同行专家业内评价意见书编号：20250858237

附件1

浙江工程师学院（浙江大学工程师学院）同行专家业内评价意见书

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申报工程师职称专业类别（领域）：能源动力

浙江工程师学院（浙江大学工程师学院）制

2025年03月26日

填表说明

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四、同行专家业内评价意见书编号由工程师学院填写，编号规则为：年份4位＋申报工程师职称专业类别(领域)4位+流水号3位，共11位。

一、个人申报

（一）基本情况【围绕《浙江工程师学院（浙江大学工程师学院）工程类专业学位研究生工程师职称评审参考指标》，结合该专业类别(领域)工程师职称评审相关标准，举例说明】

1.对本专业基础理论知识和专业技术知识掌握情况(不少于200字)

本人掌握高等数学、线性代数、概率统计等工具，能建立电机控制微分方程模型；具备大学物理电磁学理论基础，支撑电路设计与电磁兼容分析。并且，系统掌握电力系统分析（潮流计算、短路电流仿真）、电机与拖动（异步电机矢量控制）、电力电子技术（IGBT/MOSFET器件特性）等核心课程，完成基于Matlab/Simulink的“光伏逆变器并网谐波抑制”仿真研究。跟踪新能源领域动态，研究氢燃料电池混合储能系统、SiC器件在电动汽车充电桩的应用；熟悉数字孪生技术在智能电网故障预测中的实践案例。此外，对于行业标准，我掌握GB/T 14549-93《电能质量公用电网谐波》、DL/T 5161-2018《电气装置安装工程质量检验规范》，在课程设计中严格遵循IEC 61850通信协议标准。并且，我分析过《电力业务许可证管理规定》《可再生能源法》对分布式光伏电站建设的影响，熟悉欧盟CE认证流程。

2.工程实践的经历(不少于200字)

1.我曾参与浙江海上风电基地及电网系统规划研究，调研海上风电汇集送出系统的典型拓扑结构，研究多风电场电力汇集及送出关键技术，研究多个海上风电场汇聚至陆上送出技术，提出风电基地送出系统规划方案。
2.我参与过浙江的大受端电力系统灵活调节能力挖掘关键技术等研究，研究电力系统动态平衡机理，调研不同调节资源的动态平衡能力作用机理及路径，对极端场景下的灵活性资源调节能力进行深度挖掘，并提出极端场景生成方法，以及在持续失衡扰动下的多类型非常态资源进行深度挖掘。
3.我参与了国家重点研发计划——促进系统调节能力提升的城市级电-气-热-储多能协同调控关键技术，并研究电-气-热-储多能系统协同优化控制技术，经常参与线下、线上项目讨论会议，并前往吉林长春、松原等地调研当地的综合能源情况，明确电、热、气资源的协同作用机理，挖掘极端场景下综合能源系统的韧性提升策略，研究提高系统韧性的关键技术。

3.在实际工作中综合运用所学知识解决复杂工程问题的案例（不少于1000字）

近年来，极端沙尘暴对综合能源系统造成的严重危害引起了社会的广泛关注。极端沙尘暴由于其影响范围广、破坏程度强，使得目前的能源系统难以针对性预防。其中，2017年春季新疆发生大规模沙尘天气，风力发电设施的发电效率下降约20%，部分设备因积尘过多而停止运行，甚至导致电力传输中断；2018年美国亚利桑那州发生大规模沙尘暴，导致太阳能发电效率下降30%左右，超过一半地区的太阳能农场运营中断；2024年3月13日，蒙古国肯特、东方等多省发生强沙尘暴灾害，部分地区出现大面积停电事故。极端灾害对能源系统带来了严峻的挑战，同时造成了重大的经济损失和人员伤亡，严重威胁了人们的生活用电安全。如何在极端灾害来临前做好预防并快速恢复能源供应成为研究的重点。
随着能源之间耦合程度的不断增强，以电力系统为主体融合气-热能源的综合能源系统（Integrated Energy Systems, IES）的发展已成为能源转型和优化的必然趋势。长远来看，随着能源结构转型的加速和实现“碳达峰、碳中和”目标的迫切需求，传统的单一能源电力系统正在逐步向IES转型。在这过程中，电能将与天然气、热力等多种能源形式深度融合，最终构建以电力为核心的新型能源体系。IES打破了传统电力、天然气、热能等能源形式独立规划和运行的模式，采用多

能互补、供需互动为核心的创新技术架构[3]，使能源系统耦合更为紧密，提高能源的利用效率。

IES的韧性是指IES对极端灾害的抗性、降低极端灾害对系统影响的规模及持续时间的能力。IES韧性评估不仅可以量化系统在应对灾害时的性能，同时可以根据结果辨别系统薄弱环节，合理进行资源优化调度，更有利于IES抵御极端灾害，减少灾后IES的负荷损失同时增强系统的韧性。

