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METHODS
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A Double-Layer Optimization Maintenance Strategy for Photovoltaic Power Generation Systems Considering Component Correlation and Availability

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Aiming at the problem that the maintenance method based on the status information of the photovoltaic power generation system cannot effectively reflect the influence of the comprehensive correlation of the components on the maintenance strategy, on the basis of optimizing maintenance cost and availability, a new double-layer optimization maintenance strategy for photovoltaic power generation systems based on component dependencies and availability is proposed. First, the comprehensive correlation of components in the system is analyzed, and the availability of the system and components is modeled by improving the Markov model. Then, the idea of opportunistic maintenance is introduced. The upper-level optimization model that aims at the lowest maintenance cost is established by considering the economic correlation. The highest availability of the system is taken as the objective function, and the limit of the availability of components is used as a constraint to establish a lower-level optimization model for verification. The influence of failure correlation on the maintenance strategy is verified by introducing failure-related strength. The example shows that when there is a fault correlation between components, the affected components need to spend more maintenance costs, and the maintenance strategy also changes. By introducing the weather accessibility to analyze its influence on the maintenance cost and the rate of change in the availability of the system, the results show that in the double-layer optimization maintenance model, the saving rate of maintenance cost and the reduction ratio of system availability under the condition of low weather accessibility are greater. Taking a photovoltaic power station in the west as an example, the results from comparing different maintenance plans show that the maintenance strategy proposed in this study can effectively reduce maintenance costs and downtime, while increasing system availability.

Keywords: photovoltaic power generation system, component correlation, availability, failure-related strength, weather accessibility, double-layer optimization

INTRODUCTION

The operating environment of photovoltaic power plants is complex, and the availability of each component is easily affected by various random and uncertain factors. Therefore, formulating reasonable and effective maintenance strategies is of great significance to the safe, economical, and stable operation of photovoltaic power plants.

The maintenance strategy of photovoltaic power generation systems is mainly divided into post-maintenance and preventive maintenance. Post-maintenance will cause varying degrees of damage to components and systems, thereby reducing their reliability. Preventive maintenance has over-repair and under-repair problems and cannot take into account the requirements of repair costs and optimal availability. At present, research on maintenance strategies of photovoltaic power generation systems mainly focuses on optimizing the maintenance time intervals, maintenance based on condition monitoring and prediction, and failure correlation analysis. In the work by Spertino et al. (2021), the effects of maintenance activities, reliability, and availability of photovoltaic systems on energy loss are described, but specific maintenance strategies are not given. Perdue and Gottschalg (2015) analyzed the relationship between the maintenance cycle and maintenance cost and concluded that the longer the maintenance cycle, the lower the maintenance cost, and the lower the reliability. In the work by Gunda et al. (2020), the failure types of equipment are distinguished by machine learning, which lays the foundation for formulating condition-based maintenance strategies. In the work by Mengying et al. (2021), a phased approach for periodic inspection and maintenance is proposed, and preventive maintenance is performed on equipment that is at risk of failure after inspection. In the work by Colombi Gomes and Rodrigues Muniz (2020), an economically optimized maintenance scheme is proposed, but this method is a preventively planned maintenance for cleaning the main dust of PV modules and fails to take into account the whole PV plant. Mahani et al. (2018) proposed a maintenance method of double-layer optimization of the microgrid, which has a certain contribution in reducing the waste of funds but fails to take into account the influence of reliability and so on. In the work by Sun and Sun (2021), a selective maintenance scheme considering the maintenance sequence is proposed; the model improves the reliability of the system to a certain extent, but the maintenance effect weakens with the extension of the maintenance cycle. The aforementioned research mainly determined the maintenance time or cycle with the goal of optimizing the maintenance cost. However, it failed to consider the influence of the operating state of the equipment and the related characteristics between the equipment on the maintenance strategy. If the influence is ignored, the error of maintenance time will be caused, which will increase the extra maintenance cost and reduce the availability of the system. Therefore, some scholars formulate maintenance strategies by considering the operational status of the equipment and the economic and structural dependencies of components. Verbert et al. (2017) determined the maintenance time and period through condition prediction based on the economic relevance of components. In the work by Li et al. (2021), taking reliability as a constraint, preventive opportunistic maintenance is performed on components by updating maintenance thresholds. In the work by Zhao et al. (2016), a state-opportunistic maintenance strategy is proposed by considering incomplete maintenance, which is widely used in the maintenance field as a typical form of preventive maintenance. Zhu and Liu (2020) proposed a maintenance strategy based on the hierarchical optimization of components and systems; the optimal maintenance strategy is derived by determining the maintenance time of components and systems. In the work by Xu et al. (2015), a condition-based maintenance model is proposed considering the functional correlation between components. In the work by Liu et al. (2015), the process of equipment deterioration and fault evolution is described by the Markov state transition equation, and the maintenance method and time interval are determined by the minimum maintenance cost. In the work by Catelani et al. (2020), a data-driven condition monitoring method and reliability-centered maintenance are proposed, but this method mainly emphasizes reliability analysis and fails to clearly point out the maintenance strategy. Oprea et al. (2019) calculated the reliability index by designing a probabilistic model based on Markov chain and proposed maintenance activities based on this to optimize the inventory of spare parts. Xu et al. (2017) predicted the future degradation and change process of the equipment based on the operation data of the equipment; an optimized maintenance program with the goal of optimizing profit is established. In the work by Wang et al. (2018), an incomplete maintenance model is proposed by considering the process of equipment degradation and shock but fails to consider the impact of special environments on maintenance strategies.

The aforementioned literatures took into account the economic and structural dependencies and state transition processes of equipment. Preventive maintenance was carried out through state prediction. Compared with regular maintenance, the aforementioned research improved the operation and maintenance efficiency and reduced the maintenance cost but failed to consider the impact of failure correlation. In terms of failure correlation, scholars mainly study the mutual influence of failure rates (Peng et al., 2020; Nguyen et al., 2019). When the relationship of fault influence is not clear, the Copula function is usually used to describe the correlation (Xu et al., 2020; Zhu et al., 2019). In the work by Fu et al. (2019), the failure correlation between components was analyzed by the Copula function, and a joint risk model based on failure interaction was established. In the work by Song et al. (2014), a reliability model was established by considering the fault correlation between components. The aforementioned research studies are mainly in the field of mechanical engineering and other fields of fault correlation analysis. However, in the field of photovoltaic operation and maintenance, the research on maintenance strategies considering fault correlation is still in its infancy.

