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Research on the Impact of Redundancy Configuration and Opportunistic Maintenance on the Reliability of Ultra-High Voltage Flexible Direct Current Transmission Systems

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Abstract

INTRODUCTION: Ultra-High Voltage Flexible Direct Current (UHVDC-F) transmission systems have become the preferred choice for long-distance power transmission due to their superior control flexibility and power quality, with their reliability directly determining regional grid stability.
OBJECTIVES: To ensure stable operation, it is essential to evaluate system reliability, quantify the enhancement effects of redundant components, and identify critical system vulnerabilities.
METHODS: This paper proposes an evaluation framework considering diverse redundancy schemes. For component-level redundancy, a state transition model incorporating spare resource constraints is developed. For sub-module level redundancy, an opportunistic maintenance strategy is introduced. The framework utilizes sequential Monte Carlo simulation to accurately capture the stochastic evolution and dynamic transitions of the system.
RESULTS: Results indicate that converter transformer redundancy most significantly boosts overall reliability. Furthermore, opportunistic maintenance for converter valves effectively mitigates degraded operation risks and extends the Mean Time Between Failures.
CONCLUSION: This research establishes a high-fidelity digital twin foundation for complex UHVDC-F operational states. Beyond enhancing assessment accuracy, these quantitative matrices can be seamlessly integrated into AI-driven asset management and cost optimization engines, transforming risk evaluation into active O&M economic scheduling to fortify large-scale grid resilience.

Keywords: Reliability evaluation, state duration sampling, Ultra-High Voltage Flexible Direct Current transmission systems, opportunistic maintenance, Standby strategy, Digital twin foundation

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1. Introduction

As Artificial Intelligence (AI) has been used more widely in recent years, the request for power supply reliability is urgent. Ultra-High Voltage Flexible Direct Current (UHVDC-F) transmission systems as an important component of modern power system[1], have irreplaceable advantages especially in long-distance and large capacity power transmission[2]. With the increasing demand for electricity and the complexity of the power grid structure, ensuring the efficient and safe

operation of UHVDC-F systems has become crucial[3]. Therefore, reliability evaluation has become an indispensable part of power system design, operation, and maintenance [4]. The commonly used reliability evaluation methods are divided into analytical methods [5], including state space method[6], fault tree analysis, etc., and simulation methods[7] including Monte Carlo simulation method. Analytical methods rely on constructing and solving complex mathematical models to derive reliability indicators of the system [8,9]. In contrast, simulation methods approximate true reliability probabilities by simulating a vast number of system states throughout the operational cycle and statistically analysing the frequency of various outcomes[10].

These methods are widely applied in power transmission system reliability assessments. Markov models[11] and matrix-based reliability evaluation methods[12] assess system reliability by establishing comprehensive mathematical models; however, their complexity is often constrained by the system scale. In contrast, Monte Carlo simulation estimates key metrics such as failure rates and frequencies by simulating stochastic failures and operating states through random sampling. This method can be specifically adapted to incorporate various reliability factors, such as the load of parallel lines[13] or the impact of wind speed and solar irradiance on power output[14]. Furthermore, techniques such as importance sampling and Latin Hypercube sampling can effectively enhance the convergence speed and computational efficiency of Monte Carlo simulations[15].

However, when a system comprises multiple components with intricate failure modes and interactions, precise mathematical modelling becomes exceptionally difficult or even unattainable[16]. The interdependence between components, the sheer number of elements, and multiple failure paths can lead to an exponential expansion of the model, rendering it computationally intractable. More importantly, given that modern engineering practices widely adopt complex redundancy configurations[17] and opportunistic maintenance strategies[18] to enhance operational reliability, analytical methods struggle to quantify the effectiveness of these strategies. This limitation has driven the application of dynamic simulation methods, such as sequential Monte Carlo simulation, in the reliability assessment of complex systems.

However, during the evolution toward modern smart grids, AI-driven grid operation and Life Cycle Cost (LCC) optimization have imposed higher demands on the 'spatiotemporal decoupling capability' and 'dynamic perception accuracy' of underlying reliability assessments. Traditional static analytical methods or simplified Markov models struggle to capture the real-time, non-linear mapping relationships between 'states and costs.' This deficiency leaves AI-based cost optimization decisions—such as reinforcement learning-triggered predictive maintenance and multi-component system-level opportunistic maintenance—short of a high-fidelity physical constraint environment.

To mitigate the state-combination explosion inherent in the modelling process and to enable dynamic evaluation incorporating maintenance strategies, this paper proposes a comprehensive reliability assessment framework based on sequential Monte Carlo simulation with state duration sampling. The framework accommodates distinct redundancy characteristics across different components: for component-level standby units, a dynamic process captured by operational variations under spare resource constraints is considered; for sub-module level redundant components (such as converter valves), an opportunistic maintenance mechanism is introduced. This framework not only yields more accurate calculations of system reliability indices, but more importantly, establishes a solid physical simulation boundary for the subsequent integration of AI algorithms (e.g., deep reinforcement learning) to facilitate collaborative, multi-source opportunistic maintenance decisions across the grid, thereby minimizing energy curtailment losses induced by unscheduled outages. The remainder of this paper elaborates on the specific formulation, case study, and results analysis of the proposed methodology.

