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Grouping Maintenance Policy for Improving Reliability of Wind Turbine Systems Considering Variable Cost

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Abstract: Wind farms have gained wide attention due to unlimited resources and clean energy. Considering that wind turbine systems are always in harsh conditions, subsystem failures could reduce the reliability of wind turbine systems. At present, the maintenance behaviors for wind turbine systems are various (e.g., corrective maintenance, preventive maintenance) when reliability is reduced below the threshold. Considering the maintenance cost and downtime, it is impossible to repair each component in a timely manner. One of the key problems is dividing components into maintenance groups to improve maintenance efficiency. In this paper, a grouping maintenance policy considering the variable cost (GMP-VC) is proposed to improve direct-drive permanent magnet (DPM) turbine systems. Grouping modes are proposed to fully consider the stated transition probability of turbine components and the variable cost of turbine systems. A maintenance model is formulated to select components as members of the group based on a RIM-VC index. An instance is given to verify the proposed GMP-VC method. The result indicates that the proposed maintenance policy may save maintenance costs over baseline plans.

Keywords: maintenance policy; system reliability; wind turbine systems; variable cost; importance measure

MSC: 90B25

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1. Introduction

1.1. Background

In recent years, with the development of power technology and increasing demand for electricity, a wind turbine system with multiple components becomes more complex to increase availability [1]. Considering that turbine systems failure is inevitable, it is important to ensure a wind farm with turbine systems provides stable power to residents through timely maintenance. Corrective maintenance only considers the maintenance of failed components. Considering carrying out preventive maintenance of other components at the same time, grouping maintenance is more matched with turbine systems by dividing components into groups to save time and cost. Grouping maintenance policy predicts each maintenance and divides groups reasonably to ensure long-term turbine system reliability.

Many scholars have researched the maintenance of wind turbine systems [2–5], but few researchers focus on the grouping maintenance of wind turbine systems due to their components' complexity. A wind turbine system plays an important part in ensuring the stable energy output of a wind farm [6]. A wind turbine system is composed of a series of turbine components, such as a blade, generator, yaw subsystem, and heat subsystem. When one of the above components fails, it would affect other components and even trigger the whole system to fail [7]. Considering the harsh maintenance environment, developing maintenance policies is widely used to improve turbine system reliability.

Determining the most valuable components is a key problem in maintenance optimization [8]. Importance measures are applied in repairable systems widely, which can be used to find weak components in the system and replace them in advance. At present, the recovery importance measure is less considered in the grouping maintenance of wind turbine systems. Since the maintenance cost of a turbine system is variable, an index based on the recovery importance measure and variable cost may be helpful for the improvement of the turbine system.

1.2. Literature Review

Due to the remote location of turbine systems and limited maintenance resources, preventive and opportunistic maintenance have been important repair methods in addition to corrective maintenance. Aafif et al. [9] analyzed the optimal preventive maintenance policies for wind turbine gearboxes. It was recommended to perform incomplete preventive maintenance actions when the temperature threshold was reached to reduce the gearbox failure rate to the value between the current gearbox and the new gearbox. Li et al. [10] developed the opportunistic maintenance strategies for floating offshore turbines based on a mirrored Bayesian network. Considering maintenance costs, the single maintenance action has been improved. Li et al. [11] proposed a data-based failure rate evaluation model to obtain maintenance strategies for onshore and offshore floating fans. Chen et al. [12] gave the intelligent group maintenance planning with usage availability constraints to systems.

Saleh et al. [13] developed the self-adaptive maintenance policy for offshore wind turbines by intelligent Petri nets, which avoids dispensable maintenance behaviors and reduces the operation and maintenance costs related to downtime. Ade Irawan et al. [14] used service operation vessels and safe transfer boats to make maintenance routing in offshore wind farms. O'Neil et al. [15] studied the joint maintenance and orienteering strategy for complex wind turbines. The required reliability threshold is met during the next run task until the next maintenance rotation. Silva et al. [16] designed the fleet size of service operation vessels and mixed location routing to repair offshore floating wind farms. Mixed integer linear programming is used to convert the routing of service ships supporting the logistics aspect of wind farm maintenance into a mathematical method and assists decision makers by offering quantitative tools to screen out the best maintenance plans.

The optimization of maintenance policies is inseparable from the development of algorithms. Wang et al. [17] proposed the optimization of maintenance for wind turbines, considering downtime, based on a hybrid ant colony algorithm. Improving the hybrid ant colony algorithm by discrete symbiosis organisms-search algorithm was used to search the maintenance plan. Khan et al. [18] studied the failed detection of wind turbine systems using SCADA data and genetic algorithm-based learning. Silva et al. [19] used the k-means clustering algorithm for wind turbines for the purpose of predictive maintenance. Zhang et al. [20] developed the turbine blade bearing fault detection with Bayesian and an adaptive Kalman Lagrangian algorithm. Yang et al. [21] researched the improved golden section optimization for optimal allocation and the scheduling of wind turbines and electric vehicle parking lots.

