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Digital twin-enhanced opportunistic maintenance of smart microgrids based on the risk-importance measure

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Abstract: Smart microgrids face more diverse and frequent risks than traditional grids due to their complexity and reliance on distributed generation. Ensuring the reliable operation of smart microgrids requires effective maintenance. Traditional maintenance methods, based on periodic inspections and fault response, struggle to adapt to the dynamics and complexity of microgrid systems. The introduction of digital twin technology provides a new solution for the opportunistic maintenance of microgrid systems. This paper presents a digital twin microgrid architecture for real-time monitoring and decision-making in opportunistic maintenance. Meanwhile, this paper introduces a risk-importance measure to optimize opportunistic strategies with limited resources. Finally, a wind-solar-storage microgrid is used to demonstrate the proposed method. Experimental results show that the method significantly reduces maintenance costs and improves reliability, effectively supporting microgrid maintenance.

Key words: digital twin; smart microgrid; opportunistic maintenance; importance measure

1 Introduction

1.1 Background

Renewable energy, as an alternative to fossil fuels, plays an important role in alleviating energy shortages and combating climate change [1], [2]. In recent years, the application of renewable energy in the power system has received great attention, and the traditional centralized energy model has been transformed into a distributed and decentralized renewable energy system [3]. Microgrids, as the basic architecture of next-generation energy systems, are potential solutions to renewable energy integration due to their environmental friendliness and flexibility [4], [5]. Microgrids are usually

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composed of multiple distributed energy sources (such as solar panels, wind turbines, etc.), which have high complexity. At the same time, the equipment distribution of microgrids is relatively scattered. Compared with traditional power grids, microgrids face more frequent and diverse risks [6]. Maintenance is a key aspect to ensure the reliable and efficient operation of microgrids [7]. The maintenance and optimization of microgrid equipment help improve the system performance, including energy efficiency and power supply quality. However, improper maintenance strategies can lead to over - or under-maintenance, which will affect the microgrid reliability and lead to higher maintenance and failure costs. Digital twin (DT) technology is widely used in the industrial field relying on wireless sensor technology, 5G communication technology, artificial intelligence technology, etc. [8]. It can combine the mathematical model of the microgrid system with its actual operation process to realize the real-time monitoring, analysis, and optimization of the operation status of the microgrid system. Its introduction provides a new solution for the operation and maintenance of microgrid systems. It is of great significance for improving the precision, intelligence, and visualization of microgrid system maintenance.

1.2 Literature review

DT technology is a novel technology that connects digital systems with actual physical systems [9]. DT technology allows access to the real-time state of physical entities (e.g., power generation systems, energy storage systems) and construction of twin systems. Decisions can be simulated and implemented in the twin system [10]. The primary objective is to enable the physical system to operate with better performance and higher efficiency. Currently, DT technology is used at the maintenance, monitoring and management levels in industries including manufacturing, transportation and energy. Ren et al. [11] proposed a collaborative maintenance paradigm based on DT technology to improve intelligent O&M of aero-engine fleets. Wang et al. [12] used DT technology to enable supply chain modeling, real-time supply chain optimization, and the use of collaborative data. Krupenev et al. [13] proposed the use of digital control techniques to assess and analyze the reliability of power systems at all stages of the life cycle. Tang et al. [14] summarized and analyzed the generic

architecture, key technologies and application scenarios of DT in smart energy systems.

Reasonable maintenance strategies can not only improve the reliability of microgrids but also significantly reduce operating and maintenance costs. Currently, common maintenance approaches include corrective maintenance (CM) [15], preventive maintenance (PM) [16-18]. Zhong et al. [19] proposed a multi-objective programming model based on reliability and cost to solve the preventive maintenance scheduling problem of distributed generation systems. Based on the life cycle, Dui et al. [20] introduced a maintenance model that considers multiple component failure modes. The proposed method can provide maintenance strategies for all possible failure scenarios. Zhao et al. [21] proposed a PM strategy for multi-component systems based on the Markov process and verified the effectiveness of the proposed method with a parallel subsea transmission system. Zhang et al. [22] developed a maintenance strategy for a system with primary and secondary components to improve system performance and reduce maintenance costs. Levitin et al. [23] introduced a generalized maintenance model for complex industrial systems that includes preventive replacement and maintenance to eliminate or reduce cumulative equipment degradation.

However, given the diversity of energy sources and the complexity associated with their integration, these traditional approaches are not optimal for complex systems such as microgrids. They are costly and ineffective, which can lead to over- or under-maintenance. For example, the time of CM is usually lengthy. CM will result in longer downtime, which may negatively impact the availability of the microgrids. Long downtime leads to waste of renewable energy and affects the power supply stability for the load point. As an emerging maintenance approach in recent years, Opportunistic maintenance (OM) has received much attention from both academia and industry [24-26]. In the case of such multi-device systems as microgrids, inspection or maintenance activities on one device can provide early preventive maintenance opportunities for other devices. In other words, OM plays a critical role in improving the reliability of multi-device systems at the lowest cost. Tao et al. [27] developed a new opportunistic joint maintenance strategy for two offshore distributed generation systems considering cost and uncertainty. Song et al. [28] provided a two-stage optimization framework to

enable the layout design of offshore wind farms and the development of opportunistic maintenance strategies for turbines. Li et al. [29] proposed a preventive opportunistic maintenance model for multi-component systems considering imperfect preventive maintenance.

It is worth noting that due to the different roles of different components, maintenance sequences can have a significant impact on the improvement of system reliability. Moreover, the number of devices that can be maintained with limited resources is restricted. In recent years, the development and optimization of system maintenance strategies based on importance have been extensively studied [30-32]. Importance is an index of component reliability for the contribution to the system reliability [33, 34]. This metric helps identify critical components and vulnerabilities within a system, guiding maintenance strategies aimed at improving system performance and mitigating risks. Dui et al. [35] proposed an integrated importance measure to analyze the relationship between component performance and system performance. The integrated importance measure can be used to evaluate the contribution of component reliability improvement to system reliability. Zhang et al. [36] and Chen et al. [37] applied the integrated importance measure to offshore heave compensation systems and pod slewing systems, respectively. Importance was used to guide operators in identifying faults and determining the best maintenance strategy for different conditions to maximize performance and minimize cost. Zhang et al. [38] proposed a resilience-based importance measure to guide the maintenance sequence of failed components to quickly restore system performance. Dui et al. [39] considered the problem of preventive maintenance prioritization for two-state systems with limited resources and extended the concept of component prioritization to multistate and incoherent systems. Xing and Levitin [40] modeled the linear consecutively connected systems (e.g., radio communication networks) under different maintenance approaches.

1.3 Motivation and contribution

Microgrids, with their complex and decentralized structure, have high real-time monitoring and feedback needs. Existing research mainly focuses on power generation and energy management, with less emphasis on optimizing maintenance for reliability.

This paper uses DT technology to explore a new perspective on microgrid operation and maintenance. Specifically, the contributions of this paper are summarized below.

- (1) Develop a DT microgrid framework to provide systematic structural support for real-time monitoring and opportunistic maintenance.
- (2) Propose an opportunistic maintenance model considering device correlations to enhance efficiency and reduce costs.
- (3) Introduce a risk-importance measure to optimize maintenance strategies with limited resources.

