Front. Eng. Manag. 2025, 12(4): 1220–1235
https://doi.org/10.1007/s42524-025-4147-6

RESEARCH ARTICLE

Hongyan DUI, Qi ZENG, Min XIE

Generative AI-based spatiotemporal resilience, green and low-carbon transformation strategy of smart renewable energy systems

Abstract The extensive integration of AI with renewable energy systems is a major trend in technological advancement, but its energy consumption and carbon emissions are also a major challenge. Generative AI can quickly generate human-like content responding to cues, with excellent reasoning and generative capabilities. Generative AI-based renewable energy systems can cope with dynamic system changes and have great potential for resilience optimization and green low-carbon transition. In this paper, we first explore the role that generative AI can play in renewable energy systems and explain shock incidents. Secondly, intelligent maintenance strategies of renewable energy systems under different failure modes are developed based on generative AI. Then spatiotemporal resilience is introduced and a spatiotemporal resilience optimization model is proposed. A green and low-carbon transformation strategy for smart renewable energy systems has also been proposed. Finally, a case study is used to illustrate the utilization of the proposed method by using a wind power system as an example of a renewable energy system.

Keywords generative AI, spatiotemporal resilience, carbon transformation, smart renewable energy

Received Aug. 10, 2024; revised Jan. 29, 2025; accepted Feb. 18, 2025

Hongyan DUI (✉)
School of Management, Zhengzhou University, Zhengzhou 450001, China
E-mail: duihongvan@zzu.edu.cn

Qi ZENG
School of Safety Science, Tsinghua University, Beijing 100084, China

Min XIE
Department of Systems Engineering, City University of Hong Kong, Hong Kong 999077, China

This research was supported by the Natural Science Foundation of Henan Province, China (Grant No. 252300421005).

1 Introduction

Generative artificial intelligence (Generative AI) refers to a machine learning model that generates novel and original content without explicit programming (Bandi et al., 2023). Generative AI intelligence can generate novel and authentic data on cue. It has been widely used in different fields and has had a huge impact on several industries such as entertainment, finance, and education (Albahri et al., 2024). Models such as GPT-4 have been shown to generate highly human-like text (Kasneci et al., 2023). Ahmed Z et al. (2024) used generative AI to assist teaching and promote learning equity. Guan (2024) Completed real-time airfare prediction based on generative AI. It also has far-reaching significance for the transformation of new energy systems. Learning the historical operation data and failure data of the new energy system can identify the system risk, quickly respond to the failure, and optimize the system's resilience.

Global energy consumption is growing, and traditional fossil energy sources are environmentally unfriendly and non-renewable. Renewable energy sources such as wind, solar, and nuclear power have become options for replacing fossil energy. With the increasing capacity of renewable energy systems, higher demands are placed on their reliability, safety, resilience, and costs. The resilience of a system shows how well it can withstand a shock. The higher the resilience, the better the performance of the system. If the operation and maintenance (O&M) costs of renewable energy systems can be reduced, it will effectively increase the revenue. However, reducing the O&M costs to increase revenue is a risky behavior. Reduced maintenance behavior increases failure rates and decreases reliability and resilience, yet too many maintenance actions will increase the O&M cost and not significantly improve the revenue and resilience. In addition, to increase revenue, the loss of energy production in case of renewable energy system failure and downtime should be minimized (Izquierdo et al., 2019). Therefore, it is essential to investigate the resilience and maintenance costs of renewable energy systems, aiming to optimize the balance between enhanced resilience and minimized maintenance expenses.

Many scholars have studied the reliability of renewable power generation from different perspectives. The quantitative method of advanced importance index based on reliability was studied and the maintenance strategy based on this index was optimized (Dui et al., 2024a). However, most of the scholars selected the critical components for research and ignored the non-critical components. It was only studied that the critical components such as generators, gearboxes, bearings, etc. can cause the failure of renewable energy systems (Li et al., 2021). Zhang et al. (2022) investigated the maintenance strategy of a multi-component system consisting of auxiliary and critical components. Berrade et al. (2023) investigated a system inspection and maintenance model with critical components under type I (early failures) and type II (the system aging) failures. Although non-critical components do not cause overall failure, they can reduce the power generation efficiency, affect the operation status of critical components, and cause a loss of economic benefits and a decrease in reliability. Therefore, it is necessary to research on non-critical components.

The maintenance behavior of renewable energy systems has a significant impact on O&M costs. If we only rely on after-the-fact maintenance, each repair occurs after a fault has been generated. It will be quite high, and the downtime will also cause energy generation loss. Currently, corrective maintenance and time-based maintenance are the most applied maintenance behaviors (Ding and Tian, 2012). Corrective maintenance is economically inefficient and is gradually being replaced by preventive maintenance, which is a type of periodic maintenance aimed at preventing failures through preventive repair or replacement. Due to the rapid development of continuous monitoring and inspection techniques, condition-based maintenance is attracting attention which is proving to be cost-effective (Van Horenbeek et al., 2013). However, renewable energy systems are multi-component systems consisting of subsystems. The subsystems have dependencies that affect the overall maintenance strategy. The components of a multi-component system are linked in structure and economy. When performing maintenance actions on one subsystem, other systems need to be maintained as well. Moreover, the maintenance cost of repairing subsystems separately is different from the cost of combining different subsystems (Dekker et al., 1997). The probability of failure conditions for different components is also not consistent, contributing to the complexity of failure conditions in wind turbines. Sarker and Faiz (2016) studied preventive replacement and preventive maintenance for offshore wind turbines. It was concluded that the total maintenance cost is significantly affected by the number of age groups and component age thresholds. Opportunistic and group maintenance is the most studied maintenance strategy (Wang and Pham, 2006). Erguido et al. (2017) studied the maintenance behavior performed on another non-faulty system when one system fails in a short-term situation. Ding and Tian (2011) proposed an opportunistic maintenance model with two levels of maintenance actions. The model considers both imperfect and perfect maintenance levels from component states, which means that a system cannot always be restored to a brand-new state after maintenance. Li et al. (2020) introduced a “maintenance trigger,” which is an event that triggers the OM strategy to be applied. It is also referred to as an opportunity, emphasizing the trade-off between the frequency of preventive dispatch and the cost of performing maintenance. McMorland et al. (2023) attributed opportunities to internal and external opportunities. Where internal opportunities come from the maintenance behavior of the wind farm and external opportunities come from the weather. In addition, Li et al. (2020) used a non-homogeneous continuous-time Markov process to represent a multi-state model of an offshore wind turbine subsystem. As the operating time increases, the subsystem moves from one state to another. Compared to individual maintenance, the most cost-effective combination of qualified components is selected to reduce the maintenance cost. Dui et al. (2023a) investigated the interrelationships between importance and maintenance, resilience, and discussed maintenance resilience during the disruption phase based on importance.

Literature that considers both degradation and the effects of environmental harshness are not abundant, but stochastic environmental shocks are prevalent in the field of reliability and engineering. Many industrial systems operate in stochastic shock environments and are damaged by these shocks, which trigger state transitions in the system. Wang et al. (2020) investigated a variety of shock models, including cumulative shock model, extreme shock model, operational shock model, delta shock model, and hybrid shock model. Zhao et al. (2018) developed a shock model with a self-healing mechanism. Che et al. (2018) studied various dependencies between shocks and degradation for some complex systems. Namely, shock-degradation dependence and degradation-shock dependence. However, more scholars have studied the impact of the environment on maintenance present in component degradation. The significant effect of random shocks on renewable energy system failure has not been considered. When a renewable energy system is subjected to a major external shock resulting in immediate failure, it has a significant impact on the reliability of the system and the maintenance strategy. Even a moderate random shock event can reduce the lifetime of the system. Therefore, it is necessary to consider the impact of environmental random shock events on the reliability and maintenance strategy of the system.

Resilience can evaluate the capability of a system in various ways. In physics, resilience, the ability of a material to resist fracture when subjected to a force that deforms it, is defined as the ratio of the energy a material can absorb to its volume before fracture. For real systems, resilience is often defined as the ability of a system to resist, mitigate, and quickly recover from potential disruptions (Hosseini et al., 2016). In terms of robustness, redundancy, resourcefulness, and rapidity, Bruneau et al. (2003) have separated resilience from the technology, organization, society, economy, and other different perspectives for quantitative analysis. A generalized framework has been established accordingly. Based on this research scholars have conducted in-depth analysis in different directions. Cimellaro et al. (2010) proposed a framework for quantitative analysis of resilience and a mathematical approach based on function curves. However, this framework is more for community or organizational systems and is mostly intangible. Research on the resilience of tangible complex systems, especially critical infrastructures, is also a hot topic. Ferrario et al. (2022) investigated the predictive power of different topological measures in assessing the seismic risk and resilience of power networks. Dong et al. (2023) assessed the resilience change of transportation networks facing floods through the perspective of network reliability and stability based on the concept of link reliability. Dui et al. (2024c) proposed a multi-stage resilience assessment method for urban wastewater treatment. Rahnamay-Naeini and Hayat (2016) proposed a Markov chain framework to predict the resilience of infrastructure under cascading failures, including adaptive, absorptive, and restorative capacities. Talukder et al. (2020) measured power system resilience by quantifying the level of stability of the power system. The measures include transient stability margin, critical clearing time, relay protection margin, and performance levels. Based on this, the relative ability of different power grids to withstand the effects of unfavorable events is compared.

