An Adaptive Decision-making Approach for Transmission Expansion Planning Considering Risk Assessment of Renewable Energy Extreme Scenarios

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May 17, 2023

Abstract

The extreme power output scenarios of renewable energy sources (RES) proposed new challenges to the safe and stable operation of the power system. Transmission expansion planning (TEP) with large-scale RES grid integration needs considering the risk of extreme scenarios. In this paper, an adaptive decision-making approach for the TEP problem based on planning-risk assessment-replanning iterative process is proposed. The method obtains massive temporal and spatial correlated wind-photovoltaic (PV) power output scenarios by generalizing the historical data to describe the uncertainties. A data-driven load loss risk assessment model (RAM) based on the power system's actual operating state is built, referring to the degree of extreme scenario risks on the balance of supply and demand, and the probability of extreme scenario occurrence. The planning decision is progressively revised according to the risk assessment result. The Garver's 6-bus system and the IEEE RTS 24-bus system are adopted as simulation cases. The results show that the optimal expansion plans achieve a balance between the economy and robustness, which verifies the effectiveness of the proposed method.

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Running head/short title: Adaptive TEP Considering Risk Assessment

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Funding information:
The Science and Technology Project of Global Energy Interconnection Group Co., Ltd. of China, Grant/Award Number: SGGEIG00JYJS2200060

AUTHOR CONTRIBUTIONS
Pengfei Zhao: CRediT contribution not specified. Xinzhi Xu: Data curation; Funding acquisition. Xiaochong Dong: Methodology, Resources; Writing – review & editing. Yi Gao: Data curation; Funding acquisition. Yingyun Sun: CRediT contribution not specified.

CONFLICT OF INTEREST STATEMENT
The authors have no conflict of interest.

PERMISSION TO REPRODUCE MATERIALS FROM OTHER SOURCES
None.

DATA AVAILABILITY STATEMENT
The data that support the findings of this study are available from the corresponding author upon reasonable request.

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Abstract: The extreme power output scenarios of renewable energy sources (RES) proposed new challenges to the safe and stable operation of the power system. Transmission expansion planning (TEP) with large-scale RES grid integration needs considering the risk of extreme scenarios. In this paper, an adaptive decision-making approach for the TEP problem based on planning-risk assessment-replanning iterative process is proposed. The method obtains massive temporal and spatial correlated wind-photovoltaic (PV) power output scenarios by generalizing the historical data to describe the uncertainties. A data-driven load loss risk assessment model (RAM) based on the power system's actual operating state is built, referring to the degree of extreme scenario risks on the balance of supply and demand, and the probability of extreme scenario occurrence. The planning decision is progressively revised according to the risk assessment result. The Garver's 6-bus system and the IEEE RTS 24-bus system are adopted as simulation cases. The results show that the optimal expansion plans achieve a balance between the economy and robustness, which verifies the effectiveness of the proposed method.

keywords：renewable energy source; uncertainty; extreme scenario; transmission expansion planning; risk assessment

1. Introduction

The rapid development of renewable energy plays a crucial role in the energy transition and carbon reduction. According to statistics from the International Renewable Energy Agency (IRENA), renewable energy sources (RES), mainly wind and photovoltaic (PV) power, accounted for 40% of global installed power capacity by the end of 2022 [1]. However, the large-scale integration of RES has posed new challenges to the transmission expansion planning (TEP) problem, due to the inherent intermittent of wind and PV generation [2-3]. Specifically, the insufficient power output of RES in extreme scenarios will lead to serious energy shortages [4-5], characterized as low-probability and high-impact (HPLI) events [6]. Hence, it is essential to consider the risks of extreme power output scenarios in addressing the TEP problem with large-scale RES grid integration.

The extreme power output of most RES is heavily dependent on specific meteorological conditions, especially for wind and PV power, which are associated with variable wind speed and illumination intensity [7]. This means that the decision-making process for the TEP problem requires an efficient way to deal with uncertainties in RES output. Depending on the methods to describe uncertainties, TEP models can be categorized into robust optimization (RO), distributionally robust optimization (DRO), and stochastic optimization (SO) [8]. These optimization models evaluate extreme output scenarios differently. It is worth noting that ensuring complete resilience of the power system to the risks of load loss in all extreme scenarios will massively increase planning costs. The optimal solution must balance the trade-off between the economy and robustness while reducing the risks of extreme scenarios.

RO analyzes the worst-case scenario within a given bounded uncertainty set without requiring the exact information of probability distribution [9-10]. In contrast, DRO uses fuzzy sets of probability distribution to make decisions based on the worst-case probability distribution [11-12]. As RO only uses the boundary information of uncertainties and ignores or simplifies the spatio-temporal correlation between variables, the optimal solution tends to be overly conservative and the worst-case scenario is difficult to emerge in practice [13]. DRO reduces conservatism compared to RO but relies on subjective experience to preset the fuzzy sets [14].

SO assumes that the probability distribution is known completely and uses discrete scenarios to handle the uncertainties [15], including chance-constrained [16-17] and scenario-based [18-19] methods. Among these, scenario-based SO is preferred due to its ability to characterize the time-series correlation of uncertainties [20]. However, scenario reduction methods used to ease the computational burden often exclude low-probability extreme scenarios, leading to insufficient robustness of the optimal solution [18]. To improve the robustness of the optimal solution, reference [21] introduced conditional value at risk (CVaR) in the objective function. But the formulation of CVaR is still based on the given typical scenario set, which has limitations in assessing the risks of uncertainties over the whole range of RES output variability. Reference [22] includes the extreme historical days of the net load as representative scenarios, but ignores the load loss risks related to transmission congestion.

In recent years, with the application of information and measurement technologies in power systems, several studies have proposed data-driven adaptive or posteriori optimization methods using historical operation data of RES. Reference [23] proposed a data-adaptive RO method to reduce conservativeness by replacing the uncertainty set with several extreme scenarios selected from historical data. Reference [24-25] proposed an iteration method between a planning model and an operation model to identify the maximum cumulative lost load or the highest lost load cost scenario, thus finding the optimal solution that ensures the feasibility of all historical scenarios. These adaptive methods are essentially RO models based on historical data, with the weakness of being overly conservative or possibly infeasible.

Meanwhile, due to the generally short operating time of RES plants, the limited scale of historical data cannot cover all possible extreme scenarios in the future.

To address the problem of insufficient historical data, generative networks [26-27], which allow for implicit modeling of the correlation of uncertainties by fitting joint probability distributions based on deep neural networks, have been proposed. By generating massive time-series correlated RES output scenarios, generative networks provide an effective identification target for extreme scenario analysis. The difficulty in applying this method to the TEP problem is achieving an acceptable computational burden while making use of as much of the generated scene information as possible.

This study proposes an adaptive decision-making approach to address the above-mentioned issues related to the TEP problem. Accordingly, the present work provides the following three main contributions:

(1) The generative network based on deep neural networks is used to obtain massive power output scenarios in order to cover the range of RES output variability and to improve the accuracy of the optimal solution. Compared to historical data, the generated scenarios include more HPLI extreme scenarios.