By recognizing and assessing system weaknesses, importance measures have been widely applied in decision-making, system reliability, and risk analysis [22–24]. Although a wind turbine system ensures stable output for a wind farm, it is a more complex system. If turbine components fail, it brings great harm to the turbine system. Importance measures have been applied to wind turbine systems. Selecting components as members of the group based on the recovery importance measure ensures the reliability of the wind turbine system. Fan et al. [25] developed grouping maintenance of subsea Christmas trees with stochastic dependency. Zhang et al. [26] proposed maintenance policy optimization for multicomponent systems considering the dynamic importance measure.

Zhang et al. [27] used the resilience efficiency importance measure for the selection of a component maintenance strategy to recover system performance. Zhu et al. [28] proposed the remaining-useful-lifetime and system-remaining profit-based importance measures for decisions on preventive maintenance. Chen et al. [29] used an importance measure to formulate a maintenance optimization strategy for a pod slewing system.

1.3. Novelty and Contribution

Based on the above questions, the work done in the related literature and in this paper are compared in Table 1. Although the predecessors have done sufficient research, the maintenance method still has room for improvement. This paper studies the grouping maintenance policies of direct-drive permanent magnet (DPM) turbines under variable cost constraints. First, four kinds of grouping modes are considered to study maintenance costs for turbine systems based on state transition probability. Secondly, a RIM-VC index considering the recovery importance measure and variable cost is proposed to optimize the turbine performance. The maintenance sequences of turbines are obtained by the improved simulated annealing algorithm. Last, a wind farm case is given to verify that the proposed GM-VC policy may save maintenance costs over baseline plans. The contributions of this paper are as follows.

- A simulation system for turbine systems is established by a detailed description of its turbine components based on field research.
- Four grouping modes are proposed according to the characteristics of turbine components, which effectively measure the maintenance costs.
- The unit performance measurement method based on recovery importance measure helps to maximize system reliability.

Table 1. The comparison of the work done in the related literature and in this paper.

Attribute / Papers	System	Maintenance Behavior			Maintenance Cost	Maintenance Policy		
	Multi-State	CM	PM	Replacement	Variable Cost	Failure Modes	Maintenance Priority	Fault Sequence
El-Naggar et al., 2023 [30]		√	√				√	
Li et al., 2022 [31]	√	√	√	√	√			√
Sa'ad et al., 2022 [32]			√	√			√	√
El-Naggar et al., 2022 [33]		√	√			√	√	
Wang et al., 2022 [34]		√	√		√		√	
Tian et al., 2022 [35]			√		√		√	√
Yang et al., 2021 [36]		√	√					√
Yan et al., 2021 [37]	√		√					√
Uzunoglu et al., 2020 [38]			√			√	√	
This paper	√	√	√	√	√	√	√	√

1.4. Structure

The remainder of this paper is structured as follows. Section 2 introduces a simulation system for wind turbine systems. Section 3 establishes a GM-VC model to improve the system reliability. Section 4 uses a simulation to verify the proposed methods. Section 5 concludes the paper and proposes future work. Figure 1 shows the technical route for the proposed method.

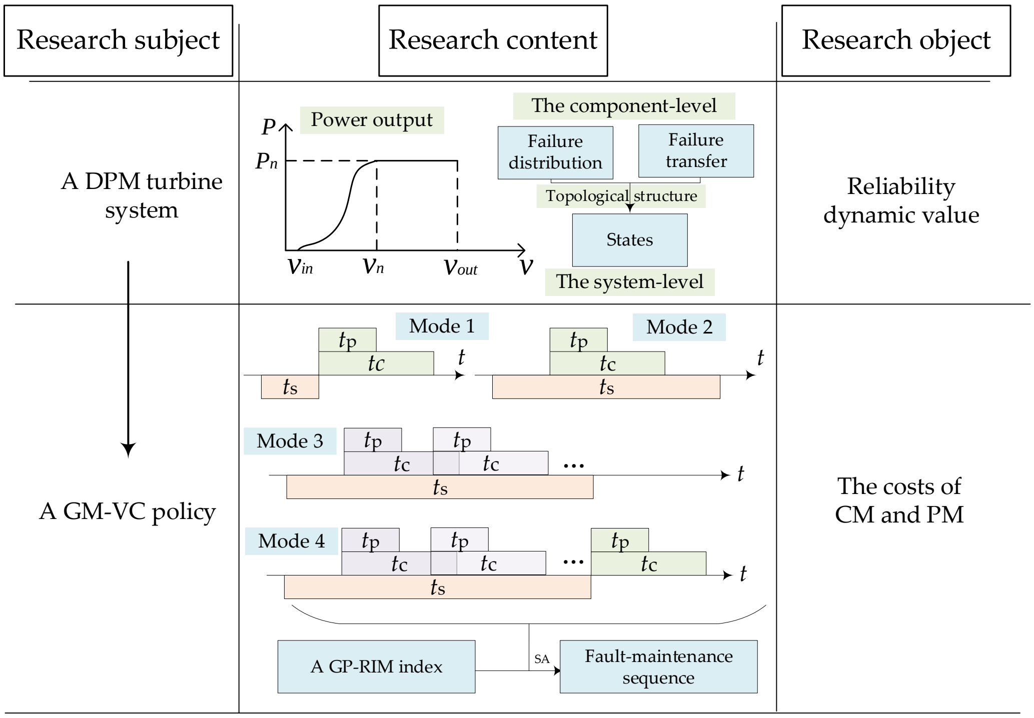

Figure 1. The technical route for the proposed method.