2. Reliability evaluation framework

2.1 Evaluation framework considering standby calls and opportunistic maintenance strategies

When using the SMCS for system reliability modelling, to ensure the accuracy and practicality of the evaluation results, it is necessary to comprehensively incorporate possible opportunistic maintenance strategies for components and call strategies for standby components. This requires the model to not only calculate state transition time based on failure rate and maintenance rate, but also to consider opportunistic maintenance activities as opportunistic events, that is, to determine whether to update specific component states based on the duration of branch states. At the same time, it is necessary to determine whether standby components need to be put into operation based on the different failure modes of the components, to ensure that the standby components can be put into operation in time when the operational component fails, and to meet the dynamic adjustment of the system's degraded operation time according to the status of the standby components when the standby quantity is insufficient. Finally, the model is required to accurately map the recorded component fault combinations to different states of the system. The comprehensive consideration of preventive measures, redundant calls, and system state judgment is the key to achieving high accuracy in dynamic reliability evaluation. The process of evaluating the system using the SMCS is shown in Figure 1:

(1) Input parameters, including the failure rate, repair rate, and installation time of constituent components, to initialize the system component status; Extract the first failure time T_{λ}^{i} of each component in the system based on the exponential distribution model, determine the first faulty component, and handle it accordingly.

The failure time is obtained by Eq. (1):

$$T_\lambda^i = -\frac{\ln(U)}{\lambda^i} \quad (1)$$

where T_λ represents the failure-free operating time of the component, and U is a random variable following a uniform distribution on the interval [0,1]. By performing random sampling for each component, a sequence of component failure times $\{T_\lambda^1, T_\lambda^2, T_\lambda^3 \cdots T_\lambda^n\}$ is generated, where n is the number of components. Within the simulation period, $\min(T_\lambda^i)$ represents the earliest moment at which a failure occurs.

(2) Process component failure events based on shared redundant component state transition logic the logic is applied to obtain the outage duration of the componentT_{fail}^i. See Section 2.2 for details.

(3) Check if any other faulty components exist during the current fault period. If so, apply step (2) to address them until no faults are detected. Record the fault combination and its duration.

If $T_\lambda^i < T_\lambda^{i+1} < T_\lambda^i + T_{fail}^i$, it indicates that the failure of the (i+1)-th component occurs within the outage duration of the i-th component. In this case, the procedure in step (2) shall be executed for the (i+1)-th component. Here, T_{fail}^i denotes the outage duration of the i-th component.

(4) Determine the status of normal components in the faulty branch based on the logic of opportunistic maintenance judgment; See Section 2.3 for details.

(5) Determine whether there are any component failures such that $T_\lambda^i + T_f^i < T_\lambda^{i+1} < 1$. If there are any other faulty components, proceed to step (2). If there are no other faulty components, proceed to the next round of simulation until the simulation cycle is completed; Calculate and output reliability indicators based on statistical results.

This model makes the following assumptions in reliability evaluation:

1. Disregarding downtime caused by personnel errors during operation or maintenance.

2. The installation time for the converter transformer is 96 hours, and the installation time for the DC reactor is 144 hours.

3. Multiple faulty components can be repaired simultaneously.

4. After repairing the equipment, follow the principle of "repairing as new".

5. The failure rate of standby components is zero.

2.2. Standby call strategy

In a power system with multiple independent transmission branches, although the core components such as converter transformers or DC reactors in each branch belong to the same type and undertake similar power transmission tasks, the hot standby type cannot be adopted in system design because standby components may need to replace any operational component on different branches in the event of a fault. Given this, in practical engineering configurations, standby components are typically configured as shared cold standby, which allows single standby components to remain offline standby. Once the primary component on any branch fails, the standby component can be scheduled and put into use. This strategy introduces a new reliability issue: When adopting a shared redundancy strategy, considering that standby components need to serve multiple operational components, when a component fails, the required standby units may become insufficient due to being replaced by other components and put into operation. The probability of such events significantly increases with the increase in the number of operational components. Therefore, when evaluating the reliability of shared redundancy systems, it is necessary to focus on in-depth analysis and modelling of such events. Figure 2 shows the component state transition diagram under shared redundancy, which can fully depict the dynamic coupling relationship between component failures and standby availability under the shared redundancy mechanism.

