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An energy IoT-driven multi-dimension resilience methodology of smart microgrids

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Abstract: Smart microgrids are significant in promoting clean energy development and improving microgrid security and reliability. However, harsh environments make them exposed to various hazards, including natural hazards such as hail and wildfire and digital hazards such as cyberattacks. Due to these complex challenges, performing performance evaluation and resilience analysis for smart microgrids in different periods (e.g., before, during, and after the hazards) and different layers (e.g., a data layer and a physical layer) is difficult. To reduce this research gap, this paper develops a new multi-layer failure and multi-dimension resilience methodology in the energy Internet of Things (IoT). This paper analyses a multi-layer failure mechanism of smart microgrids in energy IoT with the synergy of the “physical layer, perception layer, communication layer, and application layer”, establishes a multi-stage performance model for smart microgrids based on operation loops, and develops a multi-dimension resilience methodology for smart microgrids with consideration of four performance evolution processes (i.e., prevention, degradation, restoration, and reconstitution). A case adopted from the Shandong province in China is used to demonstrate the proposed method under normal operating conditions and different types of disasters.

Keyword: smart microgrids; energy management; multi-stage performance; multi-layer architecture

1 Introduction

1.1 Background

The need for energy resources is rising as a result of modernization and the industrial revolution and alternative energy sources including solar cells and biofuels are becoming increasingly important as conventional fossil fuels run out [1]. The emergence of ultra-dense 5G networks and a large number of connected devices will bring with them significant increases in energy consumption, operating costs, and CO₂ emissions [2]. In the face of the challenges of energy shortage and large-scale energy transition, microgrids provides more flexible, sustainable and secure solutions to local energy supply and demand. The Internet-connected smart microgrid (SM) is emerging as an innovative approach to ensure the energy from anywhere at any time [3]. The deep integration of emerging technologies and the power industry has become an important direction to enhance the development of digital intelligence of microgrids, which supports the comprehensive analysis of grid data and empowers the sharing and use of power data. The transformation from traditional grids to SMs boosts the efficiency, flexibility, and robustness of the systems, attributable to the escalating degrees of cybersecurity and automation. SMs are the energy Internet based on advanced metering infrastructure and distributed systems that require an instantaneous two-way flow of energy information [4]. It boosts the microgrid with the advantage of using intelligent infrastructure to aid monitoring, protection, bidirectional communication, supply safety, security and self-healing characteristics [5]. Information and

communication technology is a vital addition to modern society living and is a crucial feature of the SM. The Internet of Things (IoT) plays a vital role in SMs [6]. The IoT aims to transform the human society toward becoming intelligent, convenient, and efficient with potentially enormous economic and environmental benefits [7], including lower transmission costs and reduced global warming problems [8]. Various devices such as sensors are connected to the Internet through the IoT, enabling two-way interaction between users and microgrids. Therefore, research on the SM performance approach holds immense importance in improving the communication and interaction capabilities, contributing to the multilayered and collaborative management of SMs, and promoting the development of SMs in the direction of being more efficient, intelligent, sustainable, secure and reliable.

1.2 Literature review

The smart grid is a highly complex system that is being formed from the traditional grid, adding new and sophisticated communication and control devices [9]. The smart grid comes with intelligent applications that can utilize the bidirectional communication network among their entities [10]. SM is an important component of the evolving smart grids [11]. SMs are small-scale smart grids that enable machine-to-machine communications as they can operate with some degree of independence from the main grid [10]. Mbungu et al. [12] reviewed various control and estimation technologies for developing dynamic model of SMs. Kremers, Gonzalez and Barambones [9] developed a multi-agent model of a SM with an integrated approach that can process both electrical and communication flows. Gao et al. [13] developed an intelligent microgrid management system and verified the performance advantages of the system. Mohamed [14] developed an effective negotiation approach for energy cooperation between smart grid and microgrid. Li, Zhu, and Dong [15] proposed a novel energy sharing cloud mechanism for a SM with renewable energy sources and energy storage. Wang et al. [16] addressed SM energy management in the presence of distributed generation and active loads. Quijano et al. [17] proposed a price-based strategy to coordinate electric springs for demand side management in SMs. Zheng et al. [18] modelled a smart grid with two different power supply modes by presenting a hierarchical model. Arul et al. [19] proposed a novel method in IoT-based edge cloud computing architecture with microgrid energy management. To summarise, more authors study distributed generation, load and energy management, etc. in the physical layer of SMs. But the few focus on the digital function of SMs, e.g., perception, communication, and decision. “Smart” is a significant feature of SMs that cannot be ignored. Thus, synergistic multi-layer energy management of SMs in combination with intelligent technologies such as the IoT are necessary.

While SMs can meet the diverse demand of users and cope with various uncertainties, they are also exposed to more threats and are more susceptible to extraordinary events. Regional failures caused by natural disasters can have a large impact on the SM [20]. The cyber failures such as failures in protection and monitoring systems do not stop the operation or change the behaviour of the microgrid instantly but will adversely affect the performance of the SM against the potential failure [21]. The SM combines communication systems with sensing devices to provide intelligent management tools for fault monitoring and processing of power grids [20]. Omitaomu and Niu [22] reviewed artificial intelligence techniques applied to faults detection and security problems in the smart grids. He et al. [23] detected and analysed electric signature for power

equipment faults monitoring in smart grids. Patnaik et al. [24] proposed a smart energy solution for fault classification in SMs. Peng et al. [25] analysed dynamical failures driven by false load injection attacks against smart grids. Nguyen et al. [26] study the smart grid vulnerability and help reduce damages in case the system is suffering from the cascading failure attacks. Woodard et al. [27] proposed a method to identify components most frequently involved in system-level damages in smart grids. Jadidi, Badihi and Zhang [28] investigated innovative approaches for attack-resilient control. Balachandran et al. [29] analysed power-component failure, communication failure, and cyberattack to improve the performance of smart grids. In summary, most articles only concerned about the component failure or cyber failures, while little research has been reported on the fact that data transmission under the synergy of the data layer and physical layer may fail in SMs. Furthermore, many focus on failure monitoring or failure control methods. The exploration about the multi-stage performance change of SMs before, during and after risk disturbances is scant.

For performance of SMs, Jacob and Farzaneh [30] presented the dynamic modelling of an off-grid microgrid incorporating power control strategies for quality power output. Howlader, Matayoshi and Senjyu [31] incorporated distributed generation with the thermal generation for optimum operation of a smart grid. Jiménez et al. [32] combined an overall energy system analysis with more detailed power system analysis, where the power balance at each instant is the main item of interest rather than the energy balance. Gheouany et al. [33] introduced a multi-stage optimal energy management system in a SM that effectively predicts the next 24 h of load demand and photovoltaic power generation. Phan et al. [34] employed the multi-objective optimization for the performance of the microgrid and the facilitation of wind generation on the smart grid. Boutros et al. [35] proposed a model for the optimal sizing of an islanded microgrid considering environmental challenges. Yazdani, Baneshi and Yaghoubi [36] proposed the techno-economic and environmental multi-objective optimization of SMs. Calise et al. [37] developed suitable control strategies to improve the energy, environmental and economic performance of a smart grid. Akaber et al. [38] quantified the smart grid security based on the power flow equations and communication network characteristics. Hmadi, Mourtad and Daou [39] forecasted the performance of a smart grid in desert climate. Bhatt et al. [40] developed a cost function integrating various SM applications and different wireless communication technologies and enhance the performance of the developed strategy. In short, some authors studied SM performance from the perspective of power energy and others analysed the economy, environment and safety as performance. However, the literature on the performance model considering the multi-layer energy architecture and multi-stage operation processes of the SM is yet rare.

1.3 Research objectives and contributions

Based on the above review, although there is a relatively well-developed body of knowledge of SMs modelling, failure monitoring and control, and performance analysis, most existing literature focused on microgrids and smart grids. Little research is done on the novel SM performance approach considering multi-stage multi-layer energy management in IoT. Random risk disturbances and local equipment anomalies may induce global failures through perturbation propagation, making it difficult to assess the SM performance. Meanwhile the application of intelligent technologies further increases the difficulty of performance analysis. Models that focus on the multi-layer energy architecture of the SM in uncertain environments to assess multi-

layer performance are scant. In this paper, the multi-layer performance of SMs refers to the synergistic operation capability among its multiple layers. Accurate performance approach can provide guidance and reference for the design, construction and operation of SMs. Therefore, this paper focuses on multi-layer SMs and has the following objectives:

- (1) To model SMs in combination with intelligent technologies such as the IoT for synergistically managing the multi-layer energy architecture of SMs under uncertain environment.
- (2) To develop a multi-layer performance approach for quantifying the synergistic operation capability among the SM's multiple layers.
- (3) To propose a multi-stage performance efficiency model for evaluating the multi-layer performance of SMs.

The novelty and contributions of this paper are listed below.

- (1) The multi-stage multi-layer management approach of SMs is proposed by holistically considering the physical layer, perception layer, communication layer, and application layer in IoT.
- (2) A multi-layer performance approach with multi-layer energy architecture for SMs considering communication paths between different layers in IoT is established.
- (3) A multi-stage performance efficiency model for SMs considering operating state of the system before, during and after risk disturbances.

1.4 Overview

The remainder of this paper is organised as follows. Section 2 proposes a multi-layer energy architecture in IoT. Section 3 establishes a multi-layer performance model in multi-stage energy management for SMs. Section 4 develops the multi-stage multi-layer performance approach of SMs. Section 5 studies a case under two scenarios and discusses the results. Section 6 concludes the paper.