2. A DPM Turbine System

The research object is the direct-drive permanent magnet (DPM) turbine. Given the weakness of traditional turbines, the DPM turbine has been technically improved, which means that an impeller subsystem is directly connected with a generator subsystem to avoid the transmission loss caused by the fault-prone gearbox.

There are 10 components in a DPM turbine system, as shown in Figure 2. Different locations and types of components determine their roles in the system. A turbine system consists of several subsystems. For example, a blade, pitch, and hub form an impeller subsystem. A generator subsystem includes a rotor and a stator. When the yaw subsystem fails, the wind turbine stops. Components in such subsystems are called critical components. The wind system, heat system, cabin, and tower could not cause the system failure when they fail. They are called noncritical components. In Figure 2, the numbers in the circuit correspond to the serial number of the components. The circuit shows the connection structure between components to obtain the reliability of turbine systems.

The working process of a turbine system is described as follows. The cabin is component 9. It includes the critical components, namely the generator subsystem (components 4 and 5) and the yaw subsystem (component 6). Repairmen can enter the cabin through the tower (component 10) to maintain these series-structure components. The front end of the cabin is the impeller subsystem, namely the blade (component 1), the pitch system (component 2), and the hub (component 3). The blade captures the wind and transmits the wind to the hub attached to the spindle. The spindle directly connects the hub to the generator rotor to generate current. The yaw subsystem is used to adjust the optimal working state of the wind turbine. The motor rotates the cabin to allow the impeller to adjust the optimal cut-in angle of the wind direction. It measures wind speed and wind direction through the wind measurement system (component 7). The generator needs to be cooled when it is working, which is realized by a heat dissipation system (component 8) with two cooling methods, water cooling, and air cooling.

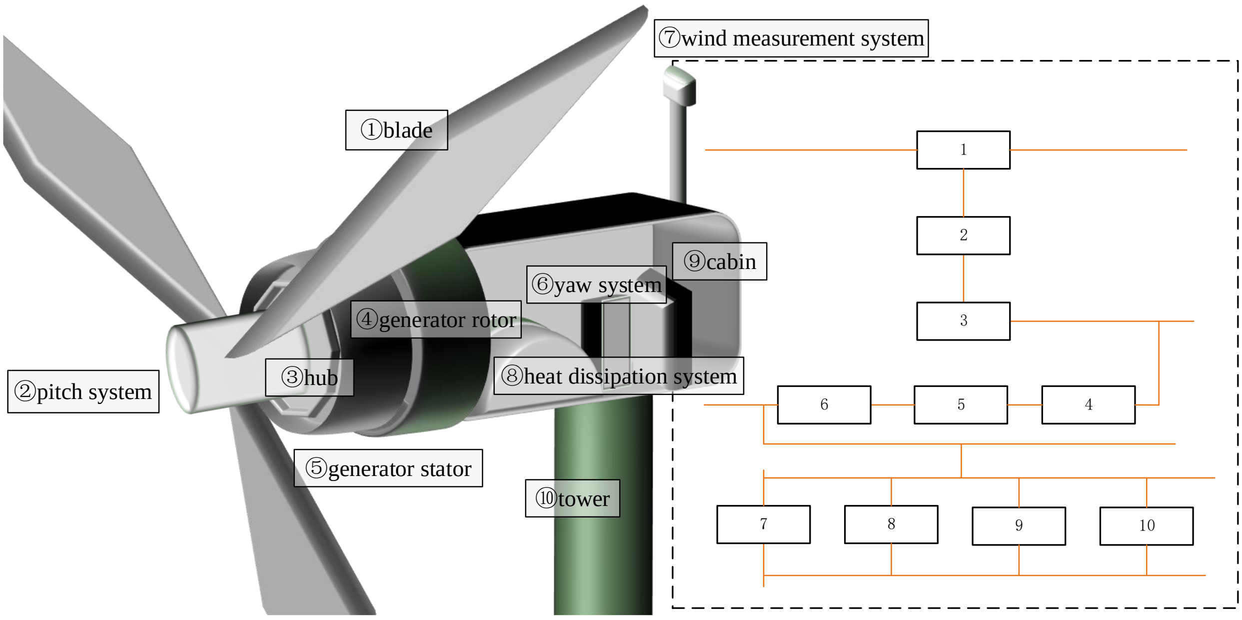

Figure 2. A wind turbine system with multiple components.

