest + Oper \tag{1}$$

$$Oper = \sum_{t} \rho_t P_t^{buy} \tag{2}$$

$$Invest = \sum_{i} cap_i cost_i \frac{IR(IR+1)^{lt_i}}{(IR+1)^{lt_i} - 1} \tag{3}$$

The model's objective function (f^{ISO}) encompasses both investment ($Invest$) and operational ($Oper$) costs, playing a pivotal role in determining the optimal configuration of the PEDF energy system in (1). In function (2), parameters underpinning this optimization process include ρ_t (denoting energy price), $cost_i$ (representing the linear investment cost per unit of capacity for the i-th component), P_t^{buy} (indicating grid electricity procurement), and cap_i (an integer variable signifying the capacity of the i-th energy device). Moreover, in function (3), the terms IR and lt_i respectively stand for the interest rate and the assumed uniform lifetime (Scenario at 20 years) of the i-th energy technology. It is essential to note this simplification of lifespan calculations for computational feasibility while retaining a reasonable approximation of long-term system dynamics.

Operational constraints serve as essential components within the model, imbuing it with a comprehensive framework that embraces critical facets, including electricity energy balance and technical constraints [15]. By incorporating energy balance considerations, the model ensures coherence between energy generation and demand, underpinning the stability and reliability of the intricate PEDF system. These constraints act as essential gatekeepers, forestalling the emergence of unrealistic or impractical scenarios that may lead to infeasible solutions. Furthermore, technical constraints encompass a multifaceted spectrum of factors, ranging from device operational limits to voltage stability, thermal restrictions, and stringent grid interface prerequisites [16]. The integration of such constraints within the model encapsulates the intricate realities of operational scenarios, affirming that the optimal system configuration aligns harmoniously with both operational requisites and technical viability, thus rendering it a potent decision-making tool in the ever-dynamic milieu of energy systems.

Energy balance constraints. The electricity demand is provided by the power grid, PV and energy storage system. The energy balance constraint per timestep t are formulated as Equation (4).

$$P_t^{buy} + P_t^{pv} + P_t^{ESS.d} - P_t^{ESS.c} \geq D_t^{flex} + D_t^{non\text{-}flex} \tag{4}$$

Comprehensive component-level modeling is crucial to capture the intricate interdependencies between input-output relationships in each energy technology while upholding essential capacity constraints. This approach enhances the feasibility and accuracy of the PEDF system's design and optimization, offering nuanced insights into operational dynamics and facilitating informed decision-making in energy system design.

$$P_t^{pv} = P_t^{pv,fore} cap_{pv} \tag{5}$$

$$cap_{pv}^{min} \leq cap_{pv} \leq cap_{pv}^{max} \tag{6}$$

Equation (5) links the maximum active PV power to installed capacity and solar irradiation, while Equation (6) sets capacity limits for each PV power plant, crucial for effective system design. Parameter $\mathrm{P_t^{pv,fore}}$ is per unit PV power output. $\mathrm{cap_{pv}^{min/max}}$ is Minimum/maximum PV power capacity.

$$E_{t+1}^{ESS} = E_t^{ESS} + P_t^{ESS.c} - P_t^{ESS.d} \tag{7}$$

$$E_t^{ESS.min} \leq E_t^{ESS} \leq cap_{ess} \tag{8}$$

Energy storage systems (ESS) are vital enhancing reliability and stabilizing renewable energy fluctuations. Equation (7) accounts for conversion losses via charging and discharging efficiency. Equation (8) ensures non-negativity and power limits for charging and discharging, crucial for system stability. Parameter $\mathrm{E_t^{ESS.min}}$ is minimum storage level of ESS. variable $\mathrm{cap_{pv}}$ is Installed capacity of ESS.

$$D_t^{flex.min} \leq D_t^{flex} \leq D_t^{flex.max} \tag{9}$$

The constraints of the decision variable of flexible load (such as electric vehicle charging load, air conditioning load) are shown in (9). Parameter $\mathrm{D_t^{flex.min/max}}$ is Minimum/maximum limits for flexible demand.