External stochastic shock events have a significant impact on the resilience of renewable energy systems, especially those subject to extreme events. Yan and Dunnett (2022) evaluated the resilience of a nuclear power plant under aging and external shock events through a Petri net model. Zeng et al. (2021) used Markov chains to characterize different aspects of system resilience through four numerical metrics: resistance, absorption, resilience, and overall resilience. A generalized framework for resilience assessment of multi-state systems subjected to extreme events was also developed. A resilience triangle model was proposed to quantify the system's ability to withstand the risk of catastrophic events (Bruneau et al., 2003). Iannacone et al. (2022) proposed a unified formulation for the degradation and recovery of infrastructures subjected to shocks to quantify their resilience over time. Liu et al. (2022) developed a resilience enhancement framework under the double-time-dimension-outage process to improve power system performance under cascading outages under extreme conditions. Cadini et al. (2017) proposed a simulation model to quantify system resilience, considering both normal degradation and the system behavior under shock events.

However, despite these contributions, there remains a notable dearth of research dedicated to optimizing resilience with a specific emphasis on maintenance costs. The prevailing focus has been on the development of resilience assessment methodologies or frameworks for various complex systems. In addition, there are still gaps in the understanding of maintenance costs, especially in environments where different shock incidents are considered. In this paper, the renewable energy system is categorized into critical and non-critical subsystems. Poisson distribution is used to describe the external shock process. Preventive maintenance and corrective maintenance are taken as the main maintenance behaviors, and opportunistic maintenance triggered by environmental random shocks is taken as the auxiliary maintenance behavior. The maintenance strategies and corresponding maintenance costs under different failure modes are investigated. Meanwhile, a spatiotemporal resilience evaluation methodology, including the temporal resilience index and spatial resilience index, is established to evaluate the resilience of renewable energy systems. A multi-objective optimization model is established to study the best system configuration state with the optimization objectives of minimizing maintenance costs and maximizing resilience. It provides a reference for the actual operation design of renewable energy systems.

A comparison of the related papers is summarized in Table 1. Table 1 shows that maintenance costs are discussed more about preventive maintenance costs and corrective maintenance costs. Critical components are also mainly discussed for the components of the system. Although the critical components are vital for the operation of the system, the role of non-critical components cannot be ignored. There are also fewer studies on the spatiotemporal resilience of systems, and based on the literature searched, it is also found that more studies are done on the properties of resilience, such as studying resistance resilience and recovery resilience.

The difference between this paper and the relevant literature is shown below.

a) The impact of environmental shock incidents is considered for both critical and non-critical components. While many literatures do not consider different levels of impacts from the environment and only critical components are considered, this paper considers both aspects more comprehensively. In this paper, for renewable energy systems, critical and non-critical components are

Table 1 Comparisons of the related papers

Attribute	Use of Smart Technologies			System components		Maintenance cost			External shock incidents			Resilience	
	IoT	Generative AI	others	critical	non-critical	PM cost	corrective maintenance cost	replacement cost	critical incidents	influential incidents	minor incidents	Spatial resilience	Temporal resilience
Li et al. (2021)				√		√	√		√	√	√		
Berrade et al. (2023)				√				√					
Dui et al. (2024b)				√	√	√	√	√					
McMorland et al. (2023)						√	√		√				
Saleh et al. (2023)			intelligent Petri nets				√						
Dui et al. (2024c)	√												
Yan and Dunnett (2022)						√			√				
Dong et al. (2023)													√
Zhang et al. (2024)			Interactive AI										
Ahmed et al. (2024)		√											
This paper	√	√		√	√	√	√	√	√	√	√	√	√

Note: IoT, Internet of things; AI, Artificial intelligence; PM, preventive maintenance.

analyzed separately, and the maintenance cost model and spatiotemporal resilience model are established under three types of shock incidents namely critical incidents, influential incidents, and minor incidents.

b) The resilience assessment in many articles is based on external performance as an indicator, which makes it difficult to improve the system performance fundamentally. In contrast, this paper synthesizes the temporal resilience and spatial resilience of renewable energy systems from the intrinsic mechanism and establishes a spatiotemporal resilience model.

c) Most articles use IoT or AI to help with resilience optimization or low-carbon strategies. However, this paper proposes the application of IoT-based generative AI in renewable energy systems, which differs in application scenarios or technologies.

This paper proposes a spatiotemporal resilience, green and low-carbon transformation strategy of smart renewable energy systems based on generative AI. In particular, the data for generative AI can be acquired using IoT. The main contributions of this paper are as follows.

a) A maintenance cost model considering external shock incidents is proposed for critical and non-critical components. In this paper, we simultaneously investigate modeling the maintenance cost of critical and non-critical components under different shock incidents from real-world scenarios.

b) A spatiotemporal resilience model based on generative AI is developed. Based on the maintenance cost model, the system temporal resilience index and spatial resilience index are established and integrated into the spatiotemporal resilience index. The model of generative AI facilitating resilience optimization is introduced.

c) Generative AI-enabled green and low-carbon transformation strategies are proposed. Particularly in the areas of system optimization, smart grid integration, and dynamic management.

The rest of this paper is organized as follows. Section 2 describes the generative AI-based analytical framework for renewable energy systems and shock incidents. Section 3 gives the maintenance analysis of renewable energy systems under different scenarios. Section 4 establishes a spatiotemporal resilience assessment methodology based on which a resilience-maintenance cost optimization model is developed. Section 5 proposed a green and low-carbon transformation strategy for smart renewable energy systems based on generative AI. Section 6 evaluates the system resilience and maintenance cost under different scenarios through case studies. Finally, the conclusion is summarized in section 7.

2 Generative AI-based renewable energy systems

This section introduces the Generative AI-based analytical and operational framework for smart renewable energy systems, which includes risk identification and planning, monitoring and early warning, and maintenance cost optimization.

Figure 1 shows the roles that generative AI can play in different phases of a renewable energy system. It mainly involves the planning, design, and construction stages, monitoring and alarm during the operation stage, and the maintenance stage after a failure. IoT technology is utilized to collect data from sensors placed in the field

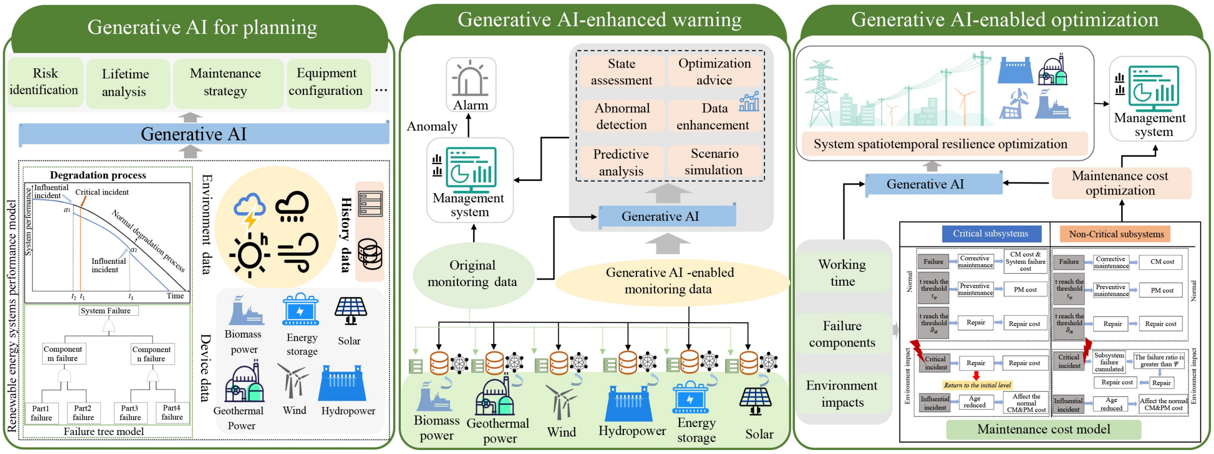

Fig. 1 Generative AI-based analytical and operational framework of renewable energy systems.

and feed it into the analytical framework of generative AI.

a) Generative AI for planning. Generative AI can play an important role in the pre-planning and design of renewable energy systems. By inputting data and information such as renewable energy system performance models, equipment data, local weather data, historical construction and operation data, and failure and maintenance information, generative AI can output the required contents. This includes system risk identification, equipment life analysis and prediction, optimal maintenance strategy design, optimal equipment configuration, etc., helping construction units to quickly judge development prospects and facility programs.

b) Generative AI-enhanced warning. After acquiring the raw operational data of the new energy system from IoT, the generative AI can initially process it and provide a spectrum of analysis. For example, Generative AI-based anomaly detection can warn timely when there is a possibility of anomalies or failures depending on historical data and experience, which is more sensitive than conventional threshold-based detection methods. When the data are somewhat incomplete or incorrect, generative AI can automatically process it to realize data enhancement.

Generative AI can also evaluate the current system operation status and give optimization suggestions. The data and conclusions output from the generative AI are stored in the management system along with the original data. This practice prevents scenarios where AI may fail to recognize patterns or produce incorrect content. At the same time, using the original fault monitoring model and the monitoring results of the generative AI output, we can find abnormalities faster, reduce the loss of faults, and realize efficient monitoring.

c) Generative AI-enabled optimization. Generative AI is useful in system performance optimization, maintenance cost optimization, and resilience optimization. For example, for the resilience optimization of renewable energy systems, a maintenance cost optimization model can be obtained from the system operating time, the characteristics of the failed components, and the environmental impact. These live data can be accessed by IoT. Based on the analysis of maintenance cost optimization, system resilience can be evaluated, and generative AI can directly output spatiotemporal resilience, and green and low-carbon transformation strategy.