在此背景下，本案例对极端沙尘暴下考虑随机扰动的综合能源系统韧性提升技术展开了研究，主要工作如下：首先，构建综合能源系统模型，搭建仿真所用的实际系统算例；其次，研究沙尘暴的移动轨迹，明确沙尘暴的时空分布特征。分析沙尘暴对综合能源系统的影响，建立沙尘暴下系统的故障模型。对极端沙尘暴下的风光场景进行生成，并与传统场景生成方法进行对比，验证所提方法的有效性，弥补数据样本的空缺；然后，基于随机动力学，对生成的风光出力序列等沙尘暴下的随机扰动进行伊藤随机微分方程建模，采用极大似然估计法对方程中的漂移系数和扩散系数进行最优求解；之后，通过电气热网的潮流方程，得出系统性能水平的随机微分方程，构建韧性指标，并计算韧性指标的概率分布；最后，结合韧性概率评估方法，考虑沙尘暴灾害的时空分布特征，优化系统中风光机组调整，结合储能调度与多能系统能源协同，考虑灾前储热，提出沙尘暴下考虑随机扰动的综合能源系统韧性提升策略，构建两阶段分布鲁棒优化模型并采用优化算法求解，确定最优策略，提高极端沙尘暴下综合能源系统的韧性。

（二）取得的业绩（代表作）【限填3项，须提交证明原件（包括发表的论文、出版的著作、专利证书、获奖证书、科技项目立项文件或合同、企业证明等）供核实，并提供复印件一份】

1.
公开成果代表作【论文发表、专利成果、软件著作权、标准规范与行业工法制定、著作编写、科技成果获奖、学位论文等】

成果名称	成果类别 [含论文、授权专利（含发明专利申请）、软件著作权、标准、工法、著作、获奖、学位论文等]	发表时间/授权或申请时间等	刊物名称/专利授权或申请号等	本人排名/总人数	备注
Probability Assessment of Power System Resilience Based on Stochastic Dynamics Under Sandstorms	会议论文	2024年11月08日	IEEE EI2 2024	1/4	EI会议收录

2.其他代表作【主持或参与的课题研究项目、科技成果应用转化推广、企业技术难题解决方案、自主研发设计的产品或样机、技术报告、设计图纸、软课题研究报告、可行性研究报告、规划设计方案、施工或调试报告、工程实验、技术培训教材、推动行业发展中发挥的作用及取得的经济社会效益等】

（三）在校期间课程、专业实践训练及学位论文相关情况	
课程成绩情况	按课程学分核算的平均成绩： 85 分
专业实践训练时间及考核情况(具有三年及以上工作经历的不作要求)	累计时间： 1 年（要求1年及以上） 考核成绩： 82 分

本人承诺
个人声明：本人上述所填资料均为真实有效，如有虚假，愿承担一切责任，特此声明！ **申报人签名：**廖贤海

22260123

二、日常表现考核评价及申报材料审核公示结果

日常表现 考核评价	非定向生由德育导师考核评价、定向生由所在工作单位考核评价： √ ☐优秀　　☐良好　　☐合格　　☐不合格 德育导师/定向生所在工作单位分管领导签字（公章）：　2025 年 3 月 26 日
申报材料 审核公示	根据评审条件，工程师学院已对申报人员进行材料审核（学位课程成绩、专业实践训练时间及考核、学位论文、代表作等情况），并将符合要求的申报材料在学院网站公示不少于5个工作日，具体公示结果如下： ☐通过　　☐不通过（具体原因：　　　　　　） 工程师学院教学管理办公室审核签字（公章）：　　　年　月　日

浙 江 大 学 研 究 生 院

攻读硕士学位研究生成绩表

学号：22260123	姓名：廖贤海	性别：男	学院：工程师学院	专业：电气工程	学制：2.5年
毕业时最低应获：24.0学分		已获得：30.0学分		入学年月：2022-09	毕业年月：
学位证书号：			毕业证书号：		授予学位：

学习时间	课程名称	备注	学分	成绩	课程性质	学习时间	课程名称	备注	学分	成绩	课程性质
2022-2023学年秋季学期	新能源发电与变流技术		2.0	96	专业学位课	2022-2023学年秋冬学期	研究生英语		2.0	84	专业学位课
2022-2023学年秋季学期	新时代中国特色社会主义理论与实践		2.0	89	专业学位课	2022-2023学年秋冬学期	研究生论文写作指导		1.0	90	专业选修课
2022-2023学年秋季学期	工程技术创新前沿		1.5	90	专业学位课	2022-2023学年春季学期	研究生英语基础技能		1.0	75	公共学位课
2022-2023学年秋冬学期	工程管理		2.0	63	跨专业课	2022-2023学年春季学期	自然辩证法概论		1.0	89	专业学位课
2022-2023学年秋冬学期	工程伦理		2.0	83	专业学位课	2022-2023学年春季学期	电气装备健康管理		2.0	94	专业选修课
2022-2023学年秋冬学期	数据分析的概率统计基础		3.0	91	专业选修课	2022-2023学年春夏学期	高阶工程认知实践		3.0	78	专业学位课
2022-2023学年冬季学期	综合能源系统集成优化		2.0	85	专业学位课	2023-2024学年秋季学期	创新创业实践训练		2.0	通过	跨专业课
2022-2023学年冬季学期	产业技术发展前沿		1.5	94	专业学位课		硕士生读书报告		2.0	通过	