Nomenclature	
<i>Abbreviations</i>	
IoT	Internet of Things
SM	Smart microgrid
<i>Symbols</i>	
BW_{ij}^{gh}	Bandwidth, where i -th and j -th nodes are in the g -th and h -th layers respectively
$D(t)$	The total performance degradation
ER_{ij}^{gh}	Bit error rate
$f(t)$	The multi-layer performance at the t -th moment
G_A	The application layer of SMs
G_C	The communication layer of SMs
G_O	The physical layer of SMs
G_P	The perception layer of SMs
PL_{ij}^{gh}	Packet loss ratio

R	The multi-stage comprehensive performance efficiency
R_{AV}	The avoidance metric of SMs in the prevention stage
R_{RO}	The robustness metric of SMs in the degradation stage
R_{RV}	The recovery metric of SMs in the restoration stage
R_{RC}	The reconstitution metric of SMs in the reconstitution stage
T_{ij}^{gh}	Communication time

2 Multi-layer energy architecture in IoT

2.1 IoT-enabled energy architecture in SMs

The SM consists of distributed power source, load, energy storage, power distribution and intelligent control centre system, covering physical layer, perception layer, communication layer and application layer, with the characteristics of information synergy, autonomous regulation and agile response. The physical layer performs power supply mission and completes the power generation, transmission, transformation and distribution, and usage processes. The perception layer provides situational awareness of the operating conditions of the physical layer and collects real-time data from the microgrid using various digital sensors. The communication layer monitors, analyses and counts microgrid data through information and communication technology and uploads it to the cloud servers to achieve various synergies such as resource synergy, application synergy, data synergy and intelligent synergy. The application layer is responsible for implementing various application functions and services, improving the adaptive capability of SMs, and realising intelligent control, management and decision-making of SMs. SMs can realise accurate perception of numerous devices, real-time processing of massive information, and collaborative sharing of diversified data, which plays an important role in guaranteeing safe and reliable supply of electrical power and promoting the development of green energy transition. A multi-layer energy architecture is shown in Fig.1.

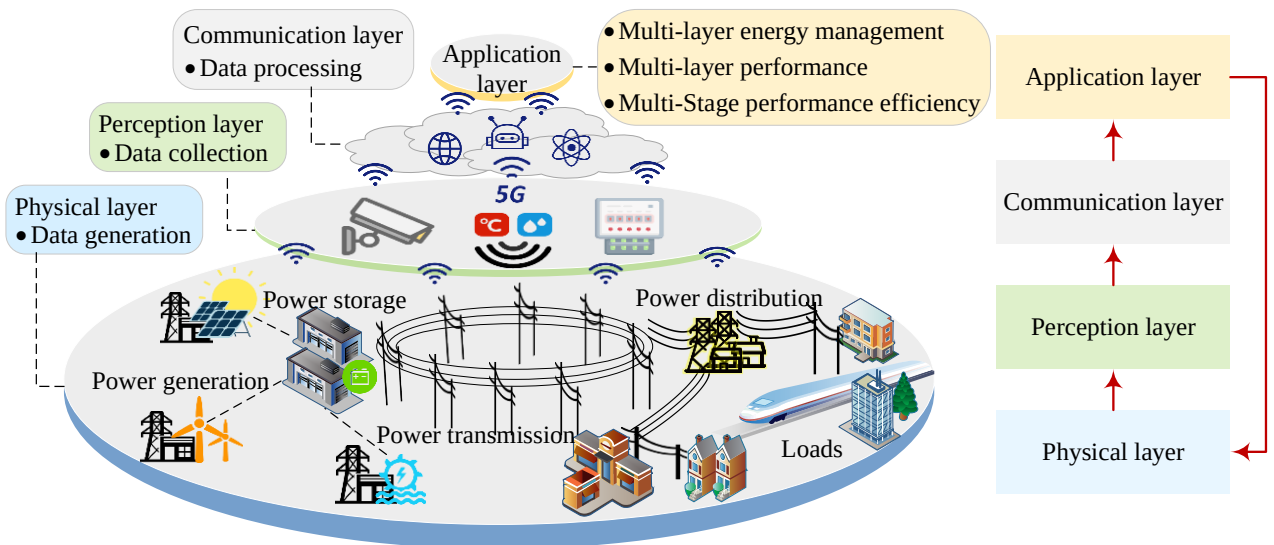


Fig.1. A multi-layer energy architecture.

As shown in Fig.1, the functions within each layer are relatively independent. The different layers interact and share information through communication paths. The details of physical layer, perception layer, communication layer and application layer are shown below.

(1) Physical layer. The physical layer is the lowest layer in a SM. The photovoltaic unit, wind turbine unit, hydro turbine unit, etc. in the physical layer of SMs can be regarded as the power generation unit. In addition, there are power storage equipment, power transmission equipment, power distribution equipment and loads, where the loads include domestic loads, industrial loads, commercial loads, public loads, etc. All of equipment can generate data.

(2) Perception layer. The main mission of the perception layer is to collect environmental data and equipment data of SMs through various smart sensors and other data acquisition devices, and to transmit these data to the superiors. The operation of SMs relies on the application and deployment of sensors. Sensors include remote terminal devices (e.g., light sensors, etc.) for SM operation and maintenance measurement systems and smart meters for individual user measurement systems.

(3) Communication layer. The communication layer firstly transmits massive data to the cloud servers based on information and communication technology, such as mobile communication network, Internet, Bluetooth, Wi-Fi, etc. The collected data are stored, processed and analysed to achieve data updating and expansion, making the microgrid smarter.

(4) Application layer. The application layer is at the top of the SM, which is a collection of solutions that fully integrates IoT and power industry domain technology to achieve a wide range of intelligent applications. The role is to analyse the data of the physical layer in the five major steps of “generation, transmission, transformation, distribution and use” in an all-round and multi-scale manner, and to develop multi-layer energy management programme. Further, the SM can better contribute to urban management, green agriculture, industrial monitoring, telemedicine, intelligent transportation, environmental monitoring, etc.

Based on the above multi-layer energy architecture, the SM model is established. A SM with the multi-layer energy architecture can be a multi-layer directed heterogeneous network consisting of nodes and edges with different functions. Based on the characteristics of the complex network model, SM are defined as $W = (G, E, \phi)$. $G = \{G_g; g \in \{O, P, C, A\}\}$ denotes the set of the multi-layer energy architecture of the SM. Specifically, G_O denotes the physical layer of the SM. G_P denotes the perception layer of the SM. G_C denotes the communication layer of the SM. G_A denotes the application layer of the SM. $G_g = (V_g, E_g)$. $V_g = \{v_i^g; i = 1, 2, \dots, I\}$ denotes the set of nodes in the layer G_g of a SM, where v_i^g is the i -th node of the layer G_g and I is the total number of nodes in the layer. $E = \{e_{ij}^g; i = 1, 2, \dots, I; j = 1, 2, \dots, J\} \cup \{e_{ij}^{gh}; i = 1, 2, \dots, I; j = 1, 2, \dots, J\}$ denotes the set of edges of the SM, where e_{ij}^g is the edge connecting two nodes in the same layer and e_{ij}^{gh} is the edge connecting two nodes in different layers. $\phi = \{\phi_{gh}; g, h \in \{O, P, C, A\}\}$ is the set of communication connectivity relationships between different layers of the SM. $\phi_{gh} = [\phi_{ij}^{gh}]_{I \times J}$.

$$\phi_{ij}^{gh} = \begin{cases} 1, & v_i^g \xrightarrow{yes} v_j^h \\ 0, & v_i^g \xrightarrow{no} v_j^h \end{cases}, \text{ where } v_j^h \text{ is the } j\text{-th node of the layer } G_h.$$

The multi-layer energy architecture cooperates with each other to perform specific operation mission, sequentially completing microgrid operation, data collection, data processing, and solution application. The operation loop about the multi-layer energy architecture in the SM is expressed as $G_O \rightarrow G_P \rightarrow G_C \rightarrow G_A \rightarrow G_O$, which is shown as a closed loop on the right side of Fig.1. The meaning of the symbols in the Table 1.

Table 1. The meaning of the symbols of an operation loop about the multi-layer energy architecture.

Symbol	Meaning
$G_O \rightarrow G_P$	The perception layer uses sensing equipment (e.g., cameras and sensors, etc.) to collect the operational data from the physical layer in the SM.
$G_P \rightarrow G_C$	The communication layer receives the data from the perception layer.
$G_C \rightarrow G_A$	The communication layer delivers its processed cloud data to the application layer.
$G_A \rightarrow G_O$	The application layer comprehensively analyses the cloud data to develop the multi-stage multi-layer synergistic operation programme and act on the physical layer.

For example, a risk occurs in the physical layer at a certain moment. The perception layer transmits the data it collects about the operational state of the physical layer to the cloud servers in the communication layer. The communication layer further transmits the processed cloud data to the application layer. The application layer compares real-time data with historical data to find anomalies in the physical layer. Based on the data characteristics of the anomalies, solutions suitable for the physical layer of the SM at the next moment are developed combined with the real-time state of the physical layer. The solutions are delivered to the physical layer for adjustment, thus improving the operation capability of the SM.

2.2 Data transmission under the synergistic operation in multi-layer energy management

The data layer of a SM refers to the perception layer, the communication layer and the application layer. The failure mechanism analysis of the data layer focuses on the communication path from perception layer to communication layer, the communication path from communication layer to application layer, and the equipment required for the functioning of the data layer. The communication path from perception layer to communication layer refers to specific paths for the signals from perception equipment to the communication equipment. The communication path from communication equipment to application layer refers to specific paths for the signals from communication layer to the application layer. The communication paths play an important role in the data transmission process of the SM. The failure process of communication paths in the SM is shown below: data transmission over communication paths is often limited by extreme weather and cyber-attacks. For example, hurricanes bring particles such as dust or water droplets into the atmosphere. These particles absorb or scatter signals. Signal attenuation can cause communication paths to fail, resulting in data transmission failures. Inevitably, the equipment in the data layer fail to perform their mission for a number of reasons, including internal degradation (e.g., aging, wear, tear, loose, etc.), natural disasters (e.g., snowstorm, lightning, hurricane, etc.), and cyber-attacks.