In summary, IoT technology can quickly collect data from the field and feed it along with historical data to generative AI for real-time analysis. Generative AI is proficient in outputting text, image, and audio content based on prompted information, and can play a significant role in all aspects of planning, monitoring, and maintenance optimization of renewable energy systems.

For components of a renewable energy system, the components that can cause system failure are called critical components. Failure of the wind measurement system, heat dissipation system, cabin, tower, etc. which cannot cause system failure and are referred to as non-critical components (Dui et al., 2023b).

The process of decreasing service life with time of use is referred to as degradation. Once the usage time reaches the replacement threshold, it must be replaced. Both preventive and corrective maintenance are imperfect repairs that cannot restore the component to its optimum condition. In practice, after the preventive maintenance of a component, the time for the component to work continuously again becomes shorter, which means that the failure rate of the component becomes larger. Nakagawa (1988) proposed a model for imperfect maintenance by introducing a decreasing factor of service age and an increasing factor of failure rate. It can model the change that the effective life of a component will be shortened after incomplete maintenance and the failure rate will increase when it is put into service again.

Random shocks in the external environment have a significant impact on the reliability of renewable energy systems. External random shocks can be divided into three categories: critical incidents, influential incidents, and minor incidents (Li et al., 2021). When the impact of the external environment is too large, it may directly damage the critical components and cause the system to fail, or it may damage non-critical components and reduce the system's power generation efficiency and performance. This type of event is referred to as a critical incident. When the external environmental shock is not enough to cause component failure, but has an impact on the performance of the component, such an event is called an influential incident. When the external shock is very small, it is called a minor incident. The impact of minor events on components is small and can be similar to the normal degradation process.

The number of random shock incidents is modeled by the non-homogeneous Poisson process. P_{CI} denotes the occurrence probability of a critical shock event and P_{II} denotes the occurrence probability of an influential event. $N_i(t)$ denotes the number of random shock events that occur during the time $[0,t]$. $\lambda_i(t)$ denotes the intensity function of the Poisson distribution of the i_{th} subsystem. Following the properties of the Poisson distribution (Leonenko et al., 2017), the mean of number of failures is $\Lambda_i(t) = \int_0^t \lambda_i(x)\,\mathrm{d}x$. It is assumed that the occurrence of a random shock will shorten the service life of the system. It can also be understood as an increase in the completed service life of the component. Use $\vartheta(t)$ to denote the reduced service life of the i_{th} component. The frequency of shock incidents has a direct bearing on the service life of a system; the higher the incidence, the shorter the expected lifespan. This induced time is contingent upon both the quantity and severity of the shock events encountered. In the case of systems subjected to critical incidents, the resultant decrease in service life is more pronounced compared to those systems that experience influential or minor incidents. Use $\vartheta_{CI}(t)$ to describe the increase in system performance after a system has been subjected to a critical incident. $\vartheta_{II}(t)$ denotes the effect of being shocked to an influential incident on the system performance.

3 Maintenance analysis of renewable energy systems under different scenarios

Renewable energy systems have two main maintenance behaviors: repair and replacement. The repair behavior can be generated by multiple factors such as component failure, service time, and external shock incidents. Replacement behavior is similar. When the replacement time threshold is reached, the replacement maintenance behavior is carried out regardless of whether it fails or not. In this paper, preventive maintenance is the primary maintenance behavior and corrective maintenance and replacement are the secondary maintenance behaviors. If the system is shocked by the external environment, it will lead to a loss of performance, which will have an impact on the preventive maintenance behavior and increase the replacement behavior of systems. The preventive maintenance strategy alone or the opportunistic maintenance strategy applies to different scenarios and triggers different maintenance responses. Neither strategy emerges as an unequivocally dominant option in the context of the maintenance cost and reliability paradigm. Scenarios with different shock incidents are considered, and the formula for calculating the maintenance cost is analyzed and presented.

Suppose that the reliability function of each component is $R_i(t)$. According to Mettas (2000), the repair cost after component failure is:

$$C_i^m(t) = c_i \cdot \mathrm{e}^{\left[(1-f_i)\frac{R_{i,\min}-R_i(t)}{R_{i,\max}-R_i(t)}\right]}, \tag{1}$$

where $C_i^m(t)$ is the repair cost of performing maintenance after failure of component i. c_i denotes the cost of repairing i_{th} component for one time. $R_{i,\min}$ denotes the minimum value of reliability of component i, and $R_{i,\max}$ denotes the maximum value of it. f_i stands for feasibility parameter to improve the reliability, which is in the range of [0,1].

Define the preventive maintenance time threshold as τ_{ip}, the preventive maintenance actions are performed at time kT_i for $k = 1,\ldots,N$. The T_i is the time interval between two adjacent preventive maintenance actions of component i and N is the number of preventive maintenance actions before a replacement. The failure rate of each component is $\lambda_{n_i}(t)$. Using the Weibull distribution to characterize the life of each subsystem, then the failure rate can be obtained as:

$$\begin{aligned} \lambda_{n_i}(t) &= \left(\prod\nolimits_{j=1}^{N_i} a_j\right)\frac{\beta}{\gamma}\left(H_{N_i} + \frac{t}{\gamma}\right)^{\beta-1} \\ H_{N_i} &= \sum\nolimits_{j=1}^{N_i} b_j T_{i,j} \end{aligned}, \tag{2}$$

where N_i is the number of times preventive maintenance has been performed by component i. γ denotes scale parameter and β is shape parameter. a_j denotes the failure rate increasing factor of the j_{th} preventive maintenance, and b_j is the age decreasing factor of it. $T_{i,j}$ is the time interval between two preventive repairs of i_{th} component, which takes the value of $T_{i,j} = \begin{cases} t_{i,(j+1)} - t_{i,j}, & j > 1 \\ 0, & j = 1 \end{cases}$. $t_{i,j}$ is the time when the j_{th} preventive maintenance of the i_{th} component occurs. H_{N_i} denotes the service age decreasing factor. $\left(\prod_{j=1}^{n_i} a_j\right)$ is the failure rate increasing factor. The reliability equation of the renewable energy systems can be obtained as $R = \prod_{i=1}^{n} \mathrm{e}^{-\int \lambda_{n_i}(t)\mathrm{d}t}$.

Then the preventive maintenance cost can be obtained as follows:

$$C^{pm}(t) = \sum_{i=1}^{n} \int_{(k-1)T}^{kT} C_i^{pm}(t)\,\mathrm{d}F(t)$$
$$= \sum_{i=1}^{n} \int_{(k-1)T}^{kT} C_i^{pm}(t)\left[Pr\{\Phi(t) \leqslant X_T | X_s(t) \geqslant \tau_{ip}\}\right]\mathrm{d}t, \tag{3}$$

where X_T denotes the failure threshold of the system component, τ_{ip} denotes the preventive maintenance time threshold of it. $X_s(t)$ denotes the utilized time. $C_i^{pm}(t)$ denotes the cost of preventive maintenance for i_{th} component. The probability on the right side of Eq. (3) represents the probability that the operating time is less than the preventive maintenance cycle and there is no failure.

The failure of critical components will lead to system failure. During the $[0,T]$time interval, the system maintenance cost is $\int_{(k-1)T}^{kT} C_s(t)\lambda_s(t)\,\mathrm{d}t$. Therefore, the overall maintenance cost $cost^M(t)$ after the failure of critical components is:

$$cost^M(t) = \sum_{i=1}^{n} \int_{(k-1)T}^{kT} C_i^m(t)\lambda_{n_i}(t)\,\mathrm{d}t + \int_{(k-1)T}^{kT} C_s(t)\lambda_s(t)\,\mathrm{d}t, \tag{4}$$

where $C_s(t)$ is the system failure cost, $\lambda_s(t)$ is the system failure rate function, and n is the number of system components. Since the failure of critical components will lead to system failure, the system failure rate is related to the failure function of 6 critical components, namely $\lambda_s(t) \approx \sum_1^{n_c} \lambda_{n_i}(t)$, where n_C is the number of critical components.

After the failure of non-critical components, it will not cause the failure of the overall system but still it needs to pay the maintenance cost. The cost at each moment can be expressed as the multiplication of the cost function and the failure function. Then the maintenance cost is its integral which can be denoted as follows:

$$cost^M(t) = \sum_{i \in \{NCN\}} \int_{(k-1)T}^{kT} C_i^m(t)\lambda_{n_i}(t)\,\mathrm{d}t. \tag{5}$$

$C_i^R(t)$ denotes the component replacement cost and ϑ_{iR} denotes the component replacement time threshold. Replacement is required when the threshold is exceeded. Then the replacement cost is:

$$C^R(t) = \sum_{i=1}^{N} \int_{(k-1)T}^{kT} C_i^R(t) \cdot \Pr\{\Phi(t) \geqslant \vartheta_{iR}\}. \tag{6}$$

Maintenance strategies will be more complex when random shock incidents occur. For critical components of renewable energy systems, exposure to critical incidents will cause subsystem failure, which will lead to system failure. An influential incident will then shorten the service life. Although influential incidents do not directly cause failure, they increase the probability of failure and the number of preventive maintenance tasks performed. For non-critical components of the system, critical impact events can lead to subsystem failure. However, scheduling maintenance actions whenever a non-critical component failure is detected will result in too many maintenance actions. The benefits generated will not be sufficient to cover the cost of maintenance. Therefore, Ψ is used to denote the threshold for the percentage of subsystems that fail as a result of a critical incident shock. When the percentage of failed non-critical components exceeds this threshold, replacement maintenance is performed. Figure 2 illustrates the maintenance costs under different scenarios of smart renewable energy systems. Sensors collect data and upload it to cloud platforms through the Internet of Things (IoTs). The acquired data are then categorized and analyzed based on critical and non-critical components, which is shown in Fig. 2.