说明：1. 研究生课程按三种方法计分：百分制，两级制（通过、不通过），五级制（优、良、中、及格、不及格）。

2. 备注中“*”表示重修课程。

学院成绩校核章：

成绩校核人：张梦依

打印日期：2025-03-20

浙江大学研究生 （60） 成绩校核章

Acceptance Notification

https://attend.ieee.org/ei2-2024/

Dear Xianhai Liao, Daren Li, Yongzhi Zhou and Zhiqiang Yuan,

Congratulations!

On behalf of the Organizing Committee, we are pleased to inform you that your paper identified below has been accepted and you are cordially invited to give a presentation at the 8th IEEE Conference on Energy Internet and Energy System Integration (IEEE EI^2 2024), which will be held in **Shenyang, P.R. China** from **November 29** to **December 2, 2024**.

- Paper ID: 5890

- Paper Title: Probability Assessment of Power System Resilience Based on Stochastic Dynamics Under Sandstorms

The conference is organized by IEEE Power and Energy Society, Chinese Society for Electrical Engineering, Shenyang University of Technology and Tsinghua University. The theme of the conference is "Towards Green and Intelligent Energy Internet", which will focus on innovative technologies and practical applications in the fields of Energy Internet and Energy System Integration (ESI), aiming at the integration of multiple energy sources such as electricity, gas, heating, cooling and transportation to shape a green, low-carbon, smart and efficient ecosystem.

The accepted papers after full registration and presentation will be included into IEEE EI^2 2024 Conference Proceedings and submitted for inclusion in the IEEE Xplore Digital Library and submitted for indexing by Ei Compendex and Scopus.

Please pay attention to the information on the next page and follow the guideline to complete all the steps involved.

Once again, congratulations! We are looking forward to your participation in the conference. If you have any questions, please contact us via email address <ei2_2024@outlook.com>.
Yours sincerely,

Qiuye Sun
IEEE EI^2 2024 Conference Chair
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No.111, Shenliao West Road, Economic & Technological Development Zone, Shenyang, 110870, P.R. CHINA

Probability Assessment of Power System Resilience Based on Stochastic Dynamics Under Sandstorms

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***Abstract*—Frequent extreme sandstorm disasters have led to power system failures and significant losses, drawing widespread international attention. Considering the impact of stochastic disturbances is crucial for assessing system resilience. This paper proposes a resilience probabilistic assessment method based on stochastic dynamics specifically for extreme sandstorm events. First, the effects of sandstorms on various aspects of the power system are examined, and a system failure model is developed. Next, a fast generative adversarial network (Fast GAN) is introduced to extract relevant features from historical sandstorm disaster data, enabling the generation of extreme disaster scenarios. Then, the Itô process from stochastic dynamics is applied to describe the system's stochastic disturbances, and resilience metrics are constructed to obtain the probabilistic distribution of system resilience indicators. Finally, a modified IEEE 14-bus system is used in a case study to validate the feasibility and effectiveness of the proposed method in generating extreme scenarios and assessing resilience probabilities.**

Keywords—extreme sandstorm disaster, resilience assessment, stochastic dynamics, Fast GAN.

I. Introduction

Large-scale development of renewable energy has become a key trend in the evolution of modern power systems. Sandstorm weather can cause immeasurable losses to power systems with a high share of renewable energy, often leading to system failures and triggering large-scale incidents. For instance, a major sandstorm in Arizona, USA, in 2018 resulted in a 30% reduction in solar power generation efficiency, causing most solar farms to halt operations. Additionally, on March 13, 2024, severe sandstorms affected multiple provinces in Mongolia, including Khentii and Dornod, resulting in widespread power outages in certain areas. Therefore, it is imperative to implement preventive measures in the power system to address the high-risk, low-probability events associated with extreme weather disasters.

Resilience of a power system refers to its ability to withstand extreme disasters and to recover and revitalize afterward [1]. To mitigate the losses caused by extreme disasters, accurate assessments of system resilience are essential. In this regard, researchers have proposed various assessment methods for system resilience. Ref. [2] introduced a resilience assessment framework for distribution networks under typhoon disasters; Ref. [3] presented a data-driven method for evaluating the resilience of urban distribution networks; Ref. [4] proposed a resilience assessment approach based on geographic information analysis; and Ref. [5] introduced a method for assessing system resilience in extreme disasters while considering cascading effects. The evaluation of power system resilience under extreme disasters has become a research hotspot. However, the aforementioned resilience assessment methods derive deterministic resilience indicators through simulations of extreme disaster scenarios. Given the uncertainty associated with extreme disasters, the resilience of the system may differ from the deterministic resilience assessments. Therefore, it is necessary to consider the impact of stochastic factors on the system during extreme disasters to achieve a comprehensive and accurate assessment of system resilience.