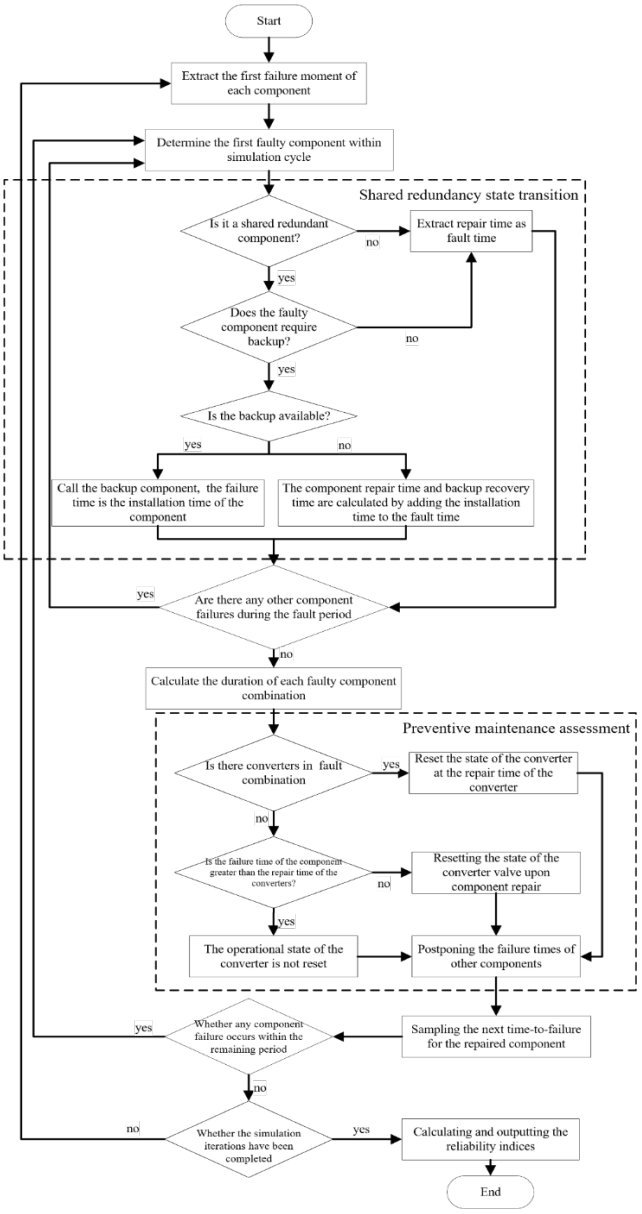

Figure 1. Reliability Evaluation Process

Under the shared redundancy strategy, when the inventory of spare components is insufficient, it is necessary to determine the time of the next system state change based on the temporal relationship between the repair of faulty components and the recovery of spare inventory.

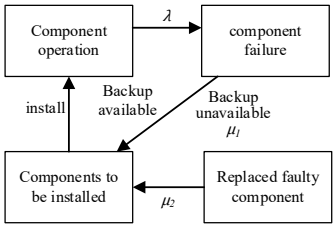

Figure 2. State transition diagram under shared redundancy

In Figure 2 λ represents the failure rate of the component, μ_1 characterizes the repair time of the component, and μ_2 denotes the equivalent transition rate (repair rate) from the moment of component failure until the restoration of the spare inventory. These values are obtained by Eq. (2).

$$\mu_2 = \frac{1}{T_{res}} = \frac{1}{(T_{\lambda 1}+T_{rep})-T_{\lambda 2}} \tag{2}$$

In the formula, $T_{\lambda 1}$ denotes the moment of component failure and the subsequent call for a spare unit, T_{rep} is the repair time of the original failed component, and T_{res} characterizes the moment the spare unit becomes available on the timeline. $T_{\lambda 2}$ represents the moment another failure occurs that requires a spare unit.

At the moment T_{f1}, when the spare is called for the failure of Component 1, the repair time T_{rep} of the original failed component is sampled. The original component then serves as a spare, which will become available at time $T_{\lambda 1} + T_{rep}$. If Component 2, which also requires a spare, fails within the interval $[T_{\lambda 1}, T_{\lambda 1} + T_{rep}]$, the spare is considered unavailable. In this case, the time at which Component 2 is put back into operation is determined by comparing the magnitudes of μ_2 (the repair rate of Component 2) and μ_1.

For components with multiple failure modes, reliability analysis will be more complex. It is necessary to clarify whether to choose on-site maintenance to restore component function as soon as possible under specific fault conditions, or to replace the faulty component with a spare component and return it to the factory for repair. This decision will directly determine the time required for the components to resume operation, thereby significantly affecting the duration of the system's degraded operation.

After considering the two key factors of shared redundancy state transition and multiple failure modes of components, the fault handling logic of shared redundancy components is clearly constructed, and the logic is shown in Figure 3.

When a component fails, the system first determines whether the component belongs to the shared standby set. Define the shared spare component set as Ω_{sh}. If component $i \in \Omega_{sh}$, it is classified as a shared spare component.

(1) If the component is a non-shared redundant component, the duration of its failure is the repair time of that component. The logic is shown in Eq. (3)

$$i \notin \Omega_{sh} \Rightarrow T_{fail} = T_{rep} \tag{3}$$

where T_{fail} is the outage duration of the component, and T_{rep} is the time required to repair the failed component itself.

(2) If it belongs to shared spare components, further judgment is needed to determine whether a spare replacement is necessary. If replacement is required, the system will check the number of spare components. If the number is sufficient, the time of failure is determined as the installation time of the spare component. The logic is shown in Eq. (4)

$$i \in \Omega_{sh} \wedge N_{spare} > 0 \Rightarrow T_{fail} = T_{inst} \tag{4}$$

where N_{spare} is the number of spare components, and T_{inst} is the installation time of the components.

(3) If the quantity is insufficient, the available time of the component must be determined according to the earlier of the recovery time of the spare component and the repair time of the faulty component, and then the installation is arranged. If there is no need to replace with spare components, the repair time can be directly extracted as the spare recovery time for that component. The logic is shown in Eq. (5)

$$T_{fail} = min(T_{rep}, T_{res}) + T_{inst} \tag{5}$$

By integrating the logic, the outage duration T_{fail} for component i can be expressed by the unified formulation in Eq. (6):

$$T_{fail,i} = \begin{cases} T_{rep}, & i \notin \Omega_{sh} \text{ or } S_{rep} = 0 \\ T_{inst}, & i \in \Omega_{sh} \wedge S_{rep} = 1 \wedge N_{spare} > 0 \\ min(T_{rep}, T_{res}) + T_{inst}, & i \in \Omega_{sh} \wedge S_{rep} = 1 \wedge N_{spare} = 0 \end{cases} \tag{6}$$

Where $S_{rep} \in \{0,1\}$: A binary decision variable, when $S_{rep} = 1$ indicates the need to replace spare components