The main discussion focuses on the impact of critical incidents and influential incidents on critical components. The impacts caused by minor incidents are too small to that is similar to normal degradation. When a critical incident occurs, it directly leads to the failure of the subsystem, using the maintenance behavior of replacement. If a critical shock event occurs at moment t_1, then the replacement cost is: $C^R(t) = C_i^R(t) \cdot \lambda_k(t_1) \cdot \mathrm{e}^{-\lambda_k(t_1)}$. The number of critical random shock incidents occurring on i_{th} component in time $[0,t]$ is denoted as $N_{CI}^i(t)$. After replacement, the performance of the subsystem returns to its initial level. The occurrence of shock incidents is randomized in the $[0,T]$ period. Then the overall maintenance cost is

$$cost(t) = \textstyle\sum_{i \in \{CN\}} \Big[\int_0^{T/N_{CI}} C_i^m(t)\lambda_i(t)\,\mathrm{d}t + \int_0^{T/N_{CI}} C_i^{pm}(t)\,\mathrm{d}F(t)$$
$$+ \textstyle\int_0^{T/N_{CI}} C_s(t)\lambda_s(t)\,\mathrm{d}t + \sum_{i \in \{CN\}} \int_0^{T} C_i^R(t) \cdot N_{CI}^i(t) \Big]. \tag{7}$$

When influential incidents occur, they will decline the performance of critical components. The larger the number of random impact events, the greater the impact. Use $N_{II}(t)$ to denote the number of influential incidents within the time interval $[0,t]$. $\vartheta_{II}(t)$ is the remaining service life shortened by the influential events, which is positively correlated with the number of it. Then we have: $\vartheta_{II}(t) = \overline{\Delta L} \cdot N_{II}(t)$, where $\overline{\Delta L}$ denotes the average life shortened by one blow from an impacted incident. The maintenance cost can be obtained as:

$$cost(t) = \textstyle\sum_{i \in \{CN\}} \int_0^T C_i^m(t)\left[Pr\{\Phi(t) \geqslant (X_T - \vartheta_{II}(t))\}\right]$$
$$+ \textstyle\sum_{i \in \{CN\}} \int_0^T C_i^{pm}(t)\Pr(t + \vartheta_{II}(t) \geqslant \tau_{ip}) + \int_0^T C_s(t)\lambda_s(t)\,\mathrm{d}t]^{\cdot} \tag{8}$$

When critical impact events and influential impact events occur simultaneously, multiple maintenance strategies of replacement and repair are adopted, and the life of the subsystem will be shortened. When the number of critical impact events is N_{CI}, the time of occurrence of

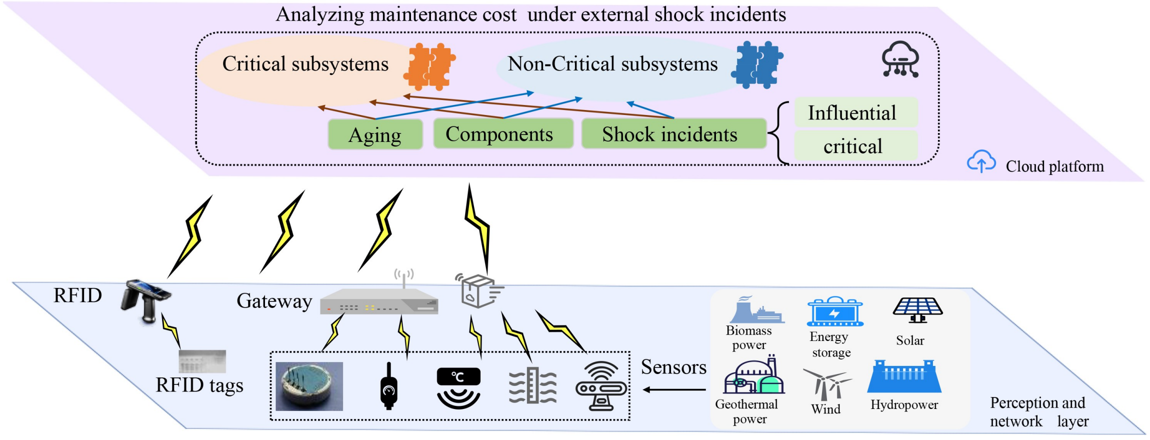

Fig. 2 Maintenance of renewable energy systems under different scenarios.

each critical impact event is set as $\frac{T}{N_{CI}}$. Then the number of influential random impact events occurring in the time $[0, \frac{T}{N_{CI}}]$ is $\frac{N_{II}(T)}{N_{CI}}$. The impact on the lifetime during each period is $\vartheta_{II}(t)=\overline{\Delta L}\cdot\frac{N_{II}(t)}{N_{CI}}$.

To summarize, when the critical component is subjected to a random shock incident from the external environment, the total maintenance cost required in $[0,T]$ is:

$$\begin{aligned}cost(t)=\sum_{i\in\{CN\}}\Big[&\int_0^{T/N_{CI}}C_i^m(t)\times[Pr\{\Phi(t)\geqslant(X_T-\vartheta_{II}(t))\}\mathrm{d}t\\&+\int_0^{T/N_{CI}}C_i^{pm}(t)\Pr(t+\vartheta_{II}(t)\geqslant\tau_{ip})\\&+\int_0^{T/N_{CI}}C_s(t)\lambda_s(t)\mathrm{d}t+\sum_{i\in\{CN\}}\int_0^{\frac{T}{N_{CI}}}C_i^R(t)\cdot N_{CI}^i(t)\Big].\end{aligned}\tag{9}$$

When a non-critical component is impacted by a critical incident, the subsystem will also fail. Once the percentage of failed non-critical components exceeds a threshold value Ψ, they are replaced. The number of critical impact events is $N_{CI}^i(t)$. Define $\{F_{NCN}\}$ to denote the set of non-critical components that fail due to a critical impact event during time $[0,T]$. $N_{F_{NCN}}$ denotes the number of failed non-critical subsystems and ς denotes the percentage of them. The occurrence probability of a critical shock event is $f_{N_{CI}}=\sum_{i=1}^{N_{F_{NCN}}}\left[\frac{\lambda_i(t_1)^{N_{CI}^i(t)}\cdot\mathrm{e}^{-\lambda_i(t_1)}}{N_{CI}^i(t)!}\right]$. Then the replacement cost of the failed subsystem is:

$$\begin{aligned}C^R(t)&=\sum_{i\in\{F_{NCN}\}}C_i^R(t)\cdot f_{N_{CI}}\\&=\sum_{i=1}^{N_{F_{NCN}}}C_i^R(t)\times\left[\frac{\lambda_i(t_1)^{N_{CI}^i(t)}\cdot\mathrm{e}^{-\lambda_i(t_1)}}{N_{CI}^i(t)!}\right](\varsigma\geqslant\Psi).\end{aligned}\tag{10}$$

When a non-critical component is shocked by an influential incident, it shortens its remaining service life, just like a critical component. And $\vartheta_{II}(t)$ is the shortened service life after being struck by it in $[0,t]$.

4 Spatiotemporal resilience of smart renewable energy systems

Resilience is a capability or quality characteristic that a system presents in response to various perturbations and changes. In other words, resilience is the ability of a system to anticipate, resist, absorb, respond, adapt, and recover from disturbances from natural or man-made incidents (Goerger et al., 2014). A comprehensive resilience evaluation methodology will be established to measure the spatiotemporal resilience of the system from two aspects: spatial resilience and temporal resilience.

The calculation of both the temporal resilience and the spatial resilience are based on the probabilities obtained in the previous process of analyzing the maintenance costs. And the critical and non-critical components are modeled separately. Spatiotemporal resilience and maintenance cost are both optimization objectives, the cost resulting from strong resilience may be too high, while the resilience cannot meet the requirements when the cost is too low. Therefore, the magnitude of resilience will affect the maintenance strategy and cost.