Occurrence probability of extreme disasters is extremely low, and the limited historical data cannot encompass all possible events, leading to inaccuracies in resilience assessments. Traditional methods for generating extreme scenarios often employ techniques such as Monte Carlo sampling and k-means clustering. However, these methods primarily rely on historical data for clustering and sampling, and since extreme scenarios like severe sandstorms have relatively few historical data samples, the scenarios generated using traditional methods may exhibit randomness. With the continuous advancement of artificial intelligence, models such as machine learning and deep learning have shown promising results in data extraction and generation.

This work is supported by State Grid Zhejiang Electric Power Co., Ltd. Science and Technology Project. (5211JY22000Z)

The output of renewable energy and load can undergo significant fluctuations due to extreme disasters, exhibiting strong randomness. Stochastic dynamics serves as an important theoretical foundation for analyzing the evolutionary characteristics of stochastic dynamic systems. It employs stochastic differential equations to describe randomness, allowing for the characterization of probability distributions and temporal correlations associated with randomness. Analytical methods based on models can incorporate the randomness of wind and solar loads into the resilience assessment of power systems by utilizing appropriate stochastic models.

The main contributions of this paper are as follows: First, the impacts of sandstorms on power systems are studied, and extreme scenarios are generated. A fast generative adversarial network (GAN) is employed to train historical wind speed and solar radiation data under extreme scenarios, yielding predicted ranges for wind speed and solar intensity, and modeling line failure scenarios. Second, based on stochastic dynamics, Itô stochastic differential equations are formulated for the predicted wind and solar load sequences, and the maximum likelihood estimation method is used to optimally solve the coefficients in the equations. Finally, a resilience probabilistic assessment method based on stochastic dynamics is proposed to calculate system performance levels, and a stochastic differential equation for resilience indicators is constructed to derive the probability distribution of these indicators. The effectiveness of this method is validated through a modified IEEE 14-bus case study.

II. MODELING FAULT SCENARIOS IN POWER SYSTEMS UNDER SEVERE SANDSTORMS

A. *The Impact of Sandstorms on Solar Power Output*

The formula for solar power output is as follows:

$$P_{pv} = Y_{pv} f_{pv} \left(\frac{G_T}{G_{T,STC}} \right) \left[1 + \alpha_p \left(T_c - T_{c,STC} \right) \right] \tag{1}$$

Where P_{pv} represents the solar power output (MW); Y_{pv} is the rated capacity of the photovoltaic array under standard test conditions; f_{pv} is the photovoltaic derating factor; G_T is the solar radiation intensity received by the photovoltaic array (kW/m²); $G_{T,STC}$ is the incident light intensity under standard test conditions; T_c is the surface temperature of the photovoltaic array (℃); $T_{c,STC}$ is the surface temperature of the photovoltaic array under standard test conditions (℃); α_P is the temperature correction coefficient. Among these, sandstorms primarily affect the solar radiation intensity received by the photovoltaic panels. When sandstorm conditions occur, the concentration of dust particles in the atmosphere increases significantly, leading to attenuation of direct solar radiation.

B. *Impact of Sandstorms on Wind Power Output*

The formula for the actual output of the wind turbine is as follows:

$$P_W = 0.5 \rho A v^3 \eta \tag{2}$$

In the equation, P_W represents output of wind turbine, ρ is air density, A denotes area of turbine blades, v represents wind speed, η is the efficiency of the wind turbine.

The template is used to format your paper and style the text. All margins, column widths, line spaces, and text fonts are prescribed; please do not alter them. You may note peculiarities. For example, the head margin in this template measures proportionately more than is customary. This measurement and others are deliberate, using specifications that anticipate your paper as one part of the entire proceedings, and not as an independent document. Please do not revise any of the current designations. The relationship between the output power of the wind turbine and wind speed during operation is described by the following equation:

$$P_W = \begin{cases} 0, & v < v_{\text{in}} \text{ or } v > v_{\text{out}} \\ P_N \dfrac{v - v_{in}}{v_n - v_{in}}, & v_{\text{in}} < v < v_n \\ P_N, & v_n \le v \le v_{\text{out}} \end{cases} \tag{3}$$

Where P_W represents rated power of wind turbine, v_{in}, v_{n}, v_{out} denote the cut-in wind speed, rated wind speed, and cut-out wind speed respectively.

C. *Generation of Wind and Solar Sequences Based on Fast GAN*

Fast Generative Adversarial Networks (FastGAN) is an improved algorithm of generative adversarial networks. The specific implementation principle is as shown in Fig 1 below [6].