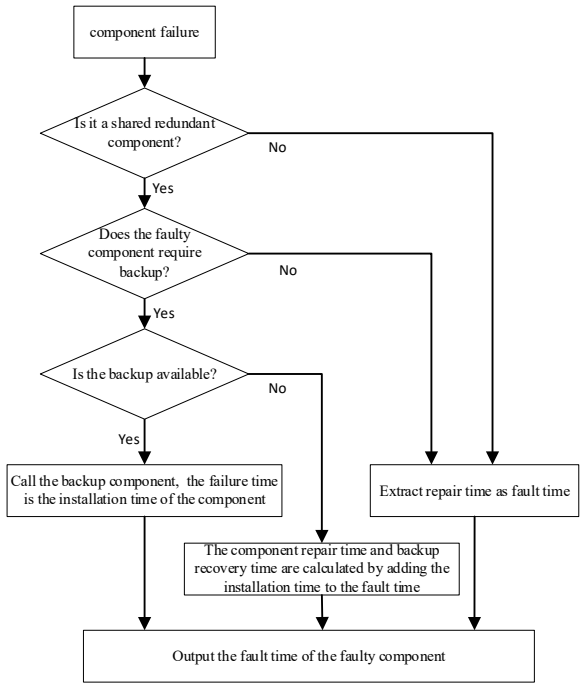

Figure 3. Process for determining the failure time of shared spare components

2.3 Opportunistic maintenance strategy

Opportunistic maintenance refers to the practice of performing maintenance on other pending components when a specific piece of equipment fails or undergoes scheduled preventive maintenance. By combining corrective maintenance (performed after a failure occurs) with preventive maintenance, this approach optimizes the utilization of maintenance resources while enhancing both the reliability and economic efficiency of system operations. For the converter components of UHVDC-F systems, redundancy is primarily reflected in the number of sub-modules within the valve arms [19,20]. This design allows the system to only replace faulty submodules during maintenance, without the need to replace the entire converter system. In view of this, the converter system has the potential for opportunistic maintenance before actual failures occur, which must be considered in the reliability model to more accurately reflect its high availability characteristics.

In the modelling process of reliability evaluation, it is necessary to focus on the state handling in the following situations:

1. When the converter valve fails alone or when the converter valve failure occurs simultaneously with other component failures in the branch, independent maintenance of the converter valve is required.

2. When the converter valve has not failure, but its branch components have failure, if the maintenance time of the branch componentsT_{down} is longer than the maintenance time of the converter $T_{rep,c}$, the faulty submodule can be replaced during the branch shutdown time. At the time of repairing the branch components, resetting the state of the converter is considered to have completed the early maintenance of the converter.

3. If the maintenance time of the branch components T_{down} is less than the maintenance time of the converter $T_{rep,c}$, the state of the converter will not be reset.

The opportunistic maintenance and state reset criteria follow Eq. (7):

$$L_c(t_{end}) = \begin{cases} 0, & T_{down} \geq T_{rep,c} \\ L_c(t_{start}), & T_{down} < T_{rep,c} \end{cases} \quad (7)$$

Where $L_c(t)$ represents the accumulated service life of the converter at time t; $L_c = 0$ indicates that the converter is in a brand-new state (reset state); and t_{end}, t_{start} denote the start and end moments of the branch failure outage, respectively.

For other components that are not submodule redundant or replaced as a whole, the following assumption is made in the reliability model: at the repair time of the branch, the time of its failure is postponed according to the branch failure time. The failure time of non-submodule redundant components is obtained by Eq. (8):

$$T'_{\lambda,j} = T_{\lambda,j} + T_{down} \quad (8)$$

where $T'_{\lambda,j}$ is the updated failure occurrence time of component j, $T_{\lambda,j}$ is the originally sampled failure time of component j, and T_{down} is the outage duration caused by the failure of other components in the branch.

It is necessary to simplify the logic by considering delaying the handling of new faults in components. This is based on practical engineering considerations: if the failure of a component during branch disconnection is identified as an invalid fault, it means that additional checks and debugging of the status of other components in the branch need to be carried out during the maintenance time when the branch is shut down. This additional activity not only significantly increases time costs but also involves emergency mobilization of maintenance personnel and spare parts, which contradicts the original intention of the branch being shut down due to existing faults. Therefore, the model adopts a strategy of delaying processing, aiming to ensure that the current maintenance tasks are completed first, avoiding stacking multiple faults in one shutdown, and making the simulation results closer to the actual operation and maintenance strategy of processing according to plan and sequence, thus improving the practicality and computational efficiency of the model. Figure 4 is a flowchart for determining whether to perform opportunistic maintenance on the converter.