4.1 Spatial resilience index

Spatial resilience is the ability of a system to resist or absorb the effects of extreme incidents or shock without degrading its performance in a different environment. The spatial resilience index is related to shock levels, which are highly correlated with spatial location. It is quantified by the likelihood that a system will continue to function normally after being subjected to a random external disaster. Essentially, a system with high resistance resilience can maintain full operational capacity post-incident without the need for repair. When the external shock incident is critical, critical subsystems will fail and immediate repair is necessary. However, non-critical subsystems may be exempt from immediate repair if the failure rate is below a certain threshold, denoted by Ψ. When the shock event is an influential incident, the life of the subsystems will be shortened. Once the preventive maintenance cycle threshold is reached, repair is required. Therefore, the system's spatial resilience index involves the probability that the subsystem has not reached the preventive maintenance threshold during the time interval $[0, T]$, either because it has not been impacted by an external shock or has only encountered an influential incident. Additionally, it encompasses the probability that non-critical subsystems, despite being subjected to a critical impact, have a failure rate of less than Ψ. Denote this probability as P_1.

$$\begin{gathered}P_1 = P_{NC1} = 1 - \{1 - \Pr(t + \vartheta_{II}(t) < \tau_{ip})\} \times \\ [Pr\{\Phi(t) \geqslant (X_T - \vartheta_{II}(t))], \\ P_1 = P_{NCN1} = 1 - [1 - \Pr(t + \vartheta_{II}(t) < \tau_{ip})] * [1 - P(\varsigma < \Psi)],\end{gathered} \tag{11}$$

P_{NC1} denotes the spatial resilience of critical subsystems and P_{NCN1} denotes that of non-critical components. $\{1 - \Pr(t + \vartheta_{II}(t) < \tau_{ip})\} * [F\{\Phi(t) \geqslant (X_T - \vartheta_{II}(t))]$ represents the failure probability of a critical component after an environmental impact, while $[1 - \Pr(t + \vartheta_{II}(t) < \tau_{ip})] * [1 - P(\varsigma < \Psi)]$ represents a non-critical component. The environmental impact is determined by the spatial location and includes normal dissipation and shock incidents. It can be seen that $0 \leqslant P_1 \leqslant 1$. When $P_1 = 0$, it indicates that the system does not have any spatial resilience and is in a critical collapse state. When $P_1 = 1$, the system can resist all external shocks and is in the optimal performance operation state, which has good spatial resilience.

4.2 Temporal resilience index

Temporal resilience is the ability of a system to return to a high-performance operating state within the time after being damaged by an external shock incident. In this paper, the high-performance operating state is the normal operating state. The recovery time of the system is the preventive maintenance, corrective maintenance, and replacement time of components. Since the maintenance time is small compared to the total operating time, the maintenance time is ignored in the previous discussion of maintenance cost. Let T_{Mi}, T_{PMi}, T_{Ri} be the failure maintenance time, preventive maintenance time and replacement time of different subsystems, respectively.

When a subsystem is shocked by a critical shock incident, it will fail. The recovery time of the critical subsystem is T_{Ri}, which of the non-critical subsystem is $T_{PMi} = t_\Psi - t_{CIi}$, where t_Ψ denotes the moment when the proportion of failed non-critical subsystems reaches Ψ, and t_{CIi} denotes the moment when the i_{th} non-critical component fails. When a subsystem is shocked by an influential incident, its lifetime will be shortened. When the remaining lifetime is greater than the degree of degradation caused by the influential incident, the time to return to the normal state is 0 which means that it can continue normal operation without maintenance. Only when the current component lifetime reaches the preventive maintenance threshold after the influential incident does it require preventive maintenance. The completed service time satisfies $t < \tau_{ip} - \vartheta_{II}(t)$. Suppose the time for a subsystem to return to normal operation after suffering damage from an external shock incident is T_2, where the time for critical subsystems is T_{NC2}. Conversely, the time for non-critical components is T_{NCN2}.

$$\begin{gathered}T_{NC2} = T_{Ri} \times N_{CI}^{i}(t) + T_{PMi} \times P(t < \tau_{ip} - \vartheta_{II}(t)) \\ T_{NCN2} = T_{PMi} = t_\Psi - t_{CIi} + T_{Ri} + T_{PMi} \times P(t < \tau_{ip} - \vartheta_{II}(t))\end{gathered}. \tag{12}$$

Define T_{SD} is the specified repair time and the temporal resilience is P_2, then we have

$$P_2 = \frac{T_{SD} - T_2}{T_{SD}}. \tag{13}$$

The temporal resilience of the critical subsystem is $P_{NC2} = \dfrac{T_{SD} - T_{NC2}}{T_{SD}}$, which of the non-critical subsystem is $P_{NCN2} = \dfrac{T_{SD} - T_{NCN2}}{T_{SD}}$.

It can be obtained that $0 \leqslant |P_2| \leqslant 1$. Assumed that the specified repair time is always greater than the recovery time of the subsystem, there is $0 \leqslant P_2 \leqslant 1$. Then when $P_2 = 0$, the system has no temporal resilience. The repair time of the system is longer after the shock. When $P_2 = 1$, it means that the system has not been shocked by a critical incident and has not reached the preventive maintenance threshold. The larger value of P_2 indicates that the system has better temporal resilience.

4.3 Spatiotemporal resilience optimization model

A spatiotemporal resilience evaluation methodology is established based on the established temporal resilience and spatial resilience to comprehensively assess the resilience of the system. Setting the spatiotemporal resilience as P_{SR}, which can be expressed as:

$$P_{SR} = \sqrt{P_1 \times P_2}, \tag{14}$$

P_1, P_2, P_{SR} denote the spatial resilience, temporal resilience, and spatiotemporal resilience of the system respectively. $0 \leqslant P_{SR} \leqslant 1$. When $P_{SR} = 0$, the system has no resilience. When $P_{SR} = 1$, the spatiotemporal resilience of the system is excellent, and all the resilience indexes are optimal. The larger the value of P_{SR}, the better the spatiotemporal resilience is.

Renewable energy systems are characterized by a significant proportion of O&M costs, necessitating substantial long-term investments. These costs can vary significantly depending on the maintenance strategies employed. Optimizing these strategies is crucial for enhancing the economic viability of renewable energy systems. By analyzing the structure and reliability of renewable energy systems, we can model the maintenance costs for various subsystems. The effects of random shock events are considered, detailing the maintenance costs in different cases.

Different researchers have different preferences for resilience studies. Research that seeks to minimize cost often makes resilience too low to be acceptable, while that prefers to maximize resilience results in high cost. A rational researcher will usually require the largest resilience value at the smallest cost. The three objective functions of cost minimization, reliability maximization, and spatiotemporal resilience maximization are considered simultaneously to find the maintenance strategy that can balance these targets. Avoiding the situation that the maintenance cost is too high, or the resilience and reliability are too low due to few maintenance behaviors. The optimization model is defined as:

$$\begin{cases} \max P_{SR} = \sqrt{P_1 \times P_2} \\ \min cost(t) \\ \max R = \prod_{i=1}^{n} e^{-\int \lambda_{n_i}(t)\mathrm{d}t} \end{cases}, \tag{15}$$

where $cost(t)$ denotes the total maintenance cost of critical and non-critical components of the renewable energy system and R denotes the reliability of it. P_1, P_2 P_{SR} denote the spatial resilience index, temporal resilience index, and spatiotemporal resilience index of the system respectively.

Maximizing the spatiotemporal resilience of the system while minimizing the total maintenance cost and maximizing reliability are mutually conflicting objectives. There is no optimal solution with a single objective. The adaptive grid multi-objective particle swarm algorithm is used to solve the Pareto optimal solution set (Coello et al., 2004). The particles update their state through the individual optimal position *Pbest* and the group optimal position *Gbest*. When the number of iterations is reached, the optimal position of the particle swarm is the optimal solution of the problem. The algorithm flow is as follows:

Step 1: Initialize the positions and velocities of the particles, and set the individual optimal position *Pbest* and the optimal position *Gbest* of the particle swarm.

Step 2: Set up an external archive set to store the optimal position of the particle swarm.

Step 3: Evaluate the fitness and Pareto dominance relations of the particles and copy the set of non-dominated solutions to the archive set.

Step 4: If the archive set reaches a specified size, a history solution is randomly removed from the grid containing the most non-dominated solutions.

Step 5: Update the *Gbest* by the adaptive grid method and update the velocity and position of the particles using the velocity Eq. (17) and position Eq. (18).

$$\begin{aligned} V_i^d(t+1) = {} & \omega \times V_i^d(t) + c_1 r_1 \left(Pbest_b - Posi_i^d(t)\right) \\ & + c_2 r_2 (Gbest - Posi_b(t)), \end{aligned} \tag{16}$$

$$Posi(t+1) = Posi(t) + V_i^d(t+1), \tag{17}$$

where ω denotes the inertia weight, c_1 and c_2 denote the learning factor and acceleration factor, respectively. r_1 and r_2 are random numbers between $[0, 1]$.

Step 6: Update the particle *Pbest* according to the particle position relation (19).

$$Pbest = \begin{cases} Pbest\ Pbest \propto Posi(t+1) \\ Posi(t+1)\ Posi(t+1) \propto Pbest \\ random\ select\ from\ Pbest\ or\ position(t+1)\ other \end{cases}. \tag{18}$$

The positions of individual particles are varied or perturbed in order to avoid falling into local optimal solutions. The perturbation operator P_t is computed based on the current number of iterationsand the maximum number of iterations and the mutation rate. Define t to be the current number of iterations, $Iteration$ is the maximum number of iterations and m is the mutation rate.

$$P_t = \left(1 - \frac{t-1}{Iteration - 1}\right)^{1/m}, \tag{19}$$

Compare P_t with the random number. If the random number is less than P_t, the particle is randomly selected for variation. Its position variation formula is:

$$Posi(t+1) = Position^L + \left(Position^U - Position^L\right) * Var, \tag{20}$$

where $Position^U$ and $Position^L$ are the upper and lower limits of particle motion respectively. Var is a perturbation term which is a random number in $[0, 1]$.

Step 7: Return to step 3 until the maximum number of iterations is reached.