(2) The data-driven load loss risk assessment model and the adaptive decision-making framework for the TEP problem are proposed. Effective identification of extreme scenarios can only be achieved by assessing the risks of the power system's actual operating state under given boundary conditions.

(3) The corresponding practical algorithm of the planning-risk assessment-replanning iterative process is proposed to solve the adaptive TEP problem. The lowest-risk extreme scenario is identified to affect the decision-making process. The proposed algorithm achieves a balance between economy and robustness with acceptable computationally expensive.

The rest of this paper is structured as follows. The adaptive decision-making framework for the TEP problem is presented in Section 2. Section 3 develops the corresponding algorithm for the proposed method. Section 4 presents the case studies. Section 5 draws conclusions.

2. The adaptive decision-making framework

2.1. The iterative process of the adaptive decision-making framework

This paper presents an adaptive decision-making framework for the TEP problem that considers the risks of insufficient supply in extreme scenarios of RES output, as illustrated in Figure 1. Initially, the generative network is utilized to establish a probability model of the uncertainties in RES. The model is trained with historical operation data $\boldsymbol{S}_{\text{hist}}$, and generates massive discrete time-series RES output scenarios, which compose the full-space scenario set $\boldsymbol{S}_{\text{RES}}$. These scenarios include more extreme events than historical data, and thus they enable us to better assess the risks associated with insufficient output. The typical scenario set $\boldsymbol{S}_{\text{TYP}}$ is derived from the full-space scenario set $\boldsymbol{S}_{\text{RES}}$ by using the scenario reduction method. The typical scenario set $\boldsymbol{S}_{\text{TYP}}$ at the subsequent iterations only includes several representative scenarios, thus reducing the computational burden for optimization problems. Then, a scenario-based stochastic TEP model based on the set $\boldsymbol{S}_{\text{TYP}}$ is established to determine expansion plans, which are feasible for all the typical scenarios. Finally, a data-driven load loss risk assessment model (RAM) based on the set $\boldsymbol{S}_{\text{RES}}$ is developed. RAM identifies extreme scenarios and enhances the robustness of TEP decisions in the next iteration stage by modifying the typical scenario set.

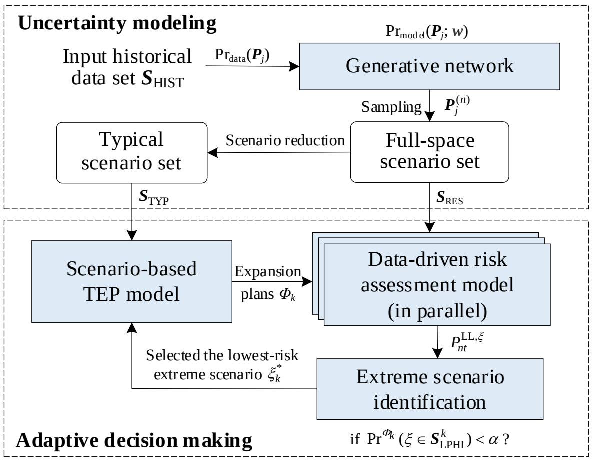


Fig. 1 Adaptive decision-making framework of the TEP problem

The adaptive decision-making framework works iteratively in two steps: determining expansion plans followed by an extreme risk assessment for the determined plans. As the iteration index k increases, the typical scenario set is revised by the selected lowest-risk extreme scenario. And extreme load loss risks caused by transmission congestion can be gradually reduced. The proposed approach allows the optimal expansion plans Φ^* to achieve a balance between economy and robustness.

2.2. Generative network-based modeling of the uncertainties in RES

The large-scale RES integration power system is still in the developmental stage. As a result, many wind and PV plants have been in operation for a short duration, which limits the amount of historical data available. The data may not include or only include a small proportion of the extreme insufficient scenarios of RES power output. The transmission expansion plans solely based on historical data (e.g., reference [23-25]) can be problematic as it fails to account for the future possible range of RES output. Moreover, due to the temporal and spatial correlations of wind-PV output uncertainties, it is challenging to develop an explicit density model that accurately captures a joint probability distribution of the uncertainties.

The uncertainties in RES output can be classified as aleatory uncertainty and epistemic uncertainty [28]. The methods of uncertainty modeling aim to reduce epistemic uncertainty, which is caused by people's limited knowledge of the system [29]. The time-series correlated output of RES containing multiple wind and PV plants is a time-varying, non-stationary, high-dimensional stochastic process that can be represented in a simplified way as an unknown complex high-dimensional joint probability distribution.

Let a series of stochastic processes $\boldsymbol{P}_j=(\boldsymbol{p}_{j1}, \boldsymbol{p}_{j2},\ldots, \boldsymbol{p}_{j\text{T}})$, represent the temporal and spatial correlated power output scenario sets of multiple RES plants, where T denotes the time horizon and $j \in \boldsymbol{\Omega}_{\text{RES}}$. That is, for each RES plant j at time t, $\boldsymbol{p}_{jt}$ is a random variable. The truth joint probability distribution is written as $\Pr_{\text{truth}}(\boldsymbol{P}_j)$, which is unknown and also difficult to describe with an explicit density model. Therefore, if the joint probability distribution is known, a series of discrete time-series samples can be obtained by sampling $\Pr_{\text{truth}}(\boldsymbol{P}_j)$ for modeling the TEP problem.

In this paper, a generative network based on deep neural networks is used as a probability model to approximately match the empirical joint probability distribution $\Pr_{\text{data}}(\boldsymbol{P}_j)$ of the historical data $\boldsymbol{S}_{\text{HIST}}$, also as the fitted probability distribution to $\Pr_{\text{truth}}(\boldsymbol{P}_j)$. The training of the generative network with historical data allows the extraction of temporal and spatial correlations of RES power output. The essence of the generative network is to construct a mapping function $g(\sim)$ between the known probability distribution $\Pr(\boldsymbol{z})$ and the unknown probability distributions $\Pr_{\text{model}}(\boldsymbol{P}_j; w)$, as shown in (1).

$$\Pr_{\text{model}}(\boldsymbol{P}_j;\boldsymbol{w}) = g(\Pr(\boldsymbol{z}),\boldsymbol{w}) \tag{1}$$

where w denotes the training parameters of the generative network. The training objective is to maximize the likelihood of the fitted probability distribution $\Pr_{\text{model}}(\boldsymbol{P}_j; w)$ over the empirical probability distribution $\Pr_{\text{data}}(\boldsymbol{P}_j)$, as shown in (2).

$$\boldsymbol{w} = \arg\min_{\boldsymbol{w}} \mathbb{E}_{\boldsymbol{P}_j \sim \Pr_{\text{data}}(\boldsymbol{P}_j)}[\log \Pr_{\text{model}}(\boldsymbol{P}_j;\boldsymbol{w})] \tag{2}$$