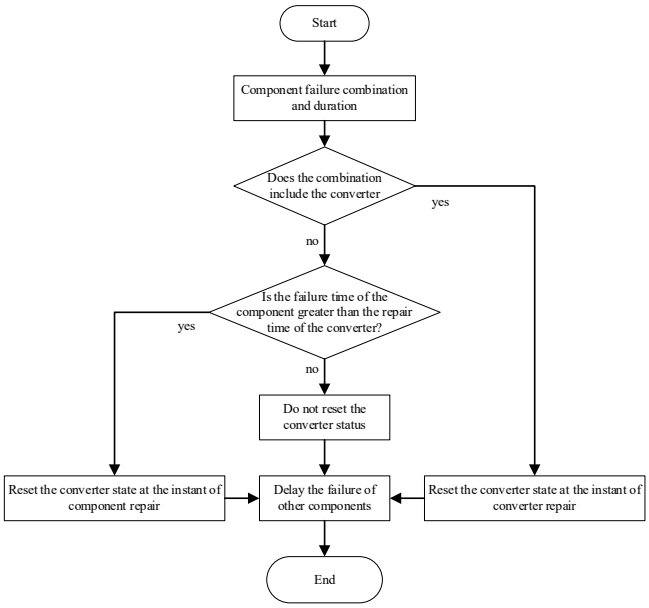

Figure 4. Opportunistic Maintenance Process Diagram

3. Structure and operational characteristics of UHVDC-F

3.1 System introduction

This article analyses the UHVDC-F system, which adopts symmetrical bipolar direct current connection and includes converter stations at the sending and receiving ends. The main components of the system are shown in Figure 5, including the converter transformer system, converter valve system, DC reactor, neutral wire component, and DC transmission line. Each converter station is equipped with two multi-level flexible DC converter valves running in parallel at each pole and matched with corresponding transformer groups. Each station is equipped with four current limiting reactors at each pole, which are connected to the pole bus and neutral bus respectively to achieve fault current limitation and system stability.

The transmission system adopts a bipolar design, and each pole is further divided into two parts: high-end and low-end, forming four independent transmission branches. This highly modular design allows each branch to operate independently for power transmission and bear 25% of the total transmission capacity. Equal allocation of capacity and independent operational capability significantly enhance the flexibility and redundancy of the system's operation.

When any device in the line fails, the protection system can respond quickly in milliseconds, ensuring that the faulty line is cut off in a timely manner and synchronously adjusting the operating mode to ensure the normal operation of other lines. When a single pole transmission line fault occurs, the system can use neutral line components to form a circuit with the opposite side converter station. This strategy ensures the continuous power transmission of another complete pole, effectively avoiding complete power interruption and greatly enhancing the system's risk resistance and power supply reliability.

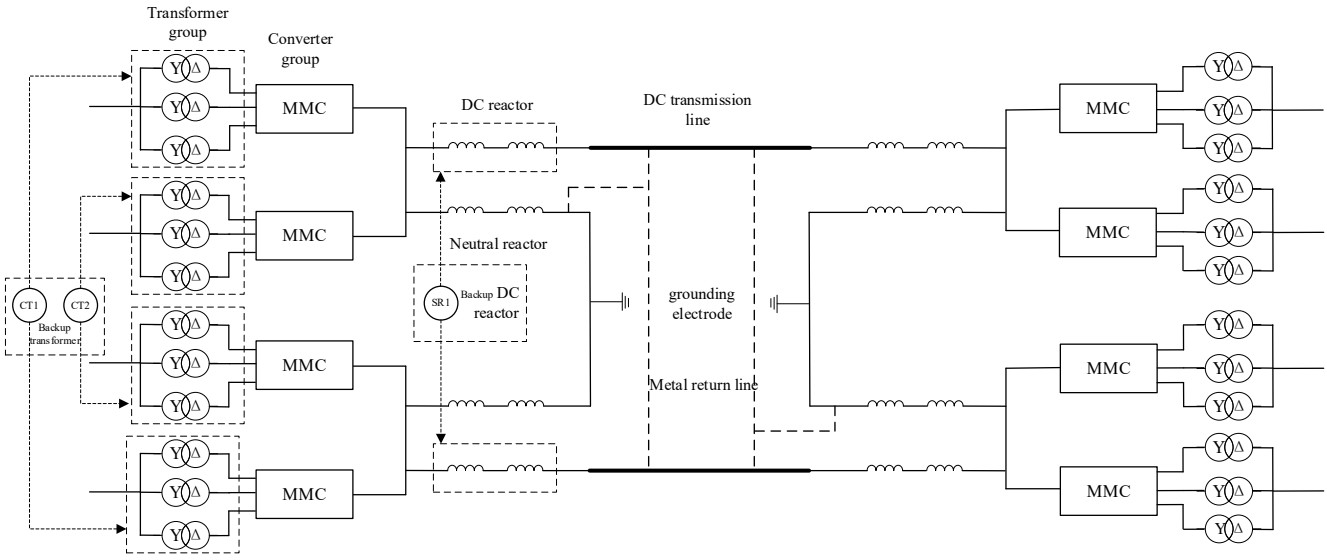

Figure 5. System Component Wiring Diagram

3.2 System configuration

Configuring redundant components in engineering is the most intuitive way to improve reliability. In terms of redundant configuration, the system adopts a shared standby strategy to

enhance system reliability while ensuring cost control. The specific measures are as follows:

Each converter station is equipped with a shared standby transformer for both the high-end and low-end. This means that when the main transformer at either end fails, this shared standby transformer can be put into use, effectively covering the risk of high/low end faults. Each converter station also has a standby current limiting reactor connected in series with the busbar. This standby reactor can be used to replace any faulty main current limiting reactor. The redundancy design of the converter is mainly reflected in the number of converter valve submodules in its bridge arm. Each converter consists of six bridge arms and other components, with each bridge arm containing 200 submodules. In order to enhance the fault tolerance of the system, this article considers two different redundancy configurations: when each bridge arm is configured with 10 redundant submodules, the redundancy rate is 5%; When the number of redundant submodules increases to 12, the corresponding redundancy rate is 6%. The redundancy of this system is 5%. These redundant submodules will be put into operation together with other normal submodules, continuously sharing the system voltage until the cumulative number of faults in the submodules of the converter valve bridge arm exceeds the preset redundancy threshold, at which point the converter will be judged as shut down. Therefore, by increasing the redundancy of the converter valve submodule, the fault tolerance of the converter valve bridge arm to single point faults can be significantly improved, thereby significantly reducing the failure rate of the converter. Table 1 presents the reliability input data for various components[6].