2.2 TSSP Model

The paradigm of the two-stage stochastic model offers a structured methodology for navigating decision complexities within uncertain environments [17]. It delineates between pre-variables (first-stage decision variables), discerned proactively in advance of uncertainty realization, and post-decision variables (second-stage decision variables), adjusted in response to revealed uncertain parameters [18]. This framework proves particularly pertinent in contexts of design quandaries, wherein pre-variables orchestrate equipment selection and sizing, while ensuing post-decision variables orchestrate operational refinements. Notably, the model's objective function, as denoted by Equation (10), bifurcates into investment and operational components, mirroring the bifocal nature of the two stages. This architectural duality adeptly harmonizes anticipatory prudence with adaptive finesse, culminating in a comprehensive strategy for judicious decision-making.

$$\min f^{TSSP} = Invest + E_s(Oper_s) \tag{10}$$

In objection function (10), the first-stage costs encapsulate the financial commitments associated with annualized investments in crucial system components, offering a comprehensive perspective on initial capital deployment. In contrast, the second-stage costs encompass variables intricately linked with the operational intricacies of energy generation, capturing the ongoing operational expenses and complexities that shape the system's temporal performance. This dichotomy departs from deterministic modeling where singular values are computed for variables in each time step; instead, in the stochastic context, these variables necessitate recalibration for each scenario within discrete time intervals. This adaptive approach acknowledges the inherent uncertainty and variability within real-world scenarios, enabling a more holistic assessment of potential outcomes. By accommodating diverse scenarios at each time step, the stochastic model provides a more comprehensive representation of the intricate interplay between variables and scenarios pertinent to the energy generation domain.

The variable of the model in the second stage needs to be added with corner mark s, is each scene has a set of operation scheme. Therefore, the model of the second stage of two-stage stochastic programming is based on

(2) and (4)–(9).

$$Oper = \sum_{t} \rho_t P_{t,s}^{buy} \tag{11}$$

$$P_{t,s}^{buy} + P_{t,s}^{pv} + P_{t,s}^{ESS.d} - P_{t,s}^{ESS.c} \geq D_{t,s}^{flex} + D_{t}^{non\text{-}flex} \tag{12}$$

$$P_{t,s}^{pv} = P_{t,s}^{pv,fore} cap_{pv} \tag{13}$$

$$cap_{pv}^{min} \leq cap_{pv} \leq cap_{pv}^{max} \tag{14}$$

$$E_{t+1,s}^{ESS} = E_{t,s}^{ESS} + P_{t,s}^{ESS.c} - P_{t,s}^{ESS.d} \tag{15}$$

$$E^{ESS.min} \leq E_{t,s}^{ESS} \leq cap_{ess} \tag{16}$$

$$D_{t}^{flex.min} \leq D_{t,s}^{flex} \leq D_{t}^{flex.max} \tag{17}$$

The objective function represents operational costs in Equation (11). Energy balance constraints for each timestep t are formulated in Equation (12). Equation (13) establishes a link between the maximum active PV power, installed capacity, and solar irradiation, while Equation (14) imposes capacity limits on each PV power plant – an essential factor in effective system design. Accounting for conversion losses via charging and discharging efficiency, Equation (15) is introduced. To ensure non-negativity and power limits for charging and discharging, vital for system stability, Equation (16) is applied. Constraints on the decision variable of flexible load, encompassing electric vehicle charging load and air conditioning load, are detailed in Equation (17).

3 Scenario Generation Method

3.1 Probability-based Method

Probabilistic Modeling of Energy Demand: To address uncertain parameters, a robust probability model is pivotal [19, 20]. This involves defining the probability distribution for these uncertainties and generating random variables based on it. The energy demand distribution, as outlined in Section 1, is treated as time-independent. Thus, each time point requires separate sampling for time series scenarios. Typically following a normal distribution this probability density distribution effectively characterizes short-term energy demand variability.