1.4 Structure

The rest of this paper is organized as follows. Section 2 presents a DT microgrid architecture and identifies the research problems of this paper. Section 3 provides a failure analysis of the microgrid. Section 4 evaluates the risk of the microgrid system. Section 5 proposes an opportunistic maintenance model for the microgrid based on the risk-importance measure. The validity of the proposed method is verified in Section 6 with an example of a wind-solar-storage microgrid. Section 7 concludes this paper and proposes future work.

2 Proposed system architecture and problem description

2.1 Architecture of the digital twin microgrid

DT microgrid means to the virtualization of physical entities and the creation of dynamic digital twins of microgrid systems (e.g., equipment, environment, and personnel) in digital space to achieve digital characterization, intelligent simulation, and optimal management of object properties, behaviors, and states. It enables real-time data acquisition, transmission, analysis, and utilization for improved decision-making on microgrid operation and maintenance. The proposed architecture is a four-layer architecture including perception layer, data layer, model layer, and application layer. Fig. 1 indicates the proposed architecture in our work.

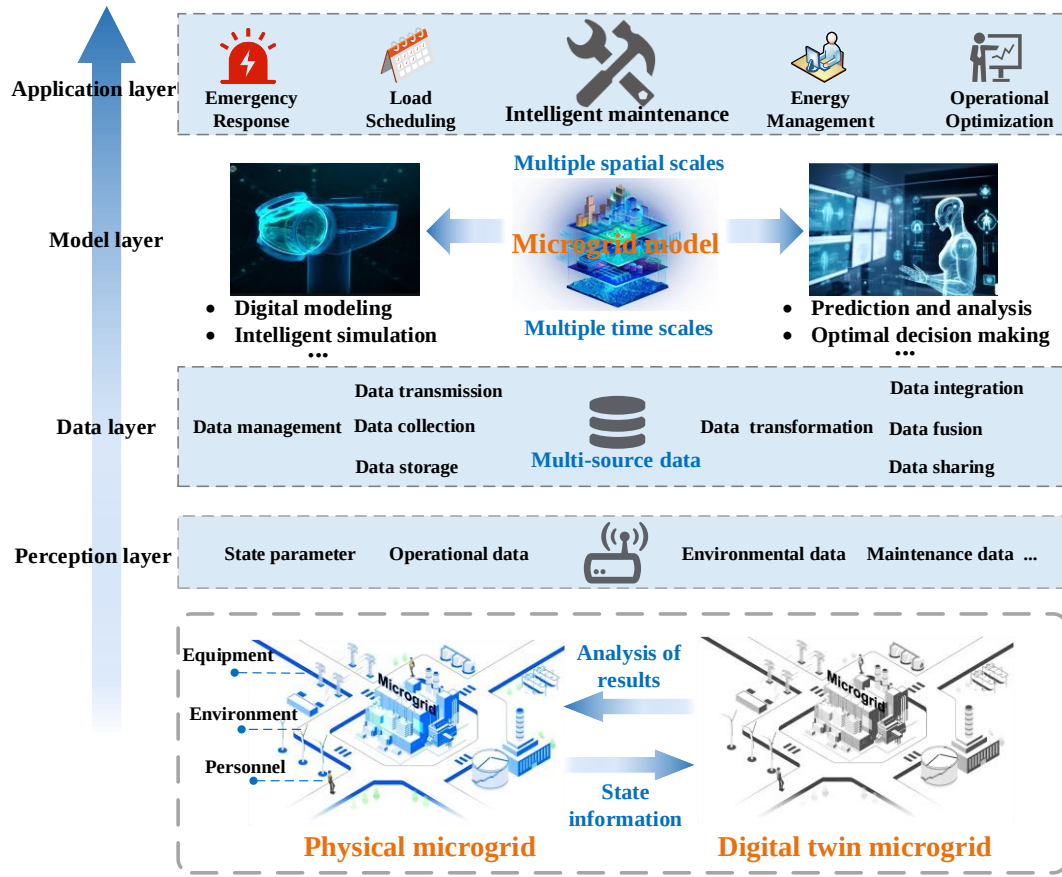


Fig. 1. The architecture of digital twin microgrid.

The perception layer is the bottom layer containing a large number of data acquisition devices. The real-time acquisition of various parameters of the microgrid relies on the application and deployment of sensors. The infrastructure information and external environment information of the microgrid are measured and sensed by sensors and various data collection devices (e.g., UAVs and cameras). The collected data include equipment state parameters, environmental data, operational data, maintenance data, etc.

The data layer manages the collected data, including its collection, transmission, and storage. It integrates heterogeneous physical data from the perception layer using digital twin technology to transform it into digital twin data for the microgrid system. The data layer not only realizes the digitization and standardization of the data of the microgrid system but also provides data management for the whole element, process, and business digitization of the physical system.

The model layer is the core of the DT microgrid, providing a real-time mirror model of the microgrid. By using real-time and historical data, it offers comprehensive information for intelligent simulation across various scenarios, timescales, and spatial

scopes. It also feeds back operation and control commands to guide preventive and targeted operation and maintenance decisions.

The application layer is the top layer, which mainly provides various services for managers. The application layer aims to optimize the digital twin model of the microgrid with the actual operation through visualization and interactive operation to achieve closed-loop feedback. It includes functions such as emergency response, operational optimization, load scheduling, energy management, and intelligent maintenance. Specifically, the intelligent maintenance service typically involves the following functions: real-time maintenance visualization, intelligent alarming, troubleshooting, user interface and control, and so on.

In short, using DT technology to build a DT microgrid enables real-time monitoring of key equipment, intelligent prevention or targeted maintenance, and visual management.

2.2 Problem description

Microgrids emerged in the late 20th century, driven by a significant increase in the demand for renewable energy and growing environmental concerns. The microgrid is a small power system composed of distributed power resources, energy storage systems, loads, monitoring and protection devices, and other equipment. The general architecture of a microgrid is shown in Fig. 2.

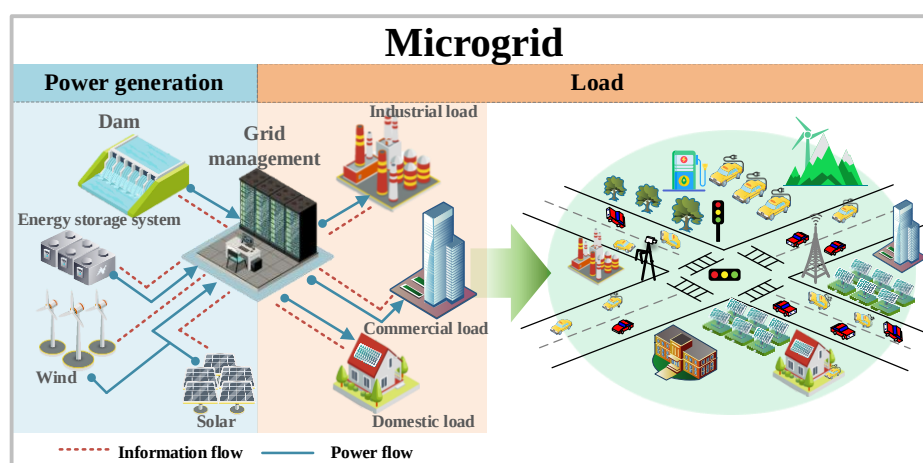


Fig. 2. The general architecture of a microgrid.