5 Generative AI-enabled green and low-carbon transformation strategy

Generative AI has excellent performance in textual content generation tasks, which can also generate synthetic data that is critical to users and systems. This capability facilitates the utilization of historical and synthetic data to implement predictive actions in response to fluctuations in the operational states of renewable energy systems. Consequently, this ensures the efficient allocation of resources and the minimization of operational expenditures. Generative AI can catalyze a green and low-carbon transformation through two primary avenues. First, based on the system, generative AI can analyze and forecast energy consumption and carbon emissions from renewable energy systems by leveraging their operational data sets. This analysis enables the generation of more effective resource planning strategies. Second, according to the information outside the system, generative AI can perform big data analysis on energy production and consumption, dynamically feedback energy information, and accurately capture the supply and demand information. It can respond quickly to supply and demand information and operating conditions, and adaptively adjust the optimal strategies to avoid additional carbon emissions. Synthesizing internal and external information, generative AI can promote the sustainable practice of green and low-carbon of the whole renewable energy systems, especially with excellent performance in the following three aspects.

a) Optimized system infrastructure. Green, low-carbon conversion strategies based on generative AI emphasize the adoption of environmentally friendly policies at the time of design and construction. For instance, considering facility characteristics, construction specifications, and ambient conditions, generative AI can be instrumental in the intelligent optimization of infrastructure deployment, thereby enhancing the efficiency of infrastructure networks and curtailing carbon emissions.

b) Integrate renewable energy smart grid. The green and low-carbon conversion strategy aims to incorporate a higher proportion of renewable energy sources, including solar, wind, and hydroelectric power. Generative AI plays a pivotal role in the efficient management of energy harvesting and optimization within renewable energy systems. It enables real-time adjustments to the capacity of renewable energy systems based on dynamic supply and demand data, thereby maximizing the synergy between renewable energy sources and the electrical grids, and diminishing dependence on fossil fuels.

c) Dynamic intelligent system management. Generative AI can intelligently adjust power generation in response to fluctuations in supply and demand, as well as varying weather and other generation conditions. It facilitates real-time, effective monitoring of energy production, consumption, and output, enabling dynamic optimization of operational tasks and resource allocation, and minimizing carbon emissions, as shown in Fig. 3.

6 Case study

In this section, we undertake the permanent magnet direct drive wind power system as an example of a renewable energy system. The wind system has 6 critical and 5 non-critical components. The critical components contain the blade subsystem, hub, yaw subsystem, generator, and pitch subsystem. The non-critical components include the converter, heat dissipation system, nacelle, tower, wind

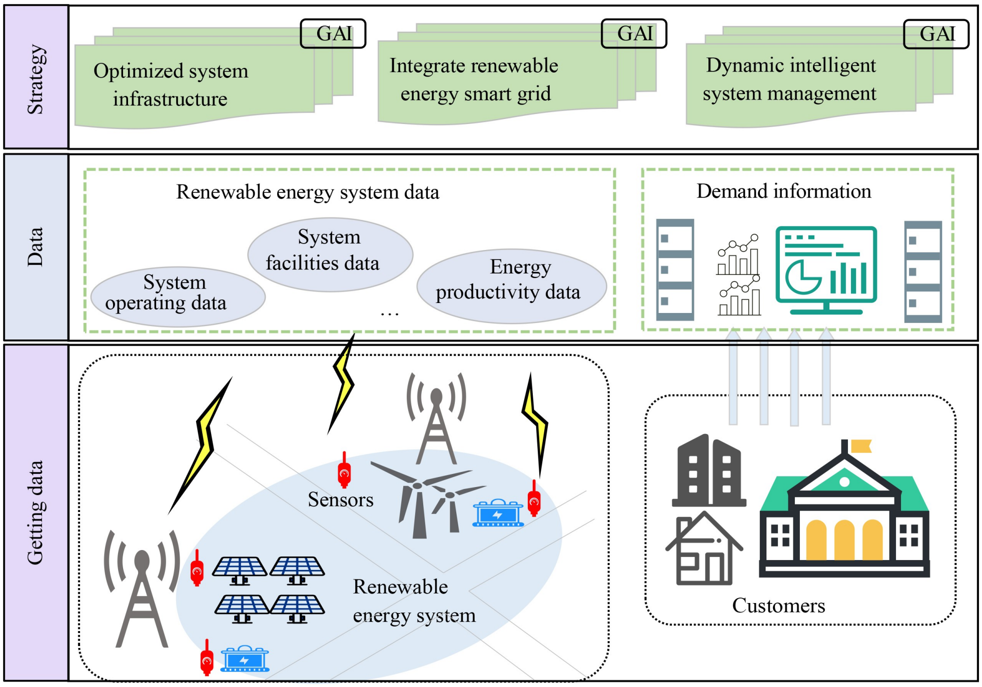

Fig. 3 Generative AI-enabled green and low-carbon transformation strategy.

measurement system, and sensors. Drawing from the work of Dui et al. (2023b), the shape parameter of each component is taken as β =[0.84,0.77,0.55,0.64,0.69,0.58, 0.53,0.51,0.75,1.25,0.54] and the scale parameter is obtained as γ =[696,638,897,803,525,563,656,782,617, 904,780]. The maximum value of reliability of the critical components is $R_{i,\max} = 0.8$ and the minimum value is $R_{i,\min} = 0$, which of the non-critical components is $R_{i,\max} = 0.9$ and $R_{i,\min} = 0$. The failure rate increment factor for the j_{th} preventive maintenance is $a_j = \dfrac{j}{9j+7}$, and the age decrement factor for it is $b_j = \dfrac{12j+1}{11.5j+1}$. The occurrence probabilities of external random shock incidents are 0.001, 0.005 and 0.994 respectively (Li et al., 2021). Let the maintenance threshold for non-critical components Ψ is equal to 0.5. Let the corrective maintenance cost for the 11 components of the wind power system be c_i = [150,180,160,50,30,45,60,30,10,10,20], the preventive maintenance cost be C_i^{pm} = [50,20, 30,45,36,30,20,25,40,10,5] , and the replacement cost be C_i^R = [260,240,250,220,180,180,40,20,30,15,10].

The proposed optimization model is solved by particle swarm algorithm with 2400 h as the simulation period. To avoid falling into the local optimal solution, the optimal maintenance cycle of the subsystem can be obtained by repeating the simulation 50 times and taking the average value. The optimal maintenance schedule for each subsystem is shown in Table 2.

Different percentage failure thresholds for non-critical components result in different maintenance costs. The change in maintenance cost due to the variation of in Ψ is demonstrated as shown in Fig. 4.

The maintenance cost can be seen to be lowest when Ψ varies within [0.15,0.175]. When $\Psi > 0.4$, it will increase dramatically. It indicates that the maintenance cost will be significantly increased when the failure ratio of non-critical components is greater than 40% before unified maintenance, while its maintenance cost is maintained at a low level when it is within 30%. When the maintenance personnel or tools and other conditions are limited, you can appropriately reduce the number of repairs to ensure that the failure ratio in the acceptable range is enough.

Table 2 Optimal maintenance schedule for each subsystem

Subsystem	Optimal maintenance schedule (h)
Blade subsystem	852.7262
Hub	1030.151
Yaw subsystem	1016.255
Generator	942.786
Pitch subsystem	976.2841
Convertor	1055.757
Heat dissipation system	1204.481
Nacelle	1016.255
Tower	1192.787
Wind measurement system	1016.255
Sensors	875.1086

In Fig. 5, both critical incidents and influential incidents can make the maintenance cost larger. Yet the maintenance cost increment caused by the critical incident is more. The extremities of component reliability—both the maximum and minimum values—exert a significant influence on the scale of corrective maintenance costs.

Figure 6 delineates the maintenance cost variances in response to different threshold values of reliability. As the minimum reliability threshold, denoted as $R_{\min}$, escalates, there is a corresponding increase in the maintenance expenses for the power system. This implies that elevating the minimum acceptable threshold of component reliability will, in turn, augment the aggregate maintenance costs. Such a relationship necessitates a nuanced analysis that consider the specific operational context and usage patterns of the power system.

Assessing the spatiotemporal resilience of a system necessitates a dual approach: a precise conceptualization of the system's inherent resilience and an accurate simulation of the external shocks it may encounter. Such shocks have the potential to precipitate system failures or

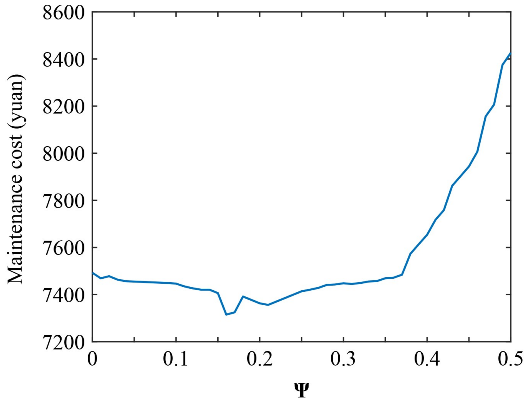

Fig. 4 Maintenance cost with respect to the proportion of non-critical component.

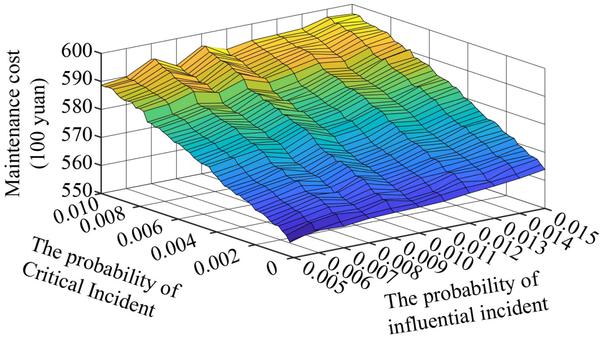

Fig. 5 Maintenance costs for different probabilities of occurrence of critical and influential events.

