

Multi-stage Sensitivity Analysis of Distributed Energy Systems: A Variance-based Sobol Method

Shangshang Wei, Yiguo Li, Xianhua Gao, Kwang Y. Lee, *Fellow, IEEE*, and Li Sun

Abstract—In the face of the pressing environmental issues, the past decade witnessed the booming development of the distributed energy systems (DESSs). A notable problem of DESSs is the inevitable uncertainty that may make DESSs deviate significantly from the deterministically obtained expectations, in both aspects of optimal design and economic operation. It thus necessitates the sensitivity analysis to quantify the impacts of the massive parametric uncertainties. This paper aims to give a comprehensive quantification, and carries out a multi-stage sensitivity analysis on DESSs from the perspectives of evaluation criteria, optimal design and economic operation. First, a mathematical model of a DES is developed to present the solutions to the three stages of the DES. Second, the Monte-Carlo simulation is carried out subject to the probabilistic distributions of the energy, technical and economic parameters. Based on the simulation results, the variance-based Sobol method is applied to calculate the individual importance, interactional importance and total importance of various parameters. The comparison of the multi-stage results shows that only a few parameters play critical roles while the uncertainty of most of the massive parameters has little impact on the system performance. In addition, the influence of parameter interactions in the optimal design stage are much stronger than that in the evaluation criteria and operation strategy stages.

Index Terms—Sensitivity analysis, uncertainty, operation, design, optimization, parameter characteristic, distributed energy system (DES).

I. INTRODUCTION

DISTRIBUTED energy systems (DESSs), which incorporate different renewable energies and various loads [1], have attracted worldwide attention due to the high efficiency, environmental friendliness and high flexibility [2], [3]. However, there still remains some obstacles that prohibit the development of DESSs, such as the parametric sensitivity that may significantly deteriorate the performance from determin-

istically obtained expectations. To this end, sensitivity analysis is employed to investigate the influence of the numerous parameters in the DESSs. Considering that each parameter may have different volatilities, the importance of the parameters should be carefully examined, which will be beneficial for the optimal design and economic operation of DESSs [4].

Currently, there are two primary methods for sensitivity analysis: local sensitivity analysis (LSA) and global sensitivity analysis (GSA) [5]. However, most of the literature related to sensitivity analysis of DESSs adopts the LSA method because of its simplicity. These studies are mainly carried out in one of the three stages, i.e., the evaluation criteria, optimal design, and operation strategy.

Sensitivity analysis of the evaluation criteria has been extensively studied, considering that there are many evaluation criteria of the DESSs. These studies are performed in various types of criteria, e.g., economy [6], [7], energy [8], [9], exergy [10], and environmental performance [11], [12]. In addition to these criteria, sensitivity analysis of the optimal design has also been extensively investigated. The chosen parameters for sensitivity analysis are generally divided into three categories: energy, economic, and technical parameters. The energy parameters are either from the user side, namely the different kinds of energy demand [13], [14], or from the supply side of the renewable energies such as wind speed [15], solar irradiation [16], etc. As for economic parameters, the typical parameters for sensitivity analysis are the electricity price [17], [18], fuel price [17], [19], interest rate [19], and equipment investment cost (IC) [16], [20]. Technical parameters also affect the design results of DESSs. For example, [20] studies three values of thermal-to-electrical demand ratio to investigate their influence on the results of the optimal design. Reference [18] studies the influence of the size of absorption chiller (AC) and thermal storage device on the system performance. Compared with the two stages above, there are also many papers devoted to the sensitivity analysis of the operation strategy of DESSs using the LSA method. For instance, [21] analyzes the impact of electricity buy-back, carbon tax, and fuel switching to biogas on the operation results. The influence of penetration of renewables on daily energy cost and CO₂ emission, and the impact of penetration levels on the system performance are analyzed under the stochastic operation strategy [22].

Despite the convenience of the LSA method, it has certain drawbacks as this approach is realized by changing the chosen variable while all other variables are fixed. Hence, the LSA method can only account for the influence of a single

Manuscript received: March 5, 2020; accepted: July 17, 2020. Date of Cross-Check: July 17, 2020. Date of online publication: September 11, 2020.

This work was supported by National Natural Science Foundation of China (No. 51936003), and National Key Research and Development Program of China (No. 2018YFB1502904).

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DOI: 10.35833/MPCE.2020.000134



parameter on the output [4]. In contrast to the LSA method, not only the influence of one parameter alone, but also the effect of the interactions between the parameter and all others can be considered by GSA [23]. Moreover, the importance of the parameter and its rank can be calculated quantitatively. Therefore, the GSA can be used to analyze the parameter characteristics more accurately and comprehensively.

The GSA has been widely applied in many fields such as the building performance analysis [24], urban microclimate system [25], sinter cooling process [26], and carbon dioxide energy storage system [27]. However, only few works use the GSA to analyze the parameters of DESs. For instance, [28] applies a sensitivity analysis toolbox to examine the sensitivity analysis of the levelized cost of electricity of each technology. A two-step sensitivity analysis for the optimal design of a DES is proposed, and 12 parameters are chosen for sensitivity analysis based on the variance-based Sobol method [4]. The influence of the uncertainties of the renewable energies and the load demands on the power flow of microgrids is evaluated by a density-based GSA [29]. The uncertainty of parameters is assessed in the long-term planning of the fossil-free energy systems with high integration of wind power to identify the most critical parameters by the Morris method [30]. Sensitivity analysis of the energy demand of electric city bus is performed, and the results show that the ambient temperature, rolling resistance and payload uncertainty contribute most to the demand [31]. However, these works examine the parameters only from a specific stage of DESs. A comprehensive parameter sensitivity analysis covering the evaluation criteria, optimal design and economic operation based on GSA has not been reported. Therefore, further study about GSA of DESs is also needed.