Wind power is affected by wind speed. When the wind speed is greater than the cut-in speed or less than the cut-out speed, the blade drives the rotor subsystem to promote the generator subsystem to generate electricity. The wind system monitors the wind speed of the wind farm. When the wind speed is greater than the cut-out speed or less than the cut-in speed, the wind turbine system stops. The yaw system changes the direction of the turbine to make better use of wind speed. When the temperature of the generator subsystem is high, the heat dissipation system works to reduce the temperature. Wind speed is an important factor in the operation of all subsystems. The relationship between the output power of the wind turbine system and the wind speed is as follows.

$$\mathrm{P_w} = \begin{cases} 0;\ v < v_{\mathrm{in}} \text{ or } v > v_{\mathrm{out}} \\ \mathrm{P_n}\left(\frac{v - v_{\mathrm{in}}}{v_{\mathrm{n}} - v_{\mathrm{in}}}\right);\ v_{\mathrm{in}} \le v \le v_{\mathrm{n}} \\ \mathrm{P_n};\ v_{\mathrm{n}} \le v \le v_{\mathrm{out}} \end{cases} \tag{1}$$

The multistate transition process of a wind turbine system is shown in Figure 3. The set of states of components is denoted as $\mathrm{Q}(\mathrm{X}_i) = \{0, 1, 2, 3\}$. $\mathrm{X}_i(t) = 3$ indicates the best working state. $\mathrm{X}_i(t) = 0$ indicates the aging state. The set of wind turbine systems states is denoted as $\Phi(\mathrm{X}) = \Phi(\mathrm{X}_1, \mathrm{X}_2, \ldots, \mathrm{X}_{10})$.

$\mathrm{Pr}_{ij}(i, j = 0, 1, 2, 3; i > j)$ represents the state transition probability caused by the aging of components which is the red line in Figure 3. The blue line in Figure 3 shows the state improvement after a maintenance behavior. Pr_{03} represents the state transition probability caused by replacement. $\mathrm{Pr}_{1i(i>1)}$ represents the state transition probability caused by maintenance. $\mathrm{Pr}_{2i(i>2)}$ represents the state transition probability caused by preventive maintenance. The turbine components have a probability density function $f(t)$ which is modeled by a Weibull distribution, including scale parameter (γ) and shape parameter (β).

$$f_i(t) = \frac{\beta}{\gamma}\left(\frac{t}{\gamma}\right)^{(\beta-1)} \mathrm{e}^{-\left(\frac{t}{\gamma}\right)^{\beta}} \tag{2}$$

$$\lambda_i(t) = \frac{f_i(t)}{R_i(t)} = \frac{\beta}{\gamma}\left(\frac{t}{\gamma}\right)^{(\beta-1)} \tag{3}$$

According to Equation (3), the probability of each state at any time can be obtained. The sum of the state probability of each turbine component is given as Equation (5).

$$\mathrm{Pr}_i(t) \;=\; \sum_{j\,=\,0}^{i} \mathrm{Pr}_{j\;i}(t) - \sum_{j\,=\,i+1}^{3} \mathrm{Pr}_{i\;j}(t) \tag{4}$$

$$\sum_{i\,=\,0}^{3} \mathrm{Pr}_i(t) = 1 \tag{5}$$

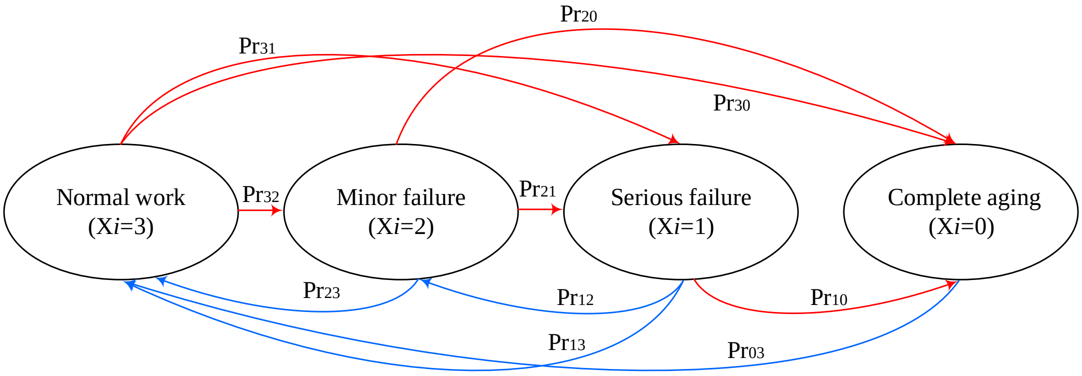

Figure 3. The multistate transition process of a wind turbine system.

3. A GM-VC Policy

This section describes the grouping maintenance policy by developing grouping modes and a maintenance model for a turbine system. Grouping modes fully consider the state transition probability of components and the variable maintenance cost of turbine systems. A maintenance model compares the improving performance for in-group components to optimize based on the recovery importance measure. The optimal maintenance orders of failed components are determined by an improved SA algorithm.

