

Stochastic Planning Method for the Building Energy System Considering Loads and Renewable Energy Uncertainties

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ABSTRACT

The building energy system faces uncertainties from renewable energy power generation and energy demand, and the design using deterministic method will introduce the risk of suboptimal decisions. In this paper, a stochastic programming model is formulated for the building energy system planning problem under source and load uncertainties. Facing the computational burden caused by massive stochastic annual scenarios, a two-level scenario reduction method of typical annual scenario reduction and typical daily scenario reduction is proposed, which ensures the solvability of the stochastic programming model and takes into account the uncertainty of design boundary. To illustrate the model's application, the design of an integrated energy system for an industrial park is investigated. The results show that the stochastic planning method can maximize the life-cycle economic benefit of the integrated energy system under uncertain design boundaries comparing with the deterministic planning method. In addition, the flexibility of the energy storage system can resist a certain degree of load forecasting deviation and improve energy supply reliability of the system.

Keywords: integrated energy system, uncertainty, stochastic optimization, scenario reduction

NOMENCLATURE

Symbols	
$k \in K$	Typical annual scenario set
$m \in M$	Equipment type
$j \in J$	Number of equipment type
$t \in T$	Time step of the model
$c \in C$	Continuous equipment

$d \in D$	Discrete equipment
$\pi(k)$	Probability of scenario k
v	Variable maintenance cost factor
Gp	Price of gas [CNY/m ³]
Ep_{τ}	Electricity price [CNY/kW]
$G_{k,ICE,m,j,\tau}$	Gas consumption of the ICE [m ³]
$P_{grid,k,\tau}$	Power purchased from grid [kW]
$q_{k,d,m,j,\tau}$	Output of discrete equipment [kW]
$q_{k,c,\tau}$	Output of continuous equipment [kW]
$\bar{q}_{pv,k,\tau}$	PV power generation per unit [kW/m ²]
$q_{k,\tau}^{in}$	Input energy of storage system [kW]
$q_{k,\tau}^{out}$	Output energy of storage system [kW]
Ca	Installed capacity of each device [kW]
η	Efficiency of each device
ρ_m	Thermoelectric ratio of ICE
ω	Minimum operating load rate
$E_{ES,k,\tau}$	Energy stored in storage battery [kWh]
A^{roof}	Available roof area [m ²]

1. INTRODUCTION

Building energy system plays an important role in the deepening reform of energy supply side and demand side. The design of building energy system is often a complex decision-making process. Firstly, it will face the optimal matching problem of numerous available energy technologies, which involves decision-making problem of multiple conflicting objectives. Secondly, design and operation are coupled, and the structure and capacity of the system not only determine the initial investment, but also affect the operation strategy, which in turn affects the energy efficiency and operation economy of the system.

In order to achieve the optimal design of complex building energy system, the optimization design method

based on mathematical programming is widely used in system technology portfolio and equipment capacity sizing^[1]. Common mathematical programming models include linear programming (LP), mixed integer and linear programming model (MILP) and non-linear programming model (NLP)^[2]. The worth of any mathematical model used in scientific research or engineering practice depends on the reliability and accuracy of its outputs. However, due to incomplete knowledge and inherent stochasticity of the system, any uncertainty of model input parameters will lead to uncertainty of model outputs as well. Uncertainty in the design process of building energy system can be traced to several aspects, such as: the stochasticity of renewable energy output and building energy demand. If deterministic boundary conditions and optimization model are used for energy system design ignoring uncertainty, the deterministic optimal solution may become a non-feasible solution when a stochastic disturbance occurs, and the design scheme will deviate from the actual requirements, which will lose the meaning of optimal design. However, in most studies, the optimization method of energy system design still adopts a deterministic approach^[3-5]. To effectively circumvent system failures due to uncertainty, designers usually use the worst-case scenario method or the factor-of-safety method to increase the design capacity, but both methods may result in redundant design, and this phenomenon seems to have formed a consensus both nationally and internationally^[6,7].

