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A framework for quantifying the value of information to mitigate risk in the optimal design of distributed energy systems under uncertainty

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Abstract:

Distributed energy systems (DESs) are regarded as promising systems for integrating renewable energy sources. However, uncertainties arising from renewable energy and loads introduce significant complexity to DES design and may even result in reliability and economic risks when the design of DESs relies on limited information. Gathering more information can reduce uncertainty, thereby improving the robustness of the DES scheme. However, obtaining information comes at a cost, and too much information can result in redundant work and unnecessary computing burden. Conversely, discarding or ignoring information may pose risks to reliability and the economy. Therefore, this study presents a framework for quantifying the value of uncertainty information, which can help to understand how information affects risk and identify key information that facilitates DES risk aversion. Two information value indices, namely the expected values of information for reliability (EVPIr) and economy (EVPIe), are developed to measure the risk reduction of reliability and economy when more information is added to the design of DESs. Furthermore, a two-layer information value quantification model based on mixed integer linear programming is built to optimize the design of DESs based on uncertain information and quantify the value of information based on a relatively complete information set. The proposed information value quantification method is tested on a real DES under three types of uncertain design boundary scenarios. The results show that the values of EVPIr and EVPIe decrease with increasing information of uncertain design boundary scenarios, indicating that more information reduces risks. An unexpected discovery is that the probability information of the scenario set is not critical for DESs. The deviations of EVPIe are within ±2%. The proposed approach offers a quantitative means to evaluate and filter key information for

planning scenarios, which can facilitate the generation of streamlined planning scenarios without compromising reliability and economy.

Keywords: value of information, uncertainty, risk assessment, distributed energy system

1. Introduction

1.1 Background and motivation

Renewable energy has emerged as the predominant source of energy supply with the ongoing energy transformation. The International Energy Agency's (IEA) Research [1] shows that the growth of renewable capacity is forecasted to accelerate in the next five years (2021-2026) to meet the COP26 targets. The distributed energy system (DES) is a promising energy system that integrates distributed renewable generation [2] and helps to mitigate climate change [3]. However, all technologies are inherently uncertain [4], and renewable energy systems, which are affected by weather conditions, exhibit even more significant uncertainty characteristics. During the planning stage, long-term predictions are required since energy system planners typically look forward 20-50 years ahead. However, perfect prediction is impossible; hence, the design of a DES under uncertainty is unavoidable, and it has attracted considerable attention.

Uncertainty quantification [5] and optimization under uncertainties [6] are two main approaches for enabling DES to adapt to uncertainties. The interval function is a simple approach to quantify uncertainties of renewable energy generation and loads with limited information [7, 8]. Correspondingly, interval optimization models [7, 8] or robust optimization methods [9] are used to optimize DES by obtaining lower and upper bounds of the optimal solution or the worst-case optimal solution. However, the interval function can only quantify the boundary information of renewable energy or load, lacking a description of the information within the interval [8] and the correlation information between different intervals [10]. To mitigate these problems, probability distributions or scenarios combined with probabilities are regarded as feasible alternatives with more information for describing uncertainties of energy prices, renewable energy generations, and loads. For instance, Mavromatidis et al. [11]

generated energy-demand probability scenarios using a feature-based clustering procedure, and four extreme energy-demand scenarios were further added for avoiding losing extreme value information. In ref. [3], the authors proposed a robust-stochastic programming model for designing a DES, in which the extreme scenarios and stochastic scenarios are considered together. Similarly, the current popular distributionally robust optimization (DRO) model [12] is developed to identify solutions that are robust against all possible probability distributions. Benefitting from the more posterior information, the DRO model can not only provide a distributionally robust solution but can also give a general solution, taking into account some risk. Uncertainty is the nature of things, and while it cannot be eliminated, it can be reduced. Therefore, many researchers aim to consider more information in the uncertainty qualification models so that the planned DES can be more robust to risk. As a result, a series of questions about the information and risk may inevitably arise: (1) How does the information of uncertain scenarios affects the design of DESs? (2) what is the value of working hard to obtain more information to reduce uncertainty? (3) How to quantify the value of information in reducing uncertainty and identify the key information for the design of DESs? This work, therefore, proposes a new framework for understanding and quantifying the information value of uncertain scenarios in the design of DESs, which is applicable to generating streamlined scenarios without causing risks.

1.2 Literature review

There are roughly three ways to understand and quantify the value of information on the design of DES under uncertainties, i.e., optimization under uncertainty, uncertainty analysis, and risk analysis. The *optimization under uncertainty* is a branch of optimization that deals with uncertainties in the data or the model. The interval optimization method [7, 8], robust optimization method [13] and stochastic optimization method [11, 14, 15] are commonly known well. In the design of a DES, uncertainties mainly include renewable energy generations, various loads, and energy prices, etc. Researchers compared a determined optimized design solution with solutions obtained through various uncertain optimization methods to demonstrate the benefits of considering uncertainty information. For instance, Majewski et al.

[16] developed a minmax robust optimization model for designing a DES under uncertainties of demands, energy prices and global warming impact. In this study, the authors utilized the interval function to quantify the uncertainties and used the worst-case scenario to ensure the optimized scheme was feasible in all uncertain scenarios, which resulted in the optimal objectives were higher than those in deterministic models. Similar conclusions were obtained in refs. [7, 13]. No matter the robust model adopted in [13] or the interval linear programming model adopted in [7], economies were all low efficiency compared to those in deterministic schemes, as only the worst-case scenario information was used in the design of DESs.

The worst-case scenario contained in the interval function is simple and easily obtained, but it is regarded as lacking information [8]. In fact, although it is very difficult to obtain accurate probability information for each scenario in the interval, we can always obtain some empirical information from historical data and generating the prior distribution by likelihood estimator, minimum Hellinger distance estimator [17]. Therefore, the decision-maker can make a decision with more information, such as the worst-case scenario and the prior distribution. That is regarded as the main concept of distributionally robust optimization method. The benefits of using more information in design of DES is obvious. For instance, when compared to the robust model, the distributionally robust optimization model significantly decreased the level of conservatism in the optimal Energy Hub [18]. However, due to the consideration of extreme scenarios, the distributionally robust optimization model in the case study [18] is still conservative compared to the stochastic model, and the economic objective of the model has increased by 1.12%. A two-stage stochastic optimization model was adopted in [11] to investigate DES design considering the randomness of energy carrier prices, emission factors, building heating and electricity demands, and incoming solar radiation patterns. Through comparing with the deterministic model solution, the results showed that the deterministic model leads to underestimations of the system costs and inaccurate estimates of the system's CO_2 emissions.

The above studies suggests that optimization models based on probabilistic scenarios, uncertainty sets, and interval sets tend to yield higher economic values in planning solutions than deterministic optimization models. However, such comparisons may overlook the fact that different optimization methods use different design scenarios, while all planning solutions will face the same operational scenarios in the future. Therefore, it is uncertain whether the above conclusion always holds. For instance, Niu et al. [15] found that the economic objective optimized by the deterministic programming model was worse than that of the stochastic programming model. In their other study [14], the authors proposed a stochastic programming model that considers complete uncertain information. Comparing the results with several deterministic models, they found that the economic performance of deterministic programming models was sometimes higher and sometimes lower than that of stochastic models. Urbanucci et al. [19] arrived at a similar conclusion in their study, stating that the deterministic method, which ignores uncertainty, tends to over-sized equipment, leading to higher costs. In another interesting study [20], the authors constructed a stochastic robust model for DES design, considering the worst-case scenario in the model. Unexpectedly, the optimal DES scheme is very close to that based on the nominal scenario. Karmellos et al. [21] and Mavromatidis et al. [22] conducted systematic comparative work to analyze the impact of different decision-making methods with varying uncertainty information on energy systems. In [21], four methods, namely, the objective-wise worst-case uncertainty, minimax regret criterion, the minimax expected regret criterion and stochastic programming were used to deal with uncertainties. Different uncertainty scenarios were considered in different models, where the worst-case scenario was used in objective-wise optimal model, while all the stochastic scenarios were used in the stochastic optimal model, resulting in significant differences between optimal solutions. In [22], more decision-making criteria, including expected value, minimum, minimax, Hurwicz criterion, value-as-risk, conditional value-at-risk and minimax regret, were compared, and results indicated that scenarios with different uncertain information could result in some solutions being conservative, while others could be aggressive.

In summary, previous studies have revealed that the results obtained from different optimization models with varying uncertainty scenarios differ significantly. For instance, some DES optimized by models are cost-effective and risk-seeking, while others are expensive and risk-averse. However, it should be noted that different models consider different uncertainty information, which means that the solutions obtained by different models are not compared on the same benchmark. However, regardless of which model's solution is obtained, it will definitely face the same scenario in the future. Therefore, considering uncertainty information in stochastic models, interval models, and robust models can only tell us that the obtained solutions are different from deterministic solutions, but cannot tell us whether these model-derived solutions are better, and cannot quantify the value of uncertainty information.

Uncertainty analysis is used to quantify the variability of the output that is due to the variability of the input [23], and is another perspective to understand the impact of uncertainty information on the design of DESs. Multiple authors have performed uncertainty analysis in the context of DESs. For instance, uncertainty analysis was adopted by Mavromatidis et al. [24] for the design of a DES considering uncertain energy demands, photovoltaic (PV) power, energy carrier prices. The results revealed significant variability in the DES configurations, total cost and carbon emissions. In [25], the system configuration obtained with one of these scenarios were evaluated by introducing performance indicators that quantify the robustness and the cost optimality attained when operating in other possible scenarios. Ahn et al. [26] performed uncertainty analysis for investigating the impact of the PV power penetration and uncertainty on the operation of a microgrid, and revealed that the annual operation cost increased by 9-13% per year when uncertainties were concerned. In [27], a comprehensive uncertainty analysis that encompassed performance characteristics of technologies and energy policies was performed for the design of district-scale multi-energy system with power-to-hydrogen. Similarly, the authors in [28] extended the uncertainty analysis to integrated energy system (IES), in which the uncertainties of wind power, PV power and energy demands were quantified by information theory and the impacts on IES were investigated. Pilpola S et al. [29] investigated the uncertainties of level of consumption, renewable resource potential and cost data for the process of deep decarbonization of the national energy structure. Results from uncertainty analysis showed that the input of energy system models brought a significant impact on the national energy system performance and the goal of carbon neutrality.

Overall, uncertainty analysis is helpful for decision-makers to clarify how uncertain the model outputs are when facing uncertain inputs. However, although the output in the uncertain analysis may vary, the fact is that the decision is always unique in the end. Additionally, any decision made now will face the same operational scenario in the future. Therefore, it seems that the uncertainty analysis is still unable to answer questions such as: what is the risk of ignoring uncertainty? what is the value of considering uncertainty? And how much does information add to the design of a DES under uncertainties?

