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Global Sensitivity Analysis of Key Parameters for Data Center Power and Energy Systems Considering Reliability#

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ABSTRACT

To provide continuous and trustworthy services to users, contemporary data centers rely significantly on a stable power supply. This power is generally obtained from main energy sources and is frequently supported by on-site uninterruptible power supply systems, which include battery storage and renewable energy solutions. However, a precise understanding of how various parameters within power and energy systems affect the reliability of the data center's power supply remains largely unexplored. This research, therefore, evaluates the influence of several critical parameters in data center power and energy systems on reliability, utilizing two prevalent global sensitivity analysis techniques: the Morris method and the Sobol method. The findings reveal that the likelihood of power grid failure, the failure probability of diesel generator and the wind turbine failure rate are the primary determinants of reliability. Moreover, the Morris method proves to be more efficient than Sobol, reducing computation time by approximately 48.9% to 49.7%, while still delivering comparable outcomes in certain cases.

Keywords: data center, reliability, power system, energy system, global sensitivity analysis.

1. INTRODUCTION

In the present day, the occurrence of sudden power failures poses a significant threat to infrastructure, with data centers (DCs) being especially noteworthy due to the considerable economic impact of system downtime, which can reach up to $9000 per minute as reported in 2016 [1]. To mitigate these risks, the power infrastructure of DCs is required to achieve a high level of dependability. Turner and colleagues have categorized DCs into four distinct tiers based on their reliability, as illustrated in Table 1 [2–4].

Under normal circumstances, the power supply of a data center is supported by multiple subcomponents, typically consisting of the main power grid, backup power systems (comprised of diesel generators (DGs) and battery energy storage systems (BESSs)), and renewable energy systems, as shown in Fig. 1. In specific geographical areas, data centers initially harness renewable energy to fulfill carbon emission reduction goals [5–7]. Owing to the fluctuating nature and generally constrained capacity of renewable energy sources, the electrical grid serves as a vital supply for the uninterrupted functioning of data centers. In the event of a power outage from the grid, backup power systems are then activated to sustain operations. Consequently, it is imperative to acknowledge the significant influence that key parameters of the power and energy systems within data centers exert on the reliability of the power supply.

To determine the influence of power and energy systems parameters on reliability, it is necessary to employ sensitivity analysis (SA) methods, which are succinctly divided into local sensitivity analysis (LSA) and global sensitivity analysis (GSA) [8,9]. The local SA (LSA) method computes or approximates the local sensitivity of the model's output with respect to specific input parameters [10]. In contrast, global SA (GSA) provides an expansive view for analyzing models. It methodically assesses the effect of each parameter, taking into account the interactions with others, thereby enabling a comprehensive examination of the parameter space [11].

Zhang et al. performed a GSA on the various parameters that affect the reliability of power systems dominated by converters, offering theoretical insights to future operators for risk mitigation strategies [12]. Li et al. utilized SA to measure the degree of controllability for security and stability control systems within interconnected power systems, across various

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configurations [13]. Koholé et al. performed a SA on hybrid renewable energy systems to determine the optimal setup for each energy source [14]. Abd-el-Motaleb' s group applied SA to assess how parameter fluctuations affect microgrid stability [15]. Chuat et al. introduced a two-step global sensitivity analysis (GSA) approach for tackling system configuration issues in district energy systems [16]. Previous studies have not focused on sensitivity analysis of the power and energy systems in data centers to ensure the high reliability requirements. Consequently, this study presents a comparative global sensitivity analysis of key parameters affecting data center power reliability, employing the widely used Morris and Sobol methods.

Table 1 The reliability-related descriptions of different data center tiers

Tier	Ⅰ	Ⅱ	Ⅲ	Ⅳ
Annual end-user downtime (hr)	28.8	22.0	1.6	0.8
Reliability (%)	99.67	99.75	99.98	99.99