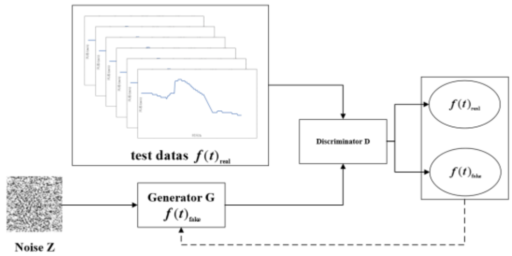


Fig. 1. Basic principle of generative adversarial networks

The given sample datas $f(t)_{\text{real}}$ are used as the training set input. Generator D creates a dataset in the same format as the real data provided by the training set and adds noise to generate fake samples $f(t)_{\text{fake}}$. Both datasets are input into discriminator D, which outputs the probabilities of the data being from the fake samples or the real samples. Then the learned data features are returned to the generator G to simulate the generation of a sample set that matches the distribution of real datas.

Building on this foundation, FastGAN improves generator by adding an adaptive feature pooling module that incorporates features from discriminator, thereby reducing the generator's reliance on large-scale datasets. Meanwhile, discriminator introduces a multi-scale discrimination mechanism to enhance the efficiency of judgment and generation.

Based on the above methods, wind speed and solar radiation time series under sandstorm conditions are input as the training set into FastGAN. By adjusting relevant parameters of the model, a sample set of wind and solar sequences under sandstorms is generated. The wind and solar power outputs are then calculated using the formulas from Sections 2.1 and 2.2.

D. *Modeling of Line Faults*

Under severe sandstorm disasters, the force exerted by strong winds on transmission lines increases. When the force on the lines exceeds their resistance level, it can lead to line breakage. Generally, the failure model of lines under strong winds is as follows [7]:

$$P_{\text{fault}} = \begin{cases} 0, & v \le V \\ \exp[0.6931(v-V)/V]-1, & V < v < 2V \\ 1, & v \ge 2V \end{cases} \tag{4}$$

Where P_{fault} represents probabilities of transmission line failures, V is maximum wind resistance speed, when actual wind speed v is less than V, the failure probability of the line is zero.When $v > 2V$, line will definitely fail. For wind speeds between these two thresholds, the failure rate of line follows (4).Based on this failure model, failure rates of all lines in the system under strong sandstorm conditions are calculated. Additionally, using system entropy theory [8], the model with the highest occurrence probability is selected as the failure scenario.

III. Model of System Resilience Assessment

A. *Resilience Assessment Indicator System*

Under extreme weather conditions, power systems often face the threat of sandstorms. Fig 2 illustrates a schematic representation of the state changes in the power system following the impacts of extreme weather.

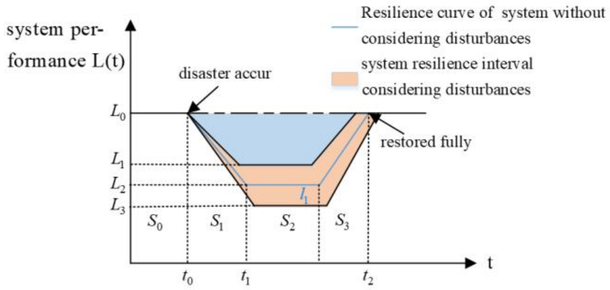


Fig. 2. Schematic diagram of system resilience curve

In Fig 2, $S_0, S_1, S_2.S_3$ represent the system's normal state, resistance phase, maintenance phase, and recovery phase respectively. L_0 denoting system's initial performance level. When the system is subjected to extreme disasters, its resilience is assessed using traditional methods, as illustrated by the curve l_1. The system resilience indicators are constructed using the "trapezoidal area method" [9] , as shown in the following formula:

$$R = \int_{t_0}^{t_2} (L_0 - L(\tau))d\tau \tag{5}$$

R represents system resilience indicator, t_0 is the moment when the disaster occurs, t_2 is the time when system returns to normal state, $L(\tau)$ is system's performance level at time τ.

Due to uncertainty of intensity of extreme disasters and random disturbances of failure scenarios, system performance level fluctuates at various time points, with its evolving state interval indicated by the orange area in Fig.2. The assessment interval of system resilience indicators can be calculated based on different confidence intervals.

B. *Stochastic Process Analysis Based on Random Dynamics*

Stochastic processes with disturbances in power system can be represented by the following Itô process model [10]:

$$dX(t) = \mu(X(t))dt + \sigma(X(t))dW_t \tag{6}$$

Where W_t is Wiener process, which is a type of stochastic process with standard properties. This stochastic differential equation quantitatively describes the relationship between the standard Wiener process W_t and the stochastic input to be modeled $X(t)$; $u(X(t))$ is system drift coefficient, representing a trend of random variable moving towards its expected value; $\sigma(X(t))$ is the system diffusion coefficient, indicating the influence of the randomness of $X(t)$ on randomness of process. In this paper, $X(t)$ represents load and renewable energy inputs with random disturbances.