By developing an implicit density model of RES uncertainties using the generative network, a discrete time-series scenario set of RES output is generated by sampling $\Pr_{\text{model}}(\boldsymbol{P}_j; w)$, referred to as the full-space scenario set $\boldsymbol{S}_{\text{RES}}$. When the size of the set $\boldsymbol{S}_{\text{RES}}$ is sufficiently large, the discrete probability distribution of the samples can be assumed to fit the truth joint probability distribution $\Pr_{\text{truth}}(\boldsymbol{P}_j)$. The generated scenario set $\boldsymbol{S}_{\text{RES}}$ is the generalization of historical data. Compared to limited historical data, the generated scenarios includes more extreme events of RES insufficient output, which can provide valid samples for subsequent extreme scenario risk assessment. The nth generated scenario in $\boldsymbol{S}_{\text{RES}}$ can be written as:

$$\boldsymbol{P}_j^{(n)} = (p_{j1}^{(n)}, p_{j1}^{(n)}, ..., p_{j\text{T}}^{(n)}) \tag{3}$$

As the generated scenario set $\boldsymbol{S}_{\text{RES}}$ includes massive scenarios, applying to the TEP problem would result in an unacceptable computational burden. Therefore, the typical scenario set $\boldsymbol{S}_{\text{TYP}}$ is obtained by applying scenario reduction methods to select representative scenarios. The size of the typical scenario set $\boldsymbol{S}_{\text{TYP}}$ is much smaller than the size of the generated scenario set $\boldsymbol{S}_{\text{RES}}$, with less computational burden. The objective of the scenario reduction problem is to find the reduced probability scenarios that approximately match the generated probability scenarios while minimizing the distance measure between the reduced and generated scenarios [30]. Scenario reduction problem can be stated as:

$$\begin{gathered} \min_{\pi} \sum_{s,s'} d_{s,s'} \pi_{s,s'} \\ s.t. \sum_{s'} \pi_{s,s'} = \Pr^{s};\ \pi_{s,s'} \geq 0 \end{gathered} \tag{4}$$

The scenario generation method and scenario reduction method proposed in this paper are not limited to specific types of methods. With a reasonable configuration of various methods, the generalization of historical data and the reduced scenarios can be achieved.

2.3. Scenario-based TEP model

In this section, a scenario-based TEP model based on the typical scenario set $\boldsymbol{S}_{\text{TYP}}$ is established to generate expansion plans $\boldsymbol{\Phi}$, as a basis for the subsequent risk assessment process. As the scenario reduction process typically excludes low-probability extreme scenarios, the optimal results of the TEP model demonstrate superior economic performance, but insufficient robustness. The TEP model proposed in this section is strictly subject to the power system security constraints for all scenarios in the typical scenario set $\boldsymbol{S}_{\text{TYP}}$. And in subsequent iterations, the typical scenario set is adjusted according to the results of the extreme risk assessment, thereby enhancing the robustness of the expansion plans.

The objective of the proposed TEP model is to minimize the total annual costs, as presented in Equation (5), which is the sum of annualized investment cost, generation cost, and the penalty cost of RES power curtailment. Each component of the objective function is represented by Equations (6)-(8).

$$\min\ C_{\text{TEP}} = C^{\text{inv}} + C^{\text{gen}} + C^{\text{cur}} \tag{5}$$

where

$$C^{\text{inv}} = \frac{r(1+r)^{T_{\text{line}}}}{(1+r)^{T_{\text{line}}} - 1} \sum_{l \in \boldsymbol{\Omega}_{\text{L+}}} c_l^{\text{line}} x_l \tag{6}$$

$$C^{\text{gen}} = \sum_{s \in \boldsymbol{S}_{\text{TYP}}} \Pr^{s} \sum_{t} \sum_{i \in \boldsymbol{\Omega}_{\text{G}}} [a_i (P_{it}^{s})^2 + b_i P_{it}^{s} + c_i] \tag{7}$$

$$C^{\text{cur}} = \sum_{s \in \boldsymbol{S}_{\text{TYP}}} \Pr^{s} \sum_{t} \sum_{j \in \boldsymbol{\Omega}_{\text{RES}}} c_j^{\text{cur}} P_{jt}^{\text{cur},s} \tag{8}$$

s.t.

$$x_l = \{0,1\},\ l \in \boldsymbol{\Omega}_{\text{L+}} \tag{9}$$

$$x_l = 1,\ l \in \boldsymbol{\Omega}_{\text{L}} \setminus \boldsymbol{\Omega}_{\text{L+}} \tag{10}$$

$$\sum_{i \in \boldsymbol{\Omega}_n^{\text{G}}} P_{it}^{s} + \sum_{j \in \boldsymbol{\Omega}_n^{\text{RES}}} P_{jt}^{s} + \sum_{l \in \boldsymbol{\Omega}_n^{\text{L}}} P_{lt}^{s} = P_{nt}^{\text{d}},\ \forall n,t,s \tag{11}$$

$$P_i^{\min} \leq P_{it}^{s} \leq P_i^{\max},\ \forall i,t,s \tag{12}$$

$$-R_i^{\text{down}} \leq P_{i(t+1)}^{s} - P_{it}^{s} \leq R_i^{\text{up}},\ \forall i,t,s \tag{13}$$

$$0 \leq P_{jt}^{s} \leq P_{jt}^{\text{fore},s},\ \forall j,t,s \tag{14}$$

$$P_{jt}^{\text{cur},s} = P_{jt}^{\text{fore},s} - P_{jt}^{s},\ \forall j,t,s \tag{15}$$

$$P_{lt}^{s} = x_l b_l (\theta_{l(i),t}^{s} - \theta_{l(j),t}^{s}),\ \forall l,t,s \tag{16}$$

$$\left|P_{lt}^{s}\right| \leq x_l \cdot P_l^{\max},\ \forall l,t,s \tag{17}$$

$$\sum_{i \in \boldsymbol{\Omega}_{\text{G}}} (P_i^{\max} - P_{it}^{s}) \geq r_{\text{d}} \sum_{n \in \boldsymbol{\Omega}_{\text{N}}} P_{nt}^{\text{d}} + r_{\text{res}} \sum_{j \in \boldsymbol{\Omega}_{\text{RES}}} P_{jt}^{\text{fore},s}, \forall t,s \tag{18}$$

$$\theta_{ref}^{s} = 0,\ \forall s \tag{19}$$

$$\theta_n^{\min} \leq \theta_{n,t}^{s} \leq \theta_n^{\max},\ \forall n,t,s \tag{20}$$

Equation (6) describes the annualized investment cost of transmission lines. The generation cost, represented by Equation (7), is the expected fuel cost of thermal generators and is modeled as a quadratic function of power generation. Additionally, Equation (8) sets the expected penalty cost for RES power curtailment, which promotes the consumption of RES. It is important to note that the generation cost and penalty cost are dependent on the representative scenarios included in the typical scenario set $\boldsymbol{S}_{\text{TYP}}$. The probability of occurrence of these typical scenarios determines their respective weight in the model.