The formulation of the maintenance strategy in existing research studies is mainly based on the operating state of the equipment, and the reliability is used as a constraint to judge whether maintenance is required, and then the maintenance strategy is optimized on the basis of considering maintenance costs. These maintenance methods reduce maintenance costs to a certain extent. However, it fails to take into account the impact of availability and comprehensive correlation and does not take into account the impact of weather

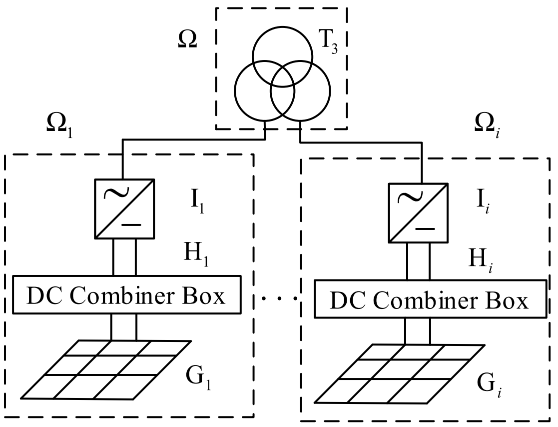

FIGURE 1 | Schematic diagram of the association set.

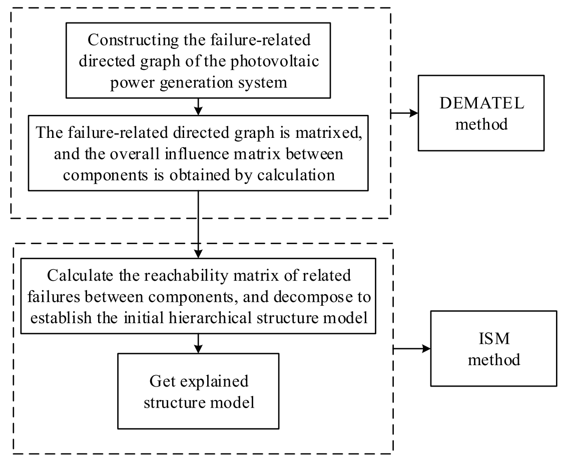

FIGURE 2 | Block diagram of failure correlation.

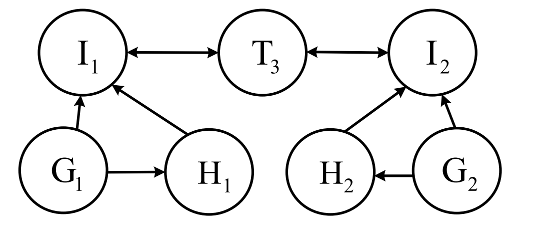

FIGURE 3 | Failure directed graph of the photovoltaic power generation system.

factors on maintenance costs and system availability. Therefore, the maintenance plan formulated is not necessarily the best maintenance plan for the system. Thus, the maximum efficiency of photovoltaic power generation cannot be guaranteed. In view of the aforementioned problems, this study first analyzes the functional dependencies and failure transfer process of equipment in photovoltaic power plants. Then, it combines the Copula theory and Sklar theorem to describe the failure correlation characteristics between devices and models the availability of the system and components by improving the Markov model. Finally, a maintenance model of double-layer optimization of the photovoltaic power generation system based on maintenance cost and availability is established. In the analysis of the failure correlation of equipment, by setting different failure-related strengths to compare the changes in availability, it verified the degree of influence of the failure correlation on the maintenance strategy and availability and provided the foundation for formulating a reasonable and effective maintenance strategy. On the issue of sensitivity analysis, by introducing weather accessibility to analyze its impact on maintenance costs and system availability, the effectiveness of the model and its universality in complex environments were verified.

CORRELATION ANALYSIS

Structural Correlation Analysis

The components of the photovoltaic system are decomposed into different association sets (subsystems) according to their structural relevance, and maintenance decisions are made in the unit of association sets. Concerning the topology of the photovoltaic power generation system network, the association set includes photovoltaic arrays, combiner boxes, inverters, transformers, and other equipment.

Figure 1 shows a schematic diagram of an association set comprising a power generation unit in a photovoltaic power generation system. Among them, T_3 is the transformer, I is the inverter, H is the DC combiner box, G is the photovoltaic array, and Ω_i is different association sets. As can be seen from the figure, the power generation unit is a series–parallel hybrid system consisting of multiple subsystems connected in parallel and then connected in series with T_3.

Failure Correlation Analysis

In this study, the decision-making experiment analysis method (DEMATEL) is combined with the interpretation structure model method (ISM) to describe the failure propagation process between the components of the photovoltaic power generation system. Specific ideas are shown in **Figure 2**. The specific steps are as follows:

Establishing a Directed Graph of System Failures

A photovoltaic power generation system is taken as an example that exists between two parallel subsystems. The failure correlation between components is analyzed through relevant data to obtain a directed graph of photovoltaic power generation system failures, as shown in **Figure 3**. If the failure of component i in the system causes the failure of component j, there is a directed edge from node i to j.

Transforming the Directed Graph Into a Matrix and Calculating the Influence Matrix Between the Components

Transforming the invalid and directed graph in **Figure 3** into a matrix to obtain the direct influence relationship matrix Y, that is,

$$\mathbf{Y} = \begin{array}{c} T_3 \\ I_1 \\ H_1 \\ G_1 \\ I_2 \\ H_2 \\ G_2 \end{array} \begin{bmatrix} 0 & 1 & 0 & 0 & 1 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 & 0 \\ 0 & 2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 3 & 3 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 2 & 0 & 0 \\ 0 & 0 & 0 & 0 & 3 & 3 & 0 \end{bmatrix},$$

where y_{ij} represents the number of times that component j is affected by the failure of component i. The matrix $\boldsymbol{Y}$ is standardized to obtain

$$\mathbf{X} = \frac{\mathbf{Y}}{\max\limits_{1<i<n} \sum_{j=1}^{n} y_{ij}}, \tag{1}$$

where $\max\limits_{1<i<n} \sum_{j=1}^{n} y_{ij}$ is the maximum value of the sum of Y matrix rows and n is the number of system components. From this, the comprehensive impact matrix T related to failures between components can be obtained:

$$\mathbf{T} = \lim_{k\to\infty}\left(\mathbf{X} + \mathbf{X^2} + \cdots + \mathbf{X^k}\right) = \mathbf{X} \cdot (\mathbf{I} - \mathbf{X})^{-1}, \tag{2}$$

that is,

$$\mathbf{T} = \begin{array}{c} T_3 \\ I_1 \\ H_1 \\ G_1 \\ I_2 \\ H_2 \\ G_2 \end{array} \begin{bmatrix} 0.0444 & 0.1556 & 0.0222 & 0 & 0.1556 & 0.0222 & 0 \\ 0.1556 & 0.0657 & 0.1522 & 0 & 0.0232 & 0.0033 & 0 \\ 0.0444 & 0.3045 & 0.0435 & 0 & 0.0066 & 0.0009 & 0 \\ 0.0857 & 0.5872 & 0.5125 & 0 & 0.0128 & 0.0018 & 0 \\ 0.1556 & 0.0232 & 0.0033 & 0 & 0.0657 & 0.1522 & 0 \\ 0.0444 & 0.0066 & 0.0009 & 0 & 0.3045 & 0.0435 & 0 \\ 0.0857 & 0.0128 & 0.0018 & 0 & 0.5872 & 0.5125 & 0 \end{bmatrix},$$