Facing the uncertainties in building energy demands and renewable energy power generation, the stochastic planning method improves the rationality of building energy system design from the concept level, including economic benefit and energy supply reliability. In this paper, we propose a stochastic planning method considering source and load uncertainties. Firstly, a stochastic programming model is formulated with the objective function of minimizing the cost during the whole project life cycle. On this basis, the scenario reduction technology is used to realize the two-level scenario reduction from stochastic annual scenario set to typical annual scenario set and from typical annual scenario set to typical daily scenario set. Finally typical daily scenarios are used as the design boundaries of the stochastic programming model. Taking an integrated energy system as the case study, the traditional deterministic scheme and the stochastic scheme are compared to verify the economic advantages of the stochastic planning method.

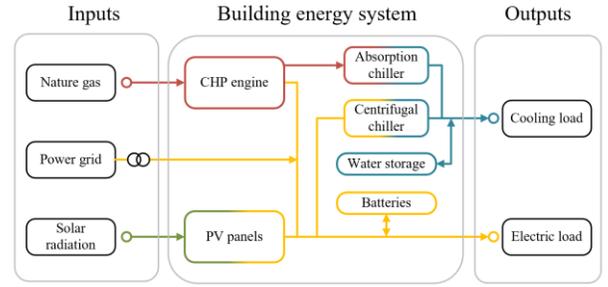


Fig. 1. Flow chart of building integrated energy system

2. MODEL FORMULATION

In order to study the optimization design method for building energy system under dual source and load uncertainty environment, this paper takes a distributed energy system for an industrial park connecting with power grid as the research case, as shown in Fig. 1. The system has electric demand and cooling demand. The cooling demand is carried by three cold sources: electric chillers, absorption chillers and water storage system. The electric demand is shared by four power sources: PV system, internal combustion engine, storage battery and grid. Water storage and battery play the dual role of source and load at the same time.

2.1 Objective function

In this paper, the two-stage compensated stochastic programming model is used to describe the whole optimization problem under uncertain design boundary conditions^[8], and Eq. (1) is the objective function of the model. The annualized initial investment costs (a: including initial investment of discrete equipment and continuous equipment), operating costs (b: gas purchase cost; c: power purchase cost), and maintenance costs (d: fixed maintenance cost; e: variable maintenance cost for discrete equipment; f: variable maintenance cost for continuous equipment) are considered.

$$\begin{aligned}
 \min \quad & \underbrace{C_{cap}^D + C_{cap}^C}_a + \\
 & \underbrace{\pi(k) \cdot \sum_k^K \sum_m^M \sum_j^J \sum_\tau^T G_{k,ICE,m,j,\tau} \cdot G_p}_b + \\
 & \underbrace{\pi(k) \cdot \sum_k^K \sum_\tau^T P_{grid,k,\tau} \cdot E p_\tau + C_{mai}^f}_c + \\
 & \underbrace{\pi(k) \cdot \sum_k^K \sum_d^D \sum_m^M \sum_j^J \sum_\tau^T q_{k,d,m,j,\tau} \cdot (1 + v_d)}_d \\
 & + \underbrace{\pi(k) \cdot \sum_k^K \sum_c^C \sum_\tau^T q_{k,c,\tau} \cdot (1 + v_c)}_e + \underbrace{\phantom{\pi(k) \cdot \sum_k^K \sum_c^C \sum_\tau^T q_{k,c,\tau} \cdot (1 + v_c)}}_f \quad (1)
 \end{aligned}$$

2.2 Model constraints

2.2.1 Energy balance constraints

Eq. (2) describes the power balance constraint and Eq. (3) describes the cooling energy balance constraint.

$$\begin{aligned} & \sum_m \sum_j q_{ICE,m,j,k,\tau}^e + \sum_{C \in (PV, grid)} q_{C,k,\tau} + q_{ES,k,\tau}^{out} \\ & \geq f_k^e \cdot \bar{L}_{k,\tau}^e + q_{ES,k,\tau}^{in} + \sum_m \sum_j p_{CC,m,j,k,\tau} \end{aligned} \quad (2)$$

$$\begin{aligned} & \sum_m \sum_j q_{CC,m,j,k,\tau} + q_{AC,k,\tau} + q_{WS,k,\tau}^{out} \\ & \geq f_k^c \cdot \bar{L}_{k,\tau}^c + q_{WS,k,\tau}^{in} \end{aligned} \quad (3)$$

In Eqs. (2)-(3), the terms $\bar{L}_{k,\tau}^e$ and $\bar{L}_{k,\tau}^c$ denote electric demand and cooling demand at time step τ in scenario k , and the terms J_k^{de} and J_k^{dc} represent the scaling factor for electric load and cooling load, respectively.