Uncertainty and risk are closely related. The essence of risk is the possibility of loss, damage, or negative consequences that arise from uncertainty, unpredictability or lacking of information [30]. Therefore, *risk analysis* is also a common method used by many industries to determine the possibility of economic and reliability losses due to insufficient information. The CVaR was introduced in [31] for a risk metric, then risk analysis was performed to investigate how the uncertainty and correlation information of electricity price and gas price impact on the economy of a park-level integrated energy system. In [32], the authors analyzed the expected risks brought by wind power uncertainty to the carbon emission target of the U.S. electricity market, and found that the cumulative carbon emission in the next 10 years (from 2020 to 2030) has a probability of about 10% exceeding expectations level. Luo et al. [33] developed a reliability assessment and risk quantitation method for microgrids, in which the uncertain information of supply and demand were considered and resulted in more comprehensive reliability assessment results. Similarly, in [34], risk analysis was performed for the reliability assessment of a microgrid considering uncertainties pertaining to renewable energy generations, energy demands and operation states of main components, which was simulated by sequential Monte Carlo simulation. The purpose of risk assessment is to test the performance of existing energy systems under specific or random scenarios. Currently, numerous studies focus on the risk assessment of system operation reliability, but only a few addresses the risk of economic loss. Although some studies examine the risk of economic loss caused by uncertain information, they tend to focus solely on operating costs and neglect the loss of DES investment costs incurred due to missing information.

Even though, as the previous paragraphs revealed, *optimization under uncertainty*, *uncertainty analysis*, and *risk analysis* were all available for investigating the impact of uncertainty on the design of DES. Nevertheless, there are specific aspects that need to be addressed. Firstly, lack of a fair baseline for quantifying the value of information: Currently deterministic, stochastic, and robust models are used to design DESs. Although different models use different design scenarios, the resulting DESs all face the same future operating scenarios. 100% real future operating scenarios are the ideal baseline for evaluation, but perfectly foreseeing future occurrences is not realistic. The lack of reasonable baseline scenarios leads to an unfair evaluation of different models, which may mislead designers to make wrong decisions; Secondly, lack of quantification method for the value of uncertainty information: information is the basis of decision-making, and loss of information can lead to underestimation of risk [32]. Although it is commonly believed that acquiring more information can help reduce uncertainty, these come with increased costs such as conducting massive stochastic simulations and collecting numerous uncertainty input parameters to improve building load simulation results [11, 15]. However, the value of acquiring additional information to reduce risk has not been explored, and blindly adding more information can result in inefficiencies, redundancy, and increased computational burden.

1.3. Contribution and organization

This paper therefore proposes a mixed integer linear optimization framework for quantifying information value considering uncertainties in the design of DESs. In this study, these aforementioned shortfalls are addressed via the following contributions:

1) Two information value indices, namely the expected value of information for reliability (EVPIr) and economy (EVPIe), are developed to measure the risk reduction of reliability and economy when more information is added to the design of DESs;
2) The value of information could be represented by risk reduction, and the quantitative model of uncertain information value and the quantitative model of information incremental value based on relatively complete information scenarios are further developed;
3) Furthermore, a two-layer information value quantification model based on mixed integer

linear programming is built to optimize the design of DESs based on uncertain information and quantify the value of information based on a relatively complete information set;

4) The application of the proposed method to a park-level DES design for a case study to illustrate the method's output and investigate what information is key for the design of DESs.

The paper is organized as follows: Section 2 introduces the method of quantifying the value of information, including proposing two information value indexes, and formulating a two-layer optimal model for calculating the indexes by the optimal design and operation of DES under uncertainty. Section 3 presents the case and the scenario generation method for different information levels. Section 5 presents and discusses the results of this study. Section 6 summarizes the main conclusions and outlines further research on this paper's topic.

2 Methodology for value of information qualification

Various uncertainties, such as energy prices, renewable energy generation, energy demands, and equipment prices may arise in the design of DESs. The uncertainty of prices will only lead to economic risks, while uncertainty of design boundaries, such as renewable energy generation, electric load, and cooling load, will cause both economic and reliability risks [25]. In this paper, we consider the uncertain boundaries, i.e., photovoltaic power generation, cooling, and electric loads, in the design of a DES. These design boundaries are also named scenarios in this paper.

The methodology for quantifying the information value in DES design is presented in Fig.1, which comprises four main steps. In Step A, two indices are defined and formulated to quantify the value of information, namely the expected value of information for reliability (EVPIr) and the expected value of information for economy (EVPIe). A detailed explanation of these two indices is provided section 2.1. In Step B, as described in Section 2.2.2, scenarios with varying amounts of information are defined and generated. In Step C, three optimal design models are built based on different scenarios in Step B, and three types of DESs will be obtained in Step C. This part will be detailed description in Section 2.2.3. Finally, in Step D, an optimal operation model is formulated as a testing platform for quantifying the reliability and economic risks of the designed DESs in Step C.

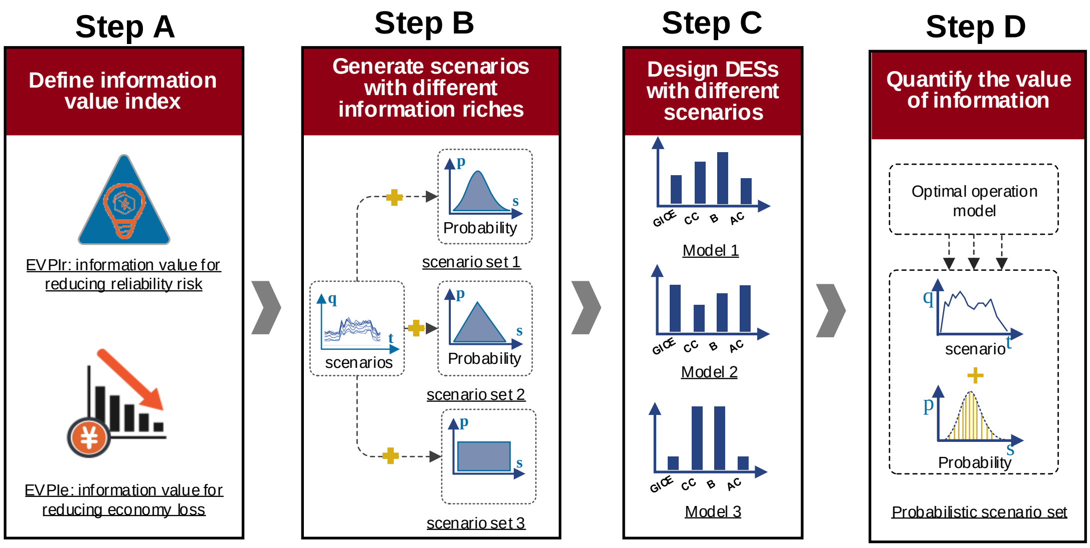

Fig.1 General workflow for quantification of information value in design of DES

2.1. Qualification model of value of information

In this section, two concepts are first introduced, one is "*a scenario with perfect information*" and the other is "*a scenario set with relatively complete information*". The former concept assumes complete knowledge of future operation scenarios, which is an idealized scenario from a perfect clairvoyant perspective. This scenario is not achievable in reality; rather, it severs as a hypothesis to introduce the concept of "value of information". The latter concept is a scenario set obtained through advanced forecasting techniques such as Monte Carlo (MC) simulation. This scenario set will contain perfect future information with a high probability, as long as the MC simulation is performed enough times [35]. A diagram (Fig. 2) is used to help understand these concepts. The circles in Fig. 2 (b) represent scenarios, each scenario including a set of hourly photovoltaic power generation, cooling load and electric load sequences. The red circle denotes the *scenario with perfect information*. The scenarios in Fig. 2(b) and the probability in Fig. 2(a) together form the *scenario set with relatively complete information*. The value of information is regarded as the amount of a decision maker would be willing to pay for information before making a decision [36]. In the design of DES, the value of information can be viewed as the difference between the objective based on the scenario with perfect information and the objective based on a forecast scenario. Although we cannot obtain the scenario with perfect information before making a decision, we will still utilize it to introduce the formulation of the value of information in Section 2.1.1. Subsequently, in Section 2.1.2, a practical method for calculating the value of information using *the scenario set with relatively complete information* will be presented.

2.1.1. Value of information based the scenario with perfect information

Assuming that the scenario with perfect information ($s' = p$) is available and denoted by the red circle in Fig. 2 (b), then a DES scheme $ch_{s'}(s' = p)$ (represented by the red square in Fig. 2 (c)) and objective $O_{s'}^{sch_{s'}}(s' = p)$ (represented by the red triangle in Fig. 2 (d)) can be optimized based on s'. In reality, designers often optimize the DES based on different typical scenarios [37, 38]. We might as well assume that scenario 6 as shown in Fig. 2(b) is a typical scenario ($s = 6$). Accordingly, an optimal DES scheme $sch_s(s = 6)$ (represented by the blue square in Fig. 2 (c)) and objective $O_s^{sch_s}(s = 6)$ (represented by the blue triangle in Fig. 2 (d)) can also be obtained based on the typical scenario ($s = 6$). If DES $sch_s(s = 6)$ operates in scenario $s'(= p)$, two risks may arise: reliability failure and economic loss. In other words, since the scenario $s'(= p)$ is assumed a scenario with perfect information, forecasting this scenario beforehand can prevent the risks of reliability and economic loss. Therefore, in essence, the true value of information lies in its ability to mitigate potential risks by using the scenario with perfect information.

(1) The value of information for reducing reliability risk

In order to measure the reliability failure (refer to the power inadequacy in DES), various of indices have been proposed, like the Loss of Power Supply Probability (LPSP) index, the Loss of Energy Expected (LOEE) index, etc., and more indices are summarized in [33]. In this study, an index is proposed for quantifying the reliability failure, formulated in Eq. (2). The loss of energy $\Delta E_{s,s'}$ of DES $sch_s(s = 6)$ when operating in scenario $s' = p$ is calculated using Eq. (1). Eq. (2) is an indicator function, in which $R_{s,s'}^{r} = 0$ means that there is no energy loss when the DES $sch_s(s = 6)$ operates in scenario $s'(= p)$. The result implies that obtaining the scenario with perfect information $s'(= p)$ in advance is worthless for improving DES reliability performance, also known as the value of information equals 0. Otherwise, $R_{s,s'}^{r} = 1$ implies the DES $sch_s(s = 6)$ is at risk of power inadequacy, which can be avoided if the scenario $s'(=p)$ is known in advance. Therefore, this paper defines $R^r_{s,s'}(s=1,2,\ldots)$ as the value of information for reliability (VPIr).

$$\Delta E_{s,s'} = \sum_t^T \Delta e^{sch_s}_{s',t}, (s=6, s'=p) \tag{1}$$

$$R^r_{s,s'} = \begin{cases} 0 \; if \; \Delta E_{s,s'} = 0 \\ 1 \; if \; \Delta E_{s,s'} > 0 \end{cases}, (s=6, s'=p) \tag{2}$$

In the above equations, *T* is the planning period. *t* is the time step of this model, 1h. $\Delta e^{sch_s}_{s',t}$ represents the energy loss in scenario $s'=p$ and time step *t*, which will be described in Section2.2.4.