where I is the identity matrix and T_{ij} represents the comprehensive influence of component i on component j (including direct and indirect influences). Then, the overall impact matrix H of the related failures between components is calculated as follows:

$$\mathbf{H} = \mathbf{T} + \mathbf{I}, \tag{3}$$

that is,

$$\boldsymbol{H} = \begin{bmatrix} 1.0444 & 0.1556 & 0.0222 & 0 & 0.1556 & 0.0222 & 0 \\ 0.1556 & 1.0657 & 0.1522 & 0 & 0.0232 & 0.0033 & 0 \\ 0.0444 & 0.3045 & 1.0435 & 0 & 0.0066 & 0.0009 & 0 \\ 0.0857 & 0.5872 & 0.5125 & 1 & 0.0128 & 0.0018 & 0 \\ 0.1556 & 0.0232 & 0.0033 & 0 & 1.0657 & 0.1522 & 0 \\ 0.0444 & 0.0066 & 0.0009 & 0 & 0.3045 & 1.0435 & 0 \\ 0.0857 & 0.0128 & 0.0018 & 0 & 0.5872 & 0.5125 & 1 \end{bmatrix}.$$

The reachable matrix $\boldsymbol{M}$ of related failures between components is calculated as follows:

$$\mathbf{M} = \begin{bmatrix} 1 & 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 1 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 0 \\ 1 & 1 & 1 & 0 & 1 & 1 & 1 \end{bmatrix},$$

where

$$m_{ij} = \begin{cases} 1, h_{ij} > \mu \\ 0, h_{ij} \le \mu \end{cases} \quad (i, j = 1, \cdots, n). \tag{4}$$

μ is a given threshold, which is taken as 0 when the number of system components is small.

The level division table is listed in **Table 1** according to the ISM method combined with the reachable matrix.

In **Table 1**, S_i represents system component i; $R(S_i)$ is the reachable set (a set consisting of the corresponding parts of the columns of all 1s in the ith row of the reachable matrix $\boldsymbol{M}$); $A(S_i)$ is the antecedent set (a set consisting of the corresponding parts of the rows of all 1s in the ith column of the reachable matrix $\boldsymbol{M}$); $C(S_i)$ is the common set of reachable and antecedent sets; and $\prod(P)$ is the result of hierarchical division. If $R(S_i) = C(S_i)$, and then the element in $\prod(P)$ is the element in $R(S_i)$.

It can be seen from **Figure 4** that the photovoltaic power generation system has a two-level hierarchical structure, and the second level affects the first level, which ultimately affects the development of system reliability. Among them, G_1 and G_2 are the failure source equipment that affect the failure of other equipment and are not affected by the failure of other equipment. The equipment other than G_1 and G_2 are nonfailure source equipment affected by the failure correlation. It can be seen that the reliability and availability of G_1 and G_2 should be ensured as much as possible during the operation of the system.

AVAILABILITY MODEL

Availability Model of Failure-Independent Failure Source Equipment

The equipment in the photovoltaic power generation system age during use, and there are also sudden failures during actual operation. Such failures are usually caused by external random factors that affect the results of maintenance decisions.

According to the IEEE Standard Guide, the operating status of power equipment is divided into normal, attention, abnormal, and serious status (IEEE, 2008). In the traditional status transition model, the serious status is generally treated as failure. In order to comprehensively consider the degraded faults and sudden faults, this study distinguishes the serious status from the faulty status and establishes an improved Markov status transition model to describe the fault law of the equipment.

Figure 5 shows the process of equipment state transition. In the figure, 0–3 indicate normal, attention, abnormal, and degraded failure states; 4–6 denote sudden failure states. It is to be noted that the transfer rate between states is marked in the figure. In addition, λ is the transfer rate and μ is the repair rate; a_1, a_2, and a_3 represent the rate of transition from fault state 6 to states 0–2; b_1 and b_2 represent the rate of transition from fault state 5 to 0.1; and parameters a_i and b_i satisfy the following relationship:

$$\begin{cases} a_1 + a_2 + a_3 = \mu_2 \\ b_1 + b_2 = \mu_1 \\ a_1, a_2, a_3, b_1, b_2 \ge 0 \end{cases}. \tag{5}$$

TABLE 1 | Process table of level division.

Collection of parts	S_i	$R(S_i)$	$A(S_i)$	$C(S_i)$	$\prod(P)$
$P-L_0$	1	1 2 3 5 6	1 2 3 4 5 6 7	1 2 3 5 6	$L_1=\{S_1,S_2,S_3,S_5,S_6\}$
	2	1 2 3 5 6	1 2 3 4 5 6 7	1 2 3 5 6	
	3	1 2 3 5 6	1 2 3 4 5 6 7	1 2 3 5 6	
	4	1 2 3 4 5 6	4	4	
	5	1 2 3 5 6	1 2 3 4 5 6 7	1 2 3 5 6	
	6	1 2 3 5 6	1 2 3 4 5 6 7	1 2 3 5 6	
	7	1 2 3 5 6 7	7	7	
$P-L_0-L_1$	4	4	4	4	$L_2=\{S_4,S_7\}$
	7	7	7	7	

*Note from **Table 1** that the system is divided into two layers, namely, $L_1=\{S_1,S_2,S_3,S_5,S_6\}$ and $L_2=\{S_4,S_7\}$, and the structural model of the system can be obtained as shown in **Figure 4**.*

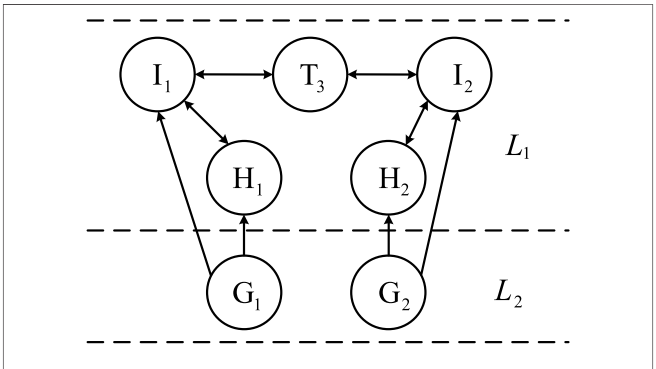

FIGURE 4 | Model diagram of the system structure.

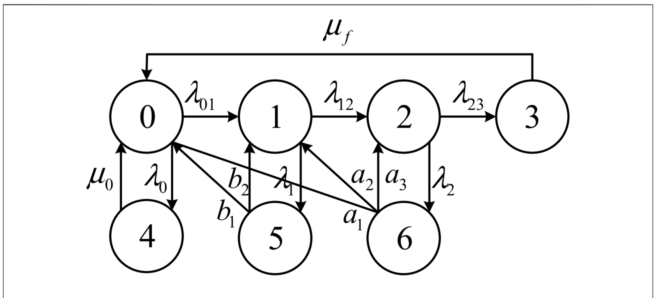

FIGURE 5 | Process of equipment state transition.