The physical layer of the SM consists of distributed generation equipment (e.g., photovoltaic units, wind turbine units and hydraulic turbine units, etc.), transmission equipment, distribution equipment, and storage equipment. Adverse weather, natural disasters and internal degradation may lead to abnormal operation of SMs. The physical layer is the foundation of a SM. The failure of equipment within this layer has a significant impact

on the other layers. The manifestations of failure for each type of equipment in physical layer are specified below: photovoltaic units are affected by weather changes. When it is sunny, the photovoltaic panels generate electricity power. Because the length of daytime is relatively short in winters and long in summers, there is a seasonal trend in the electricity power generating capacity from photovoltaic units. The design of wind turbine units is based on a specific range of wind speeds. Wind speed that is too high or too low can affect the performance of the wind turbine. When the wind speed is below the lower threshold limit, the wind turbines may not be able to produce sufficient electricity power output. When the wind speed exceeds upper threshold limit, the wind turbines are damaged due to overloading. In addition, temperature, humidity, and grid frequency, etc. all affect the normal operation of wind turbines. Hydraulic turbine units are affected by drought disasters. Hydraulic turbines stop generating electricity power during periods of drought. Hydropower is more stable and less sensitive to seasons and weather than photovoltaic and wind power. Power transmission and distribution equipment is exposed to the external environment for long periods and is influenced by all kinds of severe weather and natural disasters. Internal natural degradation such as ageing, loose, wear and tear can also lead to equipment failure.

Multi-layer data transmission process is shown as Fig.2. Failures can occur at both the physical and data layers. Uncertain environments make equipment susceptible to damage from internal and external factors and cause interruptions in data transmission between different layers, which in turn allows failure to propagate upwards.

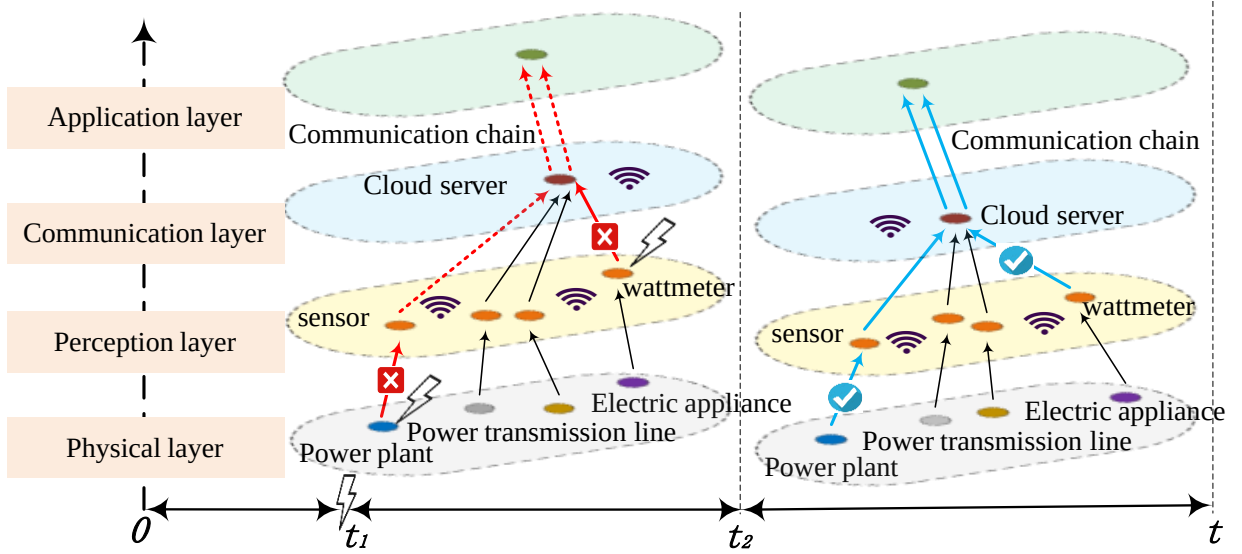


Fig.2. Multi-layer data transmission process.

Define performance degradation as the decline in the synergistic operation capability among the SM's multiple layers. The total performance degradation within the SM denoted by $D(t)$ in the period $[0, t] (t \leq t_2)$ is

$$D(t) = D_1(t) + D_2(t), \quad (1)$$

where $D_1(t)$ is the internal natural degradation within the SM and $D_2(t)$ is external stochastic degradation caused by extreme weather, natural disasters, and cyber-attacks. The SM is failure-tolerant and preventive, which is able to continue normal operation in the event of a partial failure without causing the SM to completely collapse or become inoperable. Through the redundancy design of equipment, the SM is then failure-tolerant,

thereby improving stability and reliability and ensuring that the system remains partially or fully functional in the face of problems. Therefore, D_0 is defined as the degradation threshold of the SM. $D(t) > D_0$ indicates that at the t -th moment the SM is no longer able to prevent the overall performance degradation.

Assuming that the internal natural degradation within the SM is modelled non-linearly and fitted with an exponential distribution. The internal natural degradation within the SM is

$$D_1(t) = f_0(1 - e^{-\lambda t}), \quad (2)$$

where f_0 is the initial performance of the SM and λ is internal natural degradation rate of the SM.

The external stochastic degradation, denoted by $D_2(t)$, is calculated by

$$D_2(t) = \sum_{i=1}^{N_t} d_i, \quad (3)$$

where $d_i \sim N(\mu_d, \sigma_d^2)$ represents the performance degradation value of the i -th external stochastic risk, obeying a normal distribution. N_t is the number of external stochastic risks occurrences within the SM during the period $[0, t]$, obeying a Poisson distribution. Since external stochastic risk exacerbates the degradation rate, define the average number of external stochastic risks occurrences as $\mu_d = g(\theta, N_t)$. θ is risk level. The set of risk level is $\Theta = \{1, 2, 3, 4, 5\}$. $\theta = 1$ represents the lowest risk level, which causes less negative impact on the SM. $\theta = 5$ indicates the highest risk level and a high negative impact on the SM.

3 Multi-layer performance modelling in multi-stage energy management for SMs

3.1 Multi-layer performance

There are four types of edges in the multi-layer directed heterogeneous network of SM. These edges correspond to the four symbols in Table 1 respectively. The edge quality directly affects the stability and efficiency of data transmission between different layers of the SM. High quality edges usually mean short communication time, low packet loss ratio, and large bandwidth availability. Additionally, quality edges reduce the bit error rate, which ensures the integrity and accuracy of data in the SM during transmission. Therefore, communication time, packet loss ratio, bandwidth availability and bit error rate of the SM are important to ensure the edge quality, which can effectively improve the performance of the SM. SMs are similar to dynamic complex networks in that the edge quality changes as nodes or edges fail or are repaired. Therefore, the quality of the edge e_{ij}^{gh} connecting the i -th node v_i^g in the layer G_g to the j -th node v_j^h in the layer G_h , denoted by $Q(e_{ij}^{gh})$, is expressed as

$$Q(e_{ij}^{gh}) = \Pr\{T_{ij}^{gh} \leq T_0\} \times \Pr\{PL_{ij}^{gh} \leq PL_0\} \times \Pr\{B_{ij}^{gh} \geq B_0\} \times \Pr\{ER_{ij}^{gh} \leq ER_0\}, \quad (4)$$

where $T_{ij}^{gh} \sim N(\mu_T, \sigma_T^2)$ represents the communication time in two neighbouring layers, obeying normal distribution. T_0 is the threshold for communication time. T_{ij}^{gh} is no greater than T_0 in quality edges. $PL_{ij}^{gh} \sim P(\overline{PL})$ represents packet loss ratio of an edge, obeying Poisson distribution with parameter $\overline{PL}$ in times/sec. PL_{ij}^{gh} is no greater than PL_0 in quality edges. Bandwidth, denoted by $BW_{ij}^{gh} \sim N(\mu_{BW}, \sigma_{BW}^2)$, is the maximum data capacity that can be transmitted by the communication path, obeying a normal distribution in Mbps. BW_{ij}^{gh} is no lower than BW_0 in quality edges. Bit error rate, denoted by $ER_{ij}^{gh} \sim \text{Beta}(a_{ER}, b_{ER})$, is the probability that a code element is transmitted incorrectly during data transmission, obeying beta

distribution. ER_{ij}^{gh} is no greater than ER_0 in quality edges.

Let ψ_z denote one of the operation loops in the SM. Then the performance of this operation loop, denoted by $F(\psi_z)$, is expressed as

$$F(\psi_z) = \sqrt[4]{\mathcal{Q}(e_{ij}^{OP}) \times \mathcal{Q}(e_{jk}^{PC}) \times \mathcal{Q}(e_{km}^{CA}) \times \mathcal{Q}(e_{mi}^{AO})}. \quad (5)$$

SMs usually contain many operation loops. The multi-layer synergistic operation capability of a SM is influenced by operation loops. Considering that different operation loops are responsible for different operation missions with different importance, this metric about importance of an operation mission, denoted by ω_z , is used as a weight for the performance of an operation loop. $\omega_z \in [0,1]$. In general, uniform or normal distribution can be used to represent the importance of a mission. If the importance of a mission is uniformly distributed in the interval $[0,1]$, a uniformly distributed random number can be used to describe the importance of the operation mission. More often than not, the importance of an operation mission is influenced by a number of factors and shows the tendency towards concentration. Therefore, this paper uses a normal distribution to generate random numbers to represent the importance of operation missions. $\omega_z \sim N(\mu_\omega, \sigma_\omega^2)$. The multi-layer performance of the SM under normal operating conditions, denoted by $F(W)$, is

$$F(W) = \sum_z \omega_z \times F(\psi_z). \quad (6)$$

3.2 Multi-layer performance in multi-stage energy management

In this paper, the operation of SMs is considered to consist of four stages of energy management: prevention, degradation, restoration, and reconstitution. The multi-stage evolution process of multi-layer performance is modelled based on these four stages of energy management.