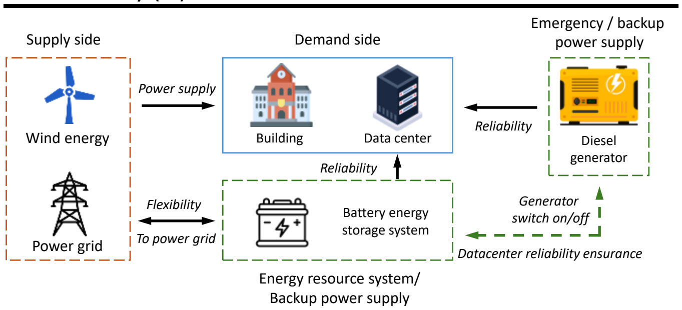


Fig. 1 The schematic diagram of data center power and energy systems

2. METHODOLOGY

2.1 Outline of power and energy systems global sensitivity analysis considering data center reliability

This paper introduces a methodology for examining the impact of power and energy systems parameters on data center power supply reliability. It begins by identifying key parameters, followed by integrating sampled data into the reliability model. The outcome is then analyzed using GSA indices, as illustrated in Fig. 2.

2.2 Data center reliability model

This paper focuses on developing a reliability model for data center (DC) integrated system, prioritizing the Loss of Load Probability (LOLP) metric. LOLP measures the likelihood of load demand exceeding generation capacity within a given time frame [17–19]. The model for reliability assessment is presented in Eq. (1).

$$\begin{cases} C_{out,n} = \sum_{t\in T} State_{DC,n,t} \\ LOLP_n = \dfrac{C_{out,n}}{C_{all,n}} \\ REL_{real,n} = 1 - LOLP_n \\ \forall n \in \{1000,2000,3000,4000,5000\} \\ \forall T \in [1,8760] \end{cases} \quad (1)$$

where, T is the yearly number of hours (8760); n is the varying simulation times; $C_{out,n}$ represents the states of DC power outages during simulation time n; $State_{DC,n,t}$ represents the operational state of the DC during simulation n and time t, with values limited to 0 and 1 (0 denotes the DC' s normal operation, while a value of 1 indicates power outage for the DC); $C_{all,n}$ represents the complete set of DC operation states (8760) at simulation time n; $REL_{real,n}$ is the reliability of DC at n.

The operation state $State_{DC,n,t}$ can be defined as Eq. (2).

$$State_{DC,n,t} = State_{DG,n,t} \cdot State_{B,n,t} \cdot State_{w,n,t} \quad (2)$$

where, $State_{DG,n,t}$ is the operating status of the DG, while 0 signifies normal operation and 1 indicates DG failure; $State_{B,n,t}$ is the BESS operating status, in which 0 indicates that the battery reserve energy is adequate to ensure the DC's normal operation, while 1 indicates insufficient battery energy to handle unforeseen emergencies like power grid outages; $State_{w,n,t}$ is the wind turbine state. The state of battery is related to power grid status and will be subsequently defined.

The DG status can be shown in Eq. (3)- Eq. (4), where $R_{DG,n,t}$ is the DG operating condition; λ_{DG} is the DG failure probability, typically ranging from 0.02% ~ 1% [20]; U_{DG} is the uniform distribution function of DG which is associated with probability of DG failure.

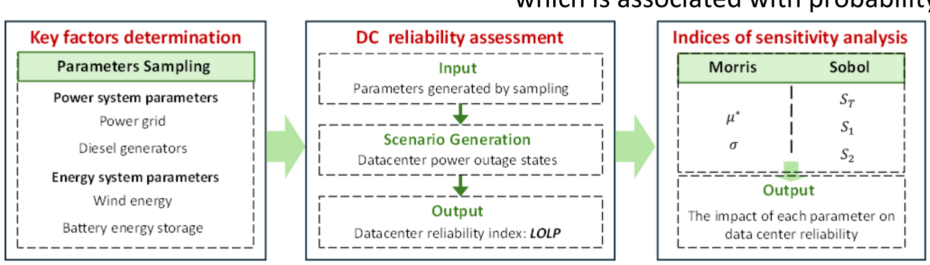


Fig. 2 The framework of data center power and energy systems global sensitivity analysis considering reliability

$$State_{DG,n,t} = step(R_{DG,n,t} - \lambda_{DG}) = \begin{cases} 0 & R_{DG,n,t} - \lambda_{DG} \geq 0 \\ 1 & R_{DG,n,t} - \lambda_{DG} < 0 \end{cases} \quad (3)$$

$$R_{DG,n,t} \sim U_{DG}(0,1) \quad \forall n \in N \quad \forall t \in T \quad (4)$$