Assuming that the initial state of the device is 0, the Markov state transition rate matrix of the device based on the aforementioned analysis is as follows:

$$\mathbf{T}=\begin{bmatrix} c_1 & \lambda_{01} & & & \lambda_0 & & \\ & c_2 & \lambda_{12} & & & \lambda_1 & \\ & & c_3 & \lambda_{23} & & & \lambda_2 \\ \mu_f & & & -\mu_f & & & \\ \mu_0 & & & & -\mu_0 & & \\ b_1 & b_2 & & & & -\mu_1 & \\ a_1 & a_2 & a_3 & & & & -\mu_2 \end{bmatrix}, \tag{6}$$

where $c_1=-(\lambda_{01}+\lambda_0), c_2=-(\lambda_{12}+\lambda_1), c_3=-(\lambda_{23}+\lambda_2)$. Let $P(t)=[P_0(t),\cdots,P_6(t)]$ be the state matrix. $P_i(t)$ represents the probability that the device is in state i at time t; then, the differential equation of C–K is as follows:

$$d\mathbf{P}(t)/dt=\mathbf{P}(t)\mathbf{T}. \tag{7}$$

Carrying out the Laplace transform on the aforementioned formula, we obtain:

$$s\begin{bmatrix} p_0(s) \\ p_1(s) \\ \dots\vdots \\ p_6(s) \end{bmatrix}-\begin{bmatrix} p_0(0) \\ p_1(0) \\ \dots\vdots \\ p_6(0) \end{bmatrix}=\mathbf{T}^T\begin{bmatrix} p_0(s) \\ p_1(s) \\ \dots\vdots \\ p_6(s) \end{bmatrix}. \tag{8}$$

Obtaining $P(s)$ from the aforementioned equation and the initial state p (0) and then performing the inverse Laplace transform to obtain $P(t)$, the equipment availability is as follows:

$$A(t)=p_0(t)+p_1(t)+p_2(t). \tag{9}$$

Availability Model of Nonfailure Source Equipment Considering Failure Correlation

When there is a failure correlation between equipment i and j, the failure correlation of components i and j is described by defining the failure correlation coefficient g_{ij}, that is,

$$g_{ij}=\phi_{ij}^a, \tag{10}$$

where ϕ_{ij} is the correlation coefficient of the actual degradation of components i and j, and a is the failure-related strength used to describe the degree of influence of failure correlation on the component failure rate; its value is determined by the failure degree of the equipment in the actual photovoltaic power generation system.

It can be obtained that the comprehensive failure rate of components is as follows:

$$\lambda_j(t)=\lambda_{Ij}(t)+\sum_{ij}g_{ij}\lambda_{ij}(t)_g, \tag{11}$$

where $\lambda_j(t)$ is the comprehensive failure rate of component j, $\lambda_{Ij}(t)$ is the independent failure rate of component j, and $\lambda_{ij}(t)_g$ is the failure rate of component i that affects the failure of component j.

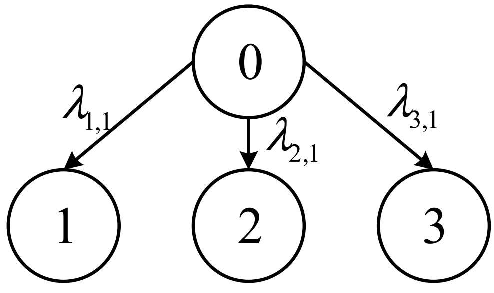

FIGURE 6 | Process of subsystem state transition.

The Copula theory connects the joint and marginal distribution functions and can systematically describe the correlation characteristics between variables. Therefore, this study proposes the use of this theory and Sklar theorem to obtain the correlation coefficient of the actual degradation. Through the aforementioned analysis combined with the description of the availability model in Fig 3.1, the availability model of nonfailure source equipment that considers the failure correlation can be obtained.

System Availability Model

To compare the availability of photovoltaic power generation systems with and without failure correlation, this section analyzes the system availability model from the point of view of the following two aspects:

Failure-Independent System Availability Model

It is to be noted from the structural analysis of the photovoltaic power generation system in *Structural Correlation Analysis* that the photovoltaic power generation system unit comprises two subsystems Ω_i in parallel and then connected in series with equipment T_3. Among them, the devices in the subsystem are in a logical series relationship in structure, and the availability of subsystem Ω_i at the start time can be expressed as follows:

$$B_{\Omega_i}(t_0) = \prod_{i=1}^{n} A_i(t_0), \tag{12}$$

where $A_i(t)$ represents the availability of component i in the subsystem and n is the number of components. Assuming that Ω_i is in the running state at the initial moment, its state transition process is shown in **Figure 6**.

In **Figure 6**, 0 represents the operating status of the subsystem. i represents the shutdown status due to the failure of component i. 1–3 represent the combiner box, inverter, and photovoltaic array, respectively. $\lambda_{i,1} = 1 - A_i(t)$ is the failure rate of the equipment.

Given that the state transition rate of the subsystem is constant, its transition can be described by a Markov process, and the transition rate matrix can be obtained as follows:

$$\boldsymbol{E} = \begin{bmatrix} -\sum_{i\in\Omega}\lambda_{i,1} & \lambda_{1,1} & \lambda_{2,1} & \lambda_{3,1} \\ 0 & 0 & 0 & 0 \\ & & \vdots & \\ 0 & 0 & 0 & 0 \end{bmatrix}. \tag{13}$$

From the aforementioned formula, the following C–K equation can be obtained:

$$\frac{d\mathbf{Q}}{dt} = \mathbf{Q}E, \tag{14}$$

where $\mathbf{Q} = (q_i(t)), i = 0, 1, 2, 3$ is the state matrix, and $q_i(t)$ is the probability that the subsystem is in state i at time t. Assuming that the subsystem is in the running state at the initial moment, that is, $q_0(0) = 1$, the probability distribution of the subsystem state can be obtained by **formula (14)** as follows:

$$q_i(t) = \begin{cases} e^{-\sum_{i\in\Omega}\lambda_{i,1}t} & i = 0 \\ \dfrac{\lambda_{i,1}}{\sum_{i\in\Omega}\lambda_{i,1}}\left(1 - e^{-\sum_{i\in\Omega}\lambda_{i,1}t}\right) & i = 1, 2, 3 \end{cases}. \tag{15}$$

Then, the availability of subsystem Ω_i is as follows:

$$B_{\Omega i}(t) = q_0(t) \cdot B_{\Omega i}(t_0). \tag{16}$$

Accordingly, the overall availability of the photovoltaic power generation unit system can be obtained as follows:

$$A_{all}(t) = A_{T_3}(t) \cdot \left[1 - \prod_{i=1}^{2}(1 - B_{\Omega i}(t))\right]. \tag{17}$$

Failure-Related System Availability Model

Based on the description in *Availability Model*, applying the availability model of nonfailure source equipment to the failure-independent system availability model can obtain a system availability model considering failure correlation.