Prevention stage of multi-stage energy management is the period before the SM is disturbed by risk. The performance of the SM remains unchanged during this period. The perception layer collects data in real time. Through cloud computing and the flexible application of the historical data, SMs can make reasonable predictions of their futural operation and environmental data, and develop a series of preventive solutions. Once the risk has signs of impeding the normal operation, the SM will activate the corresponding preventive solutions in advance and make actions to resist. The performance of the SM remains unchanged if the risk disturbance to the SM is completely controlled. $f(t) = F(W), t \in [0, t_1)$. Otherwise, the performance of the SM begins to degrade.

In the multi-stage energy management, the performance degradation process is defined as the degradation stage. If the intensity of the risk disturbance is greater than the prevention capability of the SM at the moment t_1 , the multi-layer performance is degraded. The capability to resist of the SM from t_1 to t_2 cancels out some of the effects from the risk disturbance so that the performance of the SM is not degraded to zero. After considering the risk disturbance of SMs, combining equations (2.2), (2.3) and (2.4), the multi-layer performance of SMs in the degradation stage of multi-layer energy management is $f(t) = F(W) - D(t), t \in [t_1, t_2)$.

In the restoration stage of multi-stage energy management, the SM starts to implement restoration strategies at the moment t_2 . If the capability to restoration is greater than the intensity of the risk disturbance,

the performance of the SM will continue to improve. At the moment t_3 , the restoration of the SM is close to saturation and the rate of performance enhancement decreases abruptly. Even if similar restoration strategies continue, the performance of SM rises slowly or even stops. Considering that the multi-layer performance enhancement in the restoration stage has a saturated state, a Logistic growth model is fitted to the multi-layer performance restoration, denoted by $h(t) = \frac{K}{1 + \mathcal{A}e^{-\mathcal{B}t + \mathcal{C}}}$. K is the maximum threshold for multi-layer performance enhancement (i.e., the maximum saturation value). $\mathcal{A}$ and $\mathcal{B}$ are positive constant numbers that affect the rate of growth and the shape of the growth curve respectively. $\mathcal{C}$ is constant number. Further, the multi-layer performance in the restoration stage of multi-stage energy management is $f(t) = f(t_2) + h(t), t \in [t_2, t_3]$.

If the SM does not recover the expected multi-layer performance in the restoration stage of multi-stage energy management, the reconstitution strategies begin to be implemented at the moment t_3 . By adjusting the SM network composition or topology, the saturated state in the restoration stage of multi-stage energy management is breached and performance of the SM is further improved. The multi-layer performance of the SM is restored to be as good as, or even better than, the initial multi-layer performance at the moment t_0 . For the convenience of research, this paper assumes that the multi-layer performance improvement in the reconstitution stage of multi-stage energy management conforms to a logarithmic model. The time interval of the reconstitution stage is $[t_3, t_4]$. The multi-layer performance improvement of the SM is represented as $\hbar(t) = \nu \log_a(v(t - t_3))$. ν controls the longitudinal stretching or compression of the logarithmic curve, which affects the growth rate. v controls the horizontal shift of the logarithmic curve, which affects the starting point of the curve. a and $v(t - t_3)$ are the base and true of the logarithmic function respectively. Further, the multi-layer performance in the reconstitution stage of multi-stage energy management is $f(t) = f(t_3) + \hbar(t), t \in [t_3, t_4]$. At the moment t_4 , the SM ends its reconstitution, completes the multi-stage multi-layer performance evolution and starts normal operation.

In summary, the multi-layer performance of SMs in the multi-stage energy management is

$$f(t) = \begin{cases} F(W), & t_0 \leq t < t_1 \\ f(t_1) - D(t), & t_1 \leq t < t_2 \\ f(t_2) + h(t), & t_2 \leq t < t_3 \\ f(t_3) + \hbar(t), & t_3 \leq t \leq t_4 \end{cases} \quad (7)$$

4 Multi-stage multi-layer performance approach of SMs

Based on the four stages of multi-stage energy management including prevention, degradation, restoration, and reconstitution, four metrics are proposed: avoidance metric, robustness metric, recovery metric, and reconstitution metric to quantify the evaluation for the performance of SMs at each stage. Fig.3 shows the performance evolution of a SM based on four metrics in multi-stage energy management.

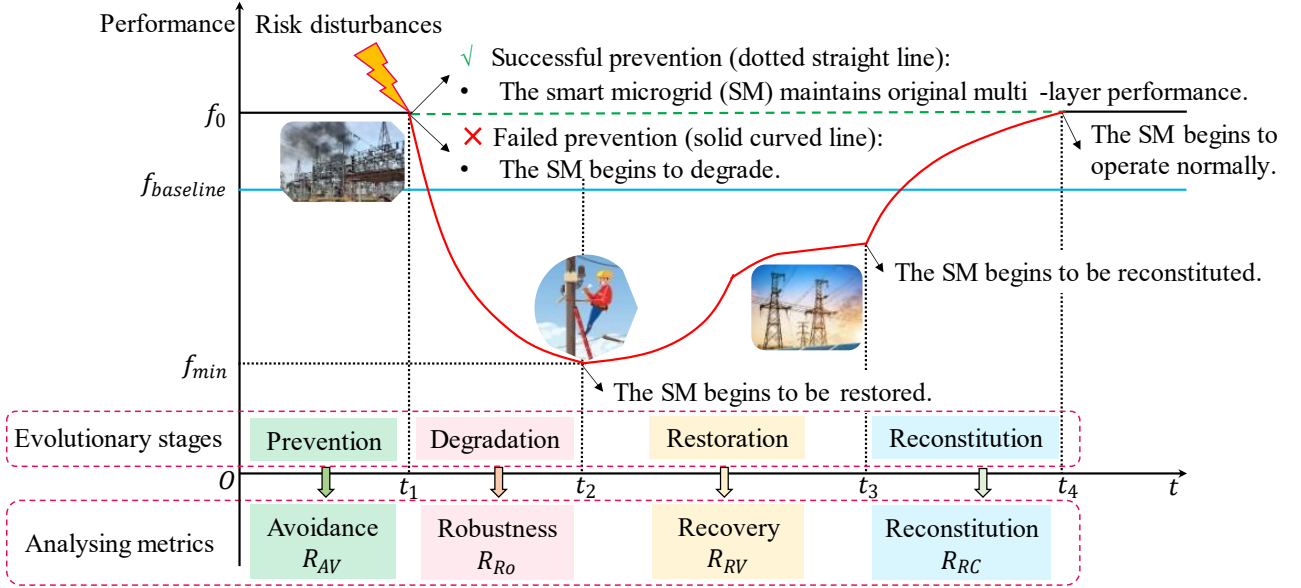


Fig.3. Performance evolution based on four metrics in multi-stage energy management.

It is worth noting that the multi-stage multi-layer performance evolution curve for the four stages is only a schematic diagram. In reality, not every SM will go through all four stages, and the rate of multi-layer performance change at each stage will vary widely.

4.1 Avoidance metric in the prevention stage of multi-stage energy management

Avoidance metric is used in the prevention stage of multi-stage energy management, which demonstrates the ability to autonomously prevent failures and stop them from having a negative impact on the SM in advance. The preventive capability of a SM is based on accurate prediction and analysis of external disasters or internal faults in order to take timely and effective protection and control measures. If SMs can accurately predict the coverage of external disasters, they can prepare for protection in advance and strengthen their monitoring, early warning and response capabilities, thus reducing the damage caused by disasters to SMs. Similarly, if SMs can take timely measures for preventive equipment maintenance, the effects of equipment wear and aging can be avoided. Therefore, the assessment of avoidance metric for SMs needs to consider risk prediction capability, equipment monitoring capability, system early warning capability and ex-ante response capability. The avoidance metric of the SM in the prevention stage of multi-stage energy management, denoted by R_{AV} , is

$$R_{AV} = p_1 \times p_3 \times p_4 + (1 - p_1) \times p_2 \times p_3 \times p_4, \quad (8)$$

where p_1 represents risk prediction capability of the SM. p_2 represents equipment monitoring capability of the SM. p_3 represents early warning capability of the SM. p_4 represents ex-ante response capability of the SM.

The preventive capability of SMs is related to the ability to predict internal and external risks. In SMs, risk prediction probability and threshold can be used to measure the ability to prevent disasters such as hailstorms, hurricanes, and earthquakes. In this paper, the risk prediction capability of the SM is expressed as $p_1 = \Pr\{\varepsilon_1 \geq \kappa_1\}, p_1 \in [0,1]$. Since the beta distribution is often used to fit various probability distributions over the interval $[0,1]$, the prediction probability of internal and external risks, i.e., the likelihood of a risk occurring, is denoted by $\varepsilon_1 \sim \text{Beta}(a_1, b_1)$. The average of this beta distribution is $a_1/(a_1 + b_1)$. κ_1 is risk

threshold, i.e., the maximum probability of occurrence of a risk that the SM can withstand. The risk threshold can be viewed as a decision point. When the prediction probability of a certain risk is higher than this risk threshold, the corresponding ex-ante protection action in the SM is triggered.

The preventive capability of SMs is related to the ability of the SM to monitor the operational status of equipment. Equipment monitoring frequency and threshold can be used to measure the equipment monitoring capability. By real-time monitoring of equipment work status, temperature, vibration and other indicators, preventive measures can be taken to avoid negative impact before failures occur. In this paper, the equipment monitoring capability of the SM is expressed as $p_2 = \Pr\{\varepsilon_2 \geq \kappa_2\}, p_2 \in [0,1]$. $\varepsilon_2 \sim P(\bar{\varepsilon}_2)$ represents the monitoring frequency obeys a Poisson distribution with parameter $\bar{\varepsilon}_2$, where $\bar{\varepsilon}_2$ is the average number of occurrences of random events per unit of time. κ_2 is the maximum threshold for monitoring frequency.