The constraints of the proposed scenario-based TEP model are discussed below. Constraints (9)-(10) specify the construction status of the candidate and existing transmission lines. Constraints (11)-(20) are related to the RES scenarios. Specifically, constraint (11) enforces the strict power balance for each bus without any unserved load demand term. Constraints (12)-(13) represent the operating constraints of thermal generators. Constraint (12) provides the lower and upper limits of power output, and constraint (13) sets the ramping rate limit. Constraints (14)-(15) determine the output bounds of RES. The sum of RES consumption and curtailment must be equal to the forecast power output for the scenario. Constraint (16) defines direct current (DC) power flow for transmission lines, including the candidate and existing lines. Transmission capacity limits are stated by constraint (17). The spinning reserve constraint, served by thermal generators, is defined in constraint (18). Constraints (19)-(20) specify the voltage angle bounds of the slack bus and the rest buses, respectively.

In addition, since constraint (16) is non-linear due to the product of continuous and binary variables, it can be easily linearised by constraint (21) through the Big-M method.

$$\left|P_{lt}^{s}-b_l(\theta_{l(i),t}^{s}-\theta_{l(j),t}^{s})\right|\le M\cdot(1-x_l),\ \forall l,t,s \tag{21}$$

In conclusion, The TEP model proposed in this study is a scenario-based stochastic optimization problem, which belongs to the mixed-integer linear programming (MILP) problem category. The model has remarkable solution efficiency, especially when dealing with a limited number of typical scenarios.

2.4. Data-driven RAM

In this section, based on the planning results of the TEP model in the previous section, the data-driven RAM is proposed to assess the feasibility of RES scenarios in the full-space scenario set $\boldsymbol{S}_{\mathrm{RES}}$. The risk assessment results depend on operational simulations under specific power system boundary conditions. The network structure associated with TEP decisions is fixed in this model. The RAM aims to minimize the penalty cost for load losses by optimizing generators' output and transmission power flow, achieving a quantification of the load loss risks under a single RES scenario.

By traversing the full-space set $\boldsymbol{S}_{\mathrm{RES}}$, the RAM delivers the amount of system load loss in every generated scenario, serving as the basis for following identifying extreme scenarios. The RAM belongs to the category of linear programming (LP) problems, which are computationally efficient and amenable to parallel processing.

For any scenario $\xi\in\boldsymbol{S}_{\mathrm{RES}}$ of RES power output, the RAM is formulated as follows:

$$\min\ C_{\mathrm{RAM}}=\sum_{t}\sum_{n\in\boldsymbol{\Omega}_{\mathrm{N}}}c_n^{\mathrm{LL}}P_{nt}^{\mathrm{LL},\xi} \tag{22}$$

s.t.

$$\sum_{i\in\boldsymbol{\Omega}_n^{\mathrm{G}}}P_{it}^{\xi}+\sum_{j\in\boldsymbol{\Omega}_n^{\mathrm{RES}}}P_{jt}^{\xi}+\sum_{l\in\boldsymbol{\Omega}_n^{\mathrm{L}}}P_{lt}^{\xi}=P_{nt}^{\mathrm{d}}-P_{nt}^{\mathrm{LL},\xi},\ \forall n,t \tag{23}$$

$$P_{nt}^{\mathrm{LL},\xi}\le P_{nt}^{\mathrm{d}},\ \forall n,t \tag{24}$$

$$P_i^{\min}\le P_{it}^{\xi}\le P_i^{\max},\ \forall i,t \tag{25}$$

$$-R_i^{\mathrm{down}}\le P_{i(t+1)}^{\xi}-P_{it}^{\xi}\le R_i^{\mathrm{up}},\ \forall i,t \tag{26}$$

$$0\le P_{jt}^{\xi}\le P_{jt}^{\mathrm{fore},s},\ \forall j,t \tag{27}$$

$$P_{lt}^{\xi}=b_l(\theta_{l(i),t}^{\xi}-\theta_{l(j),t}^{\xi}),\ \forall l,t \tag{28}$$

$$\left|P_{lt}^{\xi}\right|\le P_l^{\max},\ \forall l,t \tag{29}$$

$$\sum_{i\in\boldsymbol{\Omega}_{\mathrm{G}}}(P_i^{\max}-P_{it}^{\xi})\ge r_{\mathrm{d}}\sum_{n\in\boldsymbol{\Omega}_{\mathrm{N}}}P_{nt}^{\mathrm{d}}+r_{\mathrm{res}}\sum_{j\in\boldsymbol{\Omega}_{\mathrm{RES}}}P_{jt}^{\mathrm{fore},\xi},\forall t \tag{30}$$

$$\theta_{ref}^{\xi}=0 \tag{31}$$

$$\theta^{\min}\le\theta_{n,t}^{\xi}\le\theta^{\max},\ \forall n,t \tag{32}$$

The constraints of the RAM are similar to the operation constraints of the TEP model described earlier. In particular, the power balance constraints for each bus, defined by constraint (23), are augmented with load loss variables $P_{nt}^{\mathrm{LL},\xi}$, which permit the power system to shed loads during severe supply shortages, maintaining operational safety and ensuring the feasibility of the RAM. The upper load-shedding bounds are stated in constraint (24). The method for identifying extreme scenarios of RES output through load loss results is described below.

2.5. Method of extreme scenario identification

It is widely recognized that extreme scenarios of RES output are primarily driven by low-probability extreme weather and climate events, including extreme cold and heat, which have characteristics of "low-probability and high-impact", commonly referred to as LPHI scenarios. In contrast, conventional scenarios are characterized by "high-probability and low-impact" features, also known as HPLI scenarios [6]. In order to identify extreme scenarios, it is necessary to assess both the potential impact on the supply-demand balance and the probability of occurrence. This section proposes a method for identifying extreme scenarios that are likely to cause high risks of unserved power demand.

The risk indicators are proposed to measure the degree of imbalance between system supply and demand for a particular RES scenario. These are defined as the proportion of the hourly maximum load losses and daily cumulative load losses to the total system load. While the load losses for the proposed expansion plans Φ and the RES scenario ξ are determined by solving the RAM, the hourly load loss factor (h-LLF) and the daily load loss factor (d-LLF) are given by Equations (33)-(34).

$$h\text{–}LLF_{\xi|\Phi}=\max_{t}\left\{\frac{\sum_{n}P_{nt}^{\mathrm{LL},\xi}}{\sum_{n}P_{nt}^{\mathrm{d}}},0\right\} \tag{33}$$

$$d-LLF_{\xi|\Phi}=\frac{\sum_{t}\sum_{n}P_{nt}^{\mathrm{LL},\xi}}{\sum_{t}\sum_{n}P_{nt}^{\mathrm{d}}} \tag{34}$$

The thresholds for acceptable hourly and daily load losses, named ε_{h} and ε_{d} respectively, can be given based on manual experience or specific circumstances. Hence, an LPHI scenario is identified when either condition (35) or (36) is satisfied, while the opposite is regarded as an HPLI scenario. The initial identification of LPHI scenarios is achieved by traversing the full-space scenario set $\boldsymbol{S}_{\mathrm{RES}}$.