This paper is to explore the parameter sensitivity comprising the multi-stage of DESs instead of only a certain aspect. Moreover, the importance of parameters is evaluated quantitatively for the whole parameter set by using the variance-based Sobol method, which is a model-free approach and easy to implement [5]. Therefore, the sensitivity analysis of all the parameters of the DESs can be analyzed comprehensively.

The primary contributions of this paper are as follows.

- 1) A variance-based Sobol method is applied to a DES.
- 2) The multi-stage sensitivity analysis of the DES is performed.
- 3) Importance of the individual, interactional and total effects of 43 parameters are discussed.

The remainder of this work is as follows. The system mathematical model of a DES is established in Section II. Then, the solutions to the evaluation criteria, optimal design and economic operation strategy of the DES are presented in Section III. Next, the methodology of the variance-based Sobol method based on Monte-Carlo simulation is introduced in Section IV. Section V describes the results of sensitivity analysis at different stages, and then analyzes the multi-stage sensitivity results. Finally, conclusions are drawn in Section VI.

II. COMPONENT MODELLING OF A DES

Without loss of generality, a typical grid-connected DES scenario is exemplified for sensitivity study in this paper, as

shown in Fig. 1. It can be seen that the total cooling demand is split into the duty of electrical chiller (EC) and AC, and the heat source is even more diversified, including gas turbine (GT), gas boiler (GB) and solar thermal (ST) collector. The utility grid is able to provide the backup power in face of the shortage of power of the photovoltaic (PV) array. To describe the intermittence of solar energy and loads, a typical profile of cooling, heating and radiation is depicted in Fig. 2 [32]. Notably, a battery (BA) and thermal tank (TA) are incorporated into the DES to improve the flexibility and overall efficiency. The modelling of each component and the variables are explained thereafter.

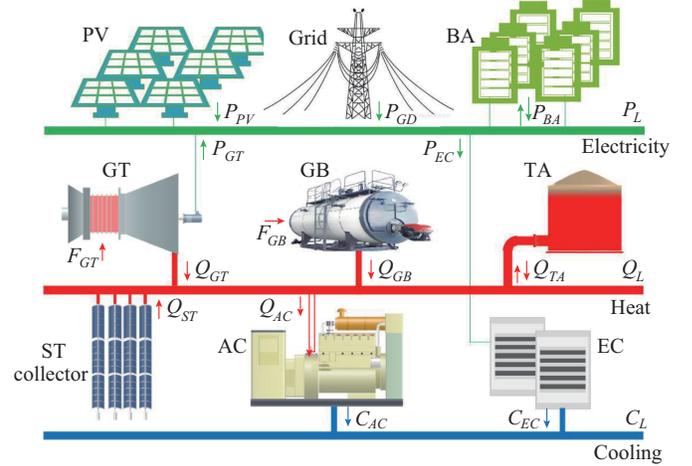


Fig. 1. Schematic diagram of proposed grid-connected DES.

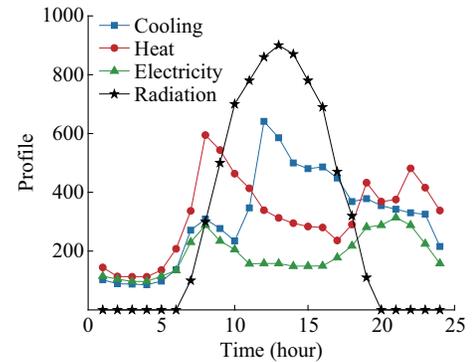


Fig. 2. Profiles of multi-energy sources and load demands.

A. PV Array and ST Collector

There are two devices to exploit solar energy: the PV array and ST collector. The electricity converted from solar radiation by the PV array, P_{PV} ; and the heat absorbed from the ST collector, Q_{ST} , are calculated [22], [32]:

$$P_{PV}(t) = \eta_{PV} A_{PV} I(t) \quad (1)$$

$$Q_{ST}(t) = \eta_{ST} A_{ST} I \quad (2)$$

where η_{PV} and η_{ST} are the electrical efficiency of a PV array and the thermal efficiency of an ST collector, respectively; A_{PV} is the PV area; A_{ST} is the total area of the collector; and I is solar radiation.

Considering the space limitation, the following constraint on the total area of the array and collector should be satis-

fied.

$$A_{ST} + A_{PV} = A \quad (3)$$

where A is the total area constraint of an ST collector and PV.

The operation costs of the PV array and the ST collector, OC_{PV} and OC_{ST} , are written as (4) and (5), respectively:

$$OC_{PV}(t) = K_{PV} P_{PV}(t) \quad (4)$$

$$OC_{ST}(t) = K_{ST} Q_{ST}(t) \quad (5)$$

where K_{PV} and K_{ST} are the maintenance costs of the PV array and ST collector, respectively.

B. GT and GB

To improve the reliability of the DES, a GT working as a controllable power source is installed to compensate for the inevitable volatility of solar radiation. The generated electricity of the GT P_{GT} can be calculated by:

$$P_{GT}(t) = \eta_{GT} F_{GT}(t) \quad (6)$$

where η_{GT} is the power efficiency; and $F_{GT}(t)$ is the supplied energy of natural gas in low heat value [13], [33].