3.1. Grouping Modes

Considering the loss caused by downtime, the maintenance cost is a monotonically increasing function of components reliability. Larger maintenance costs get better reliability, e.g., increasing the reliability of a component from $\mathrm{X}_i = 1$ to $\mathrm{X}_i = 2$ is less than that from $\mathrm{X}_i = 2$ to $\mathrm{X}_i = 3$. Thus, the derivative of the maintenance cost is a monotonically increasing function. The maintenance cost function is obtained by:

$$\mathrm{C}_i^{\mathrm{m}}(t) = a_i \cdot e^{\left|(1-f_i)\frac{R_i(t)-R_{i,\min}}{R_{i,\max}-R_i(t)}\right|}. \tag{6}$$

In Equation (6), $\mathrm{C}_i^{\mathrm{m}}$ represents the maintenance cost of component i. $R_{i,\min}$ is the minimum acceptable reliability of component i. $R_{i,\max}$ is the maximum reliability that can be obtained of component i. f_i represents the feasibility of reliability improvement, whose range is $0 < f_i < 1$.

Preventive maintenance is repairing components with their reliability within a certain range, when repairing a failed component. Preventive maintenance actions will not be performed alone, except simultaneously with corrective maintenance. Since the preventive time is less than the corrective time, other noncritical components can be repaired when a failed critical component causes a turbine system to stop. Grouping mode 1 can be described as a failed critical component and other noncritical components as a group to be repaired at the same time. The maintenance cost of a critical component is obtained by:

$$C_i^{\mathrm{cm}}(t) = \int_{t_1}^{t_3} C_i^{\mathrm{m}}(t) \cdot [F\{\Phi(X(t_3)) \geq X_T | X_i(t_3) \geq X_C\} - F\{\Phi(X(t_1)) < X_T | X_i(t_1) < X_C\}]. \tag{7}$$

In Equation (7), C_i^{cm} represents the maintenance cost of a critical component. t_1 represents the start time. t_3 represents the end time. X_T represents the failure threshold of turbine systems. X_C represents the threshold of components.

When $X_i(t) = 3$, the component can be selected to the group in mode 1. The preventive cost of noncritical components is obtained as follows.

$$\begin{gathered} C_{i,s}^{\mathrm{pm}}(t) = \sum_{s \in P} \int_{t_1}^{t_2} C_s^{\mathrm{m}}(t) \cdot [F(1_S, \mathbf{X}(t_2)) - F(1_S, \mathbf{X}(t_1))] = \\ \sum_{s \in P} \int_{t_1}^{t_2} C_s^{\mathrm{m}}(t) \cdot [F\{\Phi(X(t_2)) \leq X_T | X_s(t_2) \geq X_P\} - F\{\Phi(X(t_1)) \leq X_T | X_P \geq X_s(t_1) \geq X_C\}] \end{gathered} \tag{8}$$

In Equation (8), $C_{i,s}^{\mathrm{pm}}$ represents the maintenance cost of the noncritical components. t_2 is the end time of the preventive maintenance. X_P represents the preventive threshold. P is the set of components whose states are under X_P.

A failed noncritical component cannot impact others. Grouping mode 2 is a noncritical component as a group to be repaired. According to Equations (7) and (8), the maintenance costs of mode 2 are obtained by:

$$\begin{cases} C_{h,i}^{\mathrm{cm}}(t) = \int_{t_1}^{t_3} C_i^{\mathrm{m}}(t) \cdot \begin{bmatrix} F\{\Phi((t_3)) \geq X_T | X_i(t_3) \geq X_P\} - \\ F\{\Phi((t_1)) \geq X_T | X_i(t_1) X_C\} \end{bmatrix} \\ C_{i,s}^{\mathrm{pm}}(t) = \sum_{s \in P} \int_{t_1}^{t_2} C_s^{\mathrm{m}}(t) \cdot \begin{bmatrix} F\{\Phi((t_2)) \geq X_T | X_s(t_2) \geq X_P\} - \\ F\{\Phi((t_1)) \geq X_T | X_P \geq X_s(t_1) \geq X_C\} \end{bmatrix} \end{cases}. \tag{9}$$

When repairing a noncritical component, the other fails. Based on the above two modes, grouping mode 3 describes the continuous noncritical components failing in the turbine system. The maintenance cost of M noncritical components is obtained by:

$$C_{h,M}^{\mathrm{cm}}(t) = \sum_{i=1}^{M} \int_{t_1}^{t_3} C_m^{\mathrm{m}}(t) \cdot \begin{bmatrix} F\{\Phi(X(t_3)) \geq X_T | X_m(t_3) \geq X_P\} - \\ F\{\Phi(X(t_1)) \geq X_T | X_m(t_1) < X_C\} \end{bmatrix} \tag{10}$$

In Equation (10), h represents a turbine system. m represents one of the continuous failures. The failure sequence of M noncritical components is $U = \{1, 2, \ldots, m, \ldots M\}$.

M groups generate M preventive maintenance. The preventive cost of M groups is obtained as follows.

$$C_{M,s}^{\mathrm{pm}}(t) = \sum_{m=1}^{M} \sum_{s \in P_m} \int_{t_1}^{t_2} C_s^{\mathrm{cm}}(t) \cdot \begin{bmatrix} F\{\Phi(X(t_2)) \geq X_T | X_s(t_2) \geq X_P\} - \\ F\{\Phi(X(t_1)) \geq X_T | X_P \geq X_s(t_1) \geq X_C\} \end{bmatrix} \tag{11}$$

In Equation (11), the set of the maintenance groups is $\{P_1, P_2, \ldots, P_m, \ldots P_M\}$.