Table 1. Component Reliability Parameters

Equipment and components		Failure rate (times/year)	Repair duration (h)
Converter Transformer	Severe faults	0.015	2400
	Minor faults	0.021	7
converter（5%）		0.13	32
converter（6%）		0.041	38.4
DC reactor	Severe faults	0.01	1400
	Minor faults	0.015	5
grounding electrode		0.05	13
transmission line		0.64	10.2

Note on repair time: The 2400 hours in Table 1 represent the equivalent restoration time for severe faults, covering the full cycle of diagnosis, transportation, and tests. However, this duration does not include the on-site installation time for standby replacement (which is 96 hours for converter transformers, as defined in Section 2.1). These two time components are treated as independent sequential processes in the reliability model.

3.3 System status judgment

In the reliability evaluation of power systems, the state of the system is determined by all its internal components, and different individual or multiple component failures can cause the system to enter different operating states. The DC transmission system is divided into a series of different operating modes based on the number of faulty components and disconnected transmission branches, which are directly mapped to the stepped transmission capacity state of the system. When the system is in bipolar full operation mode, it corresponds to 100% system capacity. If the system cuts off a transmission branch, it enters a state of complete operation of one pole and partial operation of one pole, at which point the system capacity usually corresponds to 75% of the total capacity. When cutting off two transmission branches, the system capacity drops to 50%. This situation may evolve into two main modes: one is the operation state of one pole intact, one pole fault grounded or metal return line, and the other is the operation state of two pole partial. Furthermore, if three transmission branches are cut off, the system will degrade to a single pole partially grounded or metal return line operating state, with a corresponding capacity of 25%. Finally, when all four transmission branches are cut off, the system enters a complete fault state, and the transmission capacity drops to 0%. These fault operating states clearly correspond to different capacity levels of the system, including 100%, 75%, 50%, 25%, and 0%, fully reflecting the modular system's ability to provide stepped capacity support under different degrees of fault impact.

When determining the system status, the operating status of each pole is first determined based on the combination of fault states. Each pole contains two branches: the pole without faults is determined as the operating pole; If one of the branches is cut off due to a fault, the pole will enter a partial pole operation state; When a DC reactor, transmission line fault, or simultaneous disconnection of two branches occurs, the pole is determined as the faulty pole. In the fault pole state, the system needs to use neutral point components to form a transmission circuit with the opposite side converter station, thereby entering a degraded operation mode of grounding or metal return line, and combining the states of the two poles to obtain the operating status of the entire system.

3.4 System reliability indicators

When analysing the reliability of transmission systems, commonly used reliability indicators include unavailability rate, mean time between failures (MTBF), and the probability of the system's available state. To quantify the reliability of the system, we have selected the following reliability indicators that can describe the reliability level of subsystems and the overall system.

Due to the redundancy of transmission system design, the transmission system can have multiple operating modes corresponding to different capacity states. The probability of the system being in different capacity states needs to be evaluated, and the calculation formula is:

$$P_k = \frac{T_k}{T_{all}} \tag{9}$$

P_k is the probability that the system is in capacity state k. T_k is the total time under the capacity state k. T_{all} is the total time for system simulation.

Equivalent outage time (EOT) is defined as the duration of units operating in a derated state or experiencing failures, converted into an equivalent period of total downtime.

$$EOT = \text{Actual downtime} \times \left(1 - \frac{U_a}{U_r}\right) \tag{10}$$

Where U_a is the available capacity of the system during the outage period, and U_r is the rated capacity of the system.

EOT accumulation under overlapping failures: In the sequential Monte Carlo simulation, the system occupies exactly one capacity state (100%, 75%, 50%, 25%, or 0%) at any given time, determined by the current combination of component failures. The model records the time interval Δt between consecutive events and accumulates it to the corresponding T_k. When overlapping failures occur, only the actual system state during each interval is recorded. The annual EOT is then computed as $EOT = \sum_k T_k \times (1 - k/100\%)$, avoiding double-counting of derated periods.

Energy unavailability (EU) is the ratio of the total duration for which the system is unable to perform its required function to the total reference period.

$$EU = \frac{EOT}{\text{Total Duration}} \tag{11}$$

Energy availability (EA)

$$EA = 1 - EU \tag{12}$$

Mean Time Between Failures (MTBF) is the average running time of the system between two failures, calculated by the formula:

$$MTBF = \frac{\text{Total Duration}}{\text{Number of Failures}} \tag{13}$$

Mean Time to Repair (MTTR) refers to the average time required for the system to recover to normal working conditions after a failure.

$$MTTR = \frac{Total\ Repair\ Time}{Number\ of\ Repairs} \tag{14}$$

4. Calculation results and sensitivity analysis

Table 2 presents the calculation results of the probability and frequency of the capacity state of the ultra-high voltage direct current transmission system under different redundant components. It can be clearly observed from the simulation evaluation results that the overall reliability of the system is weakest in the absence of redundant component configurations. The addition of any redundant components can improve the reliability of the system to a certain extent, among which the redundant configuration of the converter transformer has the greatest benefit in improving system reliability, which can significantly increase the energy availability from 97.15% in the non-redundant state to 98.9%. However, the redundancy effect of DC reactors is relatively small, only increasing energy availability by 0.51%. From the analysis of input data, on the one hand, the failure rate of DC reactors themselves is lower than that of converter transformers, On the other hand, the number of DC reactors is less than that of converter transformers.