Under the ratio of thermal energy to the supplied energy τ_{GT} , the waste heat from the GT Q_{GT} is calculated by [33]:

$$Q_{GT}(t) = \tau_{GT} \frac{P_{GT}(t)}{\eta_{GT}} \quad (7)$$

In addition to the GT, a GB is also installed in the DES for heat supplement, and the heat generated by the GB Q_{GB} is calculated by:

$$Q_{GB}(t) = \eta_{GB} F_{GB}(t) \quad (8)$$

where $F_{GB}(t)$ is the supplied energy of natural gas; and η_{GB} is the thermal efficiency of the GB [22].

The operation cost of the GT OC_{GT} , which consists of the fuel cost and maintenance cost, is:

$$OC_{GT}(t) = \lambda_{gas} \frac{P_{GT}(t)}{\eta_{GT}} + K_{GT} P_{GT}(t) \quad (9)$$

where λ_{gas} is the gas price; and K_{GT} is the maintenance costs of GT. The operation cost of GB OC_{GB} has similar form as:

$$OC_{GB}(t) = \lambda_{gas} \frac{Q_{GB}(t)}{\eta_{GB}} + K_{GB} Q_{GB}(t) \quad (10)$$

where K_{GB} is the maintenance costs of GB.

C. AC and EC

AC is widely used in DESs due to its important characteristics that the waste heat can be used to produce cooling energy. Therefore, a double-effect AC is applied here in addition to the EC. For the given coefficient of performance (COP), the output cooling energy of the two devices can be expressed as follows [22], [34]:

$$C_{AC}(t) = Q_{AC}(t) \cdot COP_{AC} \quad (11)$$

$$C_{EC}(t) = P_{EC}(t) \cdot COP_{EC} \quad (12)$$

where $Q_{AC}(t)$ is the heat needed to produce the cooling; P_{EC} is the consumed electricity; and C_{AC} and C_{EC} are the outputs of the AC and EC, respectively.

The corresponding operation costs of the AC and the EC

are expressed as below:

$$OC_{AC}(t) = K_{AC} Q_{AC}(t) \quad (13)$$

$$OC_{EC}(t) = K_{EC} P_{EC}(t) \quad (14)$$

where K_{AC} and K_{EC} are the maintenance cost of the AC and the EC, respectively.

D. BA and TA

Storage devices are essential to shake and shift the loads, and to reduce the impact of the stochastic characteristics of solar energy. Considering the similarities of the formulations between a BA and a TA, only the model of the thermal tank is presented here. The amount of energy stored in the thermal tank S_{TA} is expressed as [1]:

$$S_{TA}(t) = S_{TA}(t-1) + Q_{TA, ch}(t) \eta_{TA, ch} \Delta t - Q_{TA, dch}(t) / \eta_{TA, dch} \Delta t \quad (15)$$

where $Q_{TA}(t)$ is the charge or discharge rate at time t ; $\eta_{TA, ch}$ and $\eta_{TA, dch}$ are the charging and discharging efficiencies, respectively; and Δt is the sampling time which is simplified as 1 hour.

During the iteration at every time instant, the state of charge/discharge of the thermal tank is decided by a binary value. Moreover, the amount of energy, charging and discharging rates of the thermal tank should satisfy the constraints:

$$\begin{cases} S_{TA, \min} \leq S_{TA}(t) \leq S_{TA, \max} \\ 0 \leq Q_{TA, ch}(t) \leq \delta_{TA, ch} Q_{TA, ch, \max} \\ 0 \leq Q_{TA, dch}(t) \leq \delta_{TA, dch} Q_{TA, dch, \max} \\ \delta_{TA, ch} + \delta_{TA, dch} \leq 1 \\ \delta \in \{0, 1\} \end{cases} \quad (16)$$

where δ is the state of charge/discharge of the thermal tank.

Under the assumption that the maintenance costs of the charge and discharge process are the same, the operation cost of the thermal storage tank can be calculated as:

$$OC_{TA}(t) = K_{TA} (Q_{TA, ch}(t) + Q_{TA, dch}(t)) \quad (17)$$

where K_{TA} is the maintenance cost of the thermal storage tank.

The cost of the purchasing electricity from the grid for the grid-connected DES is calculated as:

$$OC_{GD}(t) = \lambda_{el} P_{GD}(t) \quad (18)$$

where λ_{el} is the electricity price; and $P_{GD}(t)$ is the electricity purchased from the grid.

E. Balance of Multi-energy

As shown in Fig. 2, there are three energy demands: cooling, heat and electricity. The cooling demand is satisfied through the EC and the AC.

$$C_{AC}(t) + C_{EC}(t) = C_L(t) \quad (19)$$

The heat from the GB, GT, ST collector and thermal discharge of the tank are collected to supply the heat demand, the heat for the AC, and the charging rate according to the energy balance:

$$Q_{GB}(t) + Q_{GT}(t) + Q_{ST}(t) + Q_{TA, dch}(t) = Q_{AC}(t) + Q_L(t) + Q_{TA, ch}(t) \quad (20)$$

Similarly, the balance of the electricity is shown as below:

$$P_{GD}(t) + P_{PV}(t) + P_{GT}(t) + P_{BA,dch}(t) = P_{EC}(t) + P_L(t) + P_{BA,ch}(t) \quad (21)$$

III. MULTI-STAGE EVALUATION AND OPTIMIZATION

A. Evaluation Criteria

There are many kinds of evaluation criteria for DESs. This paper takes the annual energy consumption (AEC) from thermal engineering perspective and the annual total cost (ATC) in economic point of view as example. According to the energy conservation, the AEC is the sum of the fossil fuel needed to generate the grid electricity and the consumed natural gas for the GT and GB, which can be calculated as [32], [35]:

$$AEC = 365 \sum_{t=1}^{24} \left(\frac{P_{GD}(t)}{\eta_{gre}} + F_{GB}(t) + F_{GT}(t) \right) \quad (22)$$

where η_{gre} is the grid transport efficiency.