A critical failing after continuing noncritical failure develops the grouping mode 4. According to Equations (10) and (11), the maintenance costs of mode 4 are obtained by:

$$\begin{cases} C_{h,M+1}^{\mathrm{cm}}(t) = \sum_{i=1}^{M} \int_{t_1}^{t_3} C_m^{\mathrm{m}}(t) \cdot \begin{bmatrix} F\{\Phi(X(t_3)) \geq X_T | X_m(t_3) \geq X_P\} \\ -F\{\Phi(X(t_1)) \geq X_T | X_m(t_1) < X_C\} \end{bmatrix} + C_{M+1}^{\mathrm{cm}}(t) \\ C_{M+1,s}^{\mathrm{pm}}(t) = \sum_{m=1}^{M} \sum_{s \in P_m} \int_{t_1}^{t_2} C_s^{\mathrm{cm}}(t) \cdot \begin{bmatrix} F\{\Phi(X(t_2)) \geq X_T | X_s(t_2) \geq X_P\} - \\ F\{\Phi(X(t_1)) \geq X_T | X_P \geq X_s(t_1) \geq X_C\} \end{bmatrix} + C_{M+1}^{\mathrm{pm}}(t) \end{cases} \tag{12}$$

3.2. RIM-VC Index-Based Maintenance

Figure 4 shows the optimization policy to find an optimal sequence of time points of maintenance decisions in the turbine system. The decision process steps are as follows.

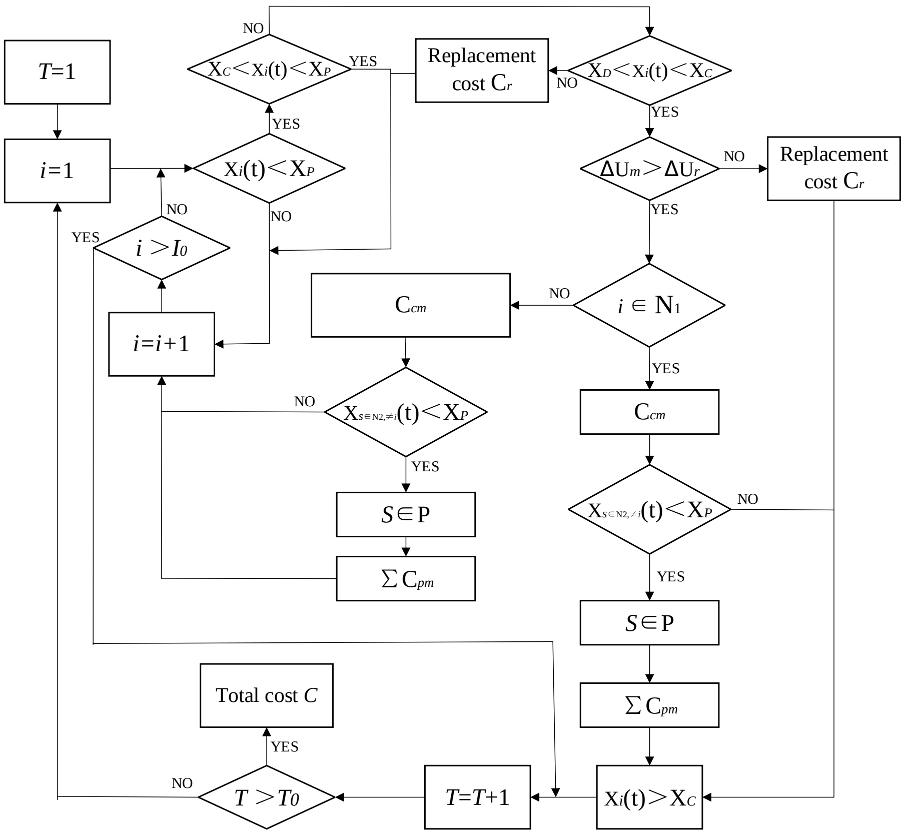

Figure 4. The grouping maintenance optimization policy.

1. Select maintenance behavior. The replacement threshold is X_D. If $X_i < X_D < X_C$, replace components. If $X_D < X_i < X_C$, the component's state is X_1. The RIM-VC index is used to determine a maintenance behavior by comparing the improved performance. ΔU_m represents the improved performance by maintenance per unit of time. ΔU_r represents the improved performance by replacement per unit of time. If $\Delta U_m < \Delta U_r$, the failed component is replaced. Otherwise, it is repaired. The improved performance by maintenance per unit of time is obtained by:

$$\Delta U_m = \frac{\mathrm{RIM}_i^{\mathrm{M}}(t)}{\mathrm{C}_i^{\mathrm{cm}}(t)}. \tag{13}$$