PHOTOVOLTAIC POWER GENERATION SYSTEM MAINTENANCE MODEL CONSIDERING COMPONENT RELEVANCE AND AVAILABILITY

Maintenance-Model Thinking Framework

The operation and maintenance of photovoltaic power generation systems must keep the lowest maintenance cost under certain availability conditions. Therefore, upper and lower optimization models are proposed.

The upper model considers the economic structure relevance, introduces the idea of opportunistic maintenance in the modeling process, and determines the maintenance method, time, and scope with the lowest maintenance cost as the objective function. The lower model is a verification based on the upper model, with the highest system availability as the objective function. The component availability is the constraint, and the maintenance plan that does not satisfy the lower model is substituted into the upper layer and optimized again until the optimal maintenance plan is obtained. In this study, the quantum genetic optimization algorithm is proposed to optimize the upper and lower models. A block diagram is shown in **Figure 7**.

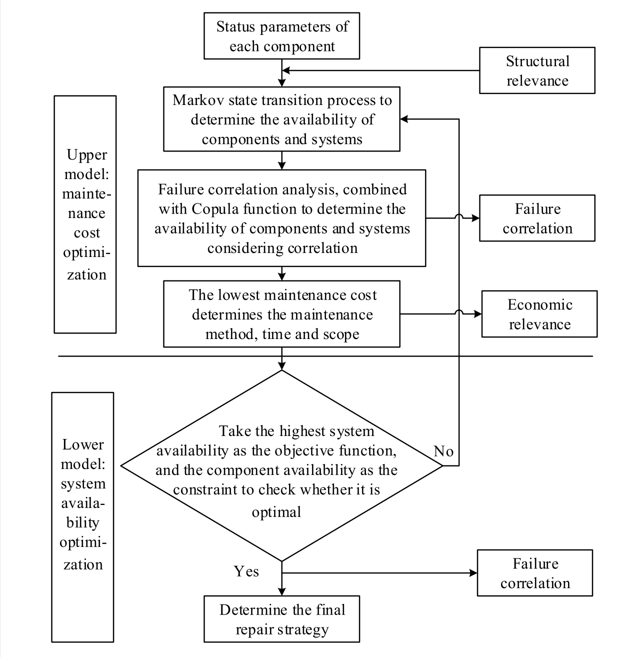

FIGURE 7 | Framework of the maintenance model.

Upper-Level Optimization Model

This study takes the lowest maintenance cost in the entire maintenance time period as the objective function and establishes the upper-level optimization model with maintenance resources and time as constraints.

The total maintenance cost of a photovoltaic power station comprises fixed maintenance cost C^i_{com}, downtime loss C^i_{loss}, and maintenance personnel cost C^i_{peo}, that is,

$$C_{\mathrm{all}} = \sum_{i=1}^{n}\left[\sum_{i=1}^{m}\left(C^i_{\mathrm{com}} + C^i_{\mathrm{loss}}\right) + C^i_{\mathrm{peo}}\right], \tag{18}$$

where n is the number of subsystems that need to be maintained and m is the number of devices that need to be maintained in the subsystem.

Fixed Cost of Maintenance C^i_{com}

The fixed cost of maintenance is determined by the maintenance method, that is, the action set = {minor repair, incomplete maintenance, overhaul} = {0,1,2}. The corresponding maintenance cost is $\{C_{\mathrm{m}}, C_{\mathrm{p}}, C_{\mathrm{f}}\}$as follows:

$$C_{\mathrm{p}} = C_{\mathrm{c}} + iC_{\mathrm{v}}, \tag{19}$$

where C_{c} is the fixed cost of incomplete maintenance and C_{v} is the variable cost.

Shutdown Loss C^i_{loss}

The traditional photovoltaic power plant maintenance model ignores the impact of different weather conditions (irradiance, temperature, etc.) on the shutdown loss and sets the shutdown loss to a fixed value that cannot effectively reflect the actual photovoltaic power station loss. Therefore, in this study, the capacity factor v is introduced to calculate the downtime loss as follows:

$$C^i_{loss} = vC_0 t_w, \tag{20}$$

where t_{w} is the downtime and C_0 is the downtime cost per unit time of the photovoltaic equipment in the rated state.

$$C_0 = \frac{x\Gamma t_i}{t_g}\mathrm{r}, \tag{21}$$

where x is the number of sub-arrays for equipment maintenance and shutdown; t_{i} is the repair time; and t_{g} is the average number of hours of sunshine per day. We assume Γ = 1900kWh and r = 0.8 yuan.

$$v = \frac{W}{P_N(t)t_g}, \tag{22}$$

where $P_N(t)$ is the rated power of the PV power station and W is the actual power generation under different conditions. The downtime t_{w} is calculated as follows:

$$\mathrm{t_w} = \mathrm{t_{w1}} + \mathrm{t_{w2}}, \tag{23}$$

$$\begin{cases} t_{\mathrm{w1}} = \sum_{j=1}^{u}\sum_{i\in G_j} d_i + ut_s \;\; G_j \in O_1 \\ t_{\mathrm{w2}} = \max\sum_{i\in G_j} d_i + t_s \;\; G_j \in O_2 \end{cases}, \tag{24}$$

where G_j is the maintenance group in the associated concentration, u is the number of maintenance groups, O_1 is the sequential maintenance execution set, O_2 is the common maintenance execution set, t_{s} is the fixed preparation time, and d_i is the specific maintenance time of equipment i, which is related to the maintenance method and maintenance effect. The following formula is also considered:

$$d_i = \frac{t_{ij}}{w}, \tag{25}$$

where t_{ij} is the average fixed maintenance time of the equipment i in different maintenance methods and w is the weather access rate.

Maintenance Personnel Cost C^i_{peo}

Maintenance personnel expenses include basic salary and bonus:

$$C^i_{peo} = \sum_{i\in O_1} N(i)\left(F_0 + F_h t_{w1}\right) + \sum_{i\in O_2} N(j)\left(F_0 + F_h t_{w2}\right), \tag{26}$$

where $N(i)$ is the personnel required for the $i-$th sequential maintenance set, $N(j)$ is the personnel required for the common maintenance set, F_{h} is the bonus of maintenance personnel per unit time, and F_0 is the basic salary.

Constraints

Constraints on Maintenance Resources

During the overhaul period, owing to resource constraints such as manpower and required materials, the equipment cannot be simultaneously overhauled. It needs to be performed in sequence. Therefore, there is

TABLE 2 | State transition rate of different devices.