To estimate system drift term μ and diffusion term σ, the maximum likelihood estimation method can be employed [11] . Assuming there is a set of historical data $X^o(0), X^o(1), ..., X^o(t)$,introduce likelihood parameter ε , allowing (6) to be expressed as follows:

$$dX(t) = \mu(X(t);\varepsilon)dt + \sigma(X(t);\varepsilon)dW_t \tag{7}$$

Where $\mu(X(t);\varepsilon)$, $\sigma(X(t);\varepsilon)$ are the parameterized drift and diffusion terms respectively. The goal of maximum likelihood is to minimize the following negative log conditional probability:

$$\min_{\varepsilon} F = -\log \Pr\{X^o(1), X^o(2), ..., X^o(t) \mid X^o(0)\} \tag{8}$$

Where F is the likelihood value of objective function. $X^o(0)$ represents initial state of system. To solve this objective function, the independence of increments in the Itô process can be utilized, yielding:

$$F = -\sum_{t=0}^{T-1} \log \Pr\left\{X^o(t+1) \middle| X^o(t)\right\} \tag{9}$$

Since in power systems, loads and renewable energy inputs are generally in discrete form, (7) can be expressed as:

$$X(t+1) = X(t) + \mu\left(X(t);\varepsilon\right)\Delta t + \sigma\left(X(t);\varepsilon\right)W_{\Delta t} \tag{10}$$

$W_{\Delta t}$ follows a normal distribution $N(0, \Delta t I)$, I means Variance. Substituting into (9) yields:

$$\min F = \frac{1}{2\sigma^2}\sum_{t=0}^{T-1}\left[X^o(t+1) - X^o(t) - \mu\Delta t\right]^2 + \sum_{t=0}^{T-1}\log\sigma \quad (11)$$

The optimal parameters can be obtained from (11) using numerical methods.

C. Method of Resilience Probability Assessment

In Section 3.2, stochastic inputs with disturbances have been described using Itô stochastic process. Further, power system network is considered to calculate the values of resilience indicators.

According to DC power flow equation, it can be derived that:

$$P_i = \sum_{j\in i} B_{ij}\theta_{ij} \quad (12)$$

Where P_i represents injected power at node i, B_{ij} is imaginary part of node admittance matrix, θ_{ij} is phase angle difference of the voltages at the two ends of the branch ij. To calculate line transmission power:

$$\boldsymbol{P_l} = \boldsymbol{B_l AXP} \quad (13)$$

Where $\boldsymbol{P_l}$ represents branch flow matrix, $\boldsymbol{B_l}$ is branch admittance diagonal matrix, $\boldsymbol{A}$ is network incidence matrix, and $\boldsymbol{X}$ is inverse of node admittance matrix. $\boldsymbol{P}$ is vector of injected power at nodes.

Let $\boldsymbol{C} = \boldsymbol{B_l AX}$, because $\boldsymbol{P}$ is vector of injected power at nodes, which contains random disturbances. It can be expressed in discrete form as an Itô stochastic differential equation:

$$\Delta\boldsymbol{P_l} = \boldsymbol{C}\Delta\boldsymbol{P} \quad (14)$$

Express injected power $\boldsymbol{P}$ as an Itô process:

$$\boldsymbol{dP} = \begin{bmatrix}\boldsymbol{\mu} & \boldsymbol{\sigma}\end{bmatrix}\begin{bmatrix}\boldsymbol{dt} \\ \boldsymbol{dW_t}\end{bmatrix} \quad (15)$$

Where $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ represent system drift vector and diffusion vector respectively.

Let $\boldsymbol{D} = \begin{bmatrix}\boldsymbol{\mu} & \boldsymbol{\sigma}\end{bmatrix}$, $\boldsymbol{t} = [\boldsymbol{dt} \;\; \boldsymbol{dW_t}]$, Substituting into (14) yields:

$$\boldsymbol{dP_l} = \boldsymbol{CDt^T} \quad (16)$$

Since the branch flow will be injected into each node, then:

$$\boldsymbol{dP_{il}} = \boldsymbol{HdP_l} \quad (17)$$

Assuming the system has N nodes and M branches, $\boldsymbol{P_{il}}$ represents power flowing into node i from other branches, and $\boldsymbol{H}$ is elementary transformation matrix of size $N \times M$. Let $\boldsymbol{S}$ be the net load(i.e., the difference between power input to node and node's load), then:

$$\boldsymbol{dS} = \boldsymbol{dP_{il}} + \boldsymbol{dP} \quad (18)$$

Substituting (16) and (17) into (18) yields:

$$\boldsymbol{dS} = (\boldsymbol{HCD} + \boldsymbol{D})\boldsymbol{t^T} \quad (19)$$

When the system is operating normally, available resources exceed load demand, and there are no faults in the lines, the system is in power balance, $\boldsymbol{S} = 0$ .When $\boldsymbol{S} < 0$, it indicates that the system cannot meet the load demand, resulting in a loss of load, which reflects a decline in the system's performance level and can be reflected in system resilience curve. To calculate the system performance level at time t :

$$L(t) = L_0(t) + \int_0^t dS(\tau)d\tau \quad (20)$$

Thus, calculation formula for system resilience indicator is:

$$R = \int_{t_0}^{t_2}\int_0^t -dS(\tau)d\tau dt \quad (21)$$

When integrating (21), an initial state $S(0)$ is required. In this study, the moment immediately following the occurrence of a sandstorm disaster is used as initial state input. For the calculation of initial state, the objective function is set to minimize the decline in system performance level. Conventional constraints, such as unit output, ramp rates, and line transmission, are taken into account for optimization and solution.