The ATC consists of two parts, i.e., the IC and the annual operation cost of different devices [32], [35], which can be expressed as:

$$ATC = \sum_{j=1}^{n_e} \frac{r(1+r)^{n_j} IC(j)}{r(1+r)^{n_j} - 1} + 365 \sum_{j=1}^{n_e} \sum_{t=1}^{24} OC_j(t) \quad (23)$$

where r is the interest rate; n_j is the service life of the device j ; n_e is the number of the equipment; and IC and OC are the IC and operation cost of the devices in the DES, respectively.

In order to calculate these two criteria, the device capacity and operation strategy of each DES must be given. Table I shows the nominal capacity of each device, and the following thermal load (FTL) operation strategy is applied [32]. During the FTL operation, the heat needed for the AC is first calculated; then the equivalent heat can be obtained by adding the heat to the heat load.

TABLE I
NOMINAL CAPACITY OF DEVICES IN DES

Variable	Nominal capacity	Variable	Nominal capacity
P_{GT}	250 kW	A_{ST}	750 m ²
Q_{GB}	350 kW	A_{PV}	750 m ²
C_{AC}	200 kW	S_{TA}	800 kWh
P_{EC}	150 kW	S_{BA}	800 kWh
$Q_{TA,ch,max}$	400 kW	$P_{BA,ch,max}$	400 kW
$Q_{TA,dch,max}$	400 kW	$P_{BA,dch,max}$	400 kW

After that, the difference between the equivalent heat and the heat collected from the ST collector is calculated. If the heat is sufficient, the excess heat is sent to the thermal tank; conversely, the GT starts first, and then the GB will start next if the heat is still not enough. The shortage of cooling is replenished by the EC; then the equivalent electricity demand can be derived. During the operation, the excess electricity generated by the PV array and the GT is stored in the BA; conversely, the electricity is supplemented by the BA

first and then by the grid electricity to ensure the balance of the electricity.

B. Optimal Design of DES

Instead of giving the nominal capacity for the evaluation criteria, the purpose of the optimal design is to find the optimal capacity of devices. Taking the ATC as the objective function and considering the multiple constraints, the optimal design problem of the DES is expressed as below:

$$\begin{cases} \min ATC = \sum_{j=1}^{n_e} \frac{r(1+r)^{n_j} IC(j)}{r(1+r)^{n_j} - 1} + 365 \sum_{j=1}^{n_e} \sum_{t=1}^{24} OC_j(t) \\ \text{s.t. (3),(15),(16),(19)-(21)} \end{cases} \quad (24)$$

It can be seen that the objective function consists of two parts: the IC and the operation cost. The IC depends on the capacity of each device, while the operation cost is affected by the device capacities. Hence, the decision variables are composed of capacity variables and the operation variables.

The capacity variables of the problem are P_{GT} , Q_{GB} , C_{AC} , P_{EC} , A_{PV} , A_{ST} , S_{TA} , and S_{BA} , and their ranges are listed in Table II. Then the IC of the ATC can be calculated based on these variables. The operation variables are the hourly output of each device, i.e., $P_{GT}(t)$, $Q_{GB}(t)$, $C_{AC}(t)$, $P_{EC}(t)$, $P_{BA,ch}(t)$, $P_{BA,dch}(t)$, $Q_{TA,ch}(t)$, $Q_{TA,dch}(t)$, and the charging/discharging state sign δ for $t \in [1, 24]$. However, these operation variables must be constrained within the capacity variables, which means that the operation variables are dependent on the capacity variables. The ideas for the optimal design problem are as follows:

Step 1: define the capacity variable of each device within the given range, then the total IC can be obtained.

Step 2: define the hourly operation variables of each device, then the total operation cost can be obtained. Note that the range of these sub-variables depend on the capacity variables in *Step 1*.

Step 3: all the solution processes are coded on MATLAB, and the optimization problem is solved by the YALMIP.

TABLE II
RANGE OF CAPACITY VARIABLES FOR OPTIMAL DESIGN

Variable	Range	Variable	Range
P_{GT}	[0, 350]kW	A_{ST}	[0, 1500]m ²
Q_{GB}	[0, 350]kW	A_{PV}	[0, 1500 - A_{ST}]m ²
C_{AC}	[0, 400]kW	S_{TA}	[0, 1000]kWh
P_{EC}	[0, 200]kW	S_{BA}	[0, 1000]kWh

C. Economic Operation Strategy of DES

The purpose of the operation strategy is to coordinate different devices to satisfy the balances of electricity, and cooling and heat demand under system-level and device-level constraints. There are diverse trajectories to satisfy these requirements. Consequently, the hourly dispatch results in the evaluation criteria, and optimal design stages may be not the most economic results. Therefore, the economic operation strategy is formed as below.

$$\begin{cases} \min OC_{day} = \sum_{j=1}^{n_e} \sum_{t=1}^{24} OC_j(t) \\ \text{s.t. (15), (16), (19)-(21)} \end{cases} \quad (25)$$

As can be seen, the daily operation cost OC_{day} is the sum of different cost terms consisting of the purchased electricity and the operation costs of the GT, GB, AC, EC, BA, TA, ST collector, and PV array.