The preventive capability of SMs is related to the early warning capacity of SMs for imminent risks. The missed alarms rate, which indicates the proportion of risk disturbances that actually occur but for which the SM fails to issue an alert, can be used as a measure of the SM's early warning capability. This paper introduces the system alert sensitivity of the SM and corresponding threshold. When the alert sensitivity is less than its threshold, it usually indicates that the SM will give less alert to risk disturbances than the normal. The SM may miss important events, resulting in an increased rate of missed alarms. The missed alarms rate is the proportion of positive samples that are predicted to be negative as a percentage of the total positive samples, namely, the number of missed alarms (i.e., the number of anomalous events is not warned) as a percentage of the total number of anomalous events. In this paper, the early warning capacity of the SM is expressed as $p_3 = 1 - \varepsilon_3/\kappa_3, p_3 \in [0,1]$. $\varepsilon_3 \sim P(\bar{\varepsilon}_3)$ represents the number of missed alarms obeys a Poisson distribution with parameter $\bar{\varepsilon}_3$. $\kappa_3 \sim P(\lambda)$ represents the number of anomalous events.

The preventive capability of SMs is related to the ex-ante response capability of SMs for imminent risks. The ex-ante response capability refers to the ability to prepare and be able to respond quickly and effectively to internal and external risks before risks occur, which can be measured by preventive response time and risks occurrence time in SMs. Firstly, preventive response time is the time between the moment when a risk is predicted and the moment when the SM responds. An efficient SM quickly initiates protective actions when risks are predicted and takes effective measures to address potential risks. Secondly, risks occurrence time is the time between the moment when a potential risk is first detected and the moment when the risk occurs. During the prevention stage, the SM can adjust earlier and respond more quickly by predicting the possible time of risk occurrence, thus effectively minimising the loss and adverse impact of risks. Therefore, the preventive response time and risks occurrence time are important indicators of the SM's ex-ante response capability, which reflects the SM's flexibility in responding to potential risks. In this paper, the ex-ante response capability of the SM is expressed as $p_4 = \Pr\{\varepsilon_4 \leq \kappa_4\}, p_4 \in [0,1]$. $\varepsilon_4 \sim U(\varepsilon_{4L}, \varepsilon_{4U})$ represents preventive response time obeying uniform distribution in the intervals $[\varepsilon_{4L}, \varepsilon_{4U}]$. $\kappa_4 \sim \exp(1/\lambda)$ represents risks occurrence time obeying exponential distribution.

4.2 Robustness metric in the degradation stage of multi-stage energy management

If a SM fails to prevent risks at the moment t_1 , it enters the degradation stage of multi-stage energy management. The SM will quickly move into a defensive state when it encounters a risk disturbance. Although

the effects of risk disturbances cannot be completely cancelled out, the SM can weaken the negative effects of disturbances to some extent. Under the combination of disruptive risks and resistive behaviours, the multi-layer performance of the SM decreases to a certain threshold f_{min} instead of 0.

The robustness metric is used to assess the multi-layer performance evolution in the degradation stage of multi-stage energy management, indicating the ability of SMs to perform missions even when failures occur. Considering the SMs' capability to resist and redundancy requirements, this paper introduces the resistance coefficient and redundancy coefficient. The resistance coefficient, denoted by α_1 , is defined as the ratio of the multi-layer performance before and after the SM resists risk disturbances in the degradation stage. $\alpha_1 = f(t_2)/f(t_1)$, where $f(t_2)$ and $f(t_1)$ are the multi-layer performance at the moment t_2 and t_1 respectively. Redundancy describes replaceable functions and designs in the SM's operation. Redundancy is designed to better fulfil the power supply mission, which allows SMs to maintain a level of multi-layer performance that exceeds mission baseline. The redundancy coefficient is denoted by α_2 . $\alpha_2 = (f_0 - f_{baseline})/f_{baseline}$, where f_0 and $f_{baseline}$ are the initial multi-layer performance and the mission baseline of the SM. The larger α_2 is, the higher the redundancy of the SM, which has a positive effect on the multi-layer performance of the SM. Therefore, the robustness metric R_{RO} for the performance efficiency in the degradation stage of multi-stage energy management in the SM can be expressed as

$$R_{RO} = \frac{\int_{t_1}^{t_2} f(t)dt}{f_0 \cdot (t_2 - t_1)} \times \alpha_1 \times (1 + \alpha_2). \quad (9)$$

4.3 Recovery metric in the restoration stage of multi-stage energy management

The recovery metric is used to assess the multi-layer performance evolution in the restoration stage of multi-stage energy management, which indicates how much or how quickly multi-layer performance can be recovered after SMs failure. During the actual operation of SMs, the restoration time endpoint is often uncertain. The focus of this paper is on the ability to fulfil the power supply mission of SMs. Considering the impact of mission baseline on mission completion of SMs, β is introduced to denote the recovery coefficient of SMs.

$$\beta = \begin{cases} \frac{f(t_3)}{f_{baseline}}, & 0 \leq \frac{f(t_3)}{f_{baseline}} < 1 \\ 1, & \frac{f(t_3)}{f_{baseline}} \geq 1 \end{cases}, \quad (10)$$

where $f(t_3)$ is the multi-layer performance of the SM at the moment t_3 . The larger β indicates a better recovery of the SM, having a positive impact on the performance enhancement of the SM. Therefore, the recovery metric R_{RV} for the performance efficiency in the restoration stage of multi-stage energy management in the SM can be calculated as

$$R_{RV} = \frac{\int_{t_2}^{t_3} f(t)dt}{f_0 \cdot (t_3 - t_2)} \times \beta. \quad (11)$$

4.4 Reconstitution metric in the reconstitution stage of multi-stage energy management

The reconstitution metric is used to assess the multi-layer performance evolution in the reconstitution stage of multi-stage energy management, which indicates the structural reconstitution ability of SMs to cope with failures. Considering the different reconfiguration starting point and the different reconfiguration end

point in the different SMs, γ is introduced to denote the reconstitution coefficient of SMs. $\gamma \in [0,1]$. If $f(t_3) \geq f_{baseline}$, SMs do not need to be reconstituted to meet the multi-layer performance requirements. If $f(t_3) < f_{baseline}$, reconstitution strategies for SMs need to be considered. The multi-layer performance endpoint after reconstitution of a SM (i.e., the multi-layer performance at the moment t_4), denoted by $f(t_4)$, is often uncertain and may still be smaller than the mission baseline. But it is also possible that the reconstitution is extremely effective, making $f(t_4) > f_0$. Therefore, considering the mission baseline and the initial multi-layer performance, the reconstitution coefficient is expressed as

$$\gamma = \begin{cases} \frac{f(t_4)^2}{f_0 \cdot f_{baseline}}, & f(t_3) < f(t_4) < f_{baseline} \\ \frac{f(t_4)}{f_0}, & f(t_3) < f_{baseline} \leq f(t_4) < f_0 \\ 1, & f(t_3) \geq f_{baseline} \text{ or } f(t_4) \geq f_0 \end{cases} \quad (12)$$

Therefore, the reconstitution metric R_{RC} for the performance efficiency in the reconstitution stage of multi-stage energy management in the SM can be calculated as

$$R_{RC} = \frac{\int_{t_3}^{t_4} f(t) dt}{f_0 \cdot (t_4 - t_3)} \times \gamma. \quad (13)$$

4.5 Multi-stage comprehensive performance approach of SMs

The multi-stage comprehensive performance efficiency metric system for SMs includes avoidance metric R_{AV} , robustness metric R_{RO} , recovery metric R_{RV} , and reconstitution metric R_{RC} . Four multi-layer performance evolution for SMs, with coherent timing and interrelated behaviours, are dedicated to prevention, resist, recovery and reconfiguration of SMs. Evaluating the overall performance of the complex systems like SMs is a very complex work, and there is no authoritative methodology for doing so. Based on these metrics in the multi-stage energy management, the following comprehensive performance efficiency model for SMs is proposed to evaluate the multi-stage multi-layer performance in this paper. The multi-stage comprehensive performance efficiency, denoted by R , is defined as

$$R = \sqrt[4]{R_{AV} \times R_{RO} \times R_{RV} \times R_{RC}} \quad (14)$$

where $R_{AV} \in [0,1]$, $R_{RO} \in [0,1]$, $R_{RV} \in [0,1]$, and $R_{RC} \in [0,1]$. Thus, $R \in [0,1]$. The closer R is to 0, the weaker the SM's ability to prevent, resist, restore and reconstitute in the face of risk disturbances. Further, the multi-layer performance is lower, and the multi-stage comprehensive performance efficiency of SMs is worse. $R = 1$ shows that SMs experience no loss of multi-layer performance when exposed to risk disturbances and have the greatest multi-stage comprehensive performance efficiency.

By the Monte Carlo method, the steps for solving the multi-layer performance and the multi-layer comprehensive performance efficiency of SMs based on operation loop are as follows.

Step 1. Establish the multi-layer energy architecture of a SM and input model parameters.

Step 2. Calculate the edge quality, the operation loop performance, and the multi-layer performance of the SM under normal operating conditions.

Step 3. Simulate the multi-stage multi-layer performance evolution of SMs and calculate the multi-layer performance of degradation, restoration and reconstitution stages sequentially.

Step 4. Calculate the avoidance metric, robustness metric, recovery metric, and reconstitution metric in the multi-layer energy management.

Step 5. Calculate the multi-stage comprehensive performance efficiency of a SM.