In general, a microgrid is a kind of smart grid. Adaptive power generation, distribution, and consumption using smart grid technology. Microgrid is mainly

composed of power systems and information systems. The power systems include the primary equipment of the traditional power system (bus, switch, etc.) and various distributed power resources, energy storage devices, controllers, etc. Information systems usually include intelligent power management equipment, communication network equipment, etc., which is mainly responsible for the operation control and energy management of microgrids. The two-way flows of electricity and information in microgrids have brought great innovation for distributed generation, distributed energy storage, intelligent control, and more.

It can operate independently or interconnect with the main grid to improve the flexibility and resilience of the grid. However, the power generation systems of the microgrid rely on renewable energy, and the instability of energy and various environmental factors (temperature, humidity, etc.) can easily accelerate the aging and damage of the equipment. At the same time, there is a complex interaction between microgrid devices, and the failure of devices may lead to the propagation of faults. This will affect the performance of the microgrid. Therefore, it is necessary to formulate reasonable maintenance strategies for microgrid equipment to improve the system reliability and ensure the power supply quality. To clarify the proposed method of maintenance strategy for the microgrids in this work, the framework of this paper is shown in Fig. 3.

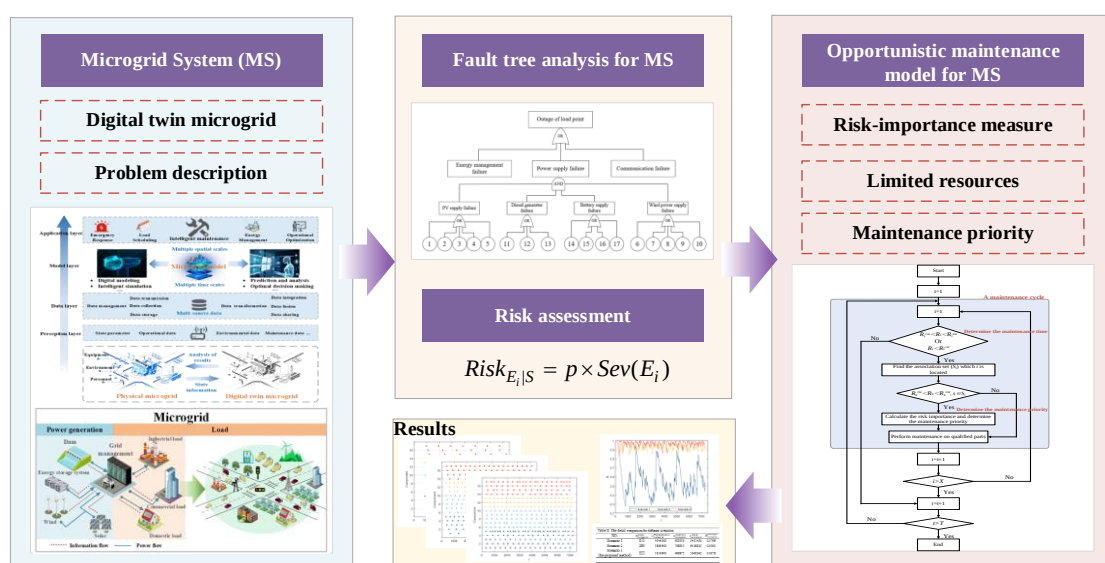


Fig. 3. The framework of this paper.

3 Failure analysis of the microgrid system

This work considers a wind-solar-storage microgrid system. The structure of the microgrid is shown in Fig. 4. The microgrid considered in this paper integrates highly distributed and scalable alternative power sources and storage. Power generation, transmission, substation, distribution, and consumption can be controlled by information technologies. The microgrid mainly includes four common types of power generation (as shown in the green box in Fig. 4). The power supply to the load point mainly includes distributed generation and energy storage supply. The data switch is responsible for data collection and transmission to ensure the reliability and security of microgrid communication. Intelligent energy management (IEM) devices use the data transmitted by the data switch to realize system monitoring, and dynamic power control management, and avoid fault propagation.

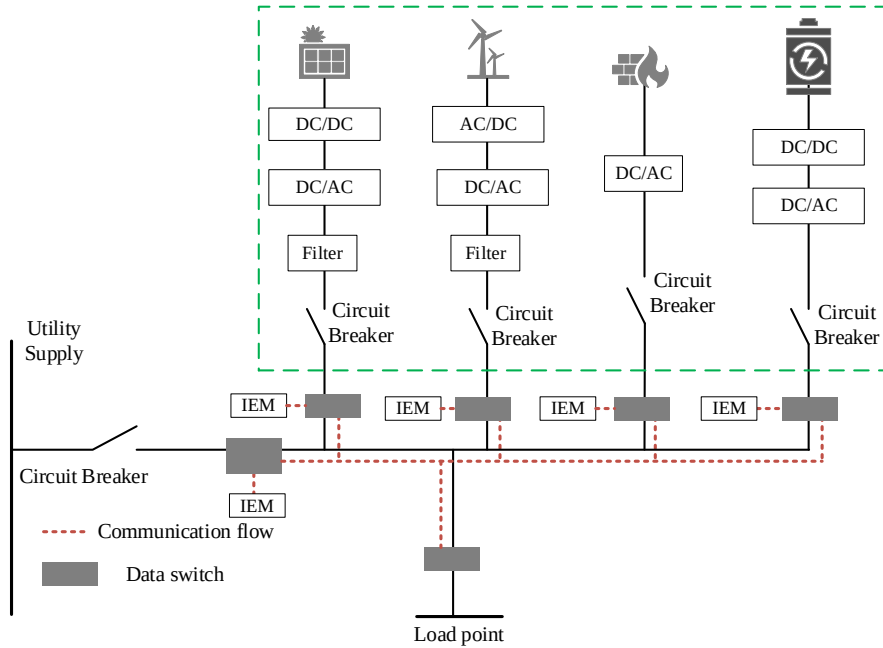


Fig. 4. The structure of the microgrid system is considered in the paper.

The failure comparison for traditional grid and microgrid is shown in Table 1.

Table 1 The failure comparison for traditional power grid system (TGS) and microgrid system (MS).

Disturbance source		TGS	MS
Internal	Electrical equipment failure	√	√
	Transmission line failure	√	√

	Bus bar failure	√	√
	Frequency voltage fluctuation caused by modal conversion	√	
	Device failure caused by modal conversion	√	
	Network topology change caused by mode conversion	√	
	Earthquakes, rainstorms, tornadoes, and other natural disasters	√	√
	Human factors such as human destruction	√	√
External	Weather factors such as rain and no wind led to the volatility, intermittency, and randomness of new energy power generation	√	

As shown in Table 1, microgrids encounter more frequent and varied faults than traditional grids due to their reliance on distributed energy sources like solar and wind, which are affected by weather, seasonal, and geographic conditions. They are also more vulnerable to market price fluctuations, policy changes, and socio-economic factors. Consequently, microgrids need enhanced resilience, adaptability, and flexible management strategies to ensure reliable power supply.

The diverse energy sources and their complex integration expose microgrids to more complex risks than traditional grids. Fault tree analysis (FTA) helps identify basic fault events and their relationships, allowing for a better understanding of these multi-source risks. FTA supports accurate reliability assessments and aids in developing effective risk management and response strategies for microgrid design and operation.