Under the nominal capacity of devices, the decision variables of economic operation are the hourly values of $P_{GT}(t)$, $Q_{GB}(t)$, $C_{AC}(t)$, $P_{EC}(t)$, $P_{BA, ch}(t)$, $P_{BA, dch}(t)$, $Q_{TA, ch}(t)$, $Q_{TA, dch}(t)$, and the charging/discharging state sign δ for $t \in [1, 24]$, while the outputs of renewable energy P_{PV} and Q_{ST} are uncontrollable variables. The decision variables are similar to the operation variables in the optimal design stage with the difference being the objectives. The economic operation is formulated as a mixed-integer linear optimization problem which can be readily solved similarly.

IV. SENSITIVITY ANALYSIS METHODOLOGY

After the introduction of the evaluation criteria, the optimal design and economic operation of the DES, this section describes how to perform sensitivity analysis of various parameters. The schematic flowchart of the multi-stage sensitivity analysis is presented in Fig. 3.

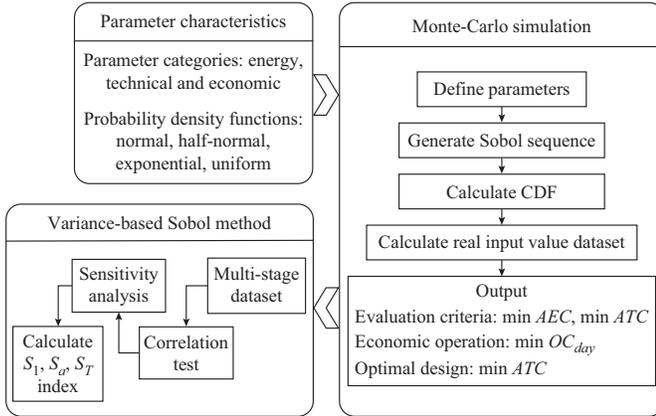


Fig. 3. Schematic flowchart of multi-stage sensitivity analysis of DES.

A. Parameter Characteristics of DES

As shown in Fig. 3, the first step in sensitivity analysis is to describe the parameter characteristics. There are many parameters in the DES whose values will deviate from the nominal values. Therefore, some known probability density functions, e.g., normal or half-normal distributions, are assigned to these parameters to simulate the possible deviations. At the same time, for a clearer description, all the parameters are broadly divided into three categories: the energy, technical and economic parameters. The technical parameters are further divided into efficiency coefficients and the service life, while the economic parameters are composed of the investment, maintenance, and the energy purchasing costs. In order to equally simulate the contributions of all parameters, their fluctuation ranges are constrained to be within the $\pm 10\%$ of the nominal value, except for some param-

eters with the maximum efficiency of 1. Detailed information for these parameters can be found in Tables AI-AIII in Appendix A where they are marked in order for convenience.

B. Monte-Carlo Simulation

There are three steps to perform the Monte-Carlo simulation. The first is to characterize the uncertainty forms. Next, samples are taken based on the probabilistic distributions. Then, the samples are inputted to the deterministic model for simulation, and the massive simulations are examined to analyze the system performance under the influence of uncertainties. After defining the probability density functions, the key point is how to sample based on the given probabilistic forms.

First, the corresponding range of the probability of each parameter is calculated according to the real input range of parameters in Tables AI-AIII in Appendix A. These probability ranges are then used to generate the Sobol sequence. This sequence is specially designed to generate samples over the unit hypercube with low discrepancy properties [36]. However, to get the real parameter value, the corresponding cumulative distribution function (CDF) of each parameter is also needed. Based on the CDF and the probability derived from the Sobol sequence, the real values of the parameters are derived. This completes the sampling process in accordance with the probability density functions of all parameters. After the sampling, the real value matrix of all parameters in the DES is shown as below:

$$\mathbf{D} = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1p} \\ x_{21} & x_{22} & \cdots & x_{2p} \\ \vdots & \vdots & & \vdots \\ x_{N1} & x_{N2} & \cdots & x_{Np} \end{bmatrix} \quad (26)$$

where x is a specific parameter; p is the number of the parameters; and N is the sample size. According to the variance-based Sobol method, N equals $k(p+1)$ if the first-order and total-order indices are exclusively calculated. k is a coefficient where its value is a trade-off between the computation cost and accuracy [36].

Based on the matrix, these samples are inputted to the DES coded for deterministic simulations. Then, the simulation results of the evaluation criteria, optimal design and economic operation are recorded. Based on the Monte-Carlo simulation results, the GSA of each stage is performed using the variance based Sobol method.

C. Variance-based Sobol Method

The variance-based Sobol method is a data-driven algorithm which can quantitatively calculate the influence of a parameter on the output. This method is essentially a variance decomposition technique [36]. For a square integrable function $Y = f(X_1, X_2, \dots, X_i, \dots, X_k)$ with its definition over k -dimensional unit hypercube, it can be decomposed as:

$$Y = f_0 + \sum_i f_i + \sum_{i < j} f_{ij} + \sum_{i < j < l} f_{ijl} + \dots \quad (27)$$

All the terms in (27) are linked by their partial variance V_{ij} , then the variance can be used to calculate the sensitivity indices S_{ij} [36]:

$$1 = \sum_i \frac{V_i}{V(Y)} + \sum_i \sum_{j>i} \frac{V_{ij}}{V(Y)} + \sum_i \sum_{j>i} \sum_{l>j} \frac{V_{ijl}}{V(Y)} + \dots = \sum_i S_i + \sum_i \sum_{j>i} S_{ij} + \sum_i \sum_{j>i} \sum_{l>j} S_{ijl} + \dots \quad (28)$$

As shown in (28), there are different sensitivity indices of the Sobol method, but the most commonly used are the first-order and the total-order sensitivity indices. This is because the first-order index only represents the influence of a single parameter change on the input, while the total-order sensitivity index considers both the influence of a parameter change itself and the interactional effect between the parameter and other parameters.