2.3 Operation constraints

The operating constraints for internal combustion engines, absorption chillers, centrifugal chillers and photovoltaic plants under each typical scenario k are shown as follows:

$$\begin{cases} q_{ICE,m,j,k,\tau}^e = p_{ICE,m,j,k,\tau} \cdot \eta_{ICE,m,j,k,\tau}^e \\ q_{ICE,m,j,k,\tau}^h = q_{ICE,m,j,k,\tau}^e \cdot \rho_m \\ bin_{ICE,m,j,k,\tau} \cdot \omega \cdot Ca_{ICE,m} \leq q_{ICE,m,j,k,\tau}^e \leq Ca_{ICE,m} \end{cases} \quad (4)$$

$$\begin{cases} q_{AC,k,\tau} = \sum_m \sum_j q_{ICE,m,j,k,\tau}^h \cdot \eta_{AC} \\ bin_{AC,k,\tau} \cdot \omega_{AC} \cdot Ca_{AC} \leq q_{AC,k,\tau} \leq Ca_{AC} \end{cases} \quad (5)$$

$$\begin{cases} q_{CC,m,j,k,\tau} = p_{CC,m,j,k,\tau} \cdot \eta_{CC,m,j,k,\tau} \\ bin_{CC,m,j,k,\tau} \cdot \omega \cdot Ca_{CC,m} \leq q_{CC,m,j,k,\tau} \leq Ca_{CC,m} \end{cases} \quad (6)$$

$$\begin{cases} q_{pv,k,\tau} \leq \frac{J_k^{pv} \cdot Ca_{pv} \cdot \bar{q}_{pv,k,\tau}}{1000} \\ Ca_{pv} \leq A^{roof} \end{cases} \quad (7)$$

In Eqs. (4)-(6), the term bin is a binary variable to constrain the start/stop state of each device. In Eq. (7), J_k^{pv} is the scaling factor for PV power generation.

2.4 Storage constraints

The energy balance of the storage battery system under each typical scenario k meets the following constraints:

$$\begin{aligned} E_{ES,k,\tau} &= (1 - \varepsilon) \cdot E_{ES,k,\tau-1} + q_{ES,k,\tau}^{in} \cdot \eta_{ES}^{in} - \frac{q_{ES,k,\tau}^{out}}{\eta_{ES}^{out}} \\ q_{ES,k,\tau}^{in} &\leq \hat{q}_{ES}^{in} \\ q_{ES,k,\tau}^{out} &\leq \hat{q}_{ES}^{out} \end{aligned} \quad (8)$$

$$SOC_{ES,k,\tau} = \frac{E_{ES,k,\tau}}{Ca_{ES}}$$

$$\underline{SOC}_{ES} \leq SOC_{ES,k,\tau} \leq \overline{SOC}_{ES}$$

In Eq. (8), the terms ε , η_{ES}^{in} , and η_{ES}^{out} represent the self-discharging losses, the charging, and the

discharging efficiencies of storage battery, respectively. Note that the charging and discharging power of storage battery should be less than \hat{q}_{ES}^{in} and \hat{q}_{ES}^{out} , respectively. The term $SOC_{ES,\tau}$ indicates the battery charge state, which is generally between the upper limit \overline{SOC}_{ES} and the lower limit \underline{SOC}_{ES} . The energy balance of water storage system is similar to that of storage battery system, which will not be repeated here.

3. PROBABILISTIC SCENARIOS GENERATION AND REDUCTION

In view of the periodic fluctuation characteristics of solar radiation patterns and load curves, this paper adopts the clustering method to achieve the double reduction from the stochastic annual scenario set to the typical annual scenario set and from the typical annual scenario set to the typical daily scenario set. For the stochastic annual scenario set of cooling load and renewable energy power generation, this paper obtains it by Monte Carlo simulation method[9]. For electric load, it is difficult to obtain a set containing a mass of stochastic scenarios from the mechanism level. Therefore, this paper ignores the uncertainty of electric load and focuses on the uncertainty of cooling load and renewable energy power generation.