Monte Carlo Sampling (MCS) vs. Latin Hypercube Sampling (LHS): The focal point of comparison lies in their respective sampling methodologies. In MCS, the samples are allocated across the input distribution, often converging in regions of elevated likelihood. Through iterative generation of new random values within the cumulative distribution, MCS effectively reconstructs the input distribution, albeit potentially encountering aggregation challenges with limited iterations. In contrast, LHS introduces a more sophisticated sampling approach, characterized by enhanced precision despite employing a reduced sample size [21]. A distinguishing attribute of LHS is its capacity to furnish a broader coverage of samples within the parameter space, engendering a reduced sample standard deviation in relation to MCS.

3.2 Simulation-based Method

Difficulties in Energy Consumption Data Collection: Obtaining energy consumption data for buildings, especially newer ones lacking historical data, can be challenging. Traditional methods, like using probability distributions for energy demand scenarios, ignore temporal autocorrelation, leading to irrational energy use curves. To address this, the MCBPS approach stands out as a preferred choice. This method effectively incorporates uncertainty from input parameters into output parameters for generating diverse energy demand scenarios.

MCBPS Approach for Energy Demand Scenarios: The MCBPS approach involves several steps to generate energy demand scenarios. It starts by assigning probability distributions to input parameters of a BPS tool, such as EnergyPlus. Multiple input files are created through parameter sampling, and these inputs are used for running multiple simulations. This approach ensures that temporal autocorrelation of energy demand is taken into account, resulting in more realistic energy demand scenarios.

Uncertainty Handling and Climate Impact: The treatment of uncertainty in input parameters within BPS is orchestrated through the application of diverse distribution types. Fundamental attributes like wall, window, and roof properties are characterized by normal distributions, while parameters such as occupant density and installed capacity for lighting and electrical equipment are characterized by triangular distributions [22]. Furthermore, the integration of the morphing method facilitates the incorporation of climate change effects on building energy consumption. To execute this, BPS input samples are systematically generated utilizing the Python programming language.

Through the enactment of N simulations, the capacity to generate N samples of building energy demand is realized [23]. Each sample assumes the form of a discrete uniform distribution, thus ensuring that all potential outcomes are endowed with equal probability. This comprehensive approach enables a holistic exploration of the potential energy demand landscape, accounting for a spectrum of uncertainties encompassing both parameter variability and climatic influences.

4 Case Study

4.1 Case Settings

This study undertakes a comprehensive and systematic comparative investigation of various methodologies for generating scenarios, encompassing Monte Carlo Sampling (MCS), Latin Hypercube Sampling (LHS), Multi-Climate Building Performance Simulation (MCBPS), and Building Performance Simulation with Monte Carlo (BPSMC). The underpinning scenario is derived from EnergyPlus and aligns with established energy efficiency design principles, utilizing representative weather data from the year 2005 to simulate an office building in Shanghai. The research design seeks to ensure robust comparisons by selecting 600 scenarios, thus accommodating the variability inherent in different scenarios and across multiple years. The scenarios are characterized by a discrete uniform distribution. The methodologies are discerned as follows: the Basic Scenario entails singular scenario generation through EnergyPlus; Scenario 1 MCS involves the application of Monte Carlo Sampling across 600 discrete time steps within the foundational scenario; Scenario 2 LHS employs Latin Hypercube Sampling to meticulously sample the foundational scenario over 600 time steps; Scenario 3 MCBPS integrates 200 input parameter samples with climate files (epw-2020 and epw-2050) to yield 600 simulations; and Scenario 4 BPSMC simulates energy demand documents for three distinct climate years and then employs MCS on these documents [19]. This rigorous examination offers critical insights into the relative efficacies and limitations of the diverse methodologies for enhancing the precision of building energy demand predictions.

In the ISO model, independent scenario optimizations were conducted for each scenario, resulting in 600 optimizations for each Scenario and a total of 2400 optimizations. In the TSSP approach, similar to ISO, 600 independent scenario optimizations were performed for each scenario. However, the excessive number of scenarios led to an increase in model variables, causing challenges in achieving reasonable computation time. To address this issue, scenario reduction techniques were employed in the stochastic programming model, a well-established method. Additionally, clustering algorithms were investigated for scenario reduction in previous studies.