2. In Equation (13), $\mathrm{RIM}_i^{\mathrm{M}}$ represents the recovery importance measure by maintenance. It comes from the important importance measure, which is obtained by:

$$\mathrm{RIM}_i^{\mathrm{M}}(t) = \mathrm{IIM}_{i,X_m}(\mathrm{t}) - \mathrm{IIM}_{i,X_f}(t), \tag{14}$$

$$\mathrm{IIM}_{i,X_f}(t) = \mathrm{P}_{iX_f} \cdot \lambda_{X_f,0}^{i} \cdot \sum_{j=1}^{J} a_j \left[\Pr\{\Phi(\alpha_i, X) = X_j\} - \Pr\{\Phi(0_i, X) = X_j\}\right], \tag{15}$$

$$\mathrm{IIM}_{i,X_m}(t) = \mathrm{P}_{iX_m} \cdot \lambda_{X_m,0}^{i} \cdot \sum_{j=1}^{J} a_j \left[\Pr\{\Phi(\beta_i, X) = X_j\} - \Pr\{\Phi(0_i, X) = X_j\}\right], \tag{16}$$

$$U = \sum_{j=1}^{J} a_j \Pr\{\Phi(X) = X_j\} = \sum_{j=1}^{J} a_j \Pr\{\Phi(X_1, X_2, \ldots, X_n) = X_j\}. \tag{17}$$

In Equations (14)–(17), X_f is the failure state of a component. $f \in \{1,2\}$. X_m is the state of a failed component after repair. IIM_{i,X_f} indicates the performance loss when component i degrades from state X_f to state 0. IIM_{i,X_m} indicates the performance improvement when component i increases from state to 0 state X_m. U indicates the performance of the turbine system, which is an important index to measure the power generation of turbines. a_j indicates the performance when the turbine state is X_j.

3. According to Equations (13)–(17), the improved performance by replacement per unit of time is obtained by:

$$\begin{cases} \Delta U_r = \frac{RIM_i^r(t)}{C_i^r} \\ RIM_i^r(t) = IIM_{i,X_r}(t) - IIM_{i,X_f}(t) \\ IIM_{i,X_r}(t) = P_{iX_r} \cdot \lambda^i_{X_r,0} \cdot \sum_{j=1}^{J} a_j \left[\Pr\{\Phi(\gamma_i, X) = X_j\} - \Pr\{\Phi(0_i, X) = X_j\} \right] \end{cases}. \quad (18)$$

In Equation (18), RIM_i^r indicates the improved turbine performance of replacement of component i from state X_f to state X_r. C_i^r is the replacement cost. X_r is the state of a failed component after replacement. The reliability of a component is 1 after the replacement. IIM_{i,X_f} indicates the performance loss when component i degrades from state X_f to state 0. IIM_{i,X_r} indicates the performance improvement when component i increases from state 0 to state X_r.

4. Obtain maintenance costs. N_1 is the set of the critical. If $i \in N_1$, i is the critical and the maintenance policy is grouping mode 1. The maintenance cost (C_i^{cm}) is obtained. N_2 is the set of the noncritical. P is the set of the noncritical whose states is under X_p. The preventive cost (C_i^{pm}) is obtained.
5. Divide grouping modes. If $i \notin N_1$, i is the noncritical and the maintenance policy is grouping mode 2. If $i + 1 \notin N_1$ and component $i + 1$ fails during repairing component i, the policy becomes grouping mode 3. If $i + 1 \in N_1$ and component $i + 1$ fails when repairing the component i, it enters mode 4.

3.3. Algorithm

The basic simulated annealing (SA) algorithm is proposed by Metropolis et al. based on Monte Carlo iterative solution strategy [39]. Considering the basic SA algorithm is prone to stagnation, which leads to a long search time, many scholars have proposed improved SA algorithms to increase its performance and efficiency by adding some links [40,41]. For example, to avoid losing the current optimal solution due to the execution probability acceptance link in the search process, the best state so far is stored by adding a storage link. In this paper, the calefactive SA algorithm is used to optimize the maintenance sequence. The improvement of the calefactive SA algorithm compared with the basic AC algorithm is: The temperature is raised appropriately to avoid a local stop in the algorithm process. The steps of the calefactive SA algorithm are presented as follows. Steps 1, 2, and 4 are the basic SA algorithm. Step 3 is an improvement.

6. Initialization. The number of failed turbine systems is H. The initial temperature is $T = 100 \times H$. The internal Markov chain length is $L = 100$. The decay parameter is $K = 0.99$. Obtain the initial maintenance sequence.
7. Updating the solution. Randomly exchange the order of two turbines in the initial solution. Obtain a new maintenance order. The Metropolis algorithm is used to determine whether to replace the old maintenance sequence, which is obtained by:

$$p = e^{-\frac{E_2 - E_1}{T}}, \quad (19)$$

$$p(1 \to 2) = \begin{cases} 1, E_2 < E_1 \\ e^{-\frac{E_2 - E_1}{T}}, E_2 \geq E_1 \end{cases}. \quad (20)$$

8. Heating-up. At a temperature, iterate L times. The temperature update function is used to modify the temperature value in the outer loop. That is $T(n+1) = K \times T(n)$. K is a constant close to 1. When the optimal solution of this iteration is less than the optimal solution of the previous iteration, $1 < K < 2$.
9. Judgment. If the termination condition is satisfied, the search is ended, and the optimization sequences is output. Otherwise, the attenuation temperature continues to be optimized.