3.1 Probabilistic scenarios generation and reduction process

The set of stochastic annual scenarios with uncertainty is obtained by 1500 Monte Carlo simulations. Such high-dimensional data is difficult to be directly used as the feature vector for clustering, and currently clustering based on eigenvalues is a common method to reduce the dimension of high-dimensional data[10]. In this paper, the feature matrix of stochastic annual scenarios is constructed based on the mean, peak value, and information entropy which contains information on the kurtosis, skewness, and variance of the probability distribution. After obtaining the typical annual scenarios, this paper uses the method in reference [11] to directly

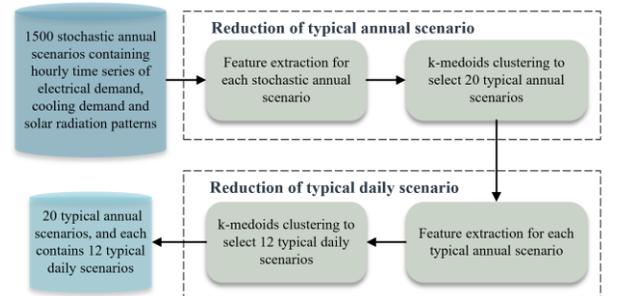


Fig. 2. Probabilistic scenario generation and reduction flowchart

take the hourly time series of daily load and daily solar radiation pattern as the feature matrix and perform scenario reduction to obtain typical daily scenarios. The specific process is shown in Fig. 2:

3.2 Input boundary of stochastic programming model

Through two scenario reductions, a low-dimensional set of typical annual scenarios as well as a set of typical daily scenarios can finally be obtained, and some of the clustering results are shown in Figs. 3-5. Three types of information can be obtained from the reduction process of the stochastic annual scenario set: (1) 20 typical annual scenarios, as shown in the dotted line example in Fig. 3; (2) The number of samples or occurrence probability for each typical annual scenario, as shown in the solid line example in Fig. 3, for instance, the number of samples is 90, corresponding to the occurrence probability value of $90/1500=6\%$; (3) The scaling factor for each typical annual scenario, which is the ratio of the average cumulative value of the solid line to the cumulative value of the dashed line in Fig. 3. Based on the 20 typical annual scenarios, further clustering can be done to obtain the same three types of information for typical daily scenarios. The typical daily load scenarios are shown in Fig. 4, and the typical daily photovoltaic power generation scenarios are shown in Fig. 5. The input boundaries of the stochastic programming model are the typical daily curves shown in Figs. 3-5, the occurrence probability of each typical annual scenario and the scaling factors.

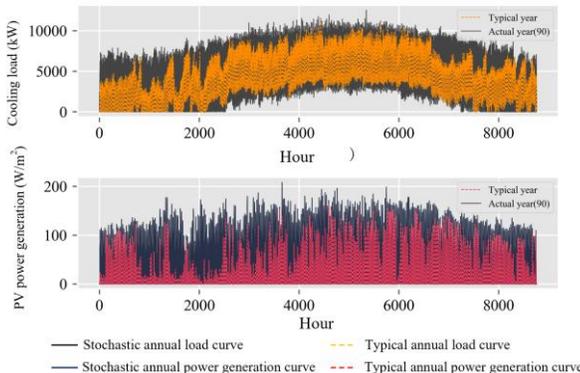


Fig. 3. Schematic diagram of clustering results of typical annual scenarios

4. CASE STUDY AND RESULTS

Taking the building integrated energy system for an industrial park as the research case, the typical daily scenarios generated above are used as the input boundary conditions of the stochastic programming model. The optimization and analysis of the stochastic programming are carried out with the help of the CPLEX

solver. Then the optimization results obtained by the stochastic programming model are compared with those obtained by the deterministic optimization model, and the specific analysis results are as follows.