$$h\text{–}LLF_{\xi|\Phi} \geq \varepsilon_{\mathrm{h}} \tag{35}$$

$$d\text{–}LLF_{\xi|\Phi} \geq \varepsilon_{\mathrm{d}} \tag{36}$$

Furthermore, when the size of the set $\boldsymbol{S}_{\mathrm{RES}}$ is large enough, the probability of occurrence of extreme scenarios can be evaluated by calculating the proportion of the sample size of the LPHI scenario set $N(\boldsymbol{S}_{\mathrm{LPHI}})$ to the sample size of the generated scenario set $N(\boldsymbol{S}_{\mathrm{RES}})$, as shown in Equation (37), which is related to the proposed expansion plans Φ.

$$\Pr^{\Phi}(\xi \in \boldsymbol{S}_{\mathrm{LPHI}}) \approx \frac{N(\boldsymbol{S}_{\mathrm{LPHI}})}{N(\boldsymbol{S}_{\mathrm{RES}})} \tag{37}$$

Assuming that the occurrence of extreme scenarios is a small probability event for a given level of significance α, in which case the risks of extreme scenarios can be disregarded during the power system planning process. Hence, the optimal expansion plans are obtained. The probability of occurrence of extreme scenarios related to expansion plans Φ should satisfy the condition as follows:

$$\Pr^{\Phi}(\xi \in \boldsymbol{S}_{\mathrm{LPHI}}) \leq \alpha \tag{38}$$

3. Solution algorithm of the adaptive decision-making approach for the TEP problem

This section presents an adaptive decision-making approach for the TEP problem with the risk assessment of extreme RES output scenarios. The proposed method is based on a planning-risk assessment-replanning iterative process. This approach achieves a balance between economy and robustness through a progressive iterative revision of the expansion plans, which is based on the identification of extreme scenarios.

The iteration index k is initialized to 1. The solution algorithm of the proposed adaptive decision-making approach for the TEP problem follows the steps outlined below and is presented in Algorithm 1. The initial typical scenario set $\boldsymbol{S}_{\mathrm{TYP}}^{1}$ is determined based on the full-space scenario set $\boldsymbol{S}_{\mathrm{RES}}$.

Step 1: Solve the TEP model to determine expansion plans. The TEP model proposed in Section 2.3 is solved based on the typical scenario set $\boldsymbol{S}_{\mathrm{TYP}}^{k}$ to determine the expansion plans Φ_k at iteration k. As the number of iterations increases, the size of the typical scenario set $\boldsymbol{S}_{\mathrm{TYP}}^{k}$ gradually increases, improving the robustness of the planning results.

Step 2: Identify extreme scenarios by solving RAM in parallel. Based on the expansion plans Φ_k in Step 1, the RAM is solved in parallel for each generated scenario $\xi \in \boldsymbol{S}_{\mathrm{RES}}$ to achieve the load losses $P_{nt}^{\mathrm{LL},\xi}$ at each bus n. Risk indicators, $h\text{–}LLF_{\xi|\Phi_k}$ and $d\text{–}LLF_{\xi|\Phi_k}$, are obtained for every scenario according to Conditions (33) and (34), respectively. LPHI scenarios are identified according to Equation (35) or (36), and the probability of occurrence of extreme scenarios $\Pr^{\Phi_k}(\xi \in \boldsymbol{S}_{\mathrm{LPHI}})$ is evaluated by Equation (37). The termination criterion is checked referring to Condition (38). If it is satisfied, the optimal expansion plans Φ^* are obtained and the iteration is terminated. If not, the process proceeds to Step 3.

Step 3: Adjust the typical scenario set. In order to gradually improve the robustness of planning results while maintaining superior economics, select the lowest-risk scenario ξ_k^* in the LPHI scenario set $\boldsymbol{S}_{\mathrm{LPHI}}^{k}$, and add this scenario to the set $\boldsymbol{S}_{\mathrm{TYP}}^{k}$ as a new typical scenario set. The revised set $\boldsymbol{S}_{\mathrm{TYP}}^{k+1}$ at the next iteration k+1 is shown as follows:

$$\xi_k^* = \arg\min\{h\text{–}LLF_{\xi|\Phi_k}, d\text{–}LLF_{\xi|\Phi_k}\}, \ \xi \in \boldsymbol{S}_{\mathrm{LPHI}}^{k} \tag{39}$$

$$\boldsymbol{S}_{\mathrm{TYP}}^{k+1} = \boldsymbol{S}_{\mathrm{TYP}}^{k} \cup \{\xi_k^*\} \tag{40}$$

The weight of the lowest-risk scenario ξ_k^* in the TEP model is considered as zero because the probability of occurrence of any single scenario is very low when the sample size of generated scenarios is sufficiently large. In other words, the planning decisions only need to satisfy the security constraints in this scenario and disregard its impact on the generation cost and the curtailment penalty cost.

The adaptive decision-making process for the TEP problem is repeated by setting k=k+1 and returning to Step 1.

Algorithm 1: Adaptive decision-making approach for the TEP problem

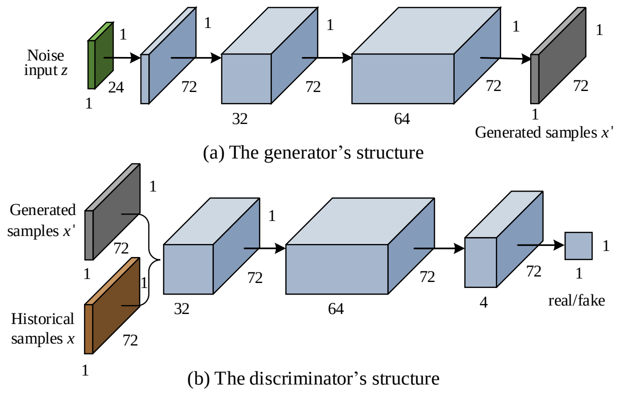
Initialization: Initialize Φ^*, α, ε_{h}, ε_{d}, and set k=1
Scenario Generation: Determine $\boldsymbol{S}_{\mathrm{RES}}$ by generalizing historical data
Scenario Reduction: Determine $\boldsymbol{S}_{\mathrm{TYP}}^{1}$ based on $\boldsymbol{S}_{\mathrm{RES}}$
repeat
  Initialize $\boldsymbol{S}_{\mathrm{LPHI}}^{k} = \varnothing$
  Determine Φ_k by solving the TEP problem based on $\boldsymbol{S}_{\mathrm{TYP}}^{k}$
  for ξ in $\boldsymbol{S}_{\mathrm{RES}}$ **do** (in parallel)
  Determine $P_{nt}^{\mathrm{LL},\xi}$ by solving RAM
    $h\text{–}LLF_{\xi|\Phi_k}$, $d\text{–}LLF_{\xi|\Phi_k}$ $\leftarrow$ Equations (33)-(34)
    if Condition (35) **or** (36) **do**
    $\boldsymbol{S}_{\mathrm{LPHI}}^{k} \leftarrow \boldsymbol{S}_{\mathrm{LPHI}}^{k} \cup \{\xi\}$
  end for
  $\Pr^{\Phi_k}(\xi \in \boldsymbol{S}_{\mathrm{LPHI}}^{k}) \leftarrow$ Equation (37)
  $\xi^* = \arg\min\{h\text{–}LLF_{\xi|\Phi_k}, d\text{–}LLF_{\xi|\Phi_k}\}$ for ξ in $\boldsymbol{S}_{\mathrm{LPHI}}^{k}$
  $\boldsymbol{S}_{\mathrm{TYP}}^{k+1} \leftarrow \boldsymbol{S}_{\mathrm{TYP}}^{k} \cup \{\xi_k^*\}$
  $k \leftarrow k+1$
until $\Pr^{\Phi_k}(\xi \in \boldsymbol{S}_{\mathrm{LPHI}}^{k}) < \alpha$
return Φ^*

4. Case studies

In this section, the modified Garver's 6-bus system [31] and the IEEE RTS 24-bus system [32] are studied to validate the superiority of the proposed TEP adaptive decision-making approach. All cases are simulated on a personal computer with CPU i9-10920X and 128G RAM, and implemented by a developed Python 3.9 based package using Gurobi 9.5.0 as the MILP/LP solver.