In this paper, the most undesirable event in the microgrid is the interruption of the customer's power supply. The causes of such interruptions include equipment failures, poor system design, inadequate power generation from controllable sources, and uncontrollable power output fluctuation caused by environmental factors. The paper uses a fault tree model to analyze these causes, with customer power supply interruption as the top event. Fig. 5 shows the fault tree model of the microgrid considered in this paper (Fig. 4).

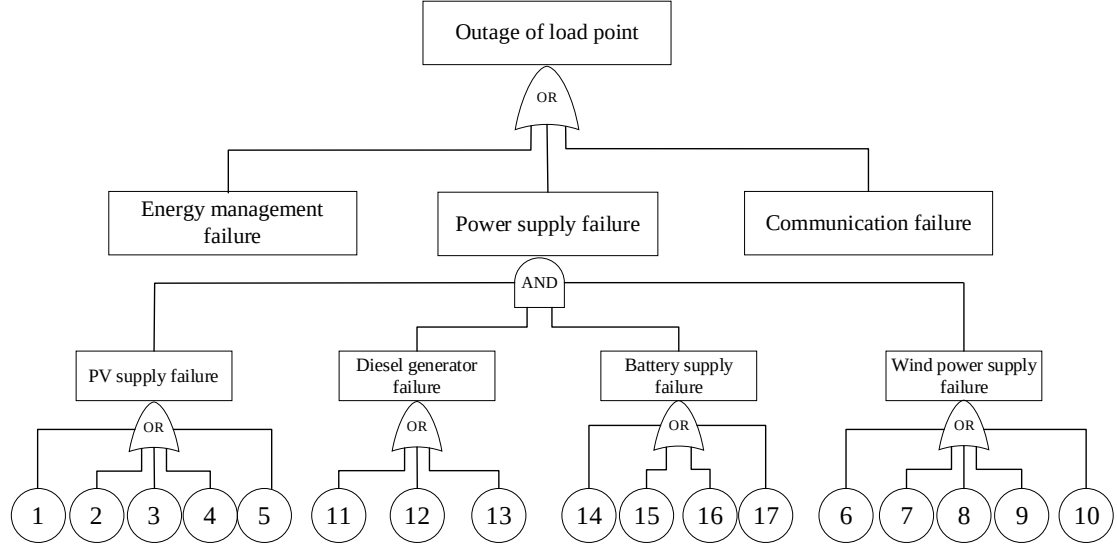


Fig. 5. The fault tree for the microgrid.

In the fault tree model, the outage of the load point is the top event. Outages at the point of load can result from failures in the power supply system, energy management, or communication, as illustrated in Fig. 5. This paper focuses solely on power supply system failures. The basic events of the fault tree are shown in Table 2.

Table 2 The basic events of the fault tree.

No.	Basic event (E_i)		No.	Basic event (E_i)	
X1	PV unit failure	E_1	X10	Circuit breaker failure	E_{10}
X2	DC/DC failure	E_2	X11	Diesel unit failure	E_{11}
X3	DC/AC failure	E_3	X12	DC/AC failure	E_{12}
X4	Filter failure	E_4	X13	Circuit breaker failure	E_{13}
X5	Circuit breaker failure	E_5	X14	Battery unit failure	E_{14}
X6	Wind unit failure	E_6	X15	DC/DC failure	E_{15}
X7	AC/DC failure	E_7	X16	DC/AC failure	E_{16}
X8	DC/AC failure	E_8	X17	Circuit breaker failure	E_{17}
X9	Filter failure	E_9			

As detailed in Table 2 and Fig. 5, if the wind power generation system, diesel power generation system, photovoltaic power generation system, and energy storage systems all fail simultaneously, the microgrid will be unable to supply power. From the concept of a standby redundant system, the power supply system of the microgrid

belongs to the hot standby system. They can work as redundant systems. In detail, if any one of the power supply systems' failures occurs, the other power supply systems can continue to provide the necessary power supply services to the user.

When a device in a power supply system fails, the power supply system will shut down to repair the failed device. Other devices within that system will also stop working and will not generate power during the maintenance period. Based on the fault tree analysis, the devices that caused local power supply failure in the power system are divided into a correlation set. Therefore, the 17 devices in the microgrid can be divided into four correlation sets. The fault tree analysis in this paper does not further analyze the fault causes of devices in the microgrid. The specific failure causes of devices are not the focus of this paper.

4 Risk assessment based on failure analysis

The product of the probability of occurrence of the undesired event and the related consequence can be applied to quantify the equipment failure risk. The risk to the microgrid system if E_i occurs is defined as

$$Risk_{E_i|S}(t) = p \cdot Sev(E_i), \quad (1)$$

where p is the probability of the undesired event, and $Sev(E_i)$ is the severity of the related consequences caused by the basic event E_i . Meanwhile, the related consequences mainly include the impact on equipment and microgrid system. During the maintenance period, CM costs and OM costs will be incurred. At the same time, the power generation of the microgrid will be affected.

Therefore, the severity of the consequences can be measured in terms of three costs.

1) Corrective maintenance costs associated with equipment failure

Corrective maintenance is the maintenance implemented after the equipment has failed. Equipment failure will incur certain maintenance costs. Servicing different types and sizes of equipment will incur different maintenance costs. At the same time, for the same equipment, the type and severity of failure will also directly affect the maintenance cost. For example, some simple failures may only require the replacement of parts or simple repairs, while more serious failures may take longer and more resources to fix, or even replace the entire equipment. The corrective maintenance cost

can be calculated by

$$C^{CM}(t) = \sum_{i \in P^*}^n c_i^{CM} \cdot t_i^{CM} \cdot X_i^{CM}, \quad (2)$$

where c_i^{CM} represents the maintenance cost of the component i in the microgrid. t_i^{CM} is the time of the CM. P^* is the set of components that need to be maintained. X_i^{CM} is the binary variable to determine whether this component needs to CM. When the reliability of the component ($R_i(t)$) in the microgrid below the failure threshold (R_i^{CM}), $X_i^{CM} = 1$. Otherwise, $X_i^{CM} = 0$.

2) Opportunistic maintenance costs

When performing CM on the failed equipment, it's beneficial to use the opportunity for PM on other equipment to enhance reliability and reduce failure risks. This maintenance strategy is called opportunistic maintenance. For the safe and continuous operation of a microgrid system, regular inspection and preventive maintenance of devices like generators, inverters, and energy storage systems are essential. This includes tasks such as cleaning, lubrication, voltage and current measurements, and charge/discharge tests. Additionally, the cost of improving reliability varies among different equipment, such as energy storage devices and wind turbines. The opportunistic maintenance cost can be calculated by

$$C^{OM}(t) = \sum_{m \in P, m \neq i}^M c_m^{OM} \cdot t^{OM} \cdot X_m^{OM}, \quad (3)$$

where c_m^{OM} represents the maintenance cost of component m in the microgrid. t^{OM} is the time of the OM. P denotes the set of components that meets the OM conditions. X_m^{OM} is the binary variable to determine whether this component needs to OM. When the reliability of component ($R_i(t)$) in the microgrid between the CM threshold (R_m^{CM}) and OM threshold (R_m^{OM}), $X_m^{OM} = 1$. Otherwise, $X_m^{OM} = 0$.