λ Part	λ_{01}	λ_{12}	λ_{23}	λ_0	λ_1	λ_2
Transformer	0.00118	0.00122	0.0028	0.001	0.003	0.005
Inverter	0.0016	0.00165	0.00377	0.001	0.003	0.005
Combiner box	0.00267	0.00275	0.00630	0.001	0.003	0.005
Photovoltaic array	0.00065	0.00067	0.00153	0.001	0.003	0.005

$$\sum_{i=1}^{n} x_i(t) r_{\varepsilon,i} \le r_\varepsilon(t), \tag{27}$$

where $x_i(t)$ is the state variable of equipment i in time period t. When $x_i(t) = 1$, the maintenance is carried out; otherwise, it is 0. $r_{\varepsilon,i}$ is the demand for resource ε when equipment i is overhauled, and $r_\varepsilon(t)$ is the available resource in time period t.

Constraint on Maintenance Time

The overhaul time is limited to the time period that can be overhauled.

$$\begin{cases} x_i(t) = 0 & t < b_i \text{ or } t > e_i \\ x_i(t) = 1 & s_i \le t \le s_i + f_i \\ x_i(t) = \{0,1\} & b_i \le t \le e_i \end{cases}, \tag{28}$$

where b_i and e_i represent the earliest and latest overhaul times, respectively, and s_i and f_i represent the start time and duration of overhaul, respectively.

Lower-Level Optimization Model

In the upper layer, the maintenance plan obtained with the lowest maintenance cost is brought to the lower layer for verification. The target is the highest availability of the photovoltaic power generation system, and the component availability is the constraint to establish the lower-layer optimization model expressed as follows:

$$\begin{cases} \max \ A_{all} \\ \text{s.t.} \ \ A_i \ge A_{i\,\min} \end{cases}, \tag{29}$$

where $A_{i\,\min}$ is the lowest availability of component i in stable operation, assumed to be 0.9 in this study. An improvement

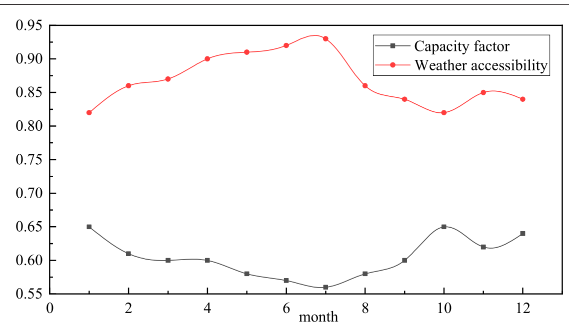

FIGURE 8 | Weather parameters.

TABLE 3 | Maintenance costs of different maintenance methods.

Maintenance cost/yuan	C_m	C_c	C_v	C_f
Photovoltaic array and combiner box	1,700	2,000	1,000	10,300
Inverter	4,500	5,000	2000	28,000
Transformer	5,000	5,000	3,000	30,000

factor is proposed to indicate the degree of recovery to describe the impact of different maintenance strategies on component performance:

$$\delta_i = \left(l \cdot \frac{c_i}{c_f} \right)^{bi}, i = 1, \cdots, n, \tag{30}$$

where l is the maintenance cost's adjustment parameter, b is the maintenance frequency's adjustment parameter, and i is the maintenance frequency. l and b are considered to be 1 and 0.0005, respectively.

SIMULATION ANALYSIS

In this study, using MATLAB software, taking a 10-MW photovoltaic power station as an example, the economic effectiveness of the model is verified by simulation. According to relevant data of the power station and previous studies, the device state transfer rate can be calculated as shown in **Table 2**, where the sudden failure rate is set as $\lambda_0 = 0.001, \lambda_1 = 0.003 = 0.003$, and $\lambda_2 = 0.005$. The fault repair rate is $\mu_f = 0.0179$ and $\mu_0 = \mu_1 = \mu_2 = 0.071$, and the unit is times/day. The maintenance costs under the different maintenance methods are listed in **Table 3**. Combining the Copula theory and Sklar theorem, the correlation coefficient of the actual degradation among equipment can be obtained as shown in **Table 4**.

Figure 8 shows the monthly weather accessibility and capacity factor based on the environment where the photovoltaic power station is located and also weather station data.

Performance Comparison Analysis

Two options were selected for comparison analysis.

Option 1: performance analysis without considering the failure correlation. option 2: performance analysis including the failure correlation.

Through the simulation, In **Figures 9A,B** are shown, respectively, the availability comparison curves of the combiner box and the system under the failure-related strength $a = 1$ and the failure-independent situation.

It can be seen from **Figure 9** that when the failure correlation is considered, the degree of decline in the availability of equipment and systems increases. It is determined by the correlation coefficient and strength between its increasing speed and equipment. The larger the correlation coefficient, the faster the availability curve of option 2 declines than that of option 1. It can be seen that ignoring the failure correlation will lead to errors in subsequent maintenance strategies and time, thus affecting the revenue of the photovoltaic power generation system.

TABLE 4 | Correlation coefficient of the actual degradation.

Part	Transformer	Inverter	Combiner box	Photovoltaic array
Transformer	1	0.00413	0	0
Inverter	0.00413	1	0.01017	0
Combiner box	0	0.01017	1	0
Photovoltaic array	0	0.01230	0.01961	1

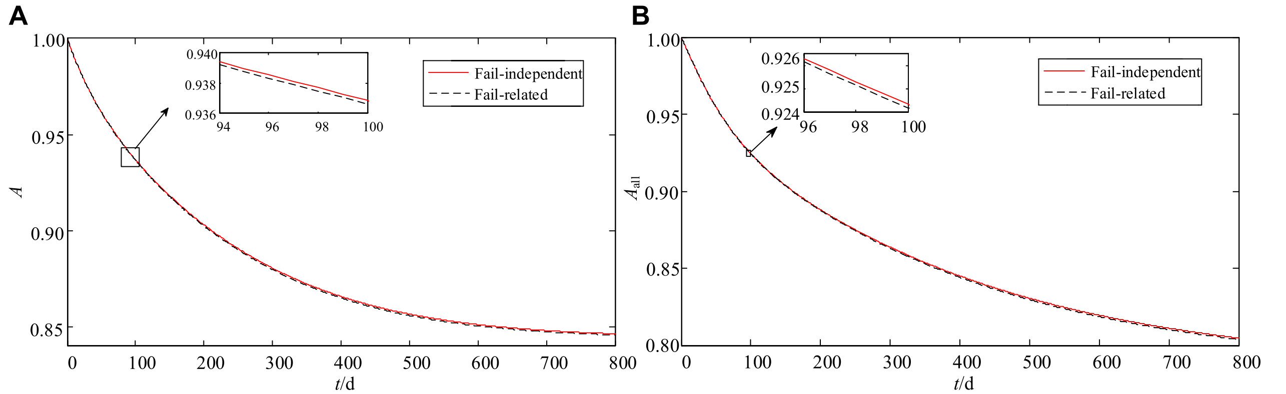

FIGURE 9 | Comparison curve of system availability. **(A)** Comparison curve of availability about H_2. **(B)** Comparison curve of system availability.