4.1. Scenario generalization based on generative network

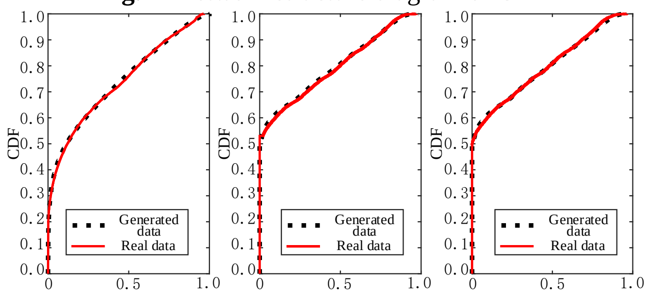
The historical RES power generation data was received from January 1, 2019 to October 31, 2020 at a wind-PV field station in northwest China, with a 1-hour data interval, 668 sets of valid historical scenarios, including one wind plant and two PV plants, named WD, PV1, and PV2, respectively. A Generative Adversarial Network (GAN) [26] is used to generalize the historical data for the three plants considering spatio-temporal correlation. The generator and discriminator network structures of GAN are shown in Figure 2. In this paper, 10,000 sets of wind-PV scenarios are generated based on GAN to form the full-space scenario set $\boldsymbol{S}_{\mathrm{RES}}$, and five sets of representative scenarios with corresponding probabilities are given based on the reduction network [30] to form the initial typical scenario set $\boldsymbol{S}_{\mathrm{TYP}}^{1}$ at the first iteration.



(a) The generator's structure

(b) The discriminator's structure

Fig. 2 Network structure diagram of GAN



(a) Output of WD (p.u.) (b) Output of PV1 (p.u.) (c) Output of PV2 (p.u.)

Fig. 3 CDF curve of historical data and generated data

The cumulative distribution function (CDF) of the generated scenarios is compared with the historical data to verify the effectiveness of GAN in scenario generalization, as shown in Figure 3. As can be seen from the figure, the CDF curve of the generated data is highly consistent with the historical data. Therefore, the generated scenarios are able to effectively cover the range of RES output variability for the risk assessment of the TEP problem.

4.2. Garver's 6-bus system

The Garver's 6-bus system has 6 buses and 15 rights-of-way, each with four parallel lines that can be added. The initial topology of the test system is illustrated in Figure 4. The thermal generator capacity and peak load are both 760MW. One 400MW wind plant is connected to Bus 6, and two 100MW PV plants are connected to Bus 1 and 2, respectively. In this study, it is assumed that the annual discount rate is 8% and the lifetime of the transmission line is 20 years. The spinning reserve capacity factors for load and RES are 1.5% and 2% respectively. The acceptable hourly and daily load losses thresholds ε_{h} and ε_{d} are set to 1% and 0.05% respectively. The significance level α for the LPHI scenario to be considered a small probability event is assumed to be 1%.

To illustrate the superiority of the proposed adaptive decision-making approach, three cases are presented in this study:

Case 1: A one-step scenario-based TEP model is built. The typical scenario set is obtained from historical data using the same scenario reduction method;

Case 2: Using the same one-step TEP model as Case 1, the typical scenario set is obtained from the generated scenarios based on GAN instead;

Case 3: Combining both the generalization of historical data and the iterative adaptive decision-making approach, the proposed method is used to solve the TEP problem in Case 3;

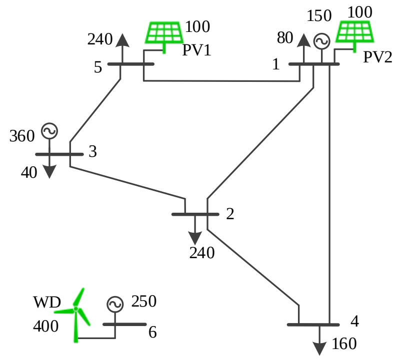


Fig. 4 Modified Garver's 6-bus system

Tab.1 Results comparison of Garver's 6-bus system

Case	Case 1	Case 2	Case 3
Num of new lines	4	4	5
Expansion plans (new lines)	3-5, 2-6, 4-6(2)	3-5, 2-6, 4-6(2)	2-3, 3-5, 4-6(3)
Investment cost (10^6\$)	10.30	10.30	12.18
Total annual cost (10^6\$)	47.35	47.86	48.25
$N(\boldsymbol{S}_{\mathrm{TYP}})$	5	5	6
$N(\boldsymbol{S}_{\mathrm{LPHI}})$	443	443	28
$\mathrm{Pr}^{\Phi^*}(\xi \in \boldsymbol{S}_{\mathrm{LPHI}})$	4.43%	4.43%	0.28%
Lowest risk scenario No.	817	817	5065

Table 1 shows the simulation results of Cases 1-3. Case 1 and Case 2 obtain the same expansion plans, further validating the effectiveness of the method of historical data generalization based on GAN. The planning results of Cases 1 and 2 are more economical, with an investment cost of 10.30×10^6\$ and 4 new lines added, and have lower investment costs and total annual costs compared to Case 3, the method proposed in this paper. This is because the scenario reduction process excludes low-probability extreme events, the typical scenario set represents the HPLI scenarios. The range of wind and PV output has been estimated too optimistically, resulting in a low level of redundancy in expansion plans. In addition, by traversing the generated scenario set $\boldsymbol{S}_{\mathrm{RES}}$ and solving the RAM model based on the results of Cases 1 and 2, the LPHI scenarios satisfying Condition (31) or (32) can be identified. The sample sizes of the LPHI scenarios of these cases are 443 and the probability of occurrence of extreme scenarios is 4.43%, both above the significance level α. At this point, the occurrence of extreme scenarios cannot be considered as a small probability event, which could lead to serious power system outages.