3) Indirect costs of microgrid

When device failures or other factors cause a power supply system to stop generating power or a microgrid to shut down, the microgrid's power generation is affected. The indirect costs during this period depend on the power loss per unit time and the duration of maintenance. Note that different types and scales of distributed

power systems have varying power generation rates per unit time. The indirect cost of the microgrid can be calculated by

$$C^{LOSS}(t) = \sum_{e=1}^e E_e \cdot T_e \cdot c^P \cdot X_e^{LOSS}, \quad (4)$$

where c^P denotes the unit power price. E_e is the power generation per unit of time. e is the number of electricity generation systems. X_e^{LOSS} is the binary variable to determine whether the generation of the electricity generation system is affected. T_e represents the time when power generation is affected.

$Sev(E_i)$ is the severity of the related consequences. It can be obtained as

$$Sev(E_i) = C^{CM}(t) + C^{OM}(t) + C^{LOSS}(t). \quad (5)$$

5 Opportunistic maintenance model for the microgrid

5.1 Risk-based importance measure

Based on the risk assessment of microgrid devices described above, we assess their importance based on the risk posed after their failure. Risk-importance measure can be used to prioritize the equipment in need of preventive maintenance and help managers prioritize the more important equipment for opportunistic maintenance under the condition of limited resources. The risk-importance measure of equipment i in a microgrid is defined as

$$I_i^{Risk} = -\frac{\partial Risk_{E_i|S}(t)}{\partial R_i(t)} = -\frac{\partial(p \cdot Sev(E_i))}{\partial R_i(t)} = -\frac{\partial((1 - R_S) \cdot Sev(E_i))}{\partial R_i(t)}, \quad (6)$$

where $Risk_{E_i|S}(t)$ is the risk to the microgrid system if E_i occurs, $R_i(t)$ denotes the reliability of the device i , R_S is the reliability of the microgrid system, $Sev(E_i)$ is the related consequences of E_i occurrence. The physical meaning of I_i^{Risk} is that when the I_i^{Risk} is large, a small change in the reliability of the device i will cause a relatively large change in the risk of the entire system. The risk-importance measure of the device in the microgrid can be calculated by Eq. (6). The higher the I_i^{Risk} value, the more important component i is to the system. Therefore, the device with high risk-importance measure should be given priority for maintenance during an OM cycle.

In a series system, the system reliability is $R_S = \prod_{i=1}^n R_i(t)$. The risk-importance

measure of device i at time t is

$$I_i^{Risk} = -\frac{\partial Risk_{E_i|S}(t)}{\partial R_i(t)} = -\frac{\partial(1 - R_1 \cdot R_2 \cdot \dots R_{i-1} \cdot R_i \cdot R_{i+1} \dots R_n) \cdot Sev(E_i)}{\partial R_k} \\ = -Sev(E_i) \cdot (-R_1 \cdot R_2 \cdot \dots R_{i-1} \cdot R_{i+1} \dots R_n) = Sev(E_i) \cdot (R_1 \cdot R_2 \cdot \dots R_{i-1} \cdot R_{i+1} \dots R_n). \quad (7)$$

In a series system, assuming that the consequences of any device failure are the same ($Sev(E_1) = Sev(E_2) = \dots Sev(E_i) = \dots Sev(E_n)$). Based on Eq. (7), if $R_1 > R_2 > \dots > R_i \dots > R_n$, then $I_1^{Risk} < I_2^{Risk} < \dots < I_i^{Risk} \dots < I_n^{Risk}$.

In the parallel system, the system reliability is $R_S = 1 - \prod_{i=1}^n (1 - R_i(t))$. The risk-importance of device i at time t is

$$I_k^{Risk} = -\frac{\partial Risk_{E_i|S}(t)}{\partial R_k(t)} \\ = -\frac{\partial(1 - R_1) \cdot (1 - R_2) \cdot \dots (1 - R_{i-1}) \cdot (1 - R_i) \cdot (1 - R_{i+1}) \dots (1 - R_n) \cdot Sev(E_i)}{\partial R_k} \\ = -Sev(E_i) \cdot (1 - R_1) \cdot (1 - R_2) \cdot \dots (1 - R_{i-1}) \cdot (1 - R_{i+1}) \dots (1 - R_n) \cdot (-1) \\ = Sev(E_i) \cdot (1 - R_1) \cdot (1 - R_2) \cdot \dots (1 - R_{i-1}) \cdot (1 - R_{i+1}) \dots (1 - R_n) \quad (8)$$

In a parallel system, assuming that the consequences of any device failure are the same ($Sev(E_1) = Sev(E_2) = \dots Sev(E_i) = \dots Sev(E_n)$). Based on Eq. (8), if $R_1 > R_2 > \dots > R_i \dots > R_n$, then $I_1^{Risk} > I_2^{Risk} > \dots > I_i^{Risk} \dots > I_n^{Risk}$.

The risk-importance of the device in the microgrid can be used to identify critical equipment that may cause a major failure or system failure during system operation. It can provide a reference for the formulation of opportunistic maintenance strategies. With limited resources, opportunistic maintenance should be performed on the devices with high risk-importance measure to maintain high system reliability and reduce sudden system failure.

5.2 Opportunistic maintenance

For multi-device systems such as microgrids, maintenance opportunities emerge to repair the remaining devices when maintenance operations need to be performed on specific devices. In the model, two types of maintenance opportunity are considered: (1) Failure-based opportunity. A maintenance opportunity is triggered when a device fails due to its degradation or external impact. (2) Age-based opportunity. An age-based opportunity occurs when the equipment does not fail, but the sensor monitors that the equipment reaches a certain level of aging. The occurrence of a maintenance

opportunity triggers a maintenance cycle. During the maintenance period, different types of maintenance can be performed based on the reliability. The reliability of different devices is shown in Fig. 6 and Fig. 7.

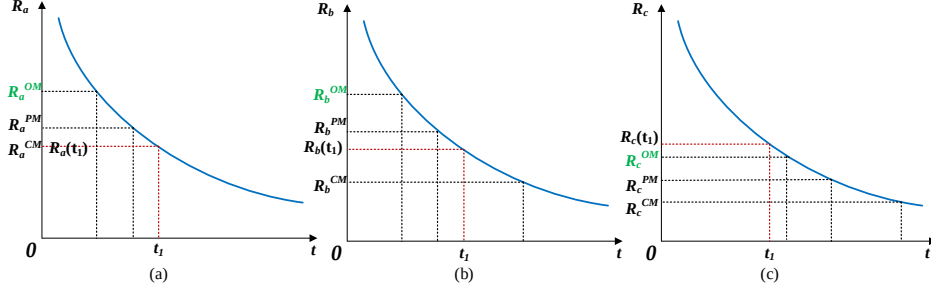


Fig. 6. The reliability of different devices at time t_1 .