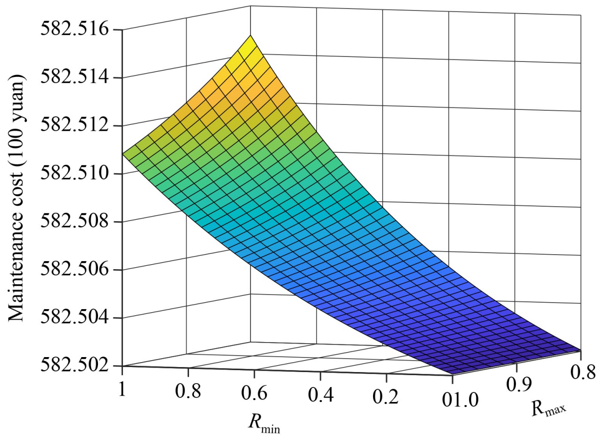

Fig. 6 Maintenance cost with different $R_{\max}$ and $R_{\min}$.

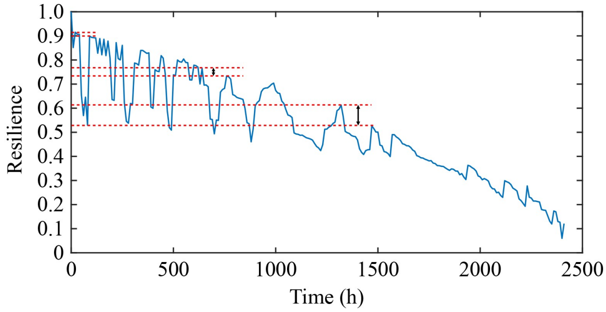

Fig. 7 Spatiotemporal resilience change over 2400 h.

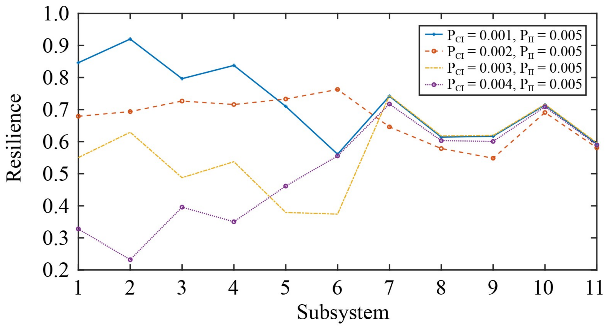

Fig. 8 Spatiotemporal resilience under different probabilities of critical incidents.

degrade performance. The spatiotemporal resilience of a system is inversely proportional to the impact it sustains post-shock or in the wake of a natural disaster. Owners of wind farms generally want a higher resilience of the wind farm, with a minimum increase in cost. Both the resistant resilience and the absorptive resilience can be derived using reliability. Recovery resilience, on the other hand, needs to be dealt with by calculating the recovery time after a failure based on the occurrence of the shock incident and reliability. It is assumed that the specified repair time $T_{SD} = 0.2T_{Mi} + 0.7T_{PMi} + 0.1T_{Ri}$. The failure repair time for different wind power system subsystems is T_{Mi} = 10,8,6,7,6,5,3,1,2,2,1]. Preventive maintenance is to check the components for integrity, wear, dust accumulation, etc., and takes less time than the failure repair time, which is defined as T_{PMi} = [3,2,1.5,2,2,1,1,0.5,0.5,1,0.5]. Replacement is disassembling the failed component and replacing it with a new one, which takes longer time and requires downtime operation of critical components. It is supposed as T_{Ri} = [30,25,15,20,15,8,8,7,10,8,8]. Based on the optimization results of cost and reliability, the maintenance ratio of non-critical components $\Psi = 0.15$ is determined. The spatiotemporal resilience of the system over 2400 h can be obtained, which is shown in Fig. 7.

The overall trend of spatiotemporal resilience change in Fig. 7 is a gradual decrease with the increase of time. But when it has been used for a shorter period, the spatiotemporal resilience is higher and its recovery ability is stronger. When shocked by an impact incident, the spatiotemporal resilience decreases but could recover to the pre-strike performance state. As time increases, the degree of spatiotemporal resilience recovery decreases and more and more resilience is lost. Spatiotemporal resilience varies from subsystem to subsystem. Yet all subsystems have spatial resilience, and temporal resilience. All of them are closely related to the probability of occurrence of external random shock incident. Their resilience varies at different moments. Figure 8 shows the spatiotemporal resilience of different subsystems under critical incidents. This result is the average value obtained after 50 repetitions of the simulation with a usage time of 240 h. It is observed that the 6 critical subsystems are more affected by the critical incident compared to non-critical subsystems. The resilience decreases as the probability of the critical incident increases. There are greater variations and gaps compared to the non-critical subsystems. Critical subsystems are more sensitive to critical incidents. It tends to affect the operation of the whole system if subjected to critical incidents. In contrast, non-critical subsystems do not succumb to immediate failure upon encountering such incidents. Instead, they exhibit resilience by continuing to function until the accumulated damage reaches a threshold that triggers system failure. This gradual degradation underscores the importance of monitoring and managing the health of non-critical components to prevent a cascade of failures that can ultimately compromise the entire system.

When the probability of influential incidents increases, the change in overall resilience is smaller than that of critical events. As depicted in Fig. 9, the overall system spatiotemporal resilience is observed to fluctuate within a range of 0.55 to 0.85 as the likelihood of influential incidents escalates from a probability of 0.005 to 0.008. Conversely, Fig. 8 illustrates that the spatiotemporal resilience of subsystems, influenced by variations in the occurrence probability of critical incidents, is distributed over a broader spectrum, ranging from 0.2 to 0.9. The

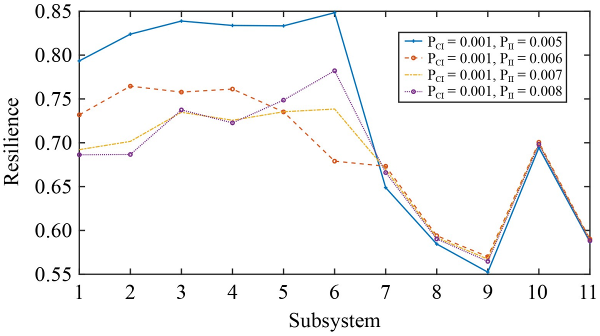

Fig. 9 Spatiotemporal resilience under different probabilities of influential incidents.

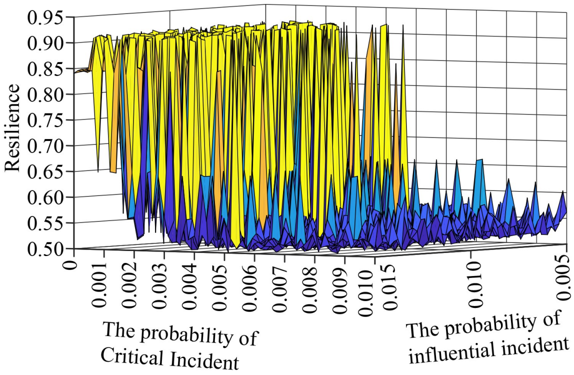

Fig. 10 Spatiotemporal resilience with different probabilities of critical versus influential incidents.

range of changes is lessened. Similarly, the critical subsystems exhibit a heightened sensitivity to fluctuations in the probability of incidents. The magnitude of these changes within critical subsystems is significantly greater than that observed in non-critical subsystems, across various probabilities of influential incident occurrences. The trends for the non-critical subsystems largely overlap, suggesting that the probability of an influential incident has little effect on the overall resilience of the non-critical subsystems within a certain range.

When the probability of external random shock incidents changes, the spatiotemporal resilience also changes. Figure 10 shows the resilience with different probabilities of critical and influential incidents. The Poisson distribution parameter of the critical incident in Fig. 10 increases from 0 to 0.01, which of the influential incident increases from 0.005 to 0.015. The spatiotemporal resilience decreases when the occurrence probability of the critical event increases. When the parameter of the critical incident is greater than 0.008, the spatiotemporal resilience decreases significantly and can only reach a maximum of 0.75, while when the parameter is less than 0.008, it can reach 0.9. The influential incident has less impact on the system resilience than the critical incident, and there is no obvious stratification. The critical incident can cause the system failure and make the system resilience plummet. Yet the influential incidents can shorten the use time, but do not cause the system to fail, and thus have less effect on the resilience.

7 Conclusions

This study is oriented to renewable energy systems and proposes a resilience, green, and low-carbon transformation strategy based on generative AI. First, the role that generative AI can play in renewable energy systems is introduced, which mainly refers to design and construction, monitoring and warning, and operation and maintenance. Secondly, the maintenance cost of renewable energy systems under external environmental shock is introduced, and spatiotemporal resilience is proposed. Then the spatiotemporal resilience optimization model is established. Finally, the wind power system is analyzed as an example of a renewable energy system.

The proposed IoT-based generative AI analysis framework to evaluate system maintenance cost and spatiotemporal resilience has unlimited expansion possibilities. First, the proposed maintenance cost model and spatiotemporal resilience model under external environmental shocks are applicable for systems affected by the external environment. IoT allows real-time monitoring and automated control, etc., and based on it, the generative AI renewable energy system can be generalized to other systems, especially in the green and low-carbon industries.