The iterative process of Case 3 satisfies the termination criterion after two iterations. The optimal expansion plans of Case 3 require 5 new lines ($n_{2\text{-}3}$=1, $n_{3\text{-}5}$=1, $n_{4\text{-}6}$=3), one more line than in Cases 1 and 2, with the total annual cost increasing from 47.86×10^6 \$ to 48.59×10^6 \$. However, the risk assessment results show that the sample size of LPHI scenarios is reduced to 28. The cumulative daily load loss ranges from 7.89 MW to 41.36 MW. The probability of occurrence of LPHI scenarios is lower than the significance level α. That means that the occurrence of extreme scenarios can be considered as a small probability event. It can be seen that the results of Case 3 effectively enhance the ability of the power system to withstand extreme wind and PV output scenarios by increasing the structural redundancy of transmission lines. The optimal expansion plans obtained by the method proposed in this paper balance economy and robustness, demonstrating the superiority of the adaptive decision-making approach.

To further illustrate the necessity for generalization to historical data, the risk of load loss for the planning results of Case 3 is evaluated based on the historical data set, and the results show that all are HPLI scenarios. The results ensure full feasibility for the historical RES scenarios, achieving the same robustness results as traditional data-driven robust optimization methods based on historical data. Moreover, The TEP model is infeasible when all of the identified extreme scenarios are added to the typical scenario set. It is further shown that the generated scenario set includes more LPHI extreme scenario events and is able to cover a wider range of RES output variability. And the risk of supply-demand imbalances cannot be completely eliminated by reducing transmission congestion.

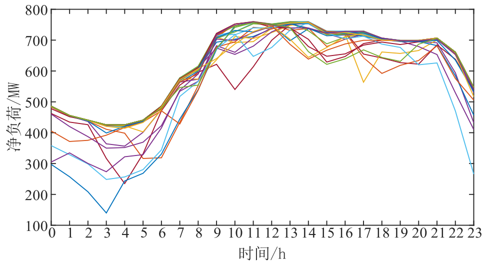


Fig. 5 Net load curves of LPHI scenarios

Tab. 2 Comparison of Pearson correlation coefficient

	S_{LPHI}	S_{TYP}	S_{RES}
PCC	-0.0941	0.3232	0.2508

The net load curves for all LPHI scenarios for the results of Case 3 are shown in Figure 5, which shows the insignificant peak effect of RES output on peak loads in extreme scenarios. Table 2 shows the correlation between each scenario set and load using the Pearson Correlation Coefficient (PCC). The PCC for the typical scenario set with load is significantly greater than the PCC for the LPHI scenario set with load, as is the case for the generation scenario set. This result indicates that the wind-PV output of the LPHI scenario has a weak correlation with load variations and is weakly supported in the peak load interval, thus leading to a supply-demand imbalance. The results demonstrate the necessity of identifying extreme RES output scenarios based on the actual operating conditions of the power system.

4.3. IEEE RTS 24-bus system

The modified IEEE RTS 24-bus system topology is shown in Figure 6, with a total peak load of 8 550 MW and 41 rights-of-way. It is assumed that up to 3 lines can be added to each corridor. One 2500MW wind plant is connected to Bus 23, and two 750MW PV plants are connected to Bus 8 and 13, respectively. The acceptable hourly and daily load losses thresholds ε_h and ε_d are set to 0.5% and 0.025% respectively. The remaining parameters in this case study are set to the same values as in Section 4.2. The significance level α is also assumed to be 1%. Using the adaptive decision-making method proposed in this paper to solve the TEP problem, the optimization results are shown in Table 3.

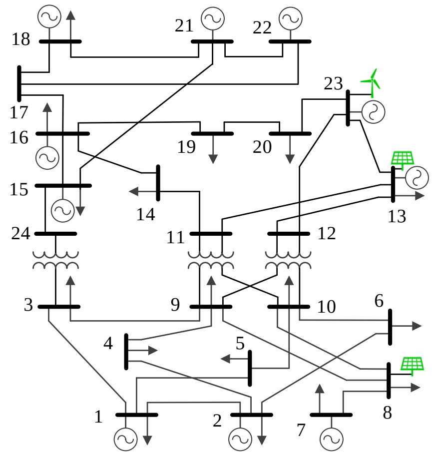


Fig. 6 IEEE RTS 24-bus system

Tab. 3 Results comparison of each iteration for IEEE RTS 24-bus system

Iteration index k	1	2	3	4
Num of new lines	6	7	6	7
Expansion plans (new lines)	6-10, 7-8(2), 10-12, 11-13, 20-23	1-5, 6-10, 7-8(2), 11-13(2), 20-23	7-8(2), 11-13(2), 20-23, 6-7	6-10, 7-8(2), 10-12, 20-23, 13-14(2)
Investment cost (10^6\$)	18.17	21.73	22.86	23.61
Total annual cost (10^6\$)	558.84	562.46	563.64	564.45
$N(\boldsymbol{S}_{TYP})$	5	6	7	8
$\Pr^{\Phi^*}(\xi \in \boldsymbol{S}_{LPHI})$	7.53%	4.07%	1.65%	0.95%
Lowest risk scenario No.	6277	4756	1075	1131

As shown in Table 3, the optimal expansion plans are obtained after four iterations for the 24-bus system ($n_{6\text{-}10}$=1, $n_{7\text{-}8}$=2, $n_{10\text{-}12}$=1, $n_{20\text{-}23}$=1, $n_{13\text{-}14}$=2). The LPHI scenario probability is 0.95%, which satisfies the given significance level α*. The extreme RES output scenarios occur as a small probability event. As the number of iteration index k increases, the investment cost and total annual cost sequentially increase, with investment cost increasing from 18.17×10^6 \$ to 23.61×10^6 \$ and total annual cost increasing from 558.84×10^6 \$ to 564.45×10^6 \$. The economy becomes worse while the robustness gradually improves. The LPHI scenario probability is reduced from 7.53% to 0.95%, achieving the goal of progressive iterative optimization of the TEP adaptive decision-making approach. By optimizing the new line decision, the optimal planning results better meet the system supply-demand balance for most wind-PV output fluctuations compared to planning results based on the typical scenario set (i.e., at k=1). The same conclusions as for the Garver's 6-bus system further validate the effectiveness of the method proposed in this paper.

The TEP model is a MILP problem and the solution time increases rapidly as the size of the typical scenario set increases, while the solution complexity is low when the size of the scenario set is small. The running time results of each iteration are shown in Table 4. The RAM is an LP problem, and the risk checks for different scenarios are independent of each other and can be run in parallel, and the traversal time for 10,000 sets of scenarios is between 856s and 880s, which is a manageable solution time. The method in this paper makes full use of the extreme information of the massive scenario set while avoiding the dimensional catastrophe problem of the traditional expectation value model in the face of large-scale scenarios, and is more practical.

Tab. 4 Running time of each iteration for IEEE RTS-24 bus system

Iteration index	1		2		3		4	
k	TEP	RAM	TEP	RAM	TEP	RAM	TEP	RAM
Time (s)	55.0	860.1	50.4	860.3	137.4	879.2	168.4	856.6

5. Conclusion

In this paper, we propose an iterative TEP adaptive decision-making approach to solve the TEP problem with the risk assessment of extreme RES output scenarios, and achieve progressive iterative optimization of the planning decision by identifying the lowest-risk extreme scenario for the given expansion plans. Compared with the traditional scenario-based planning method, the proposed method examines massive extreme scenarios included in the generated scenario set and achieves the quantitative analysis of the load loss risks of extreme scenarios, effectively balancing the economy and robustness of TEP results and enhancing the system's ability to resist the risks of extreme scenarios. The risk assessment of extreme scenarios can accurately reflect the power system's actual operating state in terms of supply and demand balance.