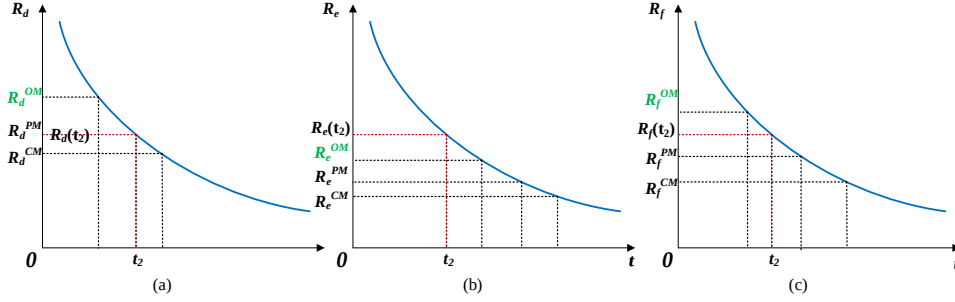


Fig. 7. The reliability of different devices at time t_2 .

Figs. 6 and 7 show the failure-based and age-based opportunities, respectively. R^{OM} , R^{PM} and R^{CM} are thresholds for OM, PM, and CM, respectively. As devices degrade over time or face external shocks, their reliability decreases. From Fig. 6, the reliability of device a falls to R^{CM} at time t_1 , and CM can be performed on it. Then, a maintenance cycle is triggered. The reliability of device b meets the OM threshold ($R_b(t_1) < R_b^{OM}$), and the reliability of the device c does not meet the OM threshold ($R_c(t_1) < R_c^{OM}$) according the real-time monitoring data. Therefore, OM can be performed on b during this maintenance cycle. From Fig. 7, the reliability of device d falls to R^{PM} at time t_2 , and PM can be performed on it. Then, a maintenance cycle is triggered. Currently, the reliability of device f meets the OM threshold ($R_f(t_2) < R_f^{OM}$), and the reliability of device e does not meet the OM threshold ($R_e(t_2) < R_e^{OM}$) according the real-time monitoring data. Therefore, OM can be performed on c during this maintenance cycle. It is worth noting that OM can maintain aging devices in

advance to avoid potential failures and reduce the risk of system failure.

There are many devices in the microgrid, and there is a certain correlation between different devices. To reduce the maintenance resources waste and power loss caused by repeated shutdowns, the devices in the microgrid system (Fig. 4) are divided into 4 correlation sets based on fault tree analysis in Section 3. For example, in the microgrid shown in Fig. 3, there are five main devices in the wind power supply system ($X_6, X_7, X_8, X_9, X_{10}$) with a common switch that can be divided as a correlation set. According to the fault tree analysis, if any device fails or meets maintenance conditions, other devices in the correlation set will stop running. In this case, the devices that reach the corresponding maintenance threshold in the same correlation set will be maintained by the opportunity.

It is worth noting that due to the different roles of different devices, maintenance sequences will significantly affect the improvement of system reliability. In addition, in the case of limited resources, the number of devices that can be maintained is limited. An optimization strategy based on the risk-importance measure is proposed to solve the problem of maintenance priority. The optimization objective of the microgrid opportunistic maintenance strategy is as follows.

$$\max \sum_{i=1}^n I_i^{Risk} \delta_i \quad (9)$$

s. t.

$$\sum_{i=1}^n c_i \delta_i \leq C \quad (10)$$

$$\sum_{i=1}^n t_i^{OM} \delta_i \leq T \quad (11)$$

$$z_i(t) = z_j(t), \forall t \quad (12)$$

$$0 < R_i^{CM} \leq R_i^{PM} \leq R_i^{OM} < 1 \quad (13)$$

Eq. (9) is the optimization objective. I_i^{Risk} is the risk-importance measure of device i . δ_i is the binary variable to determine whether the device i is maintained. When the device i is maintained, $\delta_i = 1$. Otherwise, $\delta_i = 0$. Eq. (10) is the total maintenance cost constraint. c_i is the device i maintenance cost. C is the total maintenance cost. Eq. (11) restricts the total maintenance time spent on the devices.

t_i^{OM} is the device maintenance time. Eq. (12) restricts the devices maintained to belong to the same correlation set. Eq. (13) is the constraint of maintenance thresholds. R_i^{OM} , R_i^{PM} and R_i^{CM} are thresholds for OM, PM, and CM. The flow chart of the proposed maintenance model is shown in Fig. 8.

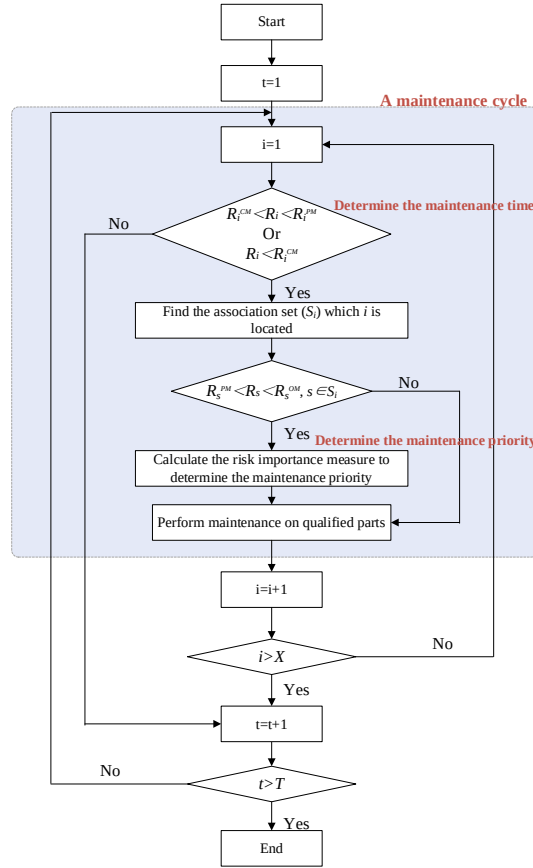


Fig. 8. Flowchart of the proposed opportunistic maintenance.

Fig. 8 clearly shows the flow of the proposed maintenance model. The detailed steps are as follows.

Step 1: Input simulation parameters.

Step 2: Determine maintenance time. DT microgrid provides real-time reliability data. Use these data to assess whether CM or PM is needed. If $R_i < R_i^{CM}$ or $R_i^{CM} < R_i < R_i^{PM}$, a maintenance cycle is started.

Step 3: Identify correlation set S_i . Use digital twins to automatically update and visualize the correlation set S_i of device i .

Step 4: Check OM conditions. Verify if devices in S_i meet OM conditions. If $R_s^{PM} < R_s < R_s^{OM}$, device s meets the OM conditions ($s \in S^{OM}$). If no device meets the conditions for OM, only devices that meet PM and CM will be maintained in the

maintenance cycle.

Step 5: Set Maintenance Priorities. Calculate the risk-importance measure of the devices in the S^{OM} according to Eq. (6).

Step 6: Perform maintenance. Use DT microgrid to simulate various maintenance scenarios and generate specific instructions for the physical system. The physical system then performs the maintenance as instructed. After completion, results are fed back into the DT microgrid, and the microgrid is monitored in real time.

6 Numerical example

This section verifies the effectiveness of the proposed opportunistic maintenance model using a wind-solar-storage microgrid system with 17 major devices. Microgrid systems are found in various environments, such as urban and rural areas, off-grid locations, and emergency scenarios. Consequently, microgrid devices are affected by external factors like temperature, humidity, and electromagnetic interference, as well as internal aging and cumulative shocks, which lead to device degradation. This paper assumes that the failure of these 17 major devices follow a *Weibull* distribution, which is $F(t) = 1 - e^{-\left(\frac{t}{\alpha}\right)^\beta}$. α and β are two parameters of *Weibull* distribution. The parameters of the *Weibull* distribution for each device are shown in Table 3.