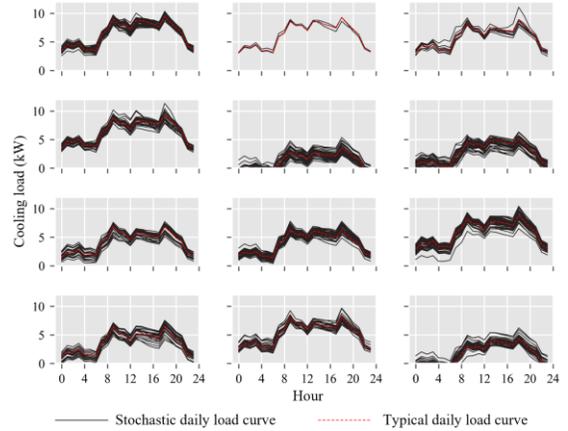


Fig. 4. Schematic diagram of clustering results of typical daily load

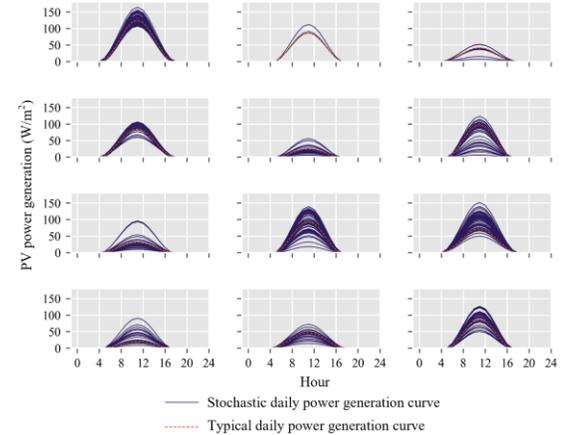


Fig. 5. Schematic diagram of the clustering results of typical daily PV power generation

Table 1 shows the optimal target values and design scheme of stochastic optimization model, as well as the optimal target values and design scheme of deterministic optimization model. Through the comparative analysis, it is revealed that the stochastic programming model and the deterministic programming model obtain entirely different design schemes. Compared with the deterministic scheme, the stochastic scheme increases the configuration of internal combustion engine and correspondingly increases the configuration of absorption chiller, so its number of the centrifugal chiller is subsequently reduced. In addition, considering the uncertainty of future load and photovoltaic power generation, the stochastic scheme significantly reduces the configuration of photovoltaic system. Since the PV configuration is reduced, the stochastic scheme is less affected by the source-side uncertainty and thus the

water storage system capacity is reduced. In accordance with the deterministic scheme, stochastic scheme will not select battery storage, mainly because: from the perspective of hourly energy balance, the water energy storage system can adjust the timing relationship between the cooling demand and the output of the chiller, which equivalently achieves the purpose of shaping electrical load curve. Therefore, the water storage system has the equivalent energy balance function as the battery storage system, while has the advantages of low investment and long service life.

In summary, the stochastic scheme tends to select a system with less renewable energy capacity due to uncertainty, while increases the investment of conventional devices and dependence on the grid. From the perspective of system reliability, stochastic scheme is a more conservative energy option.

5. DISCUSSION

The above analysis of the two design schemes is based on their respective design boundary conditions. The stochastic scheme is based on the typical daily scenario set, while the deterministic scheme's design boundary is the typical year. In order to further explore whether the stochastic scheme really has economic advantages in actual operation, the two schemes in Table 1 are brought into the deterministic optimization model respectively. And the optimization objective is changed to the annual operation cost so as to construct an operation model for both types of design schemes. Then 1500 stochastic scenarios generated by Monte Carlo simulation are brought into the operation model to test and analyze the actual operation cost of the two schemes. Here it needs to be explained again that the design boundary of the stochastic programming model is based on the reduced set of typical daily scenarios from the set of 1500 stochastic annual scenarios, and the

latter can be considered as a set containing complete uncertainty information, while the set of typical daily scenarios is incomplete due to the information loss in the process of scenario reduction, and the typical year used in the deterministic optimization model is even more incomplete. Since both design schemes are obtained under incomplete design boundaries, power outage may occur when encountering extreme operating conditions in stochastic scenarios. In order to ensure that the operation optimization model has a feasible solution, the energy balance constraints need to be relaxed. The relaxation constraints are as follows:

$$\begin{aligned} & \sum_m^M \sum_j^J q_{ICE,m,j,\tau}^e + \sum_{C=PV,grid} q_{C,\tau} + q_{ES,\tau}^{out} + q_{sl,\tau}^e \\ & \geq \bar{L}_\tau^e + q_{ES,\tau}^{in} + \sum_m^M \sum_j^J p_{CC,m,j,\tau} \\ & \left(\sum_m^M \sum_j^J q_{CC,m,j,\tau} + q_{AC,\tau} + q_{WS,\tau}^{out} + q_{sl,\tau}^c \right. \\ & \quad \left. \geq \bar{L}_\tau^c + q_{WS,\tau}^{in} \right) \end{aligned} \quad (9)$$