(2) The value of information for reducing economy risk

When the DES $sch_s(s=6)$ operates in the scenario $s'=p$ and there is no energy loss, the objective value $O^{sch_s}_{s'}(s=6, s'=p)$ must be inferior to the objective $O^{sch_{s'}}_{s'}(s'=p)$ ($O^{sch_s}_{s'} \geq O^{sch_{s'}}_{s'}$). The difference between $O^{sch_s}_{s'}$ and $O^{sch_{s'}}_{s'}$ represents the economy loss of the DES $sch_s(s=6)$. Similarly, if we can grasp the information of the scenario $s'(=p)$, the economy loss can be reduced. Therefore, this study defines $R^e_{s,s'}$ as the value of information for economy (VPIe).

$$R^e_{s,s'} = O^{sch_s}_{s'} - O^{sch_{s'}}_{s'}, (s=6, s'=p) \tag{3}$$

It should be noted that an optimal objective $O^{sch_s}_s(s=6)$ can also be obtained based on the scenario $s(=6)$, which has a distinct meaning from $O^{sch_s}_{s'}(s=6, s'=p)$. In the design of DES, the economic objective usually can be divided into two parts: the investment cost and the operation cost [15]. In the economic objective of $O^{sch_s}_s(s=6)$, the investment and operation costs are all optimized based on the scenario $(s=6)$, while they are calculated using the scenario $(s=6)$ and scenario $s'=p$ in objective $O^{sch_s}_{s'}(s=6, s'=p)$, respectively. This is in line with reality, as these typical scenarios used in the design of DES are likely to be different from the scenario $s'=p$ in the actual operation. Consequently, the operation cost may vary with the scenario, while the DES scheme cannot be temporarily changed, and so is the investment cost.

2.1.2. Value of information based on the probabilistic scenario set

In Section 2.1.1, the evaluation of the value of information for both reliability and economy assumes a scenario with perfect information. However, such a scenario is not attainable in real-world applications. To address this issue, we replace the perfect information scenario with a scenario set with relatively complete information. As illustrated in Fig. 2 (a) and (b), the probabilistic scenario set with the relatively complete information can be obtained through the Monte Carlo simulation, as explained in Section 3.2. Consequently, the VPIr, described in Eq. (1) and (2), is reformulated using Eqs. (4) ~ (6).

$$\Delta E_{s,s'} = \sum_t^T \Delta e_{s',t}^{sch_s}, (\forall s \in S, s' = 1,2, \dots) \tag{4}$$

$$R_{s,s'}^r = \begin{cases} 0 \ if \ \Delta E_{s,s'} = 0 \\ 1 \ if \ \Delta E_{s,s'} > 0 \end{cases}, (\forall s \in S, s' = 1,2, \dots) \tag{5}$$

$$R_s^r = \sum_{s'}^{S'} \omega_{s'} R_{s,s'}^r, \forall s \in S \tag{6}$$

In these equations, S represents the scenarios with different amount of information, e.g., four typical scenarios used in [39], five typical scenario used in [18], and fifteen stochastic scenario set in [11]. S' is the scenario set with relatively complete information, and used as the benchmark in this paper. $\omega_{s'}$ denotes the probability of scenario of s'. R_s^r is the expected value of $R_{s,s'}^r$. Likewise, the R_s^r will be reduced if the scenario set with relatively complete information is obtained. So, this paper defines the R_s^r as the expected value of perfect information for reliability (EVPIr).

Similarly, Eq. (3) for VPIe can be replaced by Eq. (7), where R_s^e represents the expected value of perfect information for the economy (EVPIe).

$$R_s^e = \sum_{s'}^{S'} \omega_{s'} \left(O_{s'}^{sch_s} - O_{s'}^{sch_{s'}} \right), \forall s \in S \tag{7}$$

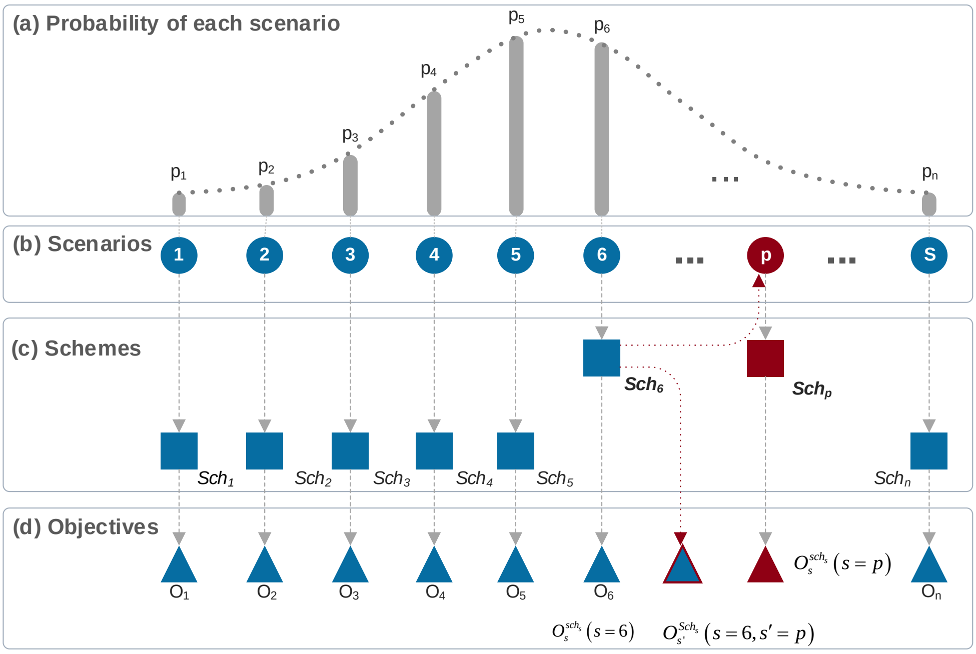

Fig. 2 Schematic diagram of information value calculation

2.2 Two-layer optimal model for quantifying the EVPIr and EVPIe

The indices for quantifying the value of information for reducing the risks of reliability (EVPIr) and economy (EVPIe) are defined in Section 2.1. This section proposes a two-layer optimal model for calculating the EVPIr and EVPIr by addressing the task of DES design and operation under uncertainties.

2.2.1 Overview of the DES system

This study investigates whether the reliability and economy of DES will be affected by the amount of information in various uncertain scenarios. A DES, designed for a battery-production plant located in Huizhou, China, is selected as a case study. Fig. 3 shows the candidate technologies for the DES, which includes gas-fired internal combustion engine (GICE), absorption chiller, centrifugal chiller (CC), and cooling energy storage (CS) and electricity storage (ES) equipment in the form of a storage tank and batteries, respectively. The photovoltaic (PV) is also an important power source candidate to provide renewable and affordable energy. Additionally, the transformer (TF) is considered in the design of DES, as the power company charges power capacity fees based on transformer capacity. The electricity demand can be met by GICE, PV, ES and power grid, among which PV power is considered as an uncertain power source. The cooling sources include AC, CC and CS, which are all deterministic sources. However, both electric and cooling loads are uncertain. The uncertainties associated with PV power generation, electric and cooling loads primarily consist of epistemic uncertainty, which can be reduced by collecting additional information. The focus of this paper is to determine whether paying a price to reduce uncertainty improves the performance of the DES planning scheme. To achieve this goal, we first construct test scenarios with different information richness, as described in Section 2.2.2.

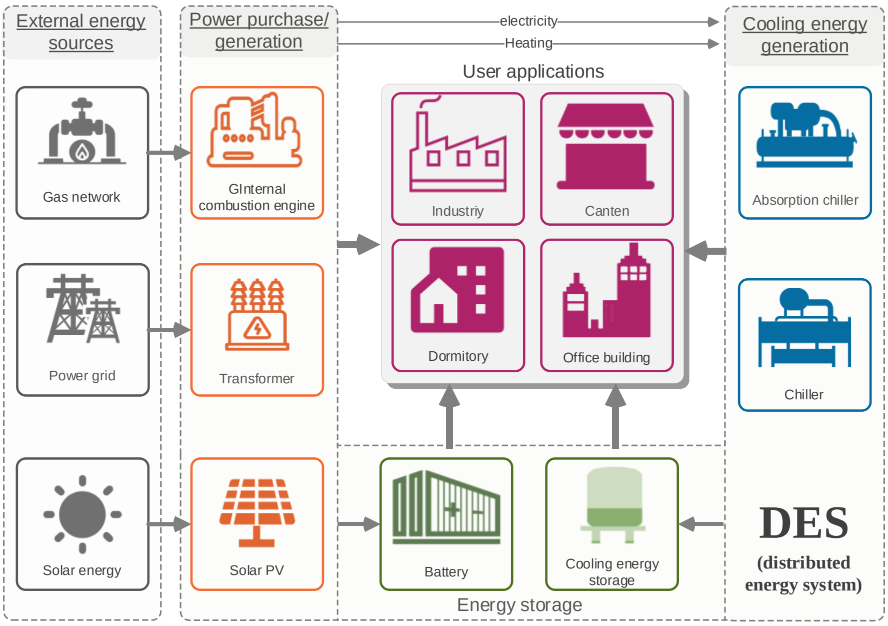

Fig. 3 Candidate energy technologies for the DES.

2.2.2 Generation of scenarios with different information volumes

Uncertainty is inherent in natural phenomena. Therefore, it is more objective to utilize two types of information, i.e., the scenario itself and the scenario probability, to depict and quantify the uncertain PV power generation, electric, and cooling loads. At present, various scenarios are employed in the stochastic design of DES. For example, one hundred scenarios with a uniform probability distribution were used in [18]; five typical scenarios with discrete probability values were employed in the design of a microgrid in [37], while fifteen typical scenarios with discrete probability values were used in [11]. The authors in [39] found that one hundred of stochastic scenarios with equal probability was accurate enough for the design of a

DES. However, the use of various scenarios and probability distributions may result in differing levels of information content. In practice, the choice of a probability density function depends on the level of knowledge pertaining to scenarios. Carpino C et.al [40] suggested that "*if an input parameter is characterized by higher uncertainty , this is modelled using the uniform distribution function. In the opposite case, namely if the uncertainty about the parameter is low, it can be modelled through the normal distribution.*" In Bayesian statistics, the uniform distribution is often referred to as a "non-informative distribution" since it conveys no information beyond the specified range of variation. In contrast, the non-uniform distribution, like the normal distribution, is known as an "informative distribution" since it incorporates detailed information regarding the parameter's variation from expert judgments, historical data, or sample measurements. [41].

Three scenario sets with different levels of information are generated based on the differences in scenarios and scenario probability information, as illustrated in Fig. 4. Fig. 4(a) shows the possible scenario set, obtained from Monte Carlo simulation. In this paper, one scenario set consists of three time-series scenarios (i.e., the PV power generation, cooling and electric loads, as shown in Fig. 7 (a)). The bule dots in Fig. 4(b) represents the scenarios. The three types of scenario sets listed in Fig. 4 (c), (d), and (e) correspond to any one single blue dot, all dots with the uniform distribution, and all dots with the normal distribution, respectively. In Section 2.2.3, these sets will be used in Model 1, Model 2, and Model 3 to design the DESs and to quantify the value of information through comparative analysis of design results.