The battery and power grid states can be shown in Eq. (5)- Eq. (10), where D_{PG} is the sampled duration of power grid outages; $\Gamma(\cdot)$ represents the Gamma function; α and β represent the shape parameter and the scale parameter of Gamma distribution respectively; $\overline{\omega}_{PG}$ is the power grid average outage duration; σ_{PG}^2 is the outage duration variance; $State_{PG,n,t}$ represents the operation state of power grid; λ_{PG} is the probability of power grid outages per hour; SET is the battery storage time; $U_{PG}(0,1)$ represents a uniform distribution function, in which $R_{PG,n,t}$, the probability of power grid outages, is randomly drawn from it in the interval [0,1].

$$State_{B,n,t} = step(D_{PG,n,t} \times State_{PG,n,t} - SET) = \begin{cases} 0 & D_{PG,n,t} \cdot State_{PG,n,t} - SET \leq 0 \\ 1 & D_{PG,n,t} \cdot State_{PG,n,t} - SET > 0 \end{cases} \quad (5)$$

$$State_{PG,n,t} = step(R_{PG,n,t} - \lambda_{PG}) = \begin{cases} 0 & R_{PG,n,t} - \lambda_{PG} \geq 0 \\ 1 & R_{PG,n,t} - \lambda_{PG} < 0 \end{cases} \quad (6)$$

$$R_{PG,n,t} \sim U_{PG}(0,1) \quad \forall n \in N \quad \forall t \in T \quad (7)$$

$$D_{PG,n,t} \sim \Gamma(\alpha, \beta) \quad (8)$$

$$\alpha = \frac{\overline{\omega}_{PG}}{\beta} \quad (9)$$

$$\beta = \sqrt{\frac{\sigma_{PG}^2}{\alpha}} \quad (10)$$

The wind turbine status can be shown in Eq. (11)- Eq. (12), where $R_{w,n,t}$ is the wind turbine operating condition; λ_w is the wind turbine failure probability, typically ranging from 1% ~ 5% [21–23]; U_w is the uniform distribution function of wind turbine which is associated with probability of its failure.

$$State_{w,n,t} = step(R_{w,n,t} - \lambda_w) = \begin{cases} 0 & R_{w,n,t} - \lambda_w \geq 0 \\ 1 & R_{w,n,t} - \lambda_w < 0 \end{cases} \quad (11)$$

$$R_{w,n,t} \sim U_w(0,1) \quad \forall n \in N \quad \forall t \in T \quad (12)$$

2.3 Sensitivity analysis model

Due to the advantages described above, this section compares the results of two GSA methods, namely Morris and Sobol. The specific models used in this study are presented below.

2.3.1 Morris screening method

The Morris approach, also recognized as the elementary effects technique, serves as an effective screening tool designed to pinpoint the subset of input variables that exert the most significant impact on the model outcomes. It provides a straightforward yet potent mechanism for identifying a handful of critical input factors from the multitude that may be present within a model [24].

The inputs can be defined as follows.

$$X = [\overline{\omega}_{PG}, \sigma_{PG}^2, \lambda_{PG}, \lambda_{DG}, SET, \lambda_w] \quad (13)$$

The concept of an elementary effect is shown below. Given a model that incorporates k autonomous input variables, denoted as X_i for $i = 1,2, \ldots, k$, these inputs are permitted to fluctuate across p selected levels within the confines of an k-dimensional unit hypercube. For a specified value of X, the elementary effect associated with the ith input parameter is characterized as follows.

$$d_i(X) = \frac{f(X_1, \ldots, X_{i-1}, X_i + \Delta, X_{i+1}, \ldots, X_k) - f(X_1, \ldots, X_{i-1}, X_i, \ldots, X_k)}{\Delta} \quad (14)$$

where Δ is a value in $\{1/(p-1), 2/(p-1), \ldots, 1 - 1/(p-1)\}$, p is the number of levels (with the value of 4), and $X = (x_1, \ldots, x_{i-1}, x_i, \ldots, x_k)$ is a random sample in the parameter space so that the transformed point $(x_1, \ldots, x_{i-1}, x_i + \Delta, \ldots, x_k)$ is still within the parameter space.