5 Case study

5.1 Description of case scenarios

Shandong Province is located on the eastern coast of China, in the lower Yellow River plains region and adjacent to the Yellow Sea, with a favourable geographical position. The province is rich in natural resources, including renewable energy resources such as wind and solar. It is an important industrial base and economic centre in China, with a high demand for electricity power, but also facing challenges such as pressure on energy supply and energy security. Shandong Province uses intelligent sensing, information communication and automatic control technology, etc. as support to enhance the intelligence of microgrids. In recent years, this Province has taken wind power and photovoltaic power as the focus, supplemented by biomass, geothermal energy and ocean energy, to promote diversified and synergistic development of renewable energy. The average annual growth rate of installed capacity of new energy-related equipment in Shandong Province exceeds 30%. By the end of October 2023, the total installed capacity of wind power and photovoltaic power reached 77.92 million kilowatts in Shandong Province, ranking first among all provinces in China. The wind power installed capacity of 24.75 million kilowatts ranked fourth in China. The photovoltaic installed capacity of 53.17 million kilowatts accounted for about 1/5 of the national photovoltaic power generation capacity, ranking first in China. The data is from http://www.shandong.gov.cn/art/2023/11/26/art_97904_619158.html. Wind power equipment is distributed in Shandong Province is in Yantai city, Binzhou city, Dongying city, etc. Solar energy equipment is distributed in Jinan city, Qingdao city, Jining city, etc. Pumped-storage power stations are in Tai'an city, Weifang city and other cities. The detail information about the layout of clean energy is from http://www.shandong.gov.cn/art/2021/8/13/art_307622_10331955.html. Fig.4 shows the layout of a part of large-scale clean energy bases in Shandong Province.

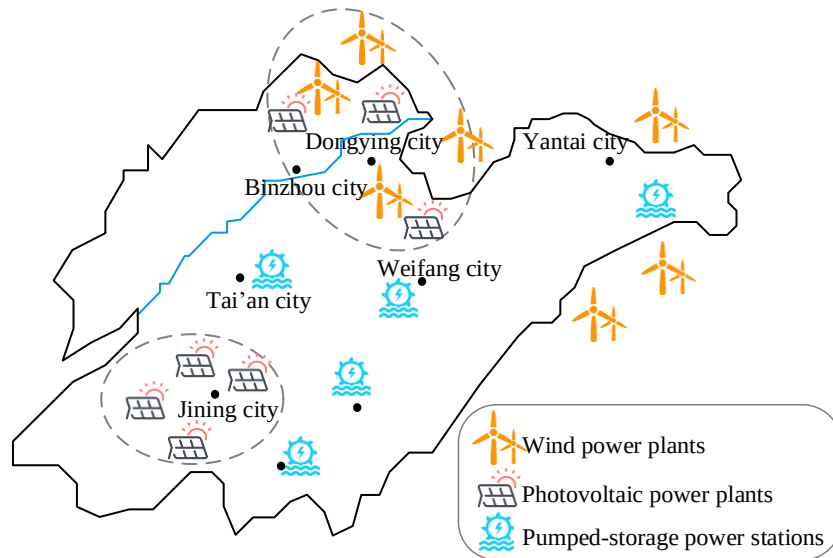


Fig.4. A schematic diagram of the layout of large-scale clean energy bases in Shandong Province.

In this paper, the SM in Shandong Province are modelled as physical layer, perception layer, communication layer and application layer. The edge quality of the different layers in the SM is related to the

communication time, packet loss ratio, bandwidth availability and bit error rate of the corresponding communication path. The parameters of the sampling distribution in the Monte Carlo method are obtained by analysing the online data set from <https://bnn.upc.edu/challenge/gnnnet2021/dataset/>. The communication time is $T_{ij}^{gh} \sim N(83.25, 11.19)$, including the time for signal reception, transmission, processing and network delays. The threshold of communication time is $T_0 = 93.125ms$. The packet loss ratio is $PL_{ij}^{gh} \sim P(7.3 \times 10^{-2})$, considering the effect of data traffic strength, network congestion, operational errors, distance and latency, buffer size, the total number of packets sent, and any other special adjustments. The threshold of the packet loss ratio is $PL_0 = 7.9 \times 10^{-2}$. The bandwidth is $BW_{ij}^{gh} \sim N(333.60, 51.41)$, considering the influence of basic bandwidth capacity, network latency, data transfer efficiency, hardware performance, network stability and external environmental conditions. The threshold of bandwidth is $BW_0 = 291.25$. The bit error rate is $ER_{ij}^{gh} \sim Beta(3.56, 345.89)$, obeying beta distribution. The threshold of the bit error rate is $ER_0 = 0.05$. The importance of missions, i.e. the operation loop weight, is $\omega_z \sim N(0.5, 0.1)$.

In 2023, natural disasters in Shandong Province of China were dominated by hailstorms and floods, with snowstorms, earthquakes and fires in forests and grasslands occurring to varying degrees. The spatial and temporal variability of natural disasters is obvious, and generally lighter than the normal. A total of 16 strong convective weather (e.g., thunderstorms, hurricanes, hailstorms) occurred. On 6 August 2023, a magnitude 5.5 earthquake struck Pingyuan County, Dezhou City, Shandong Province. The quake was 10 kilometres deep and was the strongest earthquake in Shandong Province in 28 years. Throughout 2023, various natural disasters in Shandong Province affected 152,800 people and caused direct economic losses of 479 million (Chinese Renminbi). The date is from http://yjt.shandong.gov.cn/zwgk/zdly/fzjz/zhjz/202403/t20240320_4713446.html.

Based on the above description about SMs in Shandong Province, China, the multi-layer performance of SMs under normal operating conditions (scenario 1) is analysed in section 5.2. And the multi-stage multi-layer performance of SMs under different types of disasters (scenario 2) is analysed in section 5.3, where the section 5.3.1 and section 5.3.2 focus on general disasters with sustained impacts (e.g., hailstorms) and severe disasters with instantaneous impacts (e.g., earthquakes), respectively.

5.2 Under scenario 1

Based on equation (6), the multi-layer performance of the SM is $F(W) = 576.6795$. Namely, the initial multi-layer performance is $f_0 = 576.6795$. Let the mission baseline is $f_{baseline} = 0.8f_0 = 461.3436$. The sensitivity analysis is carried out tailored for communication time T_{ij}^{gh} , packet loss ratio PL_{ij}^{gh} , bandwidth BW_{ij}^{gh} and bit error rate ER_{ij}^{gh} . The test schemes are shown in Table 2.

Table 2. Sensitivity analysis test schemes for edge quality parameters.

Test schemes	T_{ij}^{gh}	PL_{ij}^{gh}	BW_{ij}^{gh}	ER_{ij}^{gh}
1	$N(65.25, 11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60, 51.41)$	$Beta(3.56, 345.89)$
2	$N(71.25, 11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60, 51.41)$	$Beta(3.56, 345.89)$
3	$N(77.25, 11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60, 51.41)$	$Beta(3.56, 345.89)$

4	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(3.56,345.89)$
5	$N(86.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(3.56,345.89)$
6	$N(83.25,11.19)$	$P(6.4 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(3.56,345.89)$
7	$N(83.25,11.19)$	$P(6.7 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(3.56,345.89)$
8	$N(83.25,11.19)$	$P(7.0 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(3.56,345.89)$
9	$N(83.25,11.19)$	$P(7.6 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(3.56,345.89)$
10	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(339.60,51.41)$	$Beta(3.56,345.89)$
11	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(345.60,51.41)$	$Beta(3.56,345.89)$
12	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(351.60,51.41)$	$Beta(3.56,345.89)$
13	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(357.60,51.41)$	$Beta(3.56,345.89)$
14	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(1.56,325.89)$
15	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(5.56,365.89)$
16	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(7.56,385.89)$
17	$N(83.25,11.19)$	$P(7.3 \times 10^{-2})$	$N(333.60,51.41)$	$Beta(9.56,405.89)$

For the test schemes given in Table 2, the simulation results about the multi-performance of the SM under normal operating conditions are shown in Fig. 5.

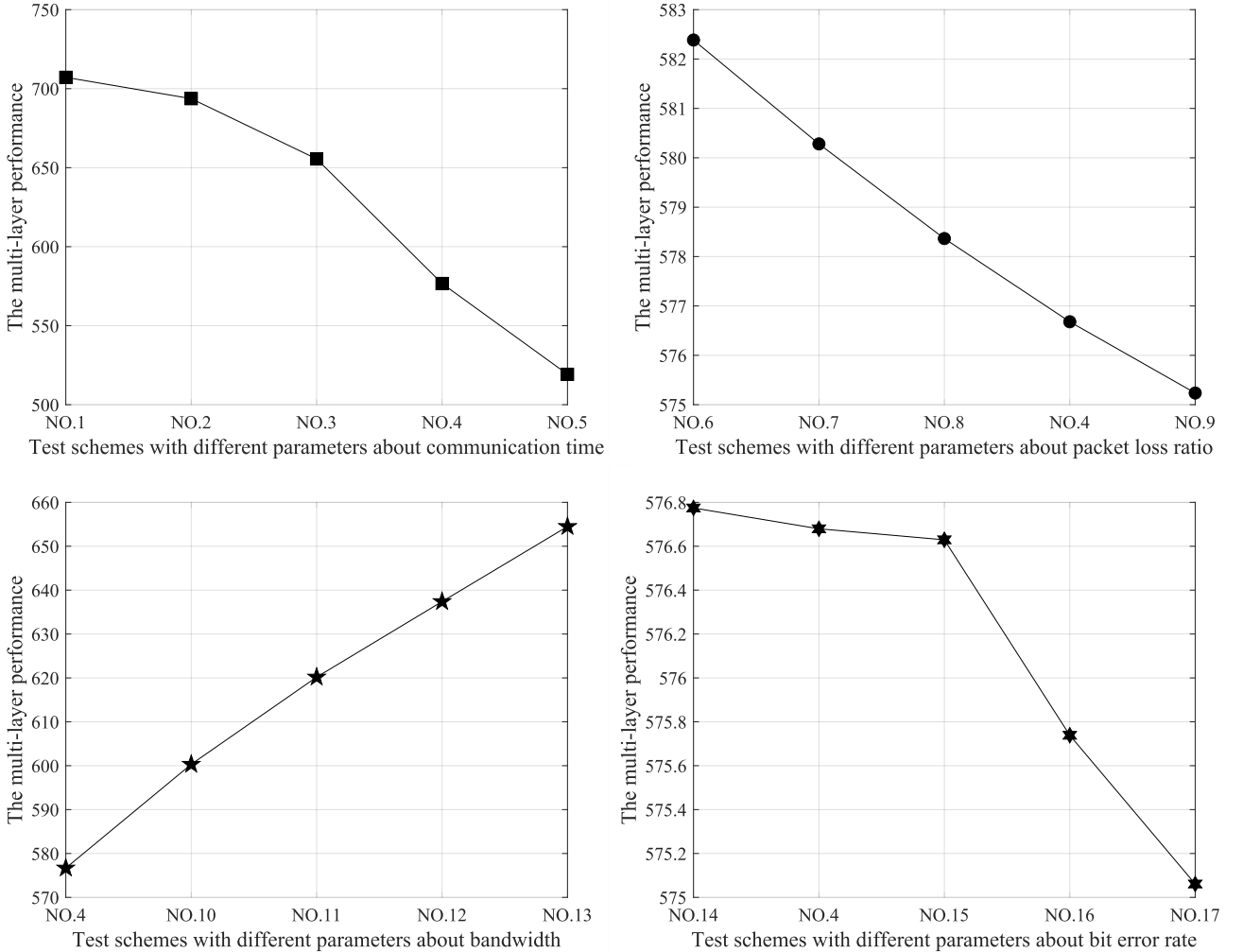


Fig.5. Influence of variations in edge quality parameters on the multi-layer performance of SMs.