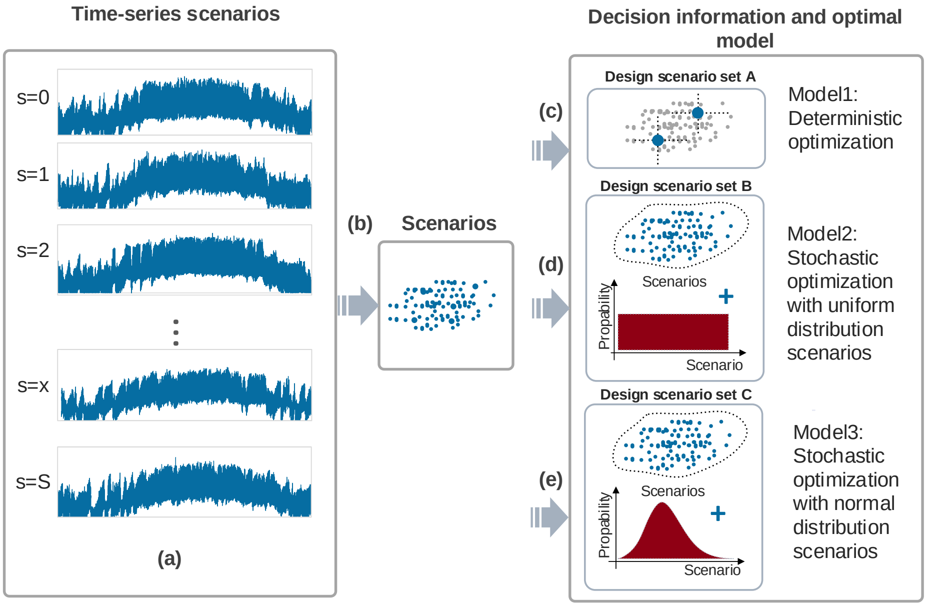

Fig .4 Schematic diagram of design scenario set, (a) the time-series scenario sets, one scenario set consists of three time-series scenarios in this paper (i. e. the PV power generation, cooling and electric loads in this paper); (b) Marker notation for scenario set, one blue dot represent one scenario set; (c) a single scenario set used in Model 1; (d) all the scenario sets with uniform distribution used in Model 2; (e) all the scenario sets with normal distribution used in Model 3.

2.2.3 The first layer model: optimal design model formulation based on scenarios with different amounts of information

(1) Mathematical formulation of Model 1

In Section 2.2.2, a total of S scenarios are generated. For Model 1, any of these scenarios could be utilized for the design of DES, since it is impossible to predict which scenario will happen. Therefore, S deterministic DES schemes will be optimized by Model 1.

The problem of designing a DES can be accommodated in a two-stage model [11, 39]. In the first stage, the types and capacities of the components to be installed in the DES are optimized. Subsequently, operation optimization is performed to determine the operating strategy, energy cost, etc. The two stages are iterated repeatedly until an optimal DES scheme is achieved.

This paper utilizes the total cost as the objective function with the aim of minimizing it.

Specifically, the equivalent annualized cost that comprises of the investment cost (Inv_s) and operation cost (Oc_s), is employed to optimize the DES. The equivalent annualized cost is formulated by Eq. (8) and (9), respectively.

$$Inv_s = \sum_i^I \left(\lambda_{s,i} \cdot FC_i + EUP_i \cdot Cap_{s,i}\right) \cdot \kappa_i + \lambda_{s,i} \cdot FM_i \cdot Cap_{s,i}, \ \ \forall s \in S \tag{8}$$

$$Oc_s = FP_{m,t} \cdot Con_{i,m,t,s} \cdot (1 + VM_i) + \beta \cdot Cap_{i=TF}, \forall s \in S \tag{9}$$

In these equations, s means the scenario used in the Model 1; the variables Inv_s, Oc_s, $\lambda_{s,i}$, $Cap_{s,i}$ and $Con_{i,m,t,s}$ are all calculated under the scenario s; $\lambda_{s,i}$ is a binary variable, denoting whether the technology i is selected ($\lambda_{s,i} = 1$) or not ($\lambda_{s,i} = 0$); κ_i is the capital recovery factor of technology i used for annualizing the total investment cost and is formulated in Eq. (A.1) in Appendix A.2; $Cap_{s,i}$ is the capacity of technology i; FC_i and EUP_i are fixed and unit investment cost of technology i; FM_i and VM_i are coefficients used to estimate the fixed and variable maintenance costs; $FP_{m,t}$ represent the consumption of fuel m at time step t; $FP_{m,t}$ denotes the unit price of fuel m, which is constant for gas, while is a time-of-use price for electricity. In addition, the cost of electricity comprises two components: the capacity price β (CNY/kW or CNY/kVA), and the electricity price $FP_{m,t}$. In many regions of China, consumers have the option to negotiate with the power company to pay the capacity price based on either the transformer capacity ($Cap_{i=TF}$) or the maximum demand. In this paper, the capacity cost is calculated using the transformer capacity.

The objective function of the Model 1 is presented in Eq. (10). It is worth noting that Tc_s is scenario-dependent, denoting the DES is optimized based on scenario s.

$$minimize \ \ Tc_s = Inv_s + Oc_s, \ \ \forall s \in S \tag{10}$$

The optimization design in Model 1 is contingent upon scenarios, which implies that the constraints in Model 1 are established independently for each scenario s. For a comprehensive list of constraints, please refer to Appendix A.2.2.

(2) Mathematical formulation of Model 2&3

In Models 2 and 3, designers have a set of possible future scenarios, along with their corresponding probability of occurrence. The optimization of DES based on scenario sets and probability information has been acknowledged as a better approach to designing against uncertainty, such as chance constrained programming and stochastic programming [11, 14, 17]. In this paper, the stochastic programming is employed to establish both Model 2 and Model 3 for optimal design of DESs. The objective functions for Model 2 and Model 3 are presented in Eq. (11) and (12), respectively.

$$\min Tc_{\nu} = Inv_{\nu} + \sum_{s}^{S} \omega_s \cdot Oc_s, \nu = S, s \in S, \omega_s \sim U[a, b] \tag{11}$$

$$\min Tc_{\upsilon} = Inv_{\upsilon} + \sum_{s}^{S} \omega_s \cdot Oc_s, \upsilon = S, s \in S, \omega_s \sim N(\mu, \sigma^2\ ) \tag{12}$$

In Model 2 and 3, the calculation of Inv_{ν}, Inv_{υ}, Tc_{ν}, and Tc_{υ} is based on all scenarios ($\nu, \upsilon = S$), which distinguishes them from the single-scenario-based objective in Model 1. The probabilities of each scenario in ν or υ are represented by ω_s. As depicted in Fig. 4, the occurrence probabilities of scenarios in Model 2 follow a uniform distribution, whereas in Model 3, they follow a normal distribution. Compared with Model 1, which relies solely on a single scenario, Model 2 and Model 3 incorporate more scenario information. The uniform distribution is regarded as non-informative, whereas the normal distribution is regarded as informative [40]. Therefore, in comparison to Model 2, more scenario information is considered in Model 3.

Models 2 and 3 take into account all scenarios when optimally designing the DESs. Therefore, in Model 2 and 3, the constraints need to be established and met in each scenario. This differs from the Model 1, where the constraints are formulated and met for only a single scenario. Appendix A.2.2 provides the constraints for Model 2 and 3.

2.2.4. The second layer model: optimal operation model for quantifying EVPIr and EVPIe-

Using Model 1 ~ Model 3, various DES schemes can be achieved, and once these schemes are implemented, the system structure and capacity will be fixed over an extended period. Even if the actual scenario differs from the scenario during the design stage, the scheme cannot be easily changed to adapt to the new scenario. With different scenarios, operational optimization is typically required to minimize operating costs or avoid the risk of insufficient power supply. At this point, the actual operating performance of the system, such as its cost and reliability, must deviate from that in the design stage, which is a result of the lack of information. The objective of operation optimization under a new scenario (s') is defined as follows:

$$\min Tc_{s'}^{sch_s} = \mathrm{Inv_s} + Oc_{s'}^{sch_s} + \vartheta_{s,s'} \cdot \mathrm{M},\ \ \forall s' \in S' \tag{14}$$

The EVPIe, defined in Eq. (7) can be further reformulated as:

$$R_s^e = \sum_{s'}^{S'}\left(\left(\mathrm{Inv_s} + \mathrm{Oc}_{s'}^{\mathrm{sch_s}}\right) - \left(\mathrm{Inv}_{s'} + \mathrm{Oc}_{s'}^{\mathrm{sch}_{s'}}\right)\right) \cdot \omega_{s'} \tag{15}$$

It worth noting that $\mathrm{Inv_s}$ and $\mathrm{Inv}_{s'}$ in Eqs. (14) and (15) are parameters, which have been optimized by the first-level model. Additionally, it should be noted that $Oc_{s'}^{sch_s}$ and $Oc_{s'}^{sch_{s'}}$ respectively represent the operating costs of scheme sch_s and $sch_{s'}$ in scenario s'. Since the scheme sch_s is designed based on the scenario s, it may face the risk of energy loss when running in the scenario s'. To account for this, a penalty term $\vartheta_{s,s'} \cdot \mathrm{M}$ is added to Eq. (14), where $\vartheta_{s,s'}$ is a binary variable. When the energy supply is insufficient, $\vartheta_{s,s'} = 1$; otherwise $\vartheta_{s,s'} = 0$. M is a large constant and is taken as 10^6 in this paper. The total energy loss ($\Delta e_{s',t}^{sch_s}$) in this paper encompasses the loss of electric power ($\Delta e_{s,s',t}^{ee}$) and loss of cooling power ($\Delta e_{s,s',t}^{ce}$), which are calculated by Eqs. (16)-(18). Eq. (19) is equivalent to Eq. (4). Eq. (20) is used to linearize the Eqs. (2) and (5). Furthermore, the EVPIr defined in Eq. (6) can be reformulated by Eq. (21).

$$p_{s,s',t}^{GICE} + p_{s,s',t}^{PV} + p_{s,s',t}^{G} + \eta^{ESo} \cdot p_{s,s',t}^{ESo} + \Delta e_{s,s',t}^{ee} = l_{s',t}^{ee} + \frac{p_{s,s',t}^{ESi}}{\eta^{ESi}}, \forall s' \in S', \forall t \in T \tag{16}$$

$$p_{s,s',t}^{CC} + p_{s,s',t}^{AC} + \eta^{CSo} \cdot p_{s,s',t}^{CSo} + \Delta e_{s,s',t}^{ce} = l_{s',t}^{ce} + \frac{p_{s,s',t}^{CSi}}{\eta^{CSi}}, \forall s' \in S', \forall t \in T \tag{17}$$

$$\Delta e_{s,s',t} = \Delta e_{s,s',t}^{ee} + \Delta e_{s,s',t}^{ce}, \forall s' \in S', \forall t \in T \tag{18}$$

$$\Delta E_{s,s'} = \sum_t^T \Delta e_{s,s',t}, \forall s' \in S' \tag{19}$$

$$\vartheta_{s,s'} \cdot M \geq \Delta E_{s,s'}, \forall s' \in S' \tag{20}$$

$$R_s^r = \sum_{s'}^{S'} \omega_{s'} \vartheta_{s,s'} \tag{21}$$

In Eqs. (14)-(21), $\mathrm{s} \in \mathrm{S}$ for Model 1, $s = \nu$ for Model 2, and $s = \upsilon$ for Model 3. S' is a probabilistic scenario set, as discussed and defined in Section 2.1.2.

2.3. Summary

Fig. 5 illustrates the main contributions of Sections 2.2.2-2.2.4. Viewed from an information theory perspective, an increase in information results in a decrease in uncertainty [42]. As shown in Fig. 5 (a), the transition from I1 to I3 represents that more information is used to describe the uncertainty set, so the uncertainty decreases, such as the process from U1 to U3. At this time, as shown in Fig. 5 (b), whether the system performance will also be improved, is the question that Section 2.2 tries to answer.