It should be noted that the optimal transmission expansion plans only address the extreme risks due to transmission congestion, which has certain limitations and cannot completely address the system loss of load due to insufficient RES output. Considering the increasing importance of flexible resources such as energy storage in the future power system, the role of energy storage in resisting extreme scenarios of RES output can be analyzed in subsequent studies to further improve the safe and stable operation of the power system.

Nomenclature

A. Indices and Sets

$l \in \boldsymbol{\Omega}_{\mathrm{L}}$	where l denotes a transmission line and $\boldsymbol{\Omega}_{\mathrm{L}}$ is the set of transmission lines.
$i \in \boldsymbol{\Omega}_{\mathrm{G}}$	where i denotes a thermal generator and $\boldsymbol{\Omega}_{\mathrm{G}}$ is the set of thermal generators.
$j \in \boldsymbol{\Omega}_{\mathrm{RES}}$	where j denotes a RES plant and $\boldsymbol{\Omega}_{\mathrm{RES}}$ is the set of RES plants.
$n \in \boldsymbol{\Omega}_{\mathrm{N}}$	where n denotes a bus and $\boldsymbol{\Omega}_{\mathrm{N}}$ is the set of buses.
$\boldsymbol{\Omega}_{\mathrm{L+}} \subset \boldsymbol{\Omega}_{\mathrm{L}}$	Subset of candidate transmission lines.
$\boldsymbol{\Omega}_n^{\mathrm{L}} \subset \boldsymbol{\Omega}_{\mathrm{L}}$	Subset of transmission lines connected to bus n.
$\boldsymbol{\Omega}_n^{\mathrm{G}} \subset \boldsymbol{\Omega}_{\mathrm{G}}$	Subset of thermal generators connected to bus n.
$\boldsymbol{\Omega}_n^{\mathrm{RES}} \subset \boldsymbol{\Omega}_{\mathrm{RES}}$	Subset of RES plants connected to bus n.
$\boldsymbol{S}_{\mathrm{HIST}}$	Set of historical scenarios.
$s \in \boldsymbol{S}_{\mathrm{TYP}}$	where s denotes a typical scenario and $\boldsymbol{S}_{\mathrm{TYP}}$ is the set of reduced typical scenarios.
$\xi \in \boldsymbol{S}_{\mathrm{RES}}$	where ξ denotes a generated scenario and $\boldsymbol{S}_{\mathrm{RES}}$ is the set of full-space generated scenarios.
t	Index of time periods.
k	Index of iteration.

B. Probability and distribution

$\boldsymbol{P}_j$	Stochastic process of the power output of RES plant j.
$\Pr(\boldsymbol{z})$	Probability distribution of variable $\boldsymbol{z}$.
$\Pr_{\mathrm{truth}}(\boldsymbol{P}_j)$	Truth joint probability distribution.
$\Pr_{\mathrm{data}}(\boldsymbol{P}_j)$	Empirical joint probability distribution.
$\Pr_{\mathrm{model}}(\boldsymbol{P}_j; \boldsymbol{w})$	Fitted joint probability distribution based on generative network with parameters $\boldsymbol{w}$.
$g(\sim)$	Mapping function.
$\Pr^s$	Probability of occurrence of typical scenario s.
$\Pr^{\Phi}$	Probability of occurrence of extreme scenarios related to expansion plans Φ
$\boldsymbol{P}_j^{(n)}$	The nth generated scenario in the set $\boldsymbol{S}_{\mathrm{RES}}$.
$d_{s,s'}$	Distance measure between scenario s and scenario s'.
$\pi_{s,s'}$	Probability of transport from scenario s to scenario s'.
$\mathbb{E}$	Expected value

C. Parameters

T	Time horizon.
w	Training parameters of the generative network.
r	Discount rate.
T_{line}	Life cycle of transmission lines [yr].
c_l^{line}	Investment cost of candidate transmission line l [$/MW].
a_i, b_i, c_i	Fuel cost coefficients of thermal generator i [$/MW].
c_j^{cur}	Penalty cost of curtailed power of RES plant j [$/MW].
c_n^{LL}	Penalty cost of unserved load demand of bus n [$/MW].
P_{nt}^{d}	Power demand of bus n at hour t [MW].
$P_i^{\min} / P_i^{\max}$	Minimum/maximum power output of thermal generator i [MW].
$R_i^{\mathrm{down}} / R_i^{\mathrm{up}}$	Ramp up/down limit of thermal generator i [$/MW].
$P_{jt}^{\mathrm{fore},s}$	Forecast power output of RES plant j at hour t, and scenario s [MW].
b_l	Susceptance of transmission line l [S].
$P_l^{\max}$	Capacity limit of transmission line l [MW].
$r_{\mathrm{d}} / r_{\mathrm{res}}$	Spinning reserve coefficient of demand/ RES output [%].
$\theta_n^{\min} / \theta_n^{\max}$	Minimum/maximum voltage angle bound [rad].
$\varepsilon_{\mathrm{h}} / \varepsilon_{\mathrm{d}}$	Threshold for acceptable hourly/daily load losses [%].
α	Given level of significance [%].
M	Big number serving as an upper bound for constraints of special purpose, M=10000.

D. Variables

x_l	Binary variable indicating the installation of transmission line l (1 if installed, otherwise 0).

P_{it}^{s}	Power output of thermal generator *i* at hour *t*, and scenario *s* [MW].
P_{jt}^{s}	Power output of RES plant *j* at hour *t*, and scenario *s* [MW].
$P_{jt}^{\mathrm{cur},s}$	Curtailed power of RES plant *j* at hour *t*, and scenario *s* [MW].
P_{lt}^{s}	Power flow through transmission line *l* at hour *t*, and scenario *s* [MW].
$P_{nt}^{\mathrm{LL},\xi}$	Unserved load demand of bus *n* at hour *t*, and scenario ξ [MW].
$\theta_{l(i),t}^{s}$	voltage angle of transmission lines *l* on the side of bus *i* at hour *t*, and scenario *s* [rad].
θ_{ref}^{s}	Phase angle of the slack bus at scenario *s* [rad].
Φ, $\Phi*$	Expansion plans and the optimal expansion plans.
$h\text{–}LLF_{\xi\|\Phi}$	Hourly load loss factor of expansion plans Φ at scenario ξ [%]
$d-LLF_{\xi\|\Phi}$	Daily load loss factor of expansion plans Φ at scenario ξ [%]
$N(\boldsymbol{S})$	Sample size of scenario set $\boldsymbol{S}$.
ξ_k^*	The lowest-risk scenario of the *k*th iteration.

ACKNOWLEDGEMENTS

This work was supported by the Science and Technology Project of Global Energy Interconnection Group Co., Ltd. of China (SGGEIG00JYJS2200060).

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