Morris introduced two metrics for sensitivity analysis: μ assesses the overall impact of each input on the output, while σ captures higher-order effects, including nonlinearities and input interactions. To determine these metrics, Q elementary effects per input are generated by randomly selecting Q points $X^{(1)}, X^{(2)}, \ldots, X^{(Q)}$ to adequately cover the design space. Campolongo et al. enhanced this approach by introducing μ_i^* to replace μ, using the subsequent formulas:

$$\mu_i^* = \frac{1}{Q} \sum_{m=1}^{Q} \left| d_i(X^{(m)}) \right| \quad (15)$$

$$\sigma_i = \sqrt{\frac{1}{Q-1} \sum_{m=1}^{Q} \left[d_i(X^{(m)}) - \frac{1}{Q} \sum_{m=1}^{Q} d_i(X^{(m)}) \right]^2} \quad (16)$$

A significant nonzero μ_i^* indicates that input i significantly influences the output overall. A large σ_i

suggests either a nonlinear impact of input i on the output or interactions with other inputs.

2.3.2 Sobol method

The Sobol method, a kind of variance-based method, is proposed to examine the primary, secondary, and aggregate sensitivity indices [25–27]. The variance-based approach employs variance ratios to gauge the significance of input factors, delineating the total variance of the model's output, $V(Y)$, through the subsequent equation:

$$V(Y) = \sum_{i=1}^{k} V_i + \sum_{i \le j \le k}^{k} V_{ij} + \cdots + \sum_{i \le \cdots k}^{k} V_{1\ldots k} \quad (17)$$

where V_i represent the first order effect for each factor $X_i (V_i = V[E(Y|X_i)])$ and $V_{ij} (V_{ij} = V[E(Y|X_i, X_j)] - V_i - V_j)$ to $V_{1\ldots k}$ the interactions among k factors.

The first-order sensitivity index S_{1i} can be calculated by

$$S_{1i} = \frac{V_i}{V(Y)} = \frac{V[E(Y|X_i)]}{V(Y)} \quad (18)$$

And the second-order sensitivity index S_{ij} can be calculated by

$$S_{ij} = \frac{V_{ij}}{V(Y)} = \frac{V\left[E\left(Y|X_i, X_j\right)\right] - V_i - V_j}{V(Y)} \quad (19)$$

Generally, the total sensitivity index can be defined as

$$S_{Ti} = \frac{E\left(V(Y|X_{\sim i})\right)}{V(Y)} \quad (20)$$

where the subscript $\sim i$ refers to all the inputs except input i. If the inputs are correlated, the variance decomposition is no longer valid. However, Eq. (20) is still a valid measure of total sensitivity.

3. RESULTS AND ANALYSIS

3.1 Morris screening

The paper gives the assumption that all the inputs are uniformly distributed in the range of the parameters, and thus the number of replications Q for Morris screening is set as 500, the level $p = 4$. Screening plots can visually represent the Morris screening measures by using modified means μ^* and standard deviations σ as the $x-$ and $y-$axes, respectively, as shown in Fig. 3. Due to the varying impact effects of each parameter on reliability, the absolute values of the μ^* are used in the plots to represent the extent of influence of each parameter.

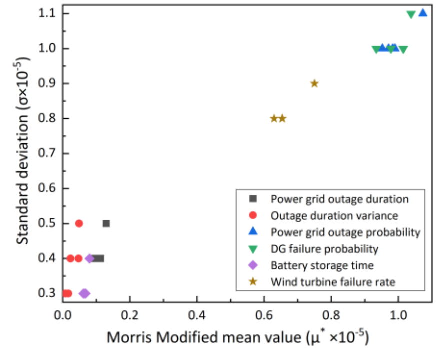
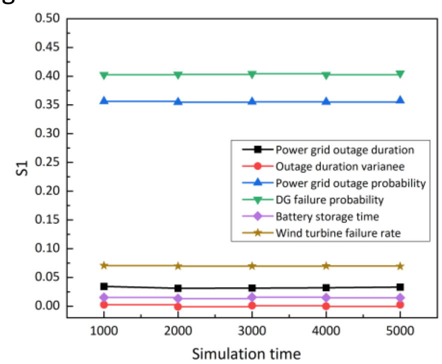