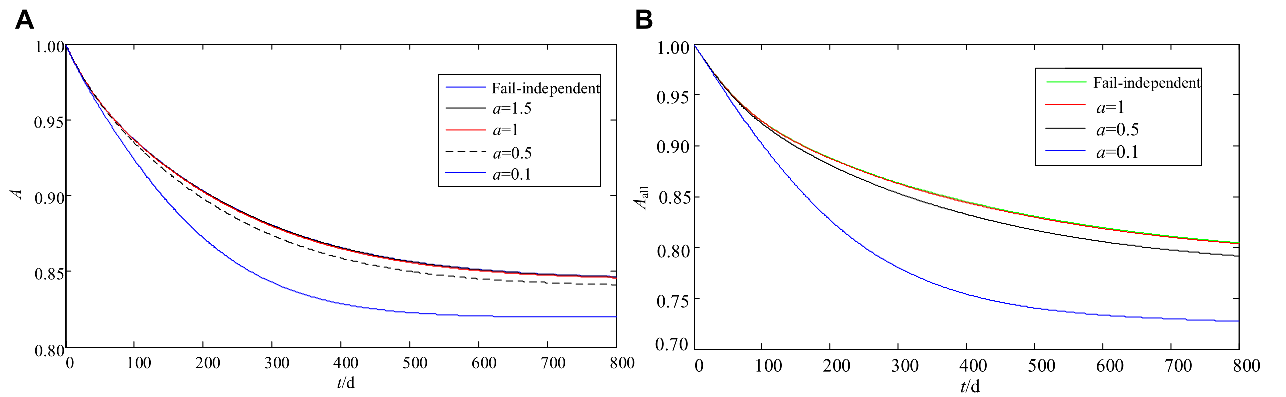

FIGURE 10 | Availability curves for different failure-related strengths. **(A)** Availability curve of the combiner box with different failure-related strengths. **(B)** Availability curve of the system with different failure-related strengths.

In order to compare the effects of different failure-related strengths on the availability of equipment and systems, the availability simulation curves are obtained by setting different failure-related strengths as shown in **Figure 10**.

It can be seen from **Figure 10** that the failure-independent availability curve is always above the failure-related availability curve, and when the failure-related strength is greater, the availability curve is closer to the failure-independent curve.

When $0 < a < 1$, with the decrease of the failure-related strength, the lowering rate of the availability curve is faster, so when the maintenance plan is formulated, the maintenance time and strategy are more obviously different than those of the failure-independent model. The photovoltaic power generation unit is a hybrid system comprising multiple devices in series and in parallel, and the structure of the parallel subsystem is symmetrical. By comparing the two figures, it can be seen that the availability curves of the system and equipment have similar changes with the failure-related strength, but the trend of the system is more evident.

Comparison of Maintenance Strategies

The following four options are used to compare and analyze: Option 1: a double-layer optimization maintenance strategy that considers component relevance and $a = 1$. Option 2: a double-layer

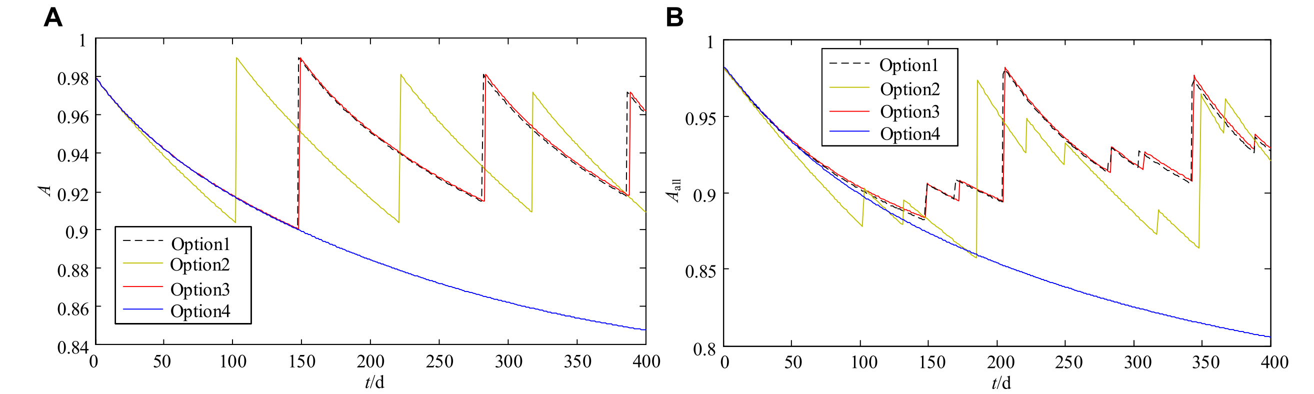

FIGURE 11 | Comparison curve of availability after maintenance. **(A)** Comparison curve of availability of H_2 after maintenance. **(B)** Comparison curve of system availability after maintenance.

optimization maintenance strategy that considers component relevance and $a = 0.1$. Option 3: a double-layer optimization maintenance strategy that does not consider component relevance. Option 4: a traditional condition maintenance strategy that does not consider component relevance.

The following results were obtained through the simulation analysis: A and B in **Figure 11** are the comparison diagrams of the changeable curves of the availability of the combiner box H_2 and the system after the maintenance of the four schemes, respectively.

It can be seen from A in **Figure 13** that the availability of the combiner box H_2 in the initial state is 0.98. If the failure is not considered, it will meet the maintenance conditions for the first time when it runs to the 149th day. If the failure is considered, it will meet the maintenance conditions for the first time when it runs to the 103rd day. Through the double-layer optimization model, it is known that it needs to be repaired slightly. After repair, the availability is increased to 0.9910, and then it continues to operate on this basis until the next repair.

B in **Figure 13** is the curve of availability change after system maintenance. If the failure correlation is not considered, the transformer needs to be repaired when the system runs to the 206th and 34th days. If the failure correlation is considered, the transformer needs to be repaired when the system runs to the 186th and 34th days, and the system availability is significantly improved after repair.

It can be seen from **Figure 11** that the availability of the double-layer optimization maintenance model is significantly improved compared with that of the traditional condition maintenance model. The maintenance time of the double-layer optimization maintenance model considering failure correlation is earlier than that of the double-layer optimization maintenance model with independent failure, and the smaller the value of a, the longer the maintenance time in advance.

Table 5 shows the common maintenance time decision set for photovoltaic power generation unit systems.

It can be seen from the table that the maintenance strategy of failure-independent system and the maintenance strategy of failure correlation are different. When the failure-related strength a is smaller, the maintenance time is earlier; the maintenance times are greater in number in the whole maintenance cycle, and the maintenance cost is higher. This is because when the failure correlation is considered, the probability of failure of the affected component will increase, so the number of repairs will increase, the maintenance cost will increase, and the maintenance strategy will also change. When the failure-related strength $a = 1$, the availability of equipment and systems is close to the failure-independent situation, so the maintenance time is not significantly different, and the maintenance strategy is basically the same.