The models and constraints presented in the appendix consist solely of linear expressions, incorporating both continuous and binary variables, which makes the developed models Mixed Integer and Linear Program (MILP) and can be solved efficiently using state-of-the-art MILP solvers. Specifically, Gurobi [43] is employed to solve the problems in this paper.

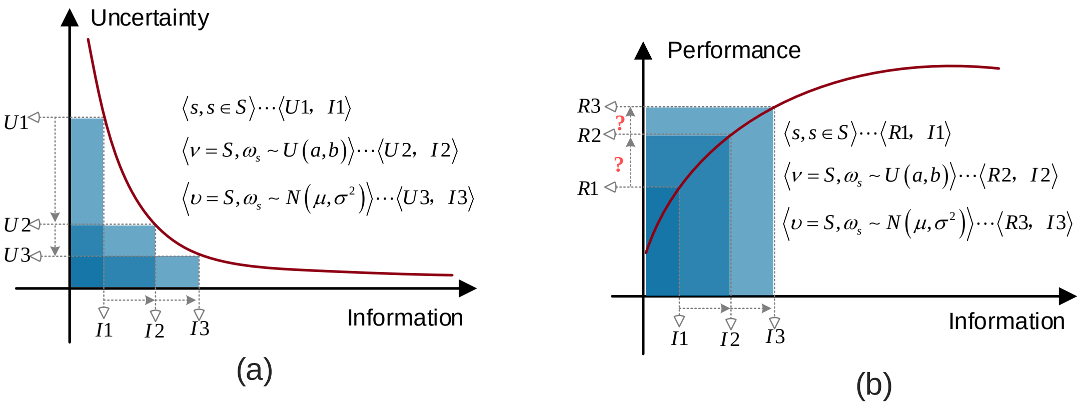

Fig. 5. Schematic diagram of the relationship between the amount of information of an uncertain set and uncertainty (Fig. 5 (a)), and the relationship between the amount of information of an uncertain set and system performance (Fig. 5 (b)).

3. Case study

3.1 A park-level distributed energy system

In this study, we present the design of a park DES under various uncertain scenarios. The chosen case study is based on a real-world example of an industrial park for battery production, which is described in detail in our previous work [44, 45]. As shown in Fig. 6 (a), five buildings (B1-B5) in this park are delimited as the research object. As planned, buildings B1-B5 are powered by a DES, whose schematic diagram is shown in Fig. 3. The layout of the buildings, DES and networks are given in Fig. 6 (b). Fig. 6(c) is the EnergyPlus [46] model for simulating the cooling and electric loads.

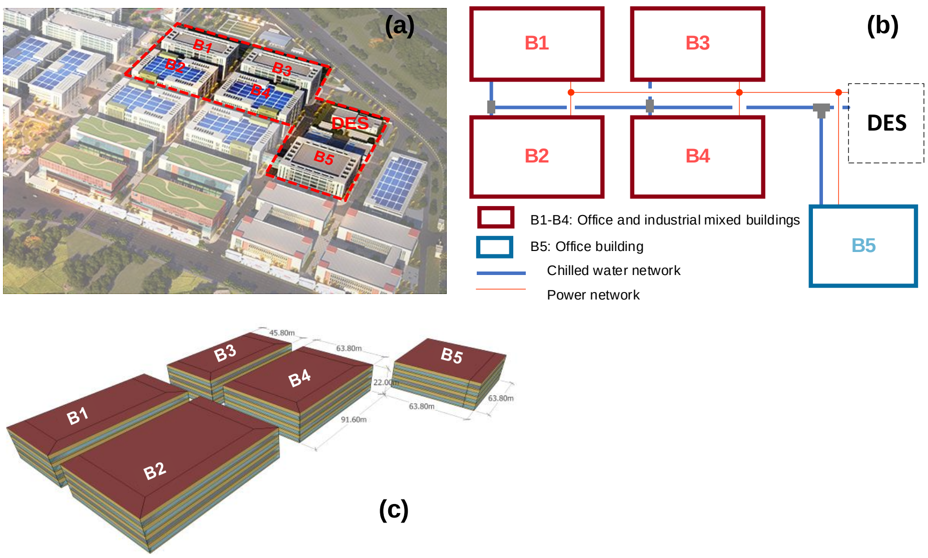

Fig. 6. (a) Regional architectural planning map (the buildings circled by the dotted line box are used in this case study), (b), Building characteristics, DES location, and networks layout, (c) 3D representation of buildings used in EnergyPlus.

3.2 Scenario generation

Monte Carlo (MC) simulation is a mathematical technique used to estimate the possible outcomes of an uncertain event. In this paper, this method is employed to generating uncertain scenarios of PV power generation, cooling and electric loads. The details of implementing the MC simulation can be found in [11, 15, 24], while uncertain inputs, such as weather conditions, internal heating sources, and building information, are described in our previous study [44]. To ensure convergence of the MC simulation and to include the scenario with perfect information (defined in Section 2.1.1) as much as possible, 3500 times of MC simulations were performed to generate a total of 3500 8760-hour scenarios. However, if all the raw scenarios are considered in Model 2 and Model 3, the mathematical programming models will become bloated and unsolvable [11, 14, 15, 44]. It is an interesting topic of selecting typical scenario for the design of DES under uncertainty, where the reducing computational burden and information loss of the original time-series scenarios should be balanced well. The typical day selection method was discussed in detail in [37, 38, 47], and is out of scope of this paper. In this study, a popular cluster methods, K-Mediods [44], is adopted to reduce the dimensionality of the model and obtain 100 typical scenarios. As suggested in [11], 4 extreme scenarios (maximum cumulative electric and cooling load scenarios, extreme electric and cooling load scenarios) are manually selected and added to these typical scenario set. In the end, 100+4=104 typical scenarios and along with their probability distribution are selected for the design and operation test of DES. As shown in Fig. 7, the 104 typical scenarios (as shown in Fig. 7 (a)) combined with the discrete frequency distribution (as shown in Fig. 7 (b-1)) constitute the probability scenario set (S') defined in Section 2.1.2. The 104 typical scenarios combined with the discrete uniform and normal frequency distributions (as shown in Fig. 7 (b-2) and (b-3)) constitute the probability scenario sets (ν, υ) used in Model 2 and 3, respectively.

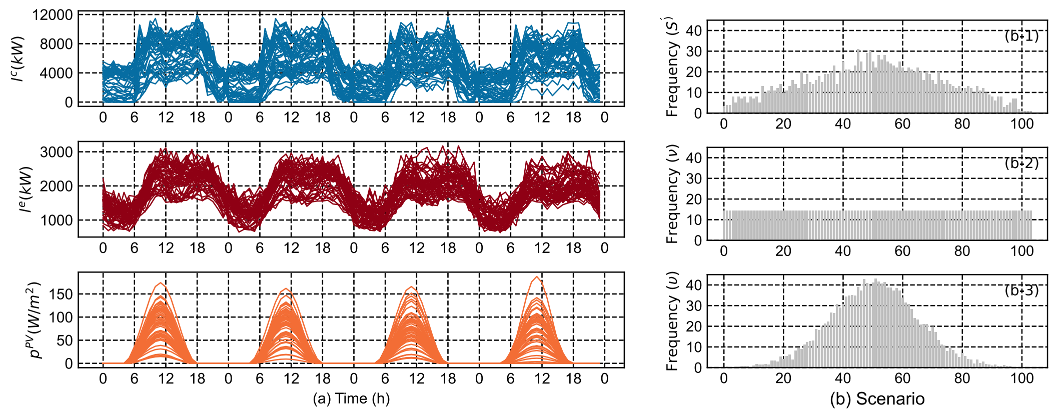

Fig. 7. Uncertain scenario sets: (a) uncertain scenario, from top to bottom are cooling loads, electric loads, and PV power generation scenarios; (b) the occurrence frequency of scenarios, from top to bottom, is the frequency distribution of relatively complete information scenarios (b-1), the uniform distribution used in model2 (b-2), and the normal distribution used in model3 (b-3, generating using the random function in NumPy library [48]).

4. Results

4.1. Optimal DES configurations

As stated in [49], a crucial characteristic of uncertainty is that "*it affects which management action is preferred*". The design objectives of DES, such as economy and reliability, depend on predicted scenarios and will change with variations in scenarios. However, once the DES configuration is determined based on one type of scenario (e.g., different scenarios shown in Fig. 7), it will not be adjusted due to changes in actual operating scenarios.

This section presents the impact of scenario uncertainty and changes in scenario uncertainty on the optimal configuration of the DES.

Fig. 8 depicts the optimized DES configurations generated by Model 1, Model 2, and Model 3. Model 1 generates a total of 104 DES configurations, with the capacity of each device represented in the box plot and strip plot. On the other hand, Model 2 and Model 3 generate a single DES configuration each, which are shown in Fig. 8 by yellow plus signs and red dots, respectively. In this plot, it can be observed the DES configurations optimized by Model 1 exhibit significant variation across different typical scenarios. For instance, the configuration capacity for PVs is 0kW in some scenarios, while it can reach up to 12000kW in others. Similar findings were reported in [24]. It is interesting that despite the different scenarios used in Models 2 and 3 (Model 2 assuming a uniform distribution and Model 3 employing a normal distribution), the resulting system configurations show remarkable similarities.

As discussed in Section 2.2.2, two types of information (the scenario itself and the scenario probability) should be used to describe a scenario. The above findings provide two significant insights. First, the information contained within the scenario itself exerts a considerable impact on the DES configuration, and posing decision-making challenges for designers. Model 1 is built upon single typical scenario with limited information, which may result in decision-making errors. For instance, the solution with the minimum cost objective (Tc_s) may not be the most economically optimal in future real scenarios. Likewise, the solution with the maximum cost objective may not be the worst economic option in future real scenario. In Sections 4.2 and 4.3, this study quantifies the risk of each DES scheme to address these concerns. Secondly, the probability information of the scenario does not seem to be the key information for DES design. Therefore, whether it is worthwhile to pay the price to obtain the accurate probability of scenario occurrence needs to be further explored. This topic will be discussed in detail in Section 5.