Different redundant configurations exhibit differentiated targeting in suppressing the probability of capacity degradation. Under non redundant configuration, the probability of 75% capacity degradation is as high as 7.51%, which is the largest risk point of capacity loss, and the main contributor to the fault is the transformer. The addition of redundant converter transformers eliminates this bottleneck and effectively suppresses the probability of this state to 1.26%, which is the key to solving the 75% capacity degradation risk. For the more severe 50% capacity degradation state, adding redundancy of DC reactors is more effective, reducing its probability from 1.73% to 0.76%, demonstrating the unique value of reactor redundancy in preventing the system from falling into deep fault mode.

Table 2. Probability and frequency of system capacity status under different component configurations

System capacity status		1	0.75	0.5	0.25	0
No component redundancy	probability (%)	90.62	7.51	1.73	0.12	1.83×10^{-2}
	frequency(times/year)	-	1.64	1.51	8.71×10^{-2}	2.3×10^{-2}
Only redundant DC reactors	probability (%)	91.56	7.59	0.76	7.36×10^{-2}	4.86×10^{-3}
	frequency(times/year)	-	1.65	1.51	7.96×10^{-2}	1.45×10^{-2}
Only redundant transformer	probability (%)	97.19	1.26	1.51	1.84×10^{-2}	1.67×10^{-2}
	frequency(times/year)	-	1.57	1.48	3.28×10^{-2}	2.21×10^{-2}

Converter valve module (6%)	probability (%)	90.80	7.33	1.72	0.11	4.05×10^{-3}
	frequency(times/year)	-	1.10	1.46	7.68×10^{-2}	2.25×10^{-2}
Three redundant components	probability (%)	98.40	1.09	0.49	1.00×10^{-2}	3.98×10^{-3}
	frequency(times/year)	-	1.02	1.45	1.83×10^{-2}	1.37×10^{-2}

Table 3. Reliability Indicators

	EOT(h)	MTTR(h)	MTBF(h)	EA (%)	EU (%)
No component redundancy	244.80	246.71	2384.23	97.15	2.85
Only redundant DC reactors	200.92	222.41	2415.74	97.66	2.34
Only redundant converter transformer	94.57	77.57	2685.67	98.90	1.10
Converter valve module (6%)	240.49	296.58	2930.00	97.20	2.80
Three redundant components	45.79	54.87	3366.00	99.46	0.54

Table 3 shows other reliability indicators of the system. From the analysis of simulation results, in terms of the average time between failures, the redundancy of the converter valve module and the redundancy of the transformer exhibit different mechanisms of action. Firstly, the increase in the number of sub modules of the converter valve directly leads to a decrease in the failure rate of the converter body, which in turn reduces the annual average frequency of the system entering a 75% capacity state, ultimately resulting in a significant increase in the MTBF of the system. Secondly, the redundant configuration of the converter transformer can also increase the MTBF. Its principle of action is not mainly dependent on reducing the failure rate of the components themselves, but by significantly increasing the duration of the system maintaining full power operation. Even if the fault frequency of the transformer remains unchanged, the redundancy capability greatly extends the time for the system to maintain high availability before recovering or downgrading from a fault state. Therefore, the overall MTBF is still effectively improved.

Table 4 and Table 5, where Group A system did not adopt opportunistic maintenance strategies, while Group B system adopted opportunistic maintenance strategies.

By comparing the simulation results of systems with and without opportunistic maintenance strategies, it can be clearly observed that implementing opportunistic maintenance for the converter valve system can significantly optimize the distribution of the system's operating status. Specifically, the application of this strategy effectively reduces the annual

Sensitivity analysis was conducted on different maintenance strategies for the converter valve in the case of redundant transformer and DC reactor configurations, as well as a 5% redundancy in the converter valve module. The results are shown in

frequency of the system operating at 75% of its rated capacity by about 14%. This decrease directly reflects the reduction of operational risk, thereby statistically extending the MTBF of the system. Although the improvement in other reliability indicators such as EA or EOT is relatively limited in this simulation scenario, the increase in MTBF fully demonstrates the unique value of opportunistic maintenance in enhancing system anti-interference resilience.

Table 4. Comparison of System Reliability Simulation with and without Opportunistic Maintenance

System capacity status		1	0.75	0.5	0.25	0
Group A	probability (%)	98.06	1.43	0.55	1.35×10^{-2}	4.12×10^{-3}
	frequency(times/year)	-	1.84	1.47	2.91×10^{-2}	1.41×10^{-2}
Group B	probability (%)	98.21	1.27	0.50	1.17×10^{-2}	4.04×10^{-3}
	frequency(times/year)	-	1.58	1.48	2.51×10^{-2}	1.39×10^{-2}

Table 5. Comparison of other indicators

	EOT(h)	MTTR(h)	MTBF(h)	EA (%)	EU (%)
Group A	53.21	49.68	2510.51	99.38	0.62
Group B	50.09	49.71	2722.64	99.41	0.59

To further analyse the impact of different components on system reliability, sensitivity analysis of component rows is conducted separately. Select different fault rates at different magnifications as input data and calculate the reliability indicators of the ultra-high voltage flexible direct current transmission system through the model. Different failure rates are based on raw data. In the case of redundant transformer and DC reactor configurations, 1/10, 1/5, 5, and 10 times the component failure rate are taken respectively. The simulation results are compared with the simulation results of the raw data to determine the degree to which the component failure rate affects the system reliability index, to further identify weak links in the system. Figure 6 shows the sensitivity analysis results.