Based on these two indices, the influence of the individual and total effect of each parameter on system performance can be obtained. According to [4] and [36], the first-order and total-order sensitivity indices can then be calculated as below.

$$S_{1,i} = \frac{V_{X_i}(E_{X_{\otimes i}}(Y|X_i))}{V(Y)} \quad (29)$$

$$S_{T,i} = \frac{E_{X_{\otimes i}}(V_{X_i}(Y|X_{\otimes i}))}{V(Y)} \quad (30)$$

where $X_{\otimes i}$ contains all parameters but parameter X_i ; $Y|X_i$ is the output value when X_i is fixed; $E_{X_{\otimes i}}(Y|X_i)$ is the mean of all outputs of $X_{\otimes i}$; $V_{X_i}(Y|X_{\otimes i})$ is the variance of all output values of X_i when the other parameters $X_{\otimes i}$ are fixed; $E_{X_{\otimes i}}(V_{X_i}(Y|X_{\otimes i}))$ is the expected value under all possible $X_{\otimes i}$, and $V_{X_i}(E_{X_{\otimes i}}(Y|X_i))$ is the variance given all possible X_i . Therefore, the S_1 index can be represented as “expected reduction in the output variance that would be obtained if X_i could be fixed” [4], [37]. Similarly, S_T index can be interpreted as “expected variance that would remain if all factors but X_i could be fixed” [4], [37].

Based on S_1 and S_T , the parameter interaction index, which represents the coupling degree of a parameter with the others, can be calculated quantitatively as:

$$S_a = S_1 - S_T \quad (31)$$

The values of S_1 , S_T , and S_a indicate the individual importance, total importance and interactional importance of a parameter, respectively, and the importance rank of all the parameters can be obtained based on the importance values. These are the main sensitivity indices of parameters in the work.

However, the correlation of the input parameters should be tested before the sensitivity analysis because high correlation data will affect the accuracy of sensitivity results [36]. Consequently, the Pearson correlation below is examined.

$$\rho = \frac{\sum_{i=1}^n (x_{i,t} - \bar{x}_i)(x_{j,t} - \bar{x}_j)}{\sqrt{\sum_{i=1}^n (x_{i,t} - \bar{x}_i)^2} \sqrt{\sum_{j=1}^n (x_{j,t} - \bar{x}_j)^2}} \quad (32)$$

where x_i is the i^{th} parameter; and \bar{x}_i is the average of n samples. The closer the result is to 1, the higher the correlations are.

After the examination of correlation test of the param-

eters, the multi-stage GSA can be carried out. According to the approach, the sensitivity of all parameters in the DES can be analyzed and compared systematically and comprehensively.

V. RESULTS AND DISCUSSION

Figure 4 illustrates the Pearson coefficients between some parameters when taking the AEC as the objective. Considering that other parameters have similar characteristics, they are not plotted here for readability. It can be clearly seen in Fig. 4 that the correlation between variables is very small. This suggests that the parameters in the DES can be considered as independent.

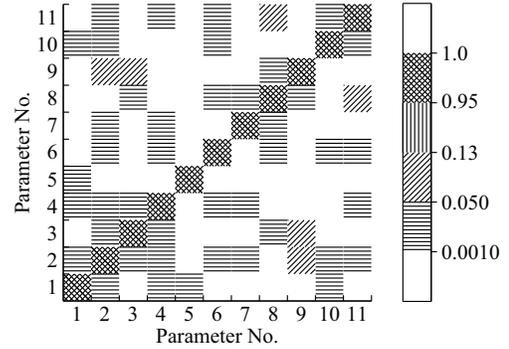


Fig. 4. Pearson coefficients between parameters.

In addition to the parameter correlation test, the sample size also has great impact on the result. Therefore, the S_1 index of the first 11 parameters in the DES is plotted in Fig. 5 with AEC as the evaluation criteria under different sample sizes. It can be obtained that with the increase of the coefficient k , the result of the S_1 index tends to stabilize. Although adopting larger k will increase the accuracy, the coefficient k , which is equal to 200, is chosen for the sensitivity analysis considering the trade-off between the accuracy and the computation cost.

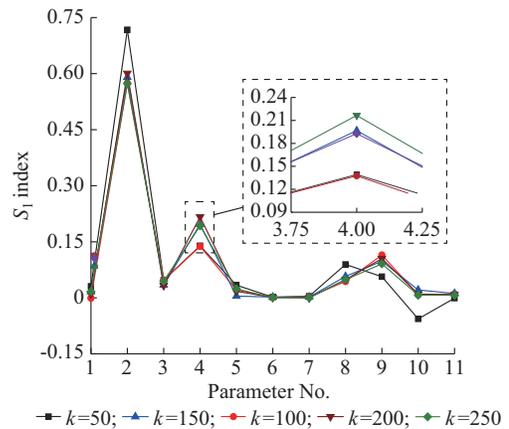


Fig. 5. S_1 index of the first 11 parameters under different coefficients k .

A. Sensitivity Analysis of Evaluation Criteria

For readability, energy parameters are marked as 1-4, efficiency coefficients and service life of devices are marked as 5-16 and 17-24, together with maintenance cost and IC as 25-32 and 41-43; while numbers 44-46 are the rate, gas

price and electricity price, respectively. Based on this numbering method, the sensitivity analysis of the evaluation criteria is shown in Fig. 6.