Fig. 3 Scatter plots for 6 parameters under different simulation times

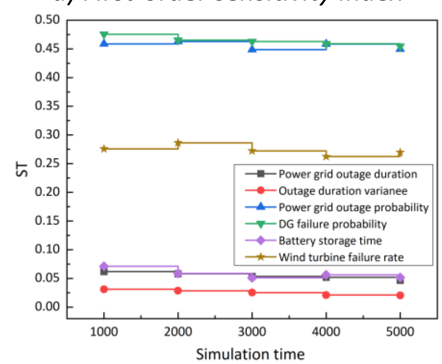
From the figure, the power grid outage probability and DG failure probability have the most significant impact on the reliability of the DC, followed by the wind turbine failure rate. The variance and duration of the power grid outage and the battery storage time have relatively minor effects.

3.2 Sobol method

Since the focus of this study is on the impact of each parameter on reliability, this section only presents the results of the first-order sensitivity index and total sensitivity index for each parameter. The results are shown in Fig. 4.



a) First-order sensitivity index



b) Total sensitivity index

Fig. 4 First-order and total sensitivity index under different simulation times

As can be observed from Fig. 4, the simulation times for the DC reliability model has a minor impact on first-order sensitivity index compared to total sensitivity index. In general, considering the computational cost associated with additional simulation times, there is no need to increase the number of simulations for the reliability model in the sensitivity analysis of DC power and energy systems. On the other hand, as the results depicted in Fig. 4 show, the S_1 and S_T sensitivity indices for the probability of power grid outage and the probability of DG failure are significantly higher than those of the other parameters. The wind turbine failure rate follows next, and the power grid outage duration and the storage time of battery also affect the result, while the variance of the power grid outage duration has the least impact on the reliability of the DC.

3.3 The computation time between two methods

Through research, it has been found that although the Morris and Sobol methods exhibit a considerable degree of consistency in the results of sensitivity analysis, there are still differences in some specific outcomes. For instance, in the Morris method, the impact of the power grid outage duration and the battery storage time on reliability is indistinguishable, whereas the Sobol method indicates that the impact of power grid outage duration is still greater than that of the battery storage time according to S_1. The power grid outage probability and DG failure probability exhibit a similar phenomenon. This indicates that the Sobol method provides distinct results for the parameters when compared with one another. Furthermore, the study reveals that there are also significant differences in computation time between the Morris and Sobol methods. The results are shown in Fig. 5.

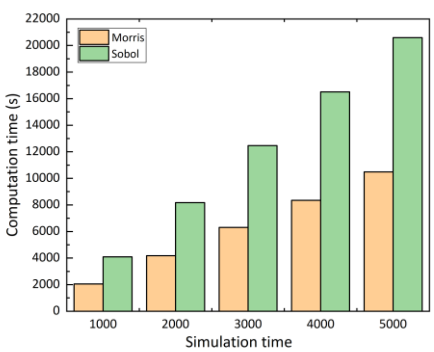


Fig. 5 Comparison of computation time between Morris and Sobol

As illustrated in Fig. 5, the Morris method requires less overall computation time compared to the Sobol method, reducing the computation time by 48.9% to 49.7% for varying numbers of simulations. However, this comes at the cost of less discriminative results. Therefore, the choice of which GSA method to employ necessitates that researchers make a selection based on the objectives of the study.

4. DISCUSSION

This study focuses on the GSA of power and energy systems considering the reliability of DC, comparing the results of two common methods, and filling a research gap. In future work, the authors plan to build upon this study by incorporating the sensitivity analysis of various parameters of integrated energy systems, providing a theoretical foundation for subsequent research and engineering practice.

5. CONCLUSIONS

The conclusions of this study are summarized as follows:

1) The Morris method shows that the power grid outage probability and the DG failure probability have the greatest impact on reliability, followed by the wind turbine failure rate. The impact of the duration variance is the least, and the degree of impact of power grid outage duration and battery storage time is indistinguishable.
2) The Sobol method reveals that the power grid outage probability and the DG failure probability have the most significant impact on reliability, followed by the wind turbine failure rate, power grid outage duration and the battery storage time, with the variance having the least impact.
3) The number of simulation times in the reliability model has a negligible impact on the results.
4) Compared to Sobol, the Morris method can reduce the computation time by 48.9%-49.7% as the simulation times varies.

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