In the first set of tests in Fig.5, the focus was on the impact of communication time on the multi-layer performance of the SM under normal operating conditions. The data, e.g., packet loss ratio, bandwidth, bit error rate, and the variance of the normal distribution obeyed by the communication time, are kept constant. And the mean of the normal distribution obeyed by the communication time is increased sequentially from scheme 1 to scheme 5. The results show that as the mean of the communication time increases, the multi-layer performance of the SM decreases.

In the second set of tests in Fig.5, the focus was on the impact of packet loss ratio on the multi-layer performance of the SM under normal operating conditions. The data, e.g., communication time, bandwidth, and bit error rate, are kept constant. And the mean of the Poisson distribution obeyed by the packet loss ratio is increased sequentially for schemes 6, 7, 8, 4 and 9. The results show that as the mean of the packet loss ratio increases, the multi-layer performance of the SM decreases.

In the third set of tests in Fig.5, the focus was on the impact of bandwidth on the multi-layer performance of the SM under normal operating conditions. The data, e.g., communication time, packet loss ratio, bit error rate, and the variance of the normal distribution obeyed by the bandwidth, are kept constant. And the mean of the normal distribution obeyed by the bandwidth is increased sequentially for schemes 4, 10, 11, 12 and 13. The results show that as the mean of the bandwidth increases, the multi-layer performance of the SM increases.

In the fourth set of tests in Fig.5, the focus was on the impact of bit error rate on the multi-layer performance of the SM under normal operating conditions. The data, e.g., communication time, packet loss ratio, and bandwidth, are kept constant. And the parameters of the beta distribution obeyed by the bit error rate is increased sequentially for schemes 14, 4, 15, 16 and 17. The results show that as the parameters of the bit error rate increases, the multi-layer performance of the SM decreases.

Sensitivity analysis is conducted tailored for the operation loop weight, i.e. the parameters of the normal distribution obeyed by the importance of the missions. Parameters of five sensitivity tests are $\omega_z \sim N(0.2, 0.1)$, $\omega_z \sim N(0.35, 0.1)$, $\omega_z \sim N(0.5, 0.1)$, $\omega_z \sim N(0.65, 0.1)$, and $\omega_z \sim N(0.8, 0.1)$. The results are showed in Fig.6.

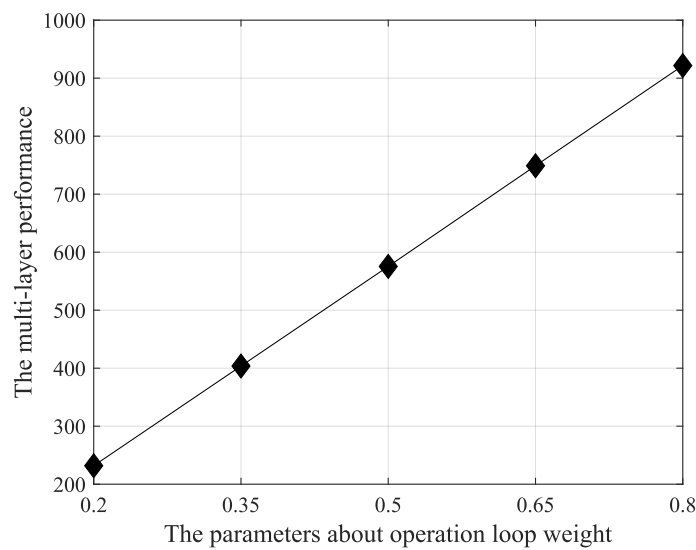


Fig.6. Influence of different operation loop weight parameters on multi-layer performance of SMs.

In Fig. 6, the multi-layer performance of the SM shows a linear growth trend as the parameter, namely the mean of the normal distribution obeyed by the operation loop weights, increases.

5.3 Under scenario 2

5.3.1 General disasters with sustained impacts

The scenario in section 5.3.1 is based on hailstorm disasters that hit Shandong Province in 2023 and has been simulated by Monte Carlo method with appropriate simplifications. The SM operates normally before the moment t_1 and is shocked at moment t_1 . In total, 5 hailstorm disasters occur during the simulation period. Meanwhile, the SM also continues to degrade for internal reasons. When the total degradation of multi-layer performance due to internal and external reasons is greater than degradation threshold ($D_0 = 20$), the SM degrades. The total degradation of multi-layer performance in the SM is calculated by equation (1). The equation (2) is used to calculate internal natural degradation, where $f_0 = 576.6795$ and $\lambda = 3 \times 10^{-3}$. The equation (3) is used to calculate external stochastic degradation, where $d_i \sim N(20, 4.23)$ is the degradation caused by the i -th hailstorm disaster and $N_t = 5$ represents five hailstorm disasters attack. Generally, if the multi-layer performance degrades too much, high-intense emergency restoration is required. But when multi-layer performance declines less relative to the mission baseline, only ordinary maintenance is required to achieve the mission baseline. In the restoration stage, if the multi-layer performance is not less than the mission baseline, the SM do not need to be reconstituted. As long as the multi-layer performance in the restoration stage or the reconstitution stage is not lower than the mission baseline ($f_{baseline} = 461.3436$), this paper considers that the minimum multi-layer performance requirements for the normal operation of the SM have been met. Assume that no performance degradation occurs during the restoration stage or the reconstitution stage.

Because hailstorm disasters are general disasters, the damage in the Fig.7 is not too serious. So low-intensity maintenance strategies in the restoration stage will be used first. Let the saturation value of performance in the restoration stage $K = 50$. The equation (7) is used to calculate multi-stage multi-layer performance, where $h(t) = 50/(1 + 0.59e^{-0.16t+10.90})$, $t \in [t_2, t_3]$. Based on the results of the restoration stage, whether to proceed to the reconstruction stage can be decided. Fig.7 shows the multi-stage multi-layer performance evolution in the SM before, during and after general disasters with sustained impacts.

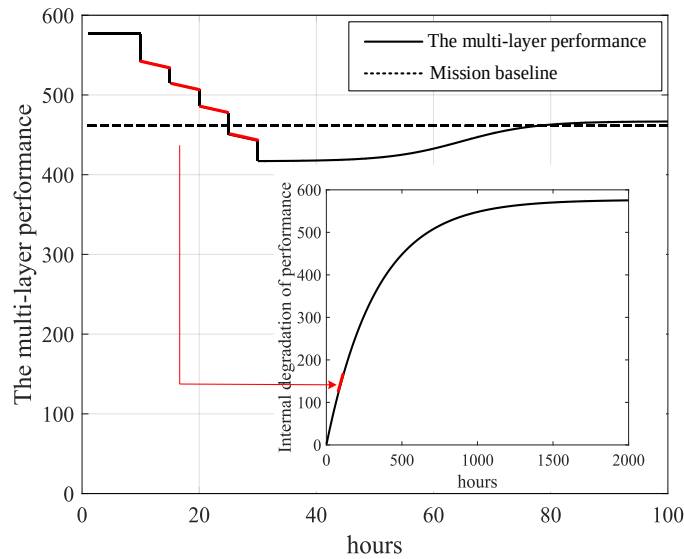


Fig.7. The multi-stage multi-layer performance evolution before, during and after general disasters.

In Fig.7, the SM is in normal operation 10 hours ago. At the 10th hour, the internal degradation of the SM is $D_1(10) = 17.0435$. $D_1(10) < D_0$. Due to the redundancy and robustness, the SM will not degrade. And the SM can still maintain its original operating state. However, a hailstorm disaster attacks at the 10th hour. $D_1(10) + d_1 > D_0$. Therefore, the SM eventually fail to maintain its original multi-layer performance and entered the degradation stage. Then, the SM is attacked by five hailstorm disasters in the 10th to 30th hour. In view of the resistance of the SM, the multi-layer performance degrades to 420.474. In the degradation stage, the internal degradation of the SM occurs simultaneously with the external disasters. However, in the restoration stage, it is assumed that there is no internal degradation of performance and no external disasters occur. The red line in 10-30 hours in the Fig.7 reflects the internal degradation that decreases exponentially, corresponding to the internal degradation of performance in the corresponding period in the lower right corner of this figure. And the same applies to 10-15 hours, 15-20 hours, and 20-25 hours. At the 30th hour, when the multi-layer performance reduces to the minimum value, the SM starts low-intensity maintenance strategies. At 30-50 hours, the multi-layer performance increases slowly. The multi-layer performance grows fast at 50-80 hours. The multi-layer performance reaches mission baseline at around 75th hour. The multi-layer performance can still be improved by maintenance within 80-90 hours, but maintenance is significantly less efficient. Maintenance is terminated at the 90th hour and the SM enters the normal operation stage.

Based on the multi-layer performance before, during and after hailstorm disasters in the SM, the avoidance metric in the prevention stage, robustness metric in the degradation stage, recovery metric in the restoration stage, reconstitution metric in the reconstitution stage, and the multi-stage comprehensive performance efficiency of the SM are analysed.