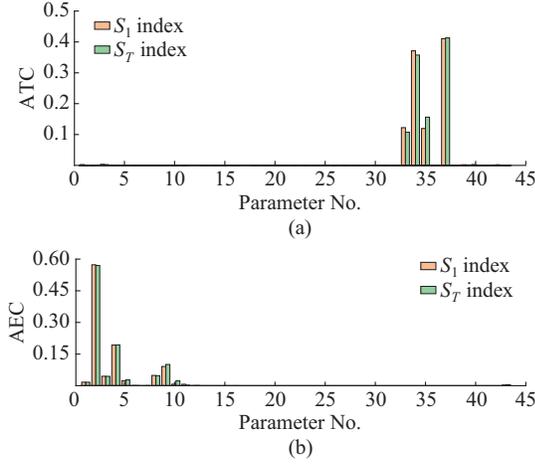


Fig. 6. Sensitivity analysis result. (a) ATC. (b) AEC.

It can be seen that the ICs IC_{PV} , IC_{ST} , IC_{GT} and IC_{BA} have a significant impact on the ATC, while the energy and technical parameters have little importance. As for the AEC, the energy parameters are the most influential ones, followed by some of the technical parameters such as COP_{AC} , η_{ST} , η_{GT} and τ_{GT} . While all the economic parameters have no effect on the AEC because there is no economic term in the AEC criteria. Therefore, the sensitivity of parameter category significantly depends on the type of the evaluation criteria.

It can also be found that among the massive parameters in the DES, only a few parameters have a critical effect on the output, while the influence of most parameters is negligible even in different criteria. This means that even though the values of these parameters fluctuate between $[-10\%, 10\%]$ of the nominal value, the change of the criteria is much smaller compared with the most influential ones. Hence, attention should be paid to the dominant parameters. What is more, the difference between S_1 and S_7 is very small for the two criteria, indicating that the interactional importance of parameters in the evaluation criteria is weak.

B. Sensitivity Analysis of Optimal Design

The S_1 index of the optimal capacity of different devices is shown in Fig. 7. It can be seen that there are also only a few parameters significantly affecting the optimal capacity of a device, while most of the parameters have little influence. More importantly, different devices have the same most important parameters, namely IC_{PV} , IC_{ST} and IC_{GT} . This suggests that the initial cost of the renewable devices takes up an influential portion of the ATC. In addition, changes in energy parameters, especially the cooling and heat parameters, also affect the optimal results of most devices. However, the contributions of the efficiency coefficients, the energy prices and interest rate are limited. But the service life and the maintenance cost of devices are the least sensitive. This suggests that the contribution of parameter categories is various. Note that the result of the thermal storage tank is not plotted since the optimal capacity is always approximately

zero under all conditions.

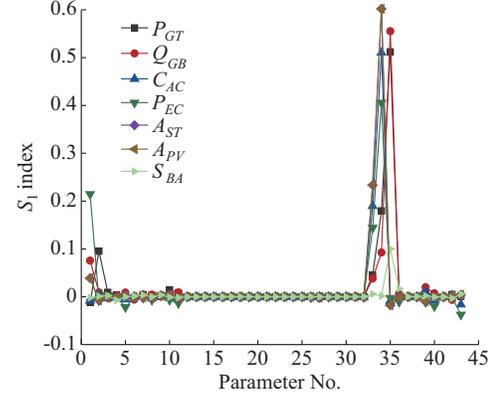


Fig. 7. S_1 index of optimal capacity.

As introduced in Section IV-C, only the individual importance of the parameter is considered in S_1 , while the difference between S_1 and S_7 indicates the influence of interactional importance on the output. Figure 8 shows the importance of parameter interactions of different devices in the DES.

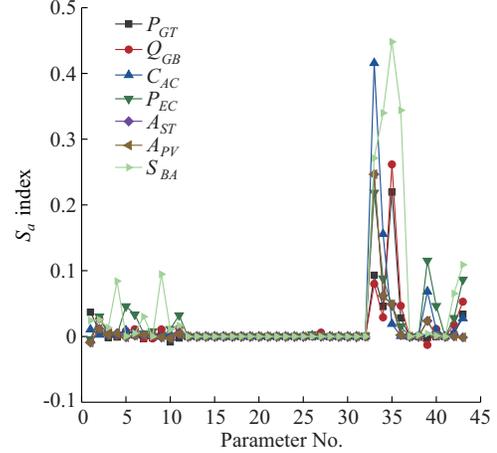


Fig. 8. S_a index of optimal capacity.

As can be seen, there is a very obvious coupling effect between parameters in the optimal design stage. The most important coupling parameters are the investment parameters IC_{PV} , IC_{ST} and IC_{GT} . The comparison between Fig. 7 and Fig. 8 suggests that some parameters have high interactional importance even though the individual importance is very small. This is demonstrated by the energy prices and interest rate, as well as some technical parameters such as λ_{el} , λ_{gas} , COP_{AC} and η_{GT} , etc. Moreover, Fig. 8 also indicates that the optimal capacity of the BA significantly depends on the parameter coupling effect providing that the importance of parameter interactions for the BA is high. This means the optimal capacity of the storage devices is a trade-off result of the optimal capacity of other devices.