Table 1 The scale and shape parameters of devices.

No.	Code	α	β	No.	Code	α	β
1	X1	3997	2.14	10	X10	2238	2.23
2	X2	3333	2.08	11	X11	3783	2.18
3	X3	2559	2.31	12	X12	3988	2.33
4	X4	2889	2.39	13	X13	2037	2.25
5	X5	2199	2.24	14	X14	3937	2.18
6	X6	3880	2.15	15	X15	2837	2.15
7	X7	2333	2.14	16	X16	2671	2.18
8	X8	2508	2.26	17	X17	2350	2.24
9	X9	2778	2.29				

In this paper, it is assumed that the lifetime of the microgrid system is fixed at 20 years. Meanwhile, maintenance activities can be completed within a predetermined time frame without being affected by any factors. Three scenarios are set up to verify

the advantage of the proposed maintenance model.

Scenario 1: OM and PM are not considered. During the operation of the microgrid, the devices should be checked and maintained regularly to ensure the stability of the power supply. Meanwhile, CM is performed on failed devices. CM threshold is 0.4. This scenario does not consider the correlation of devices in the microgrid power generation system, and the total number of shutdown times during the operation cycle is 172. The maintenance schedule for Scenario 1 is shown in Fig. 9. Maintenance time and maintenance types of Scenario 1 are shown in Table 4.

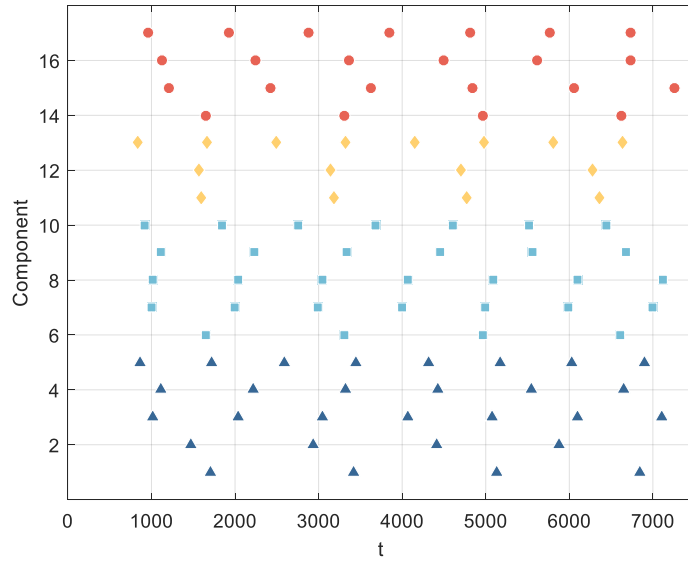


Fig. 9. The maintenance plan of microgrid for Scenario 1.

Table 4 Maintenance time and maintenance types of Scenario 1.

Maintenance type		$D_{scenario}^{total}$	Maintenance cost	$C_{scenario1}^{Indirect}$	$C_{scenario1}^{total}$	$R_{scenario1}^{average}$
CM	Periodic maintenance					
99	73	172	4349500	938100	5287600	0.56

Scenario 2: OM and the periodic maintenance are not considered. In this scenario, PM is performed on devices that reach the PM threshold. PM threshold is 0.7. PM can detect and repair potential faults in advance, and reduce the probability of sudden failure to ensure the continuous power supply capacity of the microgrid. The average system reliability during the whole operation of the microgrid can be maintained at 0.9322. However, the correlation of devices in the microgrid power generation systems is not considered in this scenario. The total number of shutdown times for different

power generation systems in the microgrid is as high as 265 times during the operation cycle. The maintenance schedule for Scenario 2 is shown in Fig. 10. The maintenance number, maintenance approach, and maintenance cost are shown in Table 5.

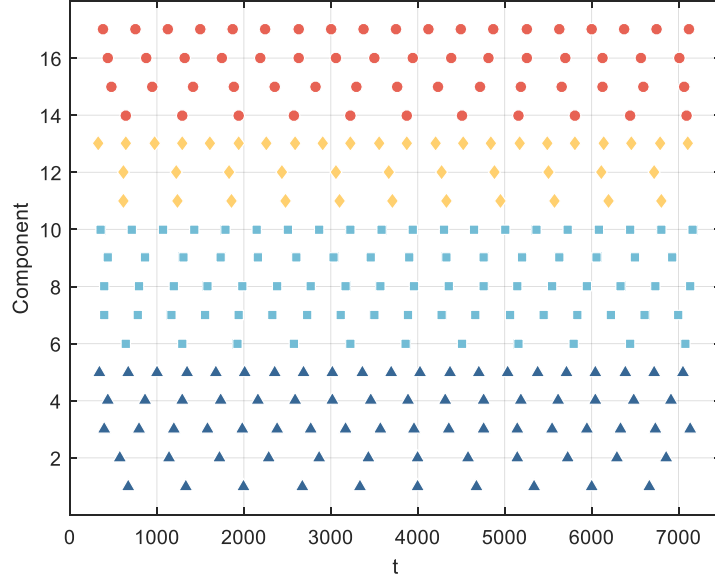


Fig. 10. The maintenance plan of microgrid for Scenario 2.

Table 5 Maintenance time and maintenance types of Scenario 2.

Maintenance type PM	$D_{scenario2}^{total}$	Maintenance cost	$C_{scenario2}^{Indirect}$	$C_{scenario2}^{total}$	$R_{scenario2}^{average}$
265	265	5410000	727950	6137950	0.93

Scenario 3: OM is considered. When PM or CM is performed on a device, the opportunistic maintenance model proposed in this paper can obtain the optimal maintenance plan for other devices. OM threshold is 0.85. The proposed method considers the correlation of devices in microgrid power generation systems and makes full use of idle time to repair and maintain the devices which meet the conditions of OM. Moreover, the average system reliability during the whole operation of the microgrid is 0.9669. Based on the opportunities triggered by maintenance, the total number of shutdown times for the microgrid is 128 during the operating cycle. The maintenance schedule for Scenario 3 is shown in Fig. 11. The maintenance number, maintenance approach, and maintenance cost are in Table 6.

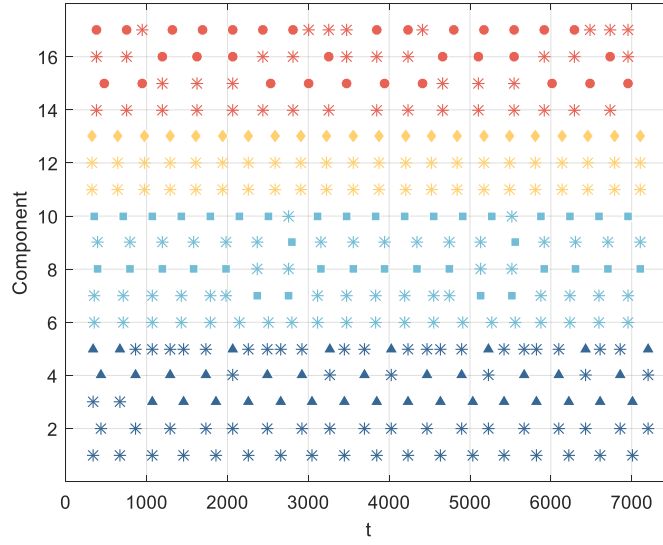


Fig. 11. The maintenance plan of microgrid for Scenario 3.