IV. Case Study

This example uses improved "IEEE 14" node system as a case study. Thermal power units are configured at nodes 1, 2, and 3, a wind power unit is configured at node 6, and a photovoltaic unit is configured at node 8, with installed capacities of 320 MW, 140 MW, 100 MW, 100 MW, and 100 MW respectively. The maximum total load of this system is 700 MW. The case study is illustrated in Fig 3:

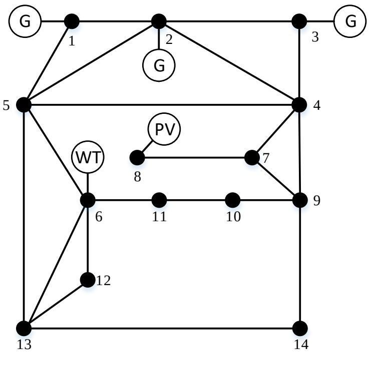


Fig. 3. Improved IEEE 14-node case

In this scenario, it is assumed that a strong sandstorm begins at $t = 4$ and lasts for 24 hours, during which it moves from the southwestern of node system towards the southeastern. The simulation time step for the experiment is set to 1 hour.

A. Wind and Solar Sequence Generation Based on FastGAN

Taking a specific area in northeastern China as a hypothetical disaster occurrence point, local wind and solar data during strong sandstorms are collected as training samples.

These samples are input into the FastGAN, and the generated solar irradiance and wind speed curves are shown in Fig 4:

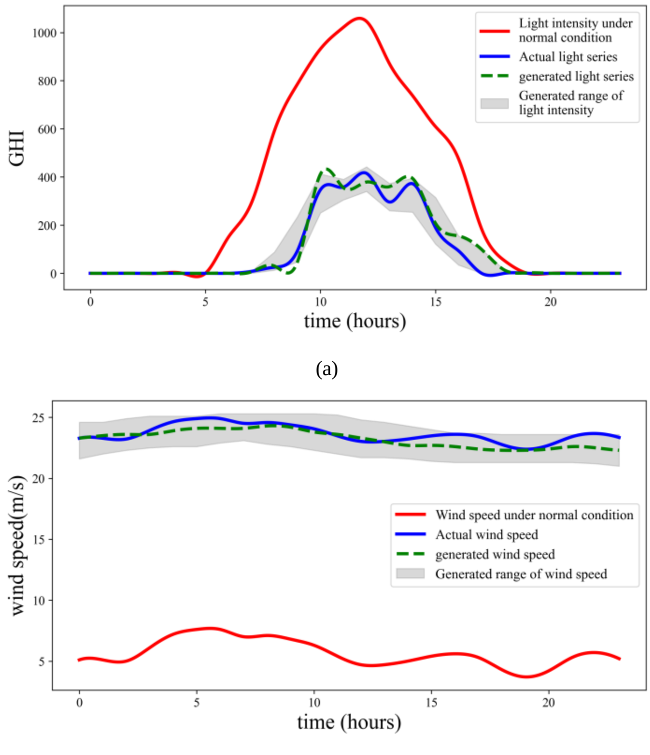


Fig. 4. Solar irradiance and wind speed curves generated by FastGAN

From Fig.4, it can be observed that the datas generated by FastGAN model are similar to the historical datas. The historical data sequences are all contained within the range of generated samples.

B. *Generation of Line Fault Scenarios*

Based on the line fault probability formula and considering the impact of sandstorm scenarios on the lines, the fault rates of each line in the system are shown in Fig 5:

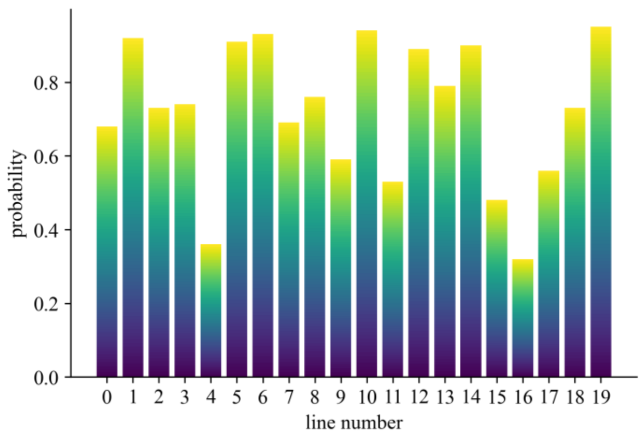


Fig. 5. Fault rates of each line

According to the system entropy theory, the fault scenario with highest entropy value is selected as the typical scenario, with the disconnected line numbers being: 1, 5, 6, 10, 12, 14, 19.