C. Sensitivity Analysis of Operation Strategy

After the evaluation criteria and optimal design, the next stage of DESs is the operation strategy. Figure 9 shows the comparison of top 6 most important parameters under two operation strategies. The result suggests that the important parameters of operation strategies mainly depend on the ener-

gy parameters, and prices of natural gas and grid electricity. Furthermore, operation strategy has a critical influence on sensitivity results of the parameters. As shown in Fig. 9, the most sensible parameters are the λ_{gas} , Δe and Δh in a descending order for the economic operation. However, in the FTL strategy, Δe and λ_{gas} are the most sensible parameters. The sensitivity results of other parameters also change under different strategies.

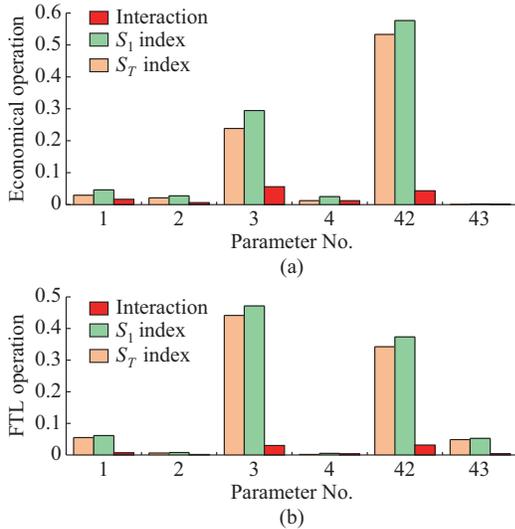


Fig. 9. Comparison of different operation strategies (top 6 important parameters).

It is interesting that although there exist a PV array and a ST collector, the operation strategy is not very sensitive to the vitality of solar radiance Δs . This suggests that the fluctuation of the renewable energy can be degraded through reasonable configuration and operation. Moreover, the effect of the electricity price is much lower than that of the gas price, indicating that the effect of time-of-use electricity price on the DES is limited. Therefore, the sensitivity analysis includes the calculation of the parameter importance, and can be very helpful to perceive the characteristics of DESs.

To illustrate the fidelity of the results, the parameters in Fig. 9 are selected to perform LSA under the economic operation. As shown in Fig. 10, the result agrees with the parameter importance rank of S_1 index. In addition, the result also suggests that the small value of the sensitivity indices only means the relatively little influence on the output instead of no influence, which is consistent with the real operation experience.

D. Multi-stage Sensitivity Analysis of DES

Hereinbefore, the sensitivity analysis for the three stages of the DES is performed separately. To clarify the multi-stage sensitivity analysis clearly, S_1 index of the multi-stage results is therefore integrated and plotted in Fig. 11.

It can be clearly seen that the sensitivity analysis of DESs is a complex and coupled process where no universally most important parameters exist, as the evaluation criteria, device capacity and operation strategy will all affect the analysis results. In addition, although there are massive parameters in the DES, most of which have little effect on system performance even in the multi-stage analysis. Moreover, the ener-

gy parameters seem to have the broadest influence on the system because the S_1 value of these parameters is relatively high even in different stages.

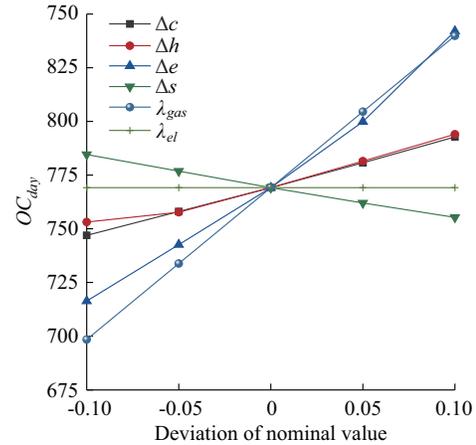


Fig. 10. Illustration of LSA under economic operation strategy (top 6 important parameters).

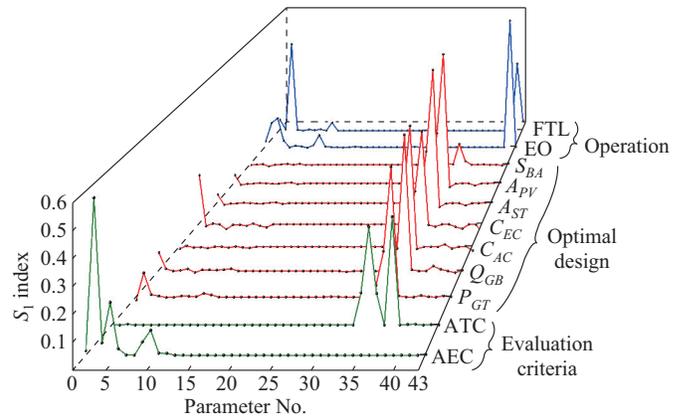


Fig. 11. S_1 index of multi-stage sensitivity analysis of 43 parameters.

Besides, the interactional importance of parameters varies in different stages. The parameter coupling effect in the optimal design stage is much stronger than that in the evaluation criteria and operation strategy stages, as shown in Fig. 12. Many parameters in the optimal design phase have high importance of parameter interactions. This means that the change in a parameter will affect the output by interacting with other parameters. Therefore, the uncertainty of the parameters in the optimal design should be considered. Moreover, the LSA is inappropriate for parameter analysis in this process considering the strong coupling effect of parameters.

VI. CONCLUSION

Considering that there are massive parameters in the DESs, the aim of this study is to quantitatively evaluate the sensitivity of various parameters from a comprehensive perspective. To achieve the goal, a mathematical model of DES is proposed, and a multi-stage sensitivity analysis of DES is carried out in terms of the evaluation criteria, optimal design and operation strategy. It is found that the variance-based Sobol method incorporated with Monte-Carlo simulation can analyze the parameter sensitivity reliably and quantitatively.

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