Our investigation encompasses 600 scenarios, each encapsulating electricity, cooling, and heating demands across 8760 hours. The intricacies of the dataset's dimensionality preclude the direct application of clustering algorithms, prompting the adoption of the feature-based k-medoids clustering approach. This strategy involves generating a simplified Scenario defined by key statistical features that succinctly characterize the original time series. The ensuing clustering algorithm operates on these condensed feature Scenarios, alleviating computational challenges associated with the original data. Our method employs six statistical features – sum, standard deviation, maximum, mean, kurtosis, and skewness – to represent each time series within a scenario. This results in an 18-feature representation for each scenario. This judicious selection optimizes computational efficiency and precision, offering a pragmatic solution to high-dimensional clustering complexities.

4.2 Results

Energy demand scenarios encompass conventional time series data, exhibiting variability when generated through different methods. This study undertakes a comprehensive comparative analysis of energy demand time series generated by distinct scenario generation techniques. Dynamic time warping (DTW), a prominent approach for assessing temporal sequence similarity, is harnessed here to quantify the likeness between two temporal sequences.

DTW operates by identifying an optimal alignment path within the distance matrix of two time series, minimizing cumulative element value summation along the path. Lower DTW values indicate greater sequence resemblance. The study draws on Andhini's methodology for DTW implementation. Two DTW variants are examined: absolute DTW, which accounts for both absolute distance and temporal offset, and shape DTW, which gauges shape similarity while ignoring absolute metrics.

Table 1 displays the average absolute DTW values between the basic scenario and each scenario, offering a measure of the numerical dissimilarity in energy demand. In Scenario 1, the electricity energy average absolute DTW is 306.25, indicating significant differences in magnitude compared to the basic scenario. Scenario 2 shows a smaller average DTW of 265.25, suggesting a relatively smaller numerical variance. In contrast, Scenario 3 has

Table 1 The results using the average absolute DTW

	Scenario 1	Scenario 2	Scenario 3			Scenario 4		
			2005	2020	2050	2005	2020	2050
Average absolute DTW of electricity energy	306.25	265.25	45.26	52.32	165.25	362.30	519.32	825.30

Table 2 The results using the average absolute DTW

	Scenario 1	Scenario 2	Scenario 3			Scenario 4		
			2005	2020	2050	2005	2020	2050
Average shape DTW of electricity energy	3.25	4.26	0.02	2.62	3.28	10.25	20.39	22.59

a remarkably low average DTW of 45.26, reflecting a close match in numerical values with the basic scenario, especially for the 2050 data. Conversely, Scenario 4 exhibits higher DTW values: 52.32 (2005), 165.25 (2020), and 362.30 (2050), indicating substantial differences in energy demand between the basic scenario and Scenario 4. Table 2 focuses on average shape DTW values, assessing the similarity in time series patterns regardless of absolute differences. Scenario 1's average shape DTW for electricity energy is 3.25, showing minor shape variation compared to the basic scenario. Scenario 2 has a slightly higher average shape DTW of 4.26, indicating a bit more noticeable shape variation. Remarkably, Scenario 3 records an average shape DTW of 0.02, indicating nearly identical time series shapes, particularly for the 2050 data. Scenario 4's shape DTW values are notably higher: 2.62 (2005), 3.28 (2020), and 10.25 (2050) highlighting shape differences in the energy demand time series between the basic scenario and Scenario 4. These tables provide insights into the nature and degree of divergence in energy demand scenarios across different sets and timeframes, considering both numerical and shape aspects. The probabilistic method generates time series scenarios with noticeable differences in trends and values compared to the original scenario, especially during peak demand periods, reinforcing the disregard for energy demand autocorrelation. On the other hand, the simulation method aligns closely with the original scenario in both shape and value, but it may not capture extreme events as well, and it requires more computation time.