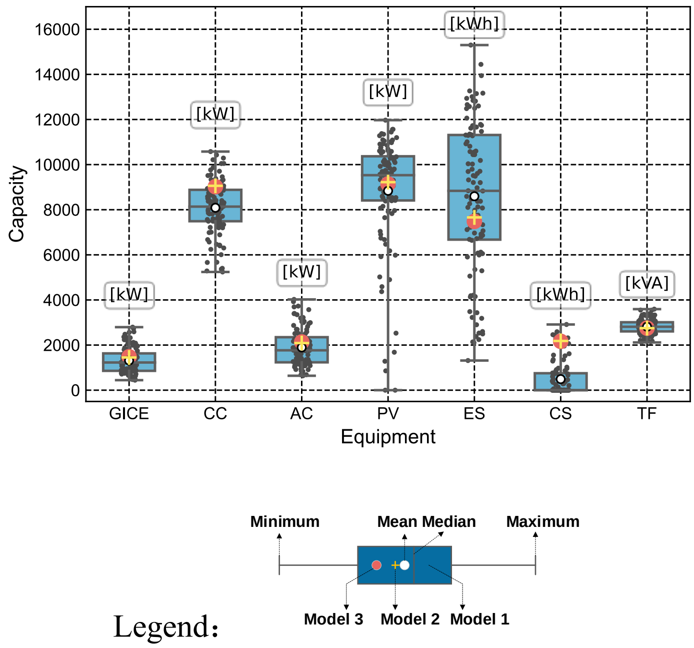

Fig. 8. Optimal configurations optimized by Model 1 (104 DES configurations displayed with the box and strip plots), Model 2 (one DES configuration marked with the yellow plus), and Model 3 (one DES configuration marked with the red dot)

4.2. Economic performance of optimal DES

The configuration of DES has a direct impact on both the investment cost and operational cost of the DES. Fig. 9 shows the economic objective values (Tc_s in Model 1, Tc_v in Model 2, and Tc_v in Model 3) of different DES design schemes. Each optimal annualized cost (Inv_s) of the 104 schemes in Model 1 is presented in a frequency histogram, and the average cost is shown by the gray dotted line. The optimal annualized cost obtained by Model 2 and Model 3 is shown by the yellow and red dotted lines, respectively. Fig. 9 and Fig. 8 show a similar phenomenon. Firstly, the economic objective value optimized by Model 1 exhibits significant differences. The minimum annualized cost is merely 1.541×10^7CNY, while the maximum can be as high as 2.163×10^7CNY. Secondly, the annualized cost of the DES schemes obtained by Model 2 and Model 3 is close to the average annualized cost of the schemes obtained by Model 1. Lastly, despite employing different scenarios for optimizing DES, the objective values of the two DES schemes obtained by Model 2 and Model 3 exhibit small differences.

As discussed in the last paragraph of Section 4.1, the DES optimized in Model 1 is based on a typical scenario with limited information. Therefore, it may not be advisable to solely rely on the optimal objective value to determine a DES scheme, as the value can vary with changes in the scenario. As shown in Fig. 10, the relationship between the annualized cost and EVPIe for 104 DES schemes generated in Model 1 is investigated. EVPIe, as defined in Eq. (7), represents the value of obtaining additional information, and is also equivalent to the economic risk of losing some information. The yellow line and dots show that the EVPIe decreases as investment cost (Inv_s) increases, suggesting that a DES scheme with higher investment may be more robust in dealing with uncertainty. Fig. 10 also shows that the operating cost (Oc_s) and investment cost (Inv_s) have a negative correlation, indicating that a DES scheme with high investment has better operating performance and lower operating cost. However, there is no obvious correlation between the annualized cost (Tc_s) and EVPIe. For instance, the black dotted line shows that when the EVPIe equals to 4.3×10^5 CNY, the annualized costs exhibit significant variation, ranging from 1.58×10^7 to 2.20×10^7 CNY. Similarly, the yellow dotted line shows that when the annualized cost equals to 1.75×10^7 CNY, the values of EVPIe differ significantly, with a range of change between 1.23×10^5 and 6.24×10^5 CNY. In order to show the trend of the aggregation points on the left side of Fig. 10 more clearly, a partial enlarged picture is plotted and shown in Fig. A1.These observations suggest that relying solely on the objective value acquired based on the planning scenario is untenable for determining a DES scheme.

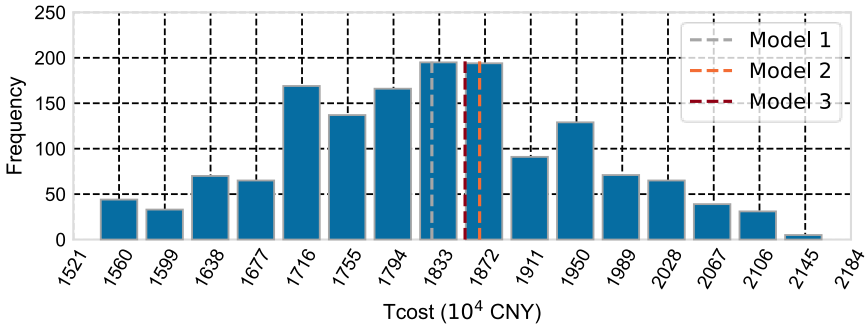

Fig. 9. Economic objectives of DES schemes based on different optimal models

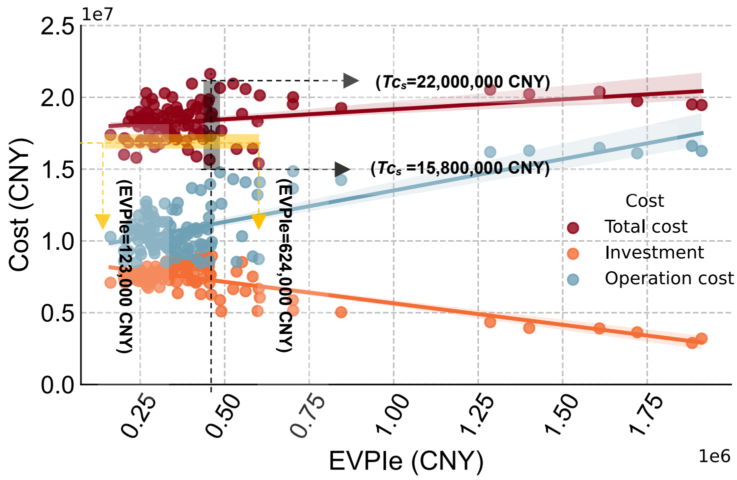

Fig. 10. The relationship between the economic objective of DES scheme and the expected value of information for economy (EVPIe)

4.3 Risks and the value of information

As discussed in Section 2.1.1, an optimally designed DES scheme based on scenarios with limited information may be vulnerable to reliability failures and economic losses when encountering unpredictable future scenarios. This section presents the reliability risks (EVPIr) of all optimal schemes obtained by Model 1 Model 2 and Model 3, as shown in Fig. 11. By analyzing the relationship between EVPIr and VPIe, it can be found that when the VPIe is less than zero, EVPIr must be greater than zero. This is due to the penalty constraint of load shedding being added in Eq. (14). This implies that even though it is unreasonable for the DES to achieve cost reduction by load shedding, the system cannot handle some extreme loads even if it exerts its maximum capacity. Therefore, load shedding also signifies a system design failure.

Back to the EVPIr values of each scheme, Fig. 11 shows that the EVPIr of the schemes obtained by Model 1 is almost greater than 0. This indicates a high probability of insufficient energy supply for the schemes obtained by Model 1. For instance, Scheme 29, 52, and 63, which are marked by blue circles, have EVPIr values close to 1, suggesting a high likelihood of unreliability in the future. In contrast, the EVPIr values of Model 2 and Model 3 are both equal to 0, indicating that the schemes obtained by these models are reliable. It is worth noting that this result is unsurprising as Model 1 only considers one typical scenario, whereas Model 2 and

3 consider all scenarios. This processing method has also been adopted by Mavromatidis et al. [22] when constructing various optimal design models for DES, to ensure that the resulting scheme is feasible under any uncertain scenario. As stated earlier in Section 2.2.2, to fully describe an uncertain scenario, two dimensions are required: the scenario itself and the corresponding probability. The results in Fig. 11 first remind us that accurate acquisition of the scenario set itself is important to design a reliable DES. The value of the probability information of the scenario can be found in Fig. 12. The following explanation briefly highlights the differences between VPIe in Fig. 11 and Fig. 12. Fig. 11 is intended to illustrate the expected value of perfect information for reliability, while Fig. 12 depicts the expected value of perfect information for economy. As shown in Fig. 11, most of the planning schemes (S1-S104 in Model 1) based on a single scenario have load shedding due to inadequate capacity configuration (EVPIr>0). Even though load shedding reduces operating costs, it also implies energy system design failures. It is believed that the premise of assessing EVPIe is that all energy systems should be reliable. Therefore, in calculating VPIe and EVPIe (shown in Fig. 12) using Model 1, constraints were established in all scenarios, namely $s = S, \forall s \in S$ for Model 1 in A.2.2. Fig. 12 shows the VPIe values as a violin plot and the EVPIe values as a dotted line for each DES scheme. A logarithmic coordinate (log10) is used to highlight the difference in EVPIe values between Model 1, Model 2, and Model 3. Firstly, the violin plots of VPIe indicate that the DES schemes obtained by Model 1 exhibit abnormally large VPIe values, especially for schemes 19, 24, 28, and 82 (marked by yellow circles). This suggests that a DES designed based on a single scenario with limited information may face the risk of extreme economic loss. Secondly, comparing the EVPIe values of different schemes (as the dotted line shown) reveals that the EVPIe values of Model 2 and 3 are smaller than those of Model 1. This indicates that since Models 2 and 3 considered more scenario information, the economy of the DES scheme is more robust when faced with future uncertain scenarios. Interestingly, the EVPIe values of Model 2 and Model 3 remained almost equal, while the information level increased from a uniform (used in Model 2) to a normal (used in Model 3) distribution. This suggests that the probability information of the scenarios had little impact on the optimal design of DES. Tab. 1

summarizes the EVPIe values of different models. It can be found that the DES scheme obtained by adopting a single scenario in Model 1 faces a maximum economic loss of 2,172,839 CNY, and the average economic loss is 501,241 CNY, accounting for 11.9% and 2.7 of the average annualized cost ($1/104\sum_s^S Tc_s$) of Model 1, respectively. In Model 2, where all scenarios and their probability information (uniform analysis) are considered, the EVPIe is reduced to 284,033 CNY, accounting for 1.5% of the annualized cost (Tc_v) of Model 2. However, compared with Model 2, the EVPIe of Model 3 has not been significantly reduced, further demonstrating that the value of the probability information of the scenario is not significant for the design of DES.

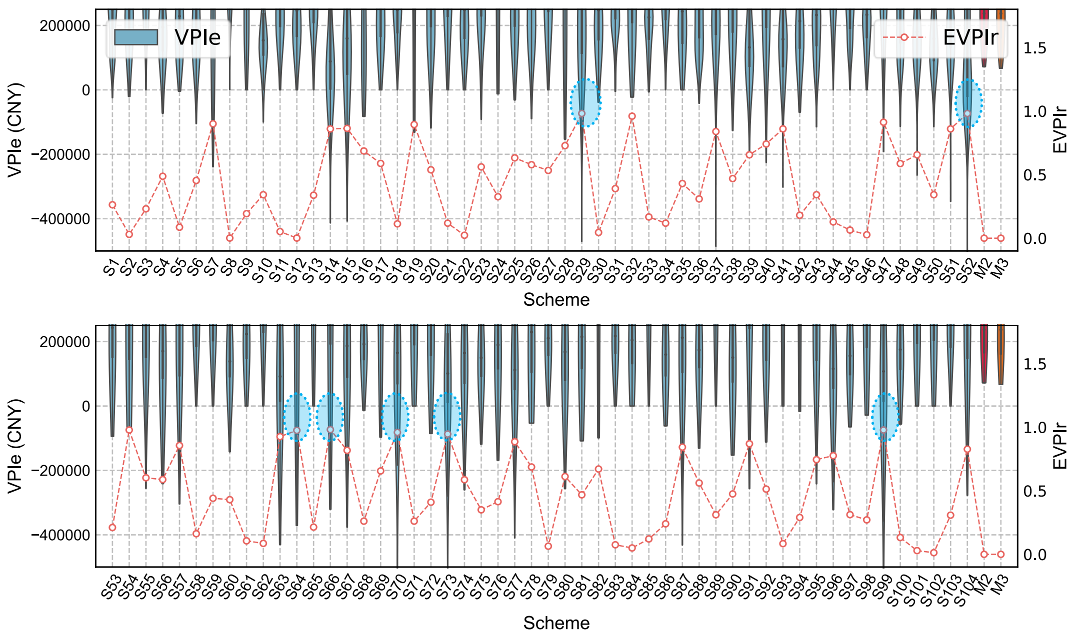

Fig. 11. Value of information for economy (VPIe) and the expected value of information for reliability (EVPIr). The results of S1-S104 in Model 1 are illustrated in blue violin plots; the results for Model 2 (M2) are depicted in a red violin plot, and the results for Model 3 (M3) are presented using a yellow violin plot.