The sensitivity analysis results clearly indicate that the converter transformer is the weakest link affecting system reliability, with the greatest impact on EU, EOT, and MTTR. However, for the MTBF, the impact of converter and transmission line failure rate is relatively more significant. In contrast, the change in fault rate of DC reactors has the least impact on the overall system reliability indicators.

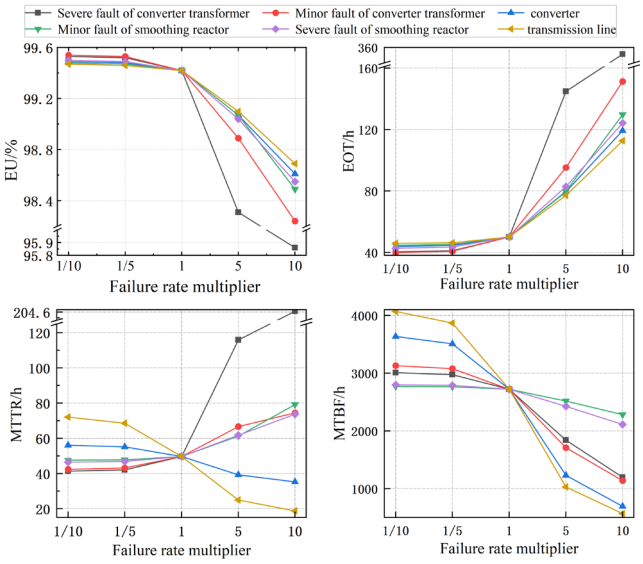

Figure 6. Sensitivity analysis results

Firstly, reducing the failure rate of transformers can effectively improve the overall reliability indicators of the system, whether it is severe or minor failures. From the analysis of input data, severe faults in converter transformers usually belong to low failure rate and low repair rate events. Once their frequency of occurrence increases, the fault will quickly become the dominant risk of the system. For example, when the failure rate of the converter transformer is one tenth (1/10) of the base value, the proportion of time it takes for the system to enter 75% capacity operation due to transformer failure significantly decreases from 74.35% when the failure rate is doubled to 59.8%. This inevitably leads to a significant increase in the system's availability and overall reliability.

Secondly, for high failure rate components such as converters and transmission lines, reducing their failure rate plays a decisive role in improving MTBF. At 1 times the basic fault frequency, the number of times the system enters 75% capacity operation due to converter faults accounts for 53.1% of the total number of faults, while the number of times it enters 50% capacity operation due to transmission line faults is as high as 78.2%. Reducing the failure rate of such high-frequency faults can significantly reduce the frequency of the system entering a degraded operating state, thereby significantly extending the system's MTBF. Therefore, transformer fault prevention is the key to ensuring short-term energy supply and availability, while fault rate control of converters and transmission lines is an important path to improve long-term system stability and MTBF.

This sensitivity evolution law provides a quantitative 'risk-cost' sensitivity matrix for AI-driven intelligent operation and maintenance decision engines. Within the paradigm of AI-enabled grid cost optimization models, the non-linear degradation characteristics revealed in this paper can be directly formulated as dynamic penalty operators for reinforcement learning. Based on the distinct life-attenuation time windows of converters and transformers, the AI agent can navigate the trade-off between the OPEX surge induced by blind, premature isolation and the massive outage risk penalties caused by deferred maintenance. Through multi-objective intelligent search, the agent automatically triggers globally optimal opportunistic maintenance work orders, thereby maximizing system-level O&M economic benefits.

5. Conclusion

This paper introduces the state transition strategy of shared redundancy and opportunistic maintenance strategy into the SMCS, effectively avoiding the problem of state combination explosion caused by establishing the entire system state transition matrix. At the same time, it also solves the complex standby problem of polymorphic components, which can better adapt to the complex reliability evaluation requirements of UHVDC-F systems.

Reliability evaluation results indicate that the redundancy of converter transformers can significantly enhance system reliability, with other reliability indices also showing substantial improvements. In contrast, while the overall gains from DC reactor redundancy are relatively smaller, its configuration primarily serves to reduce the probability of severe system failures—specifically the 50% capacity degraded operation state—since its failure affects the transmission power of an entire pole. Furthermore, increasing the number of converter valve modules effectively reduces the frequency of system degraded operation and significantly extends the system's fault-free operating time, thereby ensuring higher long-term benefits for the power grid.

Sensitivity analysis provides clear priorities for optimizing system reliability: short-term benefits and energy assurance should focus on fault prevention and technical improvement of converter transformers, as they have the greatest impact on energy availability and equivalent downtime; The long-term operational stability and extended fault free interval should focus on controlling the failure rate of converters and transmission lines to maximize the benefits of improving the MTBF.

In summary, the proposed dynamic reliability assessment methodology, which accounts for shared redundancy and opportunistic maintenance, exhibits excellent generalizability and scalability. Future research can position this framework as the perceptual foundation of the data-physics dual-driven decision chain in smart grids. By dynamically injecting the remaining useful life time windows yielded by AI predictive maintenance into the chronological sampling operators of this model, a trinity closed-loop management system encompassing 'real-time perception, dynamic reliability assessment, and AI-driven cost-optimized scheduling' can be constructed. This paradigm opens up a brand-new avenue for the resilient control and cost-effective operation of all-asset deployment within modern power systems.

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