Generative AI has an excellent performance in content generation such as text and images, and has a great development potential in renewable energy systems. It can assist in monitoring and early warning, and report abnormal situations promptly. It can also dynamically optimize the system according to the data and optimize the system resilience to maximize green and low-carbon. In the future, generative AI will provide more intelligent, correct, and sensitive services in more aspects, not only text content but also generate videos or holographic projections to promote the sustainable development of the whole system. Continued research is needed for the profound integration of generative AI with renewable energy systems.

Competing Interests The authors declare that they have no competing interests.

References

Ahmed Z, Shanto S S, Rime M H K, Morol M K, Fahad N, Hossen M J, Abdullah-Al-Jubair M (2024). The generative AI landscape in education: Mapping the terrain of opportunities, challenges, and student perception. IEEE Access: Practical Innovations, Open Solutions, 12: 147023–147050

Albahri A S, Zahid I A, Yaseen M G, Aljanabi M, Ali A H, Kaleel A (2024). Harnessing the tide of innovation: The dual faces of generative AI in applied sciences; letter to editor. Applied Data Science and Analysis, 2024: 1–3

Bandi A, Adapa P, Kuchi Y (2023). The power of generative AI: A review of requirements, models, input–output formats, evaluation metrics, and challenges. Future Internet, 15(8): 260–320

Berrade M D, Calvo E, Badía F G (2023). Maintenance of systems with critical components. Prevention of early failures and wear-out. Computers & Industrial Engineering, 181: 109–291

Bruneau M, Chang S E, Eguchi R T, Lee G C, D.O'Rourke T, Reinhorn A M, Shinozuka M, Tierney K, A.Wallace W, VON Winterfeldt D (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. Earthquake Spectra, 19(4): 733–752

Cadini F, Agliardi G L, Zio E (2017). A modeling and simulation framework for the reliability/availability assessment of a power transmission grid subject to cascading failures under extreme weather conditions. Applied Energy, 185: 267–279

Che H, Zeng S, Guo J, Wang Y (2018). Reliability modeling for dependent competing failure processes with mutually dependent degradation process and shock process. Reliability Engineering & System Safety, 180: 168–178

Cimellaro G P, Reinhorn A M, Bruneau M (2010). Framework for analytical quantification of disaster resilience. Engineering Structures, 32(11): 3639–3649

Coello C A C, Pulido G T, Lechuga M S (2004). Handling multiple objectives with particle swarm optimization. IEEE Transactions on Evolutionary Computation, 8(3): 256–279

Dekker R, Wildeman R E, van der Duyn Schouten F A (1997). A review of multi-component maintenance models with economic dependence. Mathematical Methods of Operations Research, 45(3): 411–435

Ding F, Tian Z (2011). Opportunistic maintenance optimization for wind turbine systems considering imperfect maintenance actions. International Journal of Reliability Quality and Safety Engineering, 18(5): 463–481

Ding F, Tian Z (2012). Opportunistic maintenance for wind farms considering multi-level imperfect maintenance thresholds. Renewable Energy, 45: 175–182

Dong S J, Gao X Y, Mostafavi A, Gao J X, Gangwal U (2023). Characterizing resilience of flood-disrupted dynamic transportation network through the lens of link reliability and stability. Reliability Engineering & System Safety, 232: 109071

Dui H, Liu M, Song J, Wu S (2023a). Importance measure-based resilience management: Review, methodology and perspectives on maintenance. Reliability Engineering & System Safety, 237: 109383

Dui H, Wu X, Wu S, Xie M (2024a). Importance measure-based maintenance strategy optimization: Fundamentals, applications and future directions in AI and IoT. Frontiers of Engineering Management, 1–26

Dui H, Zhang Y, Bai G (2024b). Analysis of variable system cost and maintenance strategy in life cycle considering different failure modes. Reliability Engineering & System Safety, 243: 109824

Dui H, Zhang Y, Zhang Y (2023b). Grouping maintenance policy for improving reliability of wind turbine systems considering variable cost. Mathematics, 11(8): 1954

Dui H, Zhu Y, Tao J (2024c). Multi-phased resilience methodology of urban sewage treatment network based on the phase and node recovery importance in IoT. Reliability Engineering & System Safety, 247: 110–130

Erguido A, Crespo Márquez A, Castellano E, Gómez Fernández J F (2017). A dynamic opportunistic maintenance model to maximize energy-based availability while reducing the life cycle cost of wind farms. Renewable Energy, 114(B): 843–856.

Ferrario E, Poulos A, Castro S, de la Llera J C, Lorca A (2022). Predictive capacity of topological measures in evaluating seismic risk and resilience of electric power networks. Reliability Engineering & System Safety, 217: 108040

Goerger S R, Madni A M, Eslinger O J (2014). Engineered resilient systems: A DoD perspective. Procedia Computer Science, 28: 865–872

Guan Y (2024). Flight price prediction web-based platform: leveraging generative AI for real-time airfare forecasting. Journal of Web Engineering, 23(2): 299–314

Hosseini S, Barker K, Ramirez-Marquez J E (2016). A review of definitions and measures of system resilience. Reliability Engineering & System Safety, 145: 47–61

Iannacone L, Sharma N, Tabandeh A, Gardoni P (2022). Modeling time-varying reliability and resilience of deteriorating infrastructure. Reliability Engineering & System Safety, 217: 108074

Izquierdo J, Crespo Márquez A, Uribetxebarria J, Erguido A (2019). Framework for managing maintenance of wind farms based on a clustering approach and dynamic opportunistic maintenance. Energies, 12(11): 2036

Kasneci E, Sessler K, Küchemann S, Bannert M, Dementieva D, Fischer F, Gasser U, Groh G, Günnemann S, Hüllermeier E, Krusche S, Kutyniok G, Michaeli T, Nerdel C, Pfeffer J, Poquet O, Sailer M, Schmidt A, Seidel T, Stadler M, Weller J, Kuhn J, Kasneci G (2023). ChatGPT for good? On opportunities and challenges of large language models for education. Learning and Individual Differences, 103: 102274

Leonenko N, Scalas E, Trinh M (2017). The fractional non-homogeneous Poisson process. Statistics & Probability Letters, 120: 147–156

Li M, Jiang X, Negenborn R R (2021). Opportunistic maintenance for offshore wind farms with multiple-component age-based preventive dispatch. Ocean Engineering, 231: 109062

Li M, Wang M, Kang J, Sun L, Jin P (2020). An opportunistic maintenance strategy for offshore wind turbine system considering optimal maintenance intervals of subsystems. Ocean Engineering, 216: 108067

Liu H, Wang C, Ju P, Li H (2022). A sequentially preventive model enhancing power system resilience against extreme-weather-triggered failures. Renewable & Sustainable Energy Reviews, 156: 111945

McMorland J, Collu M, McMillan D, Carroll J, Coraddu A (2023). Opportunistic maintenance for offshore wind: A review and proposal of future framework. Renewable & Sustainable Energy Reviews, 184: 113571

Mettas A (2000). Reliability allocation and optimization for complex systems. In: Annual Reliability and Maintainability Symposium. 2000 Proceedings. International symposium on product quality and integrity. IEEE, 216–221

Nakagawa T (1988). Sequential imperfect preventive maintenance policies. IEEE Transactions on Reliability, 37(3): 295–298

Rahnamay-Naeini M, Hayat M M (2016). Cascading failures in interdependent infrastructures: An interdependent Markov-chain approach. IEEE Transactions on Smart Grid, 7(4): 1997–2006

Saleh A, Chiachío M, Salas J F, Kolios A (2023). Self-adaptive optimized maintenance of offshore wind turbines by intelligent Petri nets. Reliability Engineering & System Safety, 231: 109013

Sarker B R, Faiz T I (2016). Minimizing maintenance cost for offshore wind turbines following multi-level opportunistic preventive strategy. Renewable Energy, 85: 104–113

Talukder S, Ibrahim M, Kumar R (2021). Resilience indices for power/cyberphysical systems. IEEE Transactions on Systems, Man, and Cybernetics. Systems, 51(4): 2159–2172

Van Horenbeek A, Van Ostaeyen J, Duflou J R, Pintelon L (2013). Quantifying the added value of an imperfectly performing condition monitoring system-application to a wind turbine gearbox. Reliability Engineering & System Safety, 111: 45–57

Wang H, Pham H (2006). Optimal preparedness maintenance of multi-unit systems with imperfect maintenance and economic dependence, In: Springer Series in Reliability Engineering, Springer, 135–150

Wang X, Zhao X, Wang S, Sun L (2020). Reliability and maintenance for performance-balanced systems operating in a shock environment. Reliability Engineering & System Safety, 195: 106705

Yan R, Dunnett S (2022). Resilience assessment for nuclear power plants using Petri nets. Annals of Nuclear Energy, 176: 109282

Zeng Z, Fang Y, Zhai Q, Du S (2021). A Markov reward process-based framework for resilience analysis of multistate energy systems under the threat of extreme events. Reliability Engineering & System Safety, 209: 107443

Zhang C, Qi F, Zhang N, Li Y, Huang H (2022). Maintenance policy optimization for multi-component systems considering dynamic importance of components. Reliability Engineering & System Safety, 226: 108705

Zhang R, Du H Y, Liu Y Q, Niyato D, Kang J W, Sun S M, Shen X M, Poor H V (2024). Interactive AI with retrieval-augmented generation for next generation networking. IEEE Network, 38(6): 414–424

Zhao X, Guo X, Wang X (2018). Reliability and maintenance policies for a two-stage shock model with self-healing mechanism. Reliability Engineering & System Safety, 172: 185–194