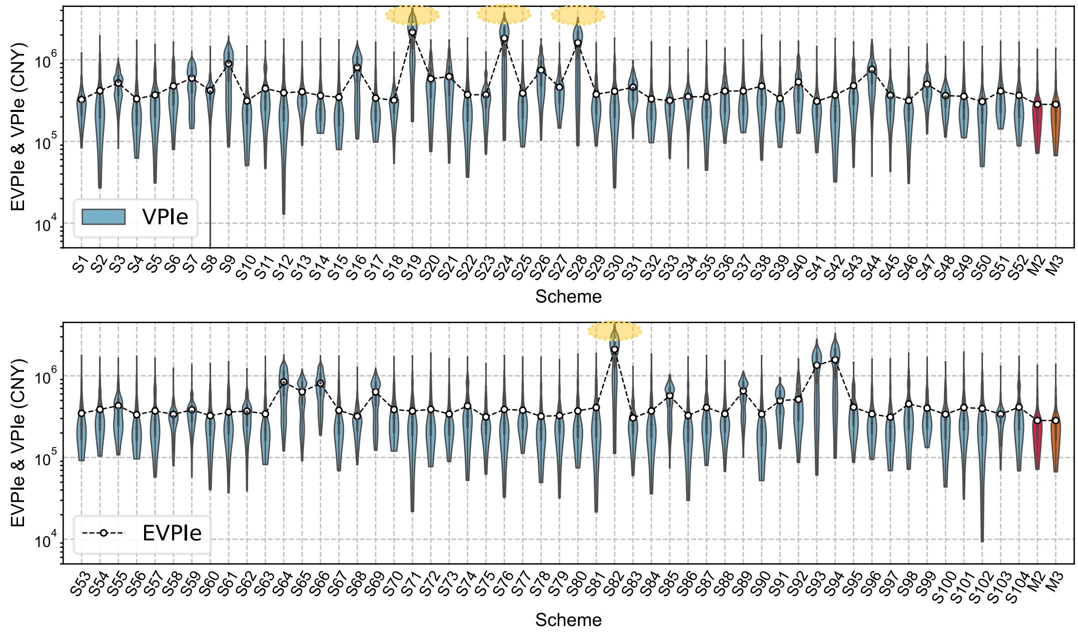

Fig. 12. Value of information for economy (VPIe) and the expected value of information for economy (EVPIe). The results of S1-S104 in Model 1 are illustrated in blue violin plots; the results for Model 2 (M2) are depicted in a red violin plot, and the results for Model 3 (M3) are presented using a yellow violin plot.

Table 1. Summary of the EVPIe and VIIe

Model	Model 1			Model 2	Model 3
	Min	Mean	Max		
EVPIe (CNY)	305750	501241	2172839	284033	283665
VIIe (CNY)	21717 (M2-M1)	217028 (M2-M1)	1888806 (M2-M1)	-	-
VIIe (CNY)	22085 (M3-M1)	217576 (M3-M1)	1889174 (M3-M1)	368 (M3-M2)	-

VIIe: value of increased information for economy

5. Discussion on the value of probability information

In the stochastic optimization model for designing DES under uncertainties, an important task is to generate scenarios and estimate scenario probabilities. For example, the authors [11] used the clustering method to obtain random scenarios for PV power, heating, and electric loads, along with their probabilities. In the literature [40], the normal distribution is considered as an informative distribution, while the uniform distribution is regarded as a non-informative distribution. However, as shown in Section 4, it was found that although the scenario probability in Model 2 obeys a uniform distribution and that in Model 3 obeys a normal distribution, the DES schemes, EVPIr and EVPIe values obtained by the two models are very similar, suggesting that the scenario probability is not the key information for the design of DES. In Fig. 13, 30 random probability distributions are generated by the Random module in Python [48] and used to further test whether it makes sense to pay a price to obtain the occurrence probability of each scenario. These probability distributions are obviously different, representing that the information used for DES design is different. The distributions shown in Fig. 13 are used to replace the uniform distribution in Model 2 or the normal distribution in Model 3 for DES design, and the results are shown in Fig. 14 and 15.

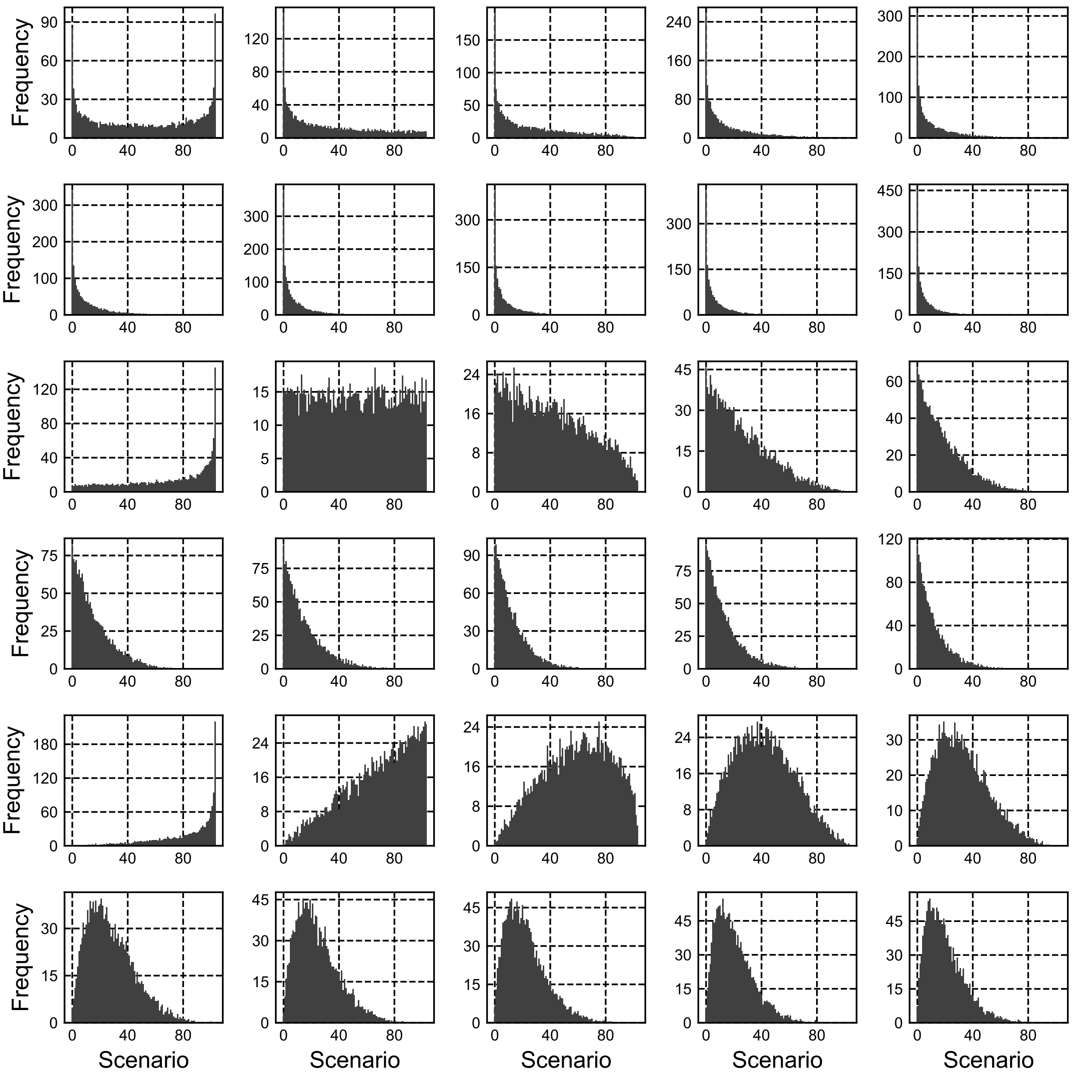

Fig. 13. Random frequency distribution of time-series scenarios $s_1 - s_{104}$ shown in Fig. 7 (a)

Compared to the result shown in Fig. 8, Fig. 14 shows that the optimal DES configurations based on scenarios with different probability distributions have little difference, confirming that the probability information of the scenario is not important for the design of DES. The VPIe and EVPIe of different DES schemes are calculated and plotted in Fig. 15. Firstly, it can be found that the distribution of VPIe of different DES schemes is similar, and the EVPIe values are also close, as shown in Fig. 15(b). As shown in Fig. 15(a), the EVPIe of Model 3 is used as a benchmark to quantify the differences in EVPIe between different DES schemes, and found that they were all within $\pm 2\%$. The above results demonstrate that the probability information of the scenario is of little value for DES design. This seems to mean that when generating uncertain scenarios for designing a DES, it is not necessary to pay too much attention to the probability information of scenario, which will greatly reduce the difficulty of scenario generation. After all, obtaining accurate scenario occurrence probabilities is often considered the key to limiting the application of stochastic programming methods [50]. As stated at the beginning of Section 2.2.2: "*Two types of information are needed to quantify an uncertain scenario: the scenario itself and the probability of the scenario*". Comparing the results of Fig. 8 and Fig. 14, and Fig. 12 and Fig. 15 , it can be found that for the stochastic programming model, the scenario is more important for designing a DES, while the probability of the scenario is unimportant information.