(1) In the prevention stage. The prediction probability of internal and external risks is $\varepsilon_1 \sim \text{Beta}(8,2)$. By 100000 Monte Carlo simulations, the risk prediction capability is $p_1 = 0.7009$. The equipment monitoring frequency is $\varepsilon_2 \sim P(30)$. By 100000 Monte Carlo simulations, the equipment monitoring capability is $p_2 = 0.4540$. The number of missed alarms is $\varepsilon_3 \sim P(7 \times 10^{-5})$. By 100000 Monte Carlo simulations, the system early warning capability is $p_3 = 0.8194$. The preventive response time is $\varepsilon_4 \sim U(1,48)$. By 100000 Monte Carlo simulations, the ex-ante response capability is $p_4 = 0.9866$. Thus, the avoidance metric is $R_{AV}^{hs} = 0.6764$.

(2) In the degradation stage. The resistance coefficient is $\alpha_1^{hs} = f_{min}/f_0 = 0.7291$. The redundancy coefficient is $\alpha_2^{hs} = \frac{f_0 - f_{baseline}}{f_{baseline}} = \frac{f_0 - 0.8 \times f_0}{0.8 \times f_0} = 0.2500$. Thus, the robustness metric is $R_{RO}^{hs} = \frac{\int_{10}^{30} (f_0 - D(t)) dt}{1 \times (30 - 10)} \times \alpha_1^{hs} \times (1 + \alpha_2^{hs}) = 0.7791$.

(3) In the restoration stage. The recovery coefficient is $\beta^{hs} = 1$. The recovery metric is $R_{RV}^{hs} = \frac{\int_{30}^{90} f(t) dt}{f_0 \cdot (90 - 30)} \times \beta^{hs} = 0.7656$. Because the multi-layer performance has reached the mission baseline, reconstitution is not required.

In summary, the multi-stage comprehensive performance efficiency of the SM under hailstorm disasters, denoted by R^{hs} , is $R^{hs} = \sqrt[3]{R_{AV}^{hs} \times R_{RO}^{hs} \times R_{RV}^{hs}} = \sqrt[3]{0.6764 \times 0.7791 \times 0.7656} = 0.7389$.

5.3.2 Severe disasters with instantaneous impacts

The scenario in section 5.3.2 is based on an earthquake that hit Shandong Province in 2023 and has been simulated by Monte Carlo method with appropriate simplifications. The total degradation of multi-layer performance in the SM is calculated by equation (1). The performance degradation caused by internal reasons is $D_1(t) = 576.6795(1 - e^{-0.003t})$. Unlike general disasters with sustained impacts, severe disasters with instantaneous impacts (e.g., earthquakes) cause greater degradation of multi-layer performance after disasters occur. Specifically, the performance degradation caused by an earthquake is $D_2(t) = \sum_{i=1}^{N_t} d_i$, where $d_i \sim N(300, 10)$ is the degradation caused by the i -th earthquake and $N_t = 1$ represents only one earthquake occurs. Let there be an earthquake at the moment t_1 and a rescue afterwards at the moment t_2 . The SM is rescued immediately after the earthquake, so $t_2 \approx t_1$. Supposed that no degradation of the multi-layer performance in the SM occurs during the restoration and reconstitution stages. Because the SM have more degradation of the multi-layer performance when an earthquake occurs than that when hailstorms occur, high-intensity emergency rescue is performed in the restoration stage. Let the saturation value of performance in the restoration stage $K = 150$. Amount of increase in multi-layer performance is $h(t) = 150/(1 + 0.002e^{-0.2t+14})$ in the restoration stage. By comparing the multi-layer performance at the last moment of the restoration stage with the mission baseline, a decision can be made as to whether or not it is necessary to enter the reconstitution stage. Fig.8 shows the multi-stage multi-layer performance evolution in the SM before, during and after severe disasters with instantaneous impacts.

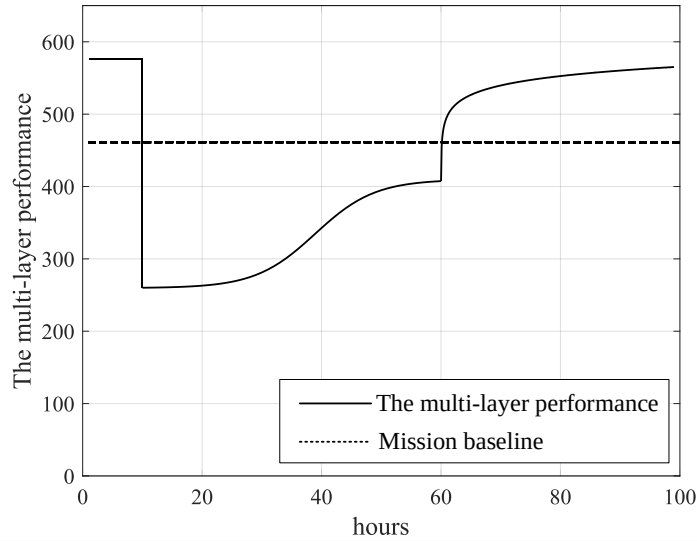


Fig.8. The multi-stage multi-layer performance evolution before, during and after severe disasters.

In Fig.8, The SM operates normally in 0-10 hours. $f(t) = 576.6795, t \in [0, 10]$. Because the internal degradation of the SM at the 10th hour is $D_1(10) = 17.0435 < 20$, the SM does not degrade due to internal reasons. However, an earthquake attacks Shandong Province at the 10th hour. The degradation of the multi-layer performance in the SM caused by the earthquake is $D_2(t) = 300$. The total degradation of the multi-layer performance is $D(t) = D_1(t) + D_2(t) > 20$. Therefore, the SM degrades. The multi-layer performance after degradation is 259.6360. After the 10th hour, the SM starts a high-intensity emergency rescue. At the 60th hour the multi-layer performance is $f(60) = 407.4516 < f_{baseline}$. At this moment, the multi-layer performance in the restoration stage has already proceeded to saturation. and it no longer makes sense to continue with repairs. It no longer makes sense for the maintenance staff to continue maintaining the SM.

Carrying out structural reorganisation of the SM in the reconstitution stage is necessary. Amount of performance improvement in the SM in the reconstitution stage from the 60th hour to the 100th hour is $\mathcal{H}(t) = 13 \log_2(115(t - 60))$. From Fig.8, we find that the multi-layer performance of the SM still shows an increasing trend at the moment of simulation termination, which is expected to exceed the initial multi-layer performance.

Based on the multi-layer performance before, during and after the earthquake in the SM, the avoidance metric in the prevention stage, robustness metric in the degradation stage, recovery metric in the restoration stage, reconstitution metric in the reconstitution stage, and the multi-stage comprehensive performance efficiency of the SM are analysed.

(1) In the prevention stage. Preventive capabilities of the SM do not vary by type of disasters. Thus, the avoidance metric of the SM still is $R_{AV}^{eq} = R_{AV}^{hs} = 0.6764$.

(2) In the degradation stage. Since the degradation occurs at the 10th hour and the SM completes the degradation process instantaneously, the robustness metric is not considered here.

(3) In the restoration stage. The recovery coefficient is $\beta^{eq} = 0.8832$. The recovery metric is $R_{RV}^{eq} = \frac{\int_{10}^{60} f(t)dt}{f_0 \cdot (60-10)} \times \beta^{eq} = 0.4947$.

(4) In the reconstitution stage. The reconstitution coefficient is $\gamma^{eq} = 0.9808$. The recovery metric is $R_{RC}^{eq} = \frac{\int_{60}^{100} f(t)dt}{f_0 \cdot (100-60)} \times \gamma^{eq} = 0.9301$.

In summary, the multi-stage comprehensive performance efficiency of the SM under the earthquake, denoted by R^{eq} , is $R^{eq} = \sqrt[3]{R_{AV}^{eq} \times R_{RV}^{eq} \times R_{RC}^{eq}} = \sqrt[3]{0.6764 \times 0.4947 \times 0.9301} = 0.6777$.

6 Conclusions

This paper develops a smart microgrid performance approach based on multi-stage multi-layer energy management in IoT. It analyses the multi-layer energy architecture in IoT, proposes a multi-layer performance model for SMs based on operation loop in multi-stage energy management, and develops a multi-stage performance efficiency model for smart microgrids.

(1) This paper elucidates the multi-layer energy architecture of smart microgrids including physical layer, perception layer, communication layer, and application layer. Data transmission under the collaboration of the data layer and physical layer is analysed, considering the nodes in the multiple layers, communication paths among the multiple layers and inter-layer failure propagation in smart microgrids.

(2) A multi-layer performance model for smart microgrids is constructed. The model driven by operation missions reveals the multi-layer performance characteristics of smart microgrids through synergic cooperation across layers. The IoT-enabled smart microgrids cross-layer synergy can push back the development of the in-depth integration of smart microgrids with information technology, communication technology, control technology and other fields and improves the operational efficiency and performance stability of smart microgrids.

(3) The approach of avoidance metric in the prevention stage, robustness metric in the degradation stage, recovery metric in the restoration stage, and reconstitution metric in the reconstitution stage of the multi-layer

energy management is proposed to achieve the accurate evaluation of performance. In the design of these metrics, many factors (e.g., risk prediction capability, equipment monitoring capability, system early warning capability and ex-ante response capability, redundancy and robustness, and mission baseline of smart microgrids) are considered comprehensively to make the performance approach more in line with the practical needs.

(4) This paper discusses the impacts of general disasters with sustained impacts and severe disasters with instantaneous impacts on the performance of smart microgrids in Shandong Province, China. On the one hand, the effectiveness of the proposed multi-layer performance approach and multi-stage performance efficiency approach is demonstrated. On the other hand, the results help to guide the optimisation and management of smart microgrids and provide an important theoretical and technological support for the technical improvement and upgrading of smart microgrids.

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