Table 3 The results of each scenario using the TSSP model

		ESS (kW)	PV (kW)	Objective Value (Million CNY/a)
Basic scenario		66.95	205.41	9.87
Scenario 1	TSSP	63.65	250.05	4.28
	ISO	61.52	229.61	5.37
Scenario 2	TSSP	58.63	260.26	5.38
	ISO	59.51	232.97	4.20
Scenario 3	TSSP	63.34	205.18	2.15
	ISO	58.44	194.97	4.92
Scenario 4	TSSP	61.62	261.19	0.74
	ISO	61.76	213.72	5.20

Table 3 presents the TSSP model's optimization outcomes for various scenario sets, encompassing the optimal equipment capacities within the energy system and the model's objective value. In this study, the expected value represents the mean of the optimization outcomes, considering a uniform distribution of scenarios within each scenario.

In Table 3, the optimization results offer valuable insights into the impact of diverse scenario sets on the optimal capacities of ESS and PV installations. Additionally, the objective values, measured in million CNY per annum, provide a comprehensive evaluation of the financial implications for each scenario. Analyzing the table, we see a clear distinction between the basic scenario and the subsequent scenario sets. The ESS and PV capacities, as well as the objective values, vary notably across different scenarios, demonstrating the sensitivity of the energy system design to different input conditions. This variance highlights the need for a flexible approach that can adapt to changing scenarios. Furthermore, the comparison between the TSSP and ISO approaches adds another layer of insight. We can observe how these two methods yield different optimal outcomes for each scenario. This contrast underscores the importance of the chosen optimization method, as it can significantly impact the final design of the energy system and, consequently, the financial implications. The findings in this table also hint at the trade-offs between optimal equipment capacities and financial objectives. For example, some scenario sets may lead to higher or lower optimal capacities of ESS and PV, and these decisions directly influence the overall financial performance of the system. This level of analysis not only provides a deeper understanding of the optimization process but also underscores the importance of considering multiple scenarios in energy system planning. It allows decision-makers to assess the resilience and efficiency of the designed system under different conditions and make informed choices that align with long-term objectives. In summary, Table 3 unveils the dynamic nature of energy system optimization, showcasing how varying scenarios and different optimization approaches can significantly impact the outcome. It emphasizes the need for adaptive strategies that can handle uncertainties, ensure robustness, and align with financial objectives in the complex domain of energy system design.

5 Conclusion

This study systematically undertook a comprehensive comparative analysis of diverse energy demand scenario generation methodologies and evaluated their implications within the context of Power and Energy Demand Forecasting (PEDF) optimization. Employing four distinct scenario generation approaches, the generated scenario sets were subjected to both isolated scenario optimization and the more intricate two-stage stochastic optimization process. Notably, the outcomes illuminated that scenario derived from inherent demand uncertainties lead to discernible elevations in peak load conditions, consequently precipitating amplified optimized system costs as juxtaposed with the baseline, unaltered system. This finding suggests an enticing equilibrium in design rationalization that thoughtfully considers the ramifications of demand uncertainty, providing valuable insights for enhancing the efficiency and cost-effectiveness of PEDF optimization in real-world applications.

Of particular significance was the methodological deployment of the Multi-Climate Building Performance Simulation (MCBPS), which exhibited a notable degree of temporal correspondence to the original scenario. This phenomenon was tangibly measured through notably reduced Dynamic Time Warping (DTW) values, distinguishing it from alternative methods. Moreover, when coupled with the Two-Stage Stochastic Optimization (TSSP) paradigm, MCBPS demonstrated the least pronounced escalation in costs, thus presenting an alluring equilibrium in design rationalization that thoughtfully contemplates the ramifications of demand uncertainty.

To enhance practical application, future work should refine the TSSP model by incorporating dynamic load profiles and more sophisticated equipment behaviors. Extended validation studies across diverse PEDF systems and conditions will strengthen the model's robustness. Additionally, integration with emerging technologies, like advanced data analytics and machine learning, holds promise for improving predictive capabilities and adaptability to evolving energy system dynamics. Addressing these areas will contribute to a more realistic and widely applicable framework for optimizing PEDF systems in real-world scenarios, aligning with the broader goals of advancing sustainable and resilient energy systems.

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