The total maintenance cost of each equipment is calculated by formulas (**19–26**), resulting in 66,800 yuan, whereas the maintenance cost is 59,200 yuan after adopting the double-layer optimization model. The saving rate reaches 12.8%, and the downtime of each equipment is 72 h for individual maintenance. The double-layer optimization maintenance model that considers opportunistic maintenance takes into account multiple maintenance equipment. The longest maintenance equipment downtime is taken as the common downtime, which is 40 h. As a result, the downtime saving rate can reach 44.4%, so the double-layer optimization model proposed in this study can effectively reduce both downtime and maintenance costs.

Sensitivity Analysis

The double-layer optimization maintenance strategy proposed in this study is affected by weather accessibility. The maintenance-cost change rate and system availability are different under different values.

Impact of Weather Accessibility on the Change Rate of Maintenance Costs

The following two options are used to compare and analyze the influence of weather accessibility on the change rate of maintenance costs:

Option 1: a double-layer optimization maintenance model considering component relevance;

Option 2: traditional condition maintenance model

TABLE 5 | Maintenance decision set.

Failure-independent			Failure-related (a = 1)			Failure-related (a = 0.1)		
Maintenance time/day	Maintenance equipment	Action set	Maintenance time/day	Maintenance equipment	Action set	Maintenance time/day	Maintenance equipment	Action set
149	H_2, I_2	{0.0}	148	H_2, I_2	{0.0}	103	H_2, I_2	{0.0}
173	H_1, I_1	{0.0}	170	H_1, I_1	{0.0}	132	H_1, I_1	{0.0}
206	T_3, G_1, G_2	{0,0,0}	205	T_3, G_1, G_2	{0,0,0}	186	T_3, G_1, G_2	{0,0,0}
284	H_2, I_2	{0.0}	282	H_2, I_2	{0.0}	222	H_2, I_2	{0.0}
308	H_1, I_1	{0.0}	304	H_1, I_1	{0.0}	250	H_1, I_1	{0.0}
344	T_3, G_1, G_2	{0,0,0}	343	T_3, G_1, G_2	{0,0,0}	318	H_2, I_2	{1.1}
389	H_2, I_2	{1.1}	387	H_2, I_2	{1.1}	349	T_3, G_1, G_2	{0,0,0}
						367	H_1, I_1	{1.1}

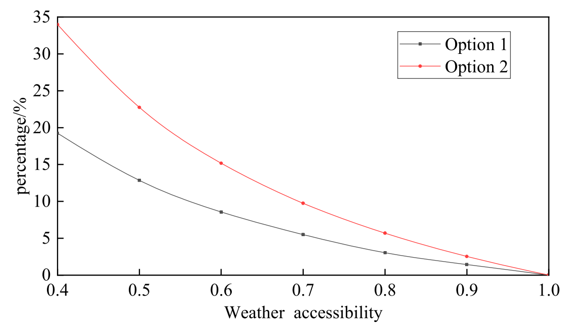

FIGURE 12 | Change rate curve of maintenance cost.

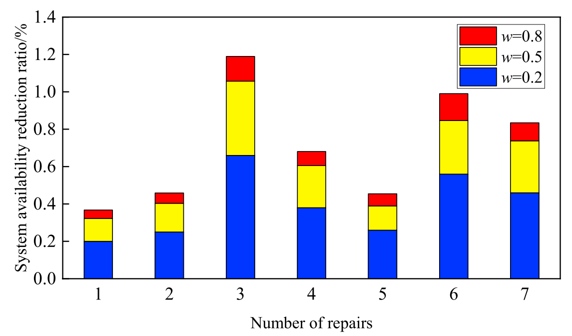

FIGURE 13 | Impact of different weather accessibility on system availability.

Figure 12 shows that as the weather accessibility increases, the maintenance shutdown loss decreases, and the reduction rate of the maintenance-cost change-rate decreases. The maintenance-cost saving rate of option 1 is lower than that of option 2. The reason is that the larger the weather accessibility, the smaller the shutdown loss, and the smaller the maintenance-cost saving rate. When $w < 0.7$, the reduction of maintenance cost is higher. When $0.7 < w < 0.85$, the reduction of maintenance cost ranks the second. When $0.85 < w < 1$, the reduction of maintenance cost is smaller. If there is more equipment to be repaired, the number of repairs in option 1 will be smaller than that in option 2. In addition, the greater the cost of downtime saved, the greater the saving rate. When the weather accessibility is lower, option 1 will have a greater reduction in maintenance costs than option 2, and the advantages become more evident. When the weather accessibility is high, the downtime loss accounts for a small proportion of the maintenance cost, the saving rate of maintenance costs in option 1 is smaller than that in option 2, and the advantage of the first option is weakened.

Impact of Weather Accessibility on System Availability

Figure 13 shows the impact of the double-layer optimization maintenance model on the availability of photovoltaic power generation systems under different weather accessibility. As shown in the figure, the lower the weather accessibility, the greater the reduction ratio of the system availability. The system reduction ratio presents a normal fluctuation state within 400 days and peaks in the third and sixth maintenance occurrences. This is related to the time required for maintenance of the transformer. It can be seen that under the condition of low access rate, ignoring the weather factor has a greater impact on the maintenance strategy.

CONCLUSION

This study considered the influence of component correlation on maintenance time and strategy and proposed a double-layer optimization maintenance strategy for photovoltaic power generation systems based on component correlation. The following conclusions were obtained through simulation:

By analyzing the failure correlation between components, a multilevel hierarchical structure model of the photovoltaic power generation system was obtained, which interpreted the failure transmission process of the system.

Through the establishment of upper and lower optimization models, the best maintenance time and strategy were obtained by comprehensively considering maintenance costs and optimal availability, thereby effectively reducing maintenance costs, reducing downtime, and improving system availability.

When the failure correlation is considered, the more the maintenance times of the affected components, the higher the maintenance cost, and the maintenance strategy is different from the maintenance model that does not consider failure correlation.

The effect of failure correlation on the availability of equipment and systems was verified by setting different failure-related strengths. The results showed that the smaller the failure-related strength, the greater the impact on the availability of system, which in turn affects the maintenance time and the formulation of maintenance strategies.

The influence of weather accessibility on maintenance costs and system availability was analyzed. The results showed that the lower the weather accessibility, the greater the maintenance cost saving rate and the reduction ratio of the system availability of the double-layer optimization maintenance model, which verified the universal applicability of the strategy in complex environments.

This study failed to consider the competitive failure problem of degradation and shock between devices in the research process. Factors such as risk were not taken into account in maintenance modeling, which will be the next step to be carried out in the future.

DATA AVAILABILITY STATEMENT

The original contributions presented in the study are included in the article/Supplementary Material, further inquiries can be directed to the corresponding author.

AUTHOR CONTRIBUTIONS

WC: direct participation, including obtaining research funding, guiding the content of articles, and reviewing. XL: direct participation, simulation analysis, data collection, manuscript writing, and revision. Others: supporting contribution and material support.

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