C. *Resilience Probability Assessment of Power System*

Calculate the Itô stochastic differential equations for initial state of the system and wind,solar and load at the time of disaster occurrence, and use the maximum likelihood estimation method to compute drift and diffusion coefficients for wind, solar, and load nodes. The drift coefficient and diffusion coefficient of wind and solar node are calculated using the maximum likelihood estimation method as follows:

TABLE I. Drift and Diffusion Coefficients of Wind and Solar Power

Node type \ Coefficient	μ	σ
Wind turbine node 6	0.204	2.02
Photovoltaic node 8	0.103	2.864

These coefficients are then substituted into resilience probability assessment method proposed in Section 3.3 of this paper to derive system resilience curve and resilience probability assessment interval, as shown in the Fig 6:

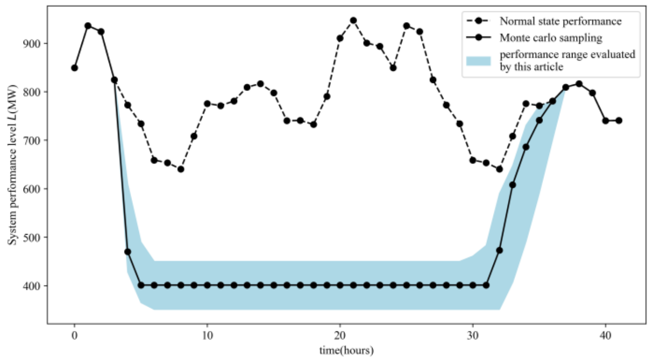
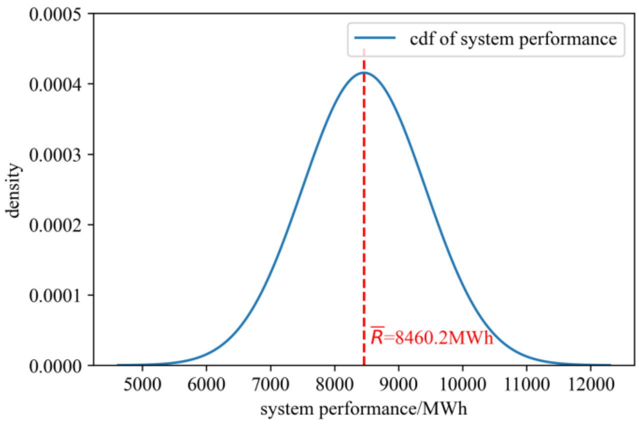
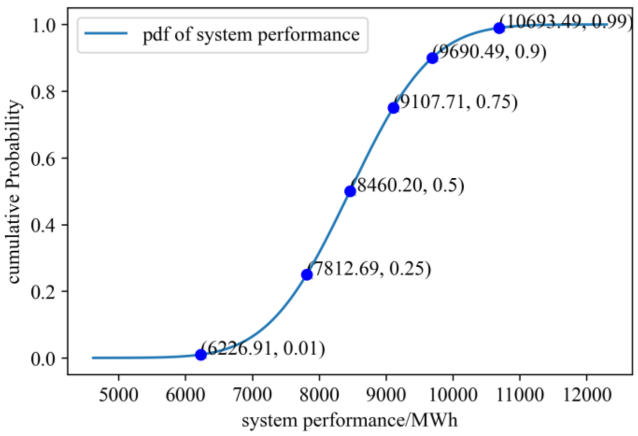


Fig. 6. System resilience curve

In Fig 6, the blue shaded area represents system performance assessment interval calculated using the method proposed in this paper. According to (5), the system resilience indicator value obtained using the Monte Carlo sampling method is R=8320.8 MWh. By employing the method proposed in this paper, the drift and diffusion coefficients corresponding to the system variable S are obtained as follows: $\mu = 4.37, \sigma = 23.12$, and the probability distribution of system's resilience indicator is shown in Fig 7:



(a)



(b)

Fig. 7. System resilience probability distribution

From Fig 7(a), the expected value of system resilience calculated using the proposed method is $\overline{R}$ =8460.2MWh, which is consistent with the resilience value obtained from the Monte Carlo sampling method. From Fig 7(b), it can be observed that there is a 99% probability that the resilience indicator of power system does not exceed 10693.5 MWh.

V. Conclusions

This paper proposes a resilience probability assessment method for power systems based on random dynamics and FastGAN. By using FastGAN to generate extreme disaster scenarios and introducing Itô process from random dynamics, the resilience probability distribution of system is calculated using analytical methods. The conclusions are as follows:

1) The FastGAN method can effectively generate extreme scenario sequences, creating potential extreme scenarios that are similar to historical data using a small amount of historical information. This provides accurate foundational conditions for resilience assessment of the system.

2) The application of random dynamics theory in power systems can accurately describe the impact of stochastic disturbances on the system, effectively capturing the influence trends of different disturbances on system behavior.

3) The resilience probability assessment method based on random dynamics can accurately characterize the system's performance under varying levels of sandstorm disasters and provide the probability distribution of resilience indicators. Compared to the traditional Monte Carlo sampling method, this analytical approach is faster and more convenient, offering decision-makers a more comprehensive reference for enhancing system resilience.

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