In Eq. (9), the terms $q_{sl,\tau}^e$ and $q_{sl,\tau}^c$ represent the slack variables of power capacity and cooling capacity respectively. When both are greater than zero, it indicates that the operation scheme has insufficient energy supply. In order to ensure that both take the value of zero under normal operating conditions, the objective function of operating cost is modified as follows:

$$\begin{aligned} C_{ope} = & \sum_m^M \sum_j^J \sum_\tau^T P_{ICE,m,j,\tau} \cdot (1 + \alpha_{ICE,m}) \cdot Gp \\ & + \sum_\tau^T P_{grid,\tau} \cdot Ep_\tau + (q_{sl,\tau}^c + q_{sl,\tau}^e) \cdot bigM \end{aligned} \quad (10)$$

In Eq. (10), the parameter is a constant, used to punish the case of insufficient energy supply.

The test results of the stochastic scheme and the deterministic scheme are plotted in Fig. 6. The red dot in Fig. 6(a) is the operating cost under each scenario, and the black pentagram is the average operating cost for 1500 stochastic scenarios. It can be found from Fig. 6(a) that the operation cost of deterministic scheme is lower than that of stochastic scheme under all test scenarios,

Table. 1. Comparison of optimization results between stochastic programming model and deterministic programming model

Model outputs	Stochastic scheme	Deterministic scheme
Equivalent annual cost (million CNY/year)	33.04	34.97
Annualized initial investment (million CNY/year)	6.11	9.40
Operation cost (million CNY/year)	26.04	24.73
Maintenance cost (million CNY/year)	0.88	0.84
Internal combustion engine (kW, number)	(1200, 2)	-
Centrifugal chiller (kW, number)	(2800, 3)	(2800, 4)
Absorption chiller (kW)	2304	-
Photovoltaic (kW)	3598	8971
Battery (kWh)	-	-
Water storage (kWh)	27322	39416

and the average operation cost can be reduced by 9.8%. This is mainly due to the larger capacity of the PV system and the water storage system in the deterministic scheme. Further statistics on the economic indicators and test results of the two schemes are shown in Fig. 6(b). It is found that the stochastic scheme still has an economic advantage under the same stochastic annual scenarios, as its equivalent annual cost is 2.02% lower than that of the deterministic scheme.

What is more noteworthy is that according to the statistics of energy supply reliability, there is no operation condition where the relaxation variable is greater than zero in both schemes, indicating that both stochastic scheme and deterministic scheme can resist the uncertainty of stochastic operation scenarios. Even if the energy system is optimized based on the design boundary with incomplete information, there is no shortage of energy supply in the actual operation process. This is mainly due to the flexibility of the energy storage system, which improves the energy supply reliability of the system.

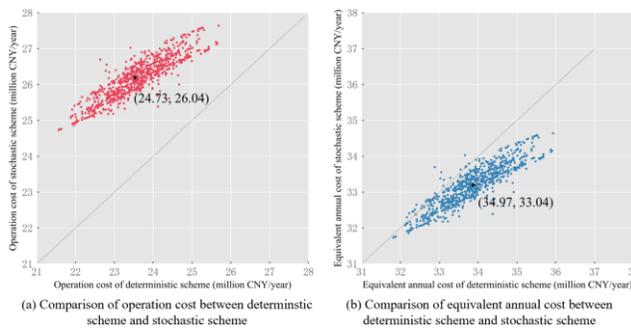


Fig. 6. Economic comparison between deterministic scheme and stochastic scheme under the same stochastic annual scenarios

6. CONCLUSION

In this paper, a stochastic programming model is formulated for the building energy system planning problem under dual source and load uncertainties. Facing massive stochastic scenarios, a two-level scenario reduction method based on clustering algorithm is proposed to obtain the typical annual scenario set and typical daily scenario set. Based on the reduced sets of typical scenarios, the uncertainty of energy demand and renewable energy generation can be taken into account on the one hand, and the optimal solution of the stochastic programming model is guaranteed on the other hand. A comparative analysis between stochastic scheme and deterministic scheme verifies the economic advantages of the stochastic programming model. In addition, it is found that the flexibility of the energy storage system can resist a certain degree of load

forecasting deviation. Therefore, facing the uncertainty of energy demand and renewable energy generation, it is necessary to focus on the planning of the energy storage system to increase energy flexibility, so as to improve system's ability to resist uncertainty.

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