Table 6 Maintenance time and maintenance types of Scenario 3.

Maintenance type		$D_{scenario3}^{total}$	Maintenance cost	$C_{scenario3}^{Indirect}$	$C_{scenario3}^{total}$	$R_{scenario3}^{average}$
PM+CM	OM					
128	207	128	3069300	450840	3520140	0.97

The maintenance times, maintenance costs, and indirect costs of the microgrid in the three scenarios are compared, as shown in Table 7.

Table 7 The detailed comparison for different scenarios.

NO.	$D_{scenario}^{total}$	Maintenance cost	$C_{scenario}^{Indirect}$	$C_{scenario}^{total}$	$R_{scenario}^{average}$
Scenario 1	172	4349500	938100	5287600	0.56
Scenario 2	265	5410000	727950	6137950	0.93
Scenario 3	128	3069300	450840	3520140	0.97

In terms of the total shutdown times, $D_{scenario2}^{total} > D_{scenario1}^{total} > D_{scenario3}^{total}$. In terms of the total maintenance cost, $C_{scenario2}^{total} > C_{scenario1}^{total} > C_{scenario3}^{total}$. The total cost of Scenario 3 decreased by 33.42% and 42.65% compared with Scenario 1 and Scenario 2, respectively. In terms of the average system reliability, $R_{scenario3}^{average} > R_{scenario2}^{average} > R_{scenario1}^{average}$. The proposed method considers the correlation of microgrid devices and carries out OM on the devices meeting the conditions. It has an obvious effect in improving the reliability of the device and ensuring the stable power supply of the microgrid. For Scenario 2, PM is performed on the devices in the

microgrid to maintain the device reliability and system reliability at a high level. However, the frequent PM may lead to over-maintenance and high maintenance costs. For Scenario 1, system reliability is low throughout the operation period. This is not conducive to ensuring the stable power supply of microgrids. In addition, in terms of total indirect cost, $C_{scenario1}^{Indirect} > C_{scenario2}^{Indirect} > C_{scenario3}^{Indirect}$. Although the number of maintenances was less in Scenario 1 than in Scenario 2, CM generally took longer. In this case, the downtime of the power generation system where the faulty device in will be prolonged, which will result in a large indirect loss.

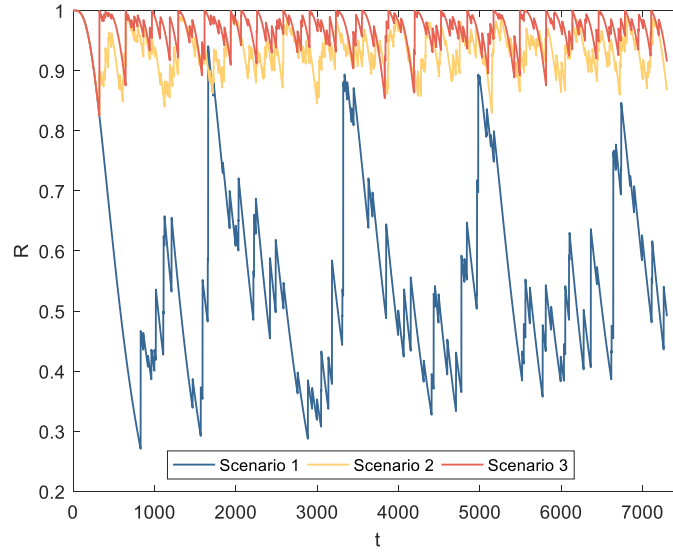


Fig. 12. The system reliability for different scenarios.

Fig. 12 shows the system reliability over the whole operation period for different scenarios. Compared with Scenario 1, the system reliability of Scenario 3 and Scenario 2 change slightly. Specifically speaking, the average reliability of Scenario 3 is 0.97, that of Scenario 2 is 0.93, and that of Scenario 1 is 0.56. In conclusion, the proposed method has obvious advantages in improving system reliability and reducing maintenance costs.

In the case of limited resources, the opportunistic maintenance model proposed in this paper can rank the devices that satisfy the opportunity maintenance conditions based on the risk-importance measure and prioritize the devices for OM. A comparison is presented to further validate the effectiveness of the proposed method. Other conditions being equal, Birnbaum importance is used to prioritize the devices for OM.

The comparison results are shown in Table 8.

Table 8 The detailed comparison for different scenarios.

Importance measure	$R_{average}$	C_{total}
Risk-based importance	0.97	3520140
Birnbaum importance	0.96	3634500

The Birnbaum importance is the partial derivative of system reliability with respect to individual component reliability. It evaluates how improving the reliability of a component affects overall system reliability. Based on Birnbaum importance, the risk-importance measure accounts for component failure risk. From Table 8, our method offers better reliability improvement and cost reduction has advantages over Birnbaum importance in improving the reliability and reducing the total cost of the microgrid system.

In the above simulation, maintenance thresholds were initially assumed to be the same for all devices. Considering the differences between various devices in the microgrid, the maintenance thresholds for different devices are randomly generated from the interval to ensure the robustness. CM thresholds ranged from [0.38, 0.43], PM thresholds from [0.68, 0.73], and OM thresholds from [0.82, 0.87]. We ran 1000 simulations for each scenario, with average results presented in Table 9.

Table 9 The detailed comparison for different scenarios with different maintenance thresholds.

NO.	$D_{scenario}^{total}$	$C_{scenario}^{Maintenance}$	$C_{scenario}^{Indirect}$	$C_{scenario}^{total}$	$R_{scenario}^{average}$
Scenario 1	175	4349500	953550	5401450	0.5799
Scenario 2	280	5689900	768915	6458815	0.9391
Scenario 3 (the proposed method)	132	3036900	469872	3660242	0.9679

From Table 9, the total cost of the proposed method is the smallest under the condition of different maintenance thresholds. Compared with scenario 1 and scenario 2, the total cost of the proposed method decreased by 32.23% and 43.33% respectively. Meanwhile, the average reliability of the microgrid can be maintained at a high level during the operation by the proposed method. These results are the same as the simulation results above.

7 Conclusion and future work

Given the diversity of microgrid energy sources and the complexity of their integration, this paper proposes a digital twin-enhanced opportunistic maintenance model. This model accounts for device correlations and utilizes a risk-importance measure to guide maintenance decisions for microgrids with limited resources. The model's effectiveness is demonstrated through a wind-solar-storage microgrid. Compared to other methods, the proposed approach maintains an average microgrid reliability of 0.97 while reducing costs by 33.42% and 42.65%, respectively. Additionally, under various maintenance thresholds, the total costs of the proposed method are lower than those of other maintenance approaches.

Future improvements to the proposed model may include addressing the high-dimensional and multi-source data in microgrids. Effective data mining could be used to determine the optimal maintenance thresholds, thereby enhancing microgrid reliability. Additionally, challenges related to sensor data transmission reliability remain. In the future, the reliability of data transmission will be considered in our model.

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