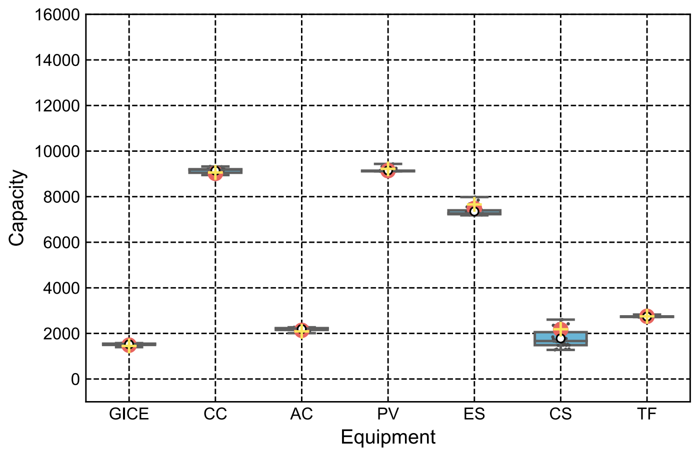

Fig. 14. DES configurations optimized based on scenarios with different frequency distributions

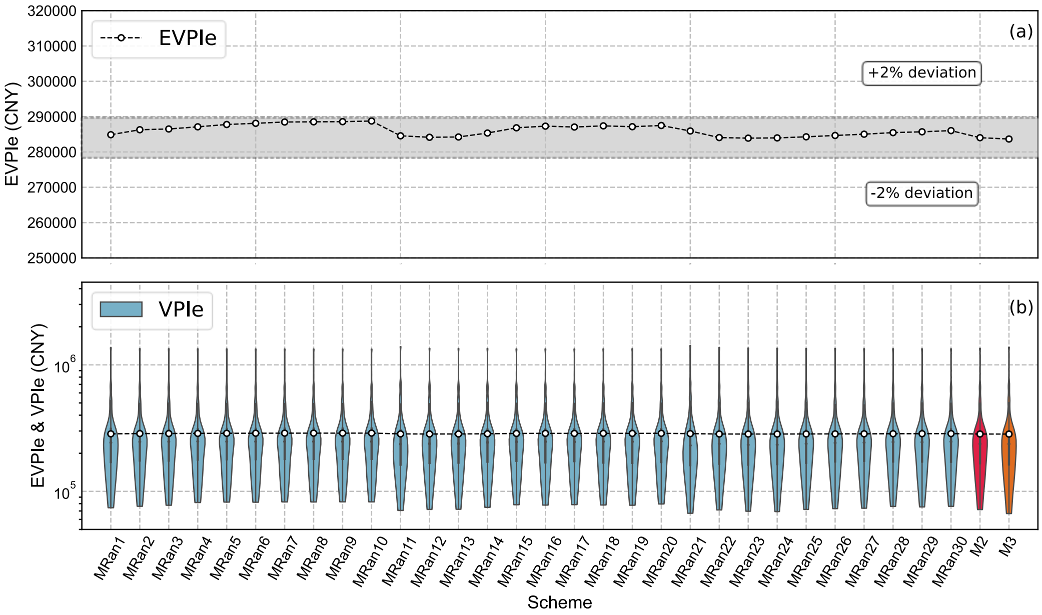

Fig. 15. The VPIe and EVPIe of the DES schemes optimized based on scenarios with different frequency distributions; (a) discrepancy in the values of EVPIe; (b) The distribution of VPIe and EVPIe.

6. **Conclusions**

Information is the basis for the design of the distributed energy system (DES) under uncertainties. This paper quantifies the effect of information volume on improving the reliability and economic performance of DES under uncertainties, so as to quantify the value of information. This work can guide designers to construct a concise and reliable set of scenarios to ensure the robustness of the DES scheme. This paper first proposed two indexes for quantify the value of uncertain information, and constructs a two-layer information value quantification model in the form of mixed integer linear programming for index calculation. A real distributed energy system is employed to demonstrate the effectiveness of the proposed method. Three experiments with different information volumes are taken on the DES for quantifying the information value of scenarios. Based on the results of the test case studies, conclusions can be drawn as follows.

In terms of optimal DES configuration, determining a DES scheme that only relies on the objective value acquired based on the planning scenario is unreasonable. The test results show that a DES scheme with low annualized cost in the planning stage may face a high risk of economic loss in the future, and vice versa; Utilizing more information in the optimal design of DES can reduce the risk of reliability and economic loss of DES planning scheme. The risk of economic loss results show that the DES scheme obtained by adopting a single scenario faces a maximum economic loss of 2,172,839 CNY, and the average economic loss is 501,241 CNY. When all scenarios and their probability information are considered, so the expected value of information for economy (EVPIe) is reduced to about 284,000 CNY; An unexpected finding is that the probability information of the scenarios is not important for the design of DESs. The results show that the deviation of the expected value of information for economy (EVPIe) value of the uncertain scenario set described by any probability distribution is within ±2%. This means that a set of scenarios described by a uniform distribution is sufficient for planning a robust DES, and this is also the most accessible.

This paper confirms that the amount of information will affect the configuration and performance of the DESs. In terms of future work, firstly, more uncertain scenarios will be introduced, such as uncertain energy prices and uncertain equipment prices, to comprehensively quantify the value of uncertainty information for DES design. Secondly, more decision criteria, besides reliability and economy, can be introduced to test how the information volume affects the performance of the decision criteria. Such work can be used for guiding the designer to generate planning scenarios with the most valuable information.

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Appendix A

A.1. Nomenclatures

Abbreviations	
DES	Distributed energy system
IES	Integrated energy system
MC	Monte Carlo simulation
GICE	Gas-fired internal combustion engine
CC	Centrifugal chiller
AC	Absorption chiller
CS	Cooling energy storage
ES	Electric energy storage

PV	Photovoltaic
TF	Transformer
VPIe	Value of information for economy
VPIr	Value of information for reliability
EVPIe	Expected value of information for economy
EVPIr	Expected value of information for reliability
LOEE	Loss of energy expected
ESi, ESo	Electricity storage chare and discharge
CSi, CSo	Cooling energy storage chare and discharge
MILP	Mixed integer and linear program
M	Model
Notations	
s', s	Scenario
S, S', v, v	Probabilistic scenario set
ω	Probability of scenario
p	Scenario with perfect information
sch	DES scheme
R	Risk
r	Reliability
e	Economy
t, T	Time step and period
i	Technology
m	Fuel type
O	Objective
l	Cooling and electric loads
ee, ce	Electric energy and cooling energy
Variables	
Tc	Total cost (first layer and second layer model)
Inv	Investment of a DES (first layer and second layer model)
Oc	Operation cost (first layer and second layer model)
Cap	Equipment capacity (first layer model)
λ	Binary variable denoting the installation of technology *i* (first layer model)
Con	Fuel consumption of technology *i* at time step *t* in scenario *s* (first layer and second layer model)
ϑ	Binary variable denoting the energy supply status (second layer model)
Δe	Energy loss at each time step (second layer model)
ΔE	Total energy loss in the period of *T* (second layer model)
p	Power output of technology *i* (first layer and second layer model)
E	Energy stored in storage module (first layer and second layer model)
Parameters	
FC, EUP	Fixed and unit investment cost of technology *i*
κ	Capital recovery factor of technology *i*

FM, VM	Coefficients for estimate the fixed and variable maintenance cost
FP	Fuel price
β	The capital price
r	Discount rate
η	Efficiency of technology i
$\underline{soc}, \overline{soc}$	lower and upper bounds of state of charge
$\varphi^{maxo}, \varphi^{maxi}$	Maximum charging and discharging rate
ϵ	Self-discharge losses of energy storage module
M	A large constant

A.2. Model formulation

A.2.1 Objective function

The objective functions of Model 1, 2, and 3 are detailed formulated in Section 2.2 by Eqs. (8)-(10), Eq. (11) and Eq. (12), respectively. In Eq. (8), κ_i is the capital recovery factor of technology i used for annualizing the total investment cost and is defined as follows.

$$\kappa_i = \frac{r(r+1)^{life_i}}{(r+1)^{life_i - 1}} \tag{A.1}$$

A.2.2. Model constraints

The first layer model formulated in Section 2.2.3 is used for the design of DES, in which the building energy demand for cooling and electricity must be met for every time step t of each scenario in Model 2 and Model 3, while only met for every time step t in one typical scenario in Model 1. Therefore, $s = \{1,2,\dots,104\}$ for Model 1, $\nu = S, \forall s \in S$ for Model 2, and $\upsilon = S, \forall s \in S$ for Model 3.

(1) Energy balances

The cooling and electricity energy balance are given in Eq. (A.2) and (A.3), respectively. It should be noted that Eq. (A.2) and (A.3) are only used in the first layer model for DES optimization design, so there is no item describing the energy supply deficit, which differs from the energy balance constraints in the second layer model, as detailed in Eq. (16) and (17).

$$p_{s,t}^{GICE} + p_{s,,t}^{PV} + p_{s,t}^{G} + \eta^{ESo} \cdot p_{s,t}^{ESo} = l_{s,t}^{ee} + \frac{p_{s,t}^{ESi}}{\eta^{ESi}}, \ \forall t \in T \quad \text{(A.2)}$$

$$p_{s,t}^{CC} + p_{s,t}^{AC} + \eta^{CSo} \cdot p_{s,t}^{CSo} = l_{s,t}^{ce} + \frac{p_{s,t}^{CSi}}{\eta^{CSi}}, \forall t \in T \tag{A.3}$$

(2) Energy storage balances

The operational conditions of electricity storage are constrained by Eqs. (A.4)-(A.10). In this paper, the electricity storage device is operated as daily storage, which means it can only deal daily fluctuations. Its initial state of charge at the beginning of the day is equal to the state at the end of the day, as Eq. (A.4) shown. Eq. (A.5) guarantees energy balance in the electricity storage device. The charging and discharging power at time step t are should be below a specific ratio of the electricity storage's capacity, as Eq. (A.8) and (A.9) shown. The energy balance constraints of the cooling energy storage are the same as that of the electric energy storage device and will not be repeated here.

$$E_{s,t=0}^{ES} = E_{s,t=23}^{ES} \tag{A.4}$$

$$E_{s,t}^{ES} = (1-\epsilon) \cdot E_{s,t-1}^{ES} + p_{s,t}^{ESi} - p_{s,t}^{ESo}, \forall t \in T \tag{A.5}$$

$$E_{s,t}^{ES} \geq \underline{soc} \cdot Cap_{s,i=ES} \tag{A.6}$$

$$E_{s,t}^{ES} \leq \overline{soc} \cdot Cap_{s,i=ES} \tag{A.7}$$

$$p_{s,t}^{ESo} \leq \varphi^{maxo} \cdot Cap_{s,i=ES} \tag{A.8}$$

$$p_{s,t}^{ESi} \leq \varphi^{maxi} \cdot Cap_{s,i=ES} \tag{A.9}$$

(3) Technical constraints

Eq. (A.10) prevent capacity violations during the operation of energy generation technology. Eq. (A.10) defines the relationship between energy generation and fuel consumption for technology *i* through the efficiency of technology *i*.

$$p_{s,t}^{i} \leq Cap_{s,i}, \forall\, i \in \{GICE, CC, AC, PV, TF\}, \forall t \in T \tag{A.10}$$

$$p_{s,t}^{i} = \eta^{i} \cdot Con_{i,m,t,s}, \forall\, i \in \{GICE, CC, AC\}, \forall t \in T \tag{A.11}$$

A.3. Supplement figure

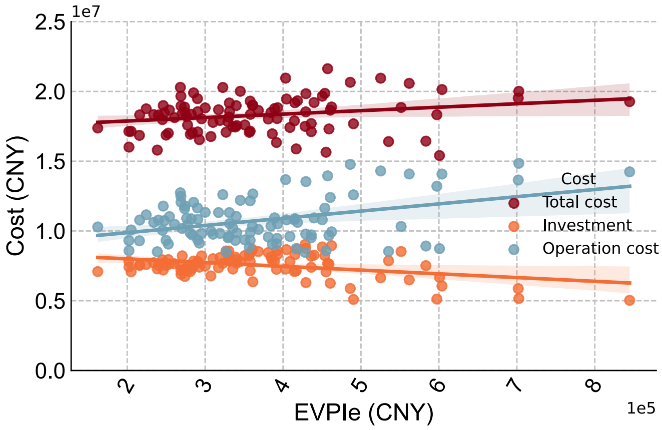

Fig. A1. The relationship between the economic objective of DES scheme and the expected value of information for economy (EVPIe). Partial enlarged view of Fig. 10.