4. Result Analysis

In this section, the grouping maintenance model in Section 3 is applied to the wind turbine system in Section 2. There are 18 turbines in a wind farm. The components of a wind turbine system are shown in Table 2. There are 7 types of subsystems. The components in the first 4 subsystems are critical components. The rest are noncritical. Table 3 gives the technical parameter of two kinds of turbine systems, including the GW165-4.0 MW turbines, and GW140-2.5 MW turbines. Then, the state transition probability of the system in Section 2 is calculated. Finally, the grouping maintenance policies are obtained according to the GM-RIM index optimization.

The parameters in Section 3 are set as follows in this section. The preventive, corrective, and replacement thresholds are $X_P = 0.6$, $X_C = 0.3$, and $X_D = 0.2$. Corrective maintenance time is $\Delta t_1 = 10$. Preventive maintenance time is $\Delta t_2 = 5$. The replacement time is $\Delta t_3 = 3$. Corrective action increases reliability to i_1 days before components fail. Preventive action increases it to i_2 days before. $i_1 = 78$. $i_2 = 86$. The parameters in Equation (6) and the various costs of the components are shown in Table 4.

Table 2. The components of a DPM turbine system.

Subsystem	Code	Name
1	X_1 X_2 X_3	Blade Pitch system Hub
2	X_4 X_5	Generator rotor Generator stator
3	X_6	Yaw system
4	X_7	Wind measurement system
5	X_8	Heat dissipation system
6	X_9	Cabin
7	X_{10}	Tower

Table 3. The technical parameter of two kinds of turbine systems.

Technical Parameter (Unit)	GW165-4.0 MW	GW140-2.5 MW
Rated power (MW)	4.0	2.5
Wind zone grade (IEC)	S	S
Cut-in wind speed (m/s)	2.5	3
Rated wind speed (m/s)	9.7	10.5
Cut-out wind speed (m/s)	26	25
Service life (year)	≥20	≥20
Operating temperature (°C)	−30 °C~+40 °C	−30 °C~+40 °C
Living temperature (°C)	−40 °C~+50 °C	−40 °C~+50 °C
Impeller diameter (m)	165	140
Swept area (m^2)	21,124	15,393
Nominal voltage (V)	950	/

Data from Jin-feng Technology Co., Ltd. in China, Xinjiang.

Table 4. The parameters and various costs of components.

Code	$R_{i,min}$	$R_{i,max}$	f_i	a_i	C_i^{cm}(k€)	C_i^{pm}(k€)	C_i^{r}(k€)
X_1	0	0.8	0.5	30	$\int 30e^{\left[\frac{R_1(t)}{2(0.8-R_1(t))}\right]}d(\Delta t_1)$	-	90
X_2				5	$\int 5e^{\left[\frac{R_2(t)}{2(0.8-R_2(t))}\right]}d(\Delta t_1)$	-	14
X_3				33	$\int 33e^{\left[\frac{R_3(t)}{2(0.8-R_3(t))}\right]}d(\Delta t_1)$	-	95
X_4				12	$\int 12e^{\left[\frac{R_4(t)}{2(0.8-R_4(t))}\right]}d(\Delta t_1)$	-	30
X_5				12	$\int 12e^{\left[\frac{R_5(t)}{2(0.8-R_5(t))}\right]}d(\Delta t_1)$	-	30
X_6				30	$\int 30e^{\left[\frac{R_6(t)}{2(0.8-R_6(t))}\right]}d(\Delta t_1)$	-	85
X_7	0	0.9	0.5	7	$\int 7e^{\left[\frac{R_7(t)}{2(0.9-R_7(t))}\right]}d(\Delta t_1)$	$\int 7e^{\left[\frac{R_7(t)}{2(0.9-R_7(t))}\right]}d(\Delta t_2)$	50
X_8				6	$\int 6e^{\left[\frac{R_8(t)}{2(0.9-R_8(t))}\right]}d(\Delta t_1)$	$\int 6e^{\left[\frac{R_8(t)}{2(0.9-R_8(t))}\right]}d(\Delta t_2)$	47
X_9				2.7	$\int 2.7e^{\left[\frac{R_9(t)}{2(0.9-R_9(t))}\right]}d(\Delta t_1)$	$\int 2.7e^{\left[\frac{R_9(t)}{2(0.9-R_9(t))}\right]}d(\Delta t_2)$	10
X_{10}				2	$\int 2e^{\left[\frac{R_{10}(t)}{2(0.9-R_{10}(t))}\right]}d(\Delta t_1)$	$\int 2e^{\left[\frac{R_{10}(t)}{2(0.9-R_{10}(t))}\right]}d(\Delta t_2)$	5

When the wind speed or temperature exceeds the parameter range of the turbines, they stop. The changes in wind speed, temperature, and power in the wind farm are shown in Figure 5. According to Figure 5a, the temperature range in the wind farm is [−8, 34], which belongs to the operating temperature of the turbines. In Figure 5b, the two red lines are the cut-out wind speeds of GW165-4.0 MW turbines and GW140-2.5 MW turbines. When the wind speed is below the red lines, turbines are shut down. In Figure 5c,d, the dynamic output power of turbines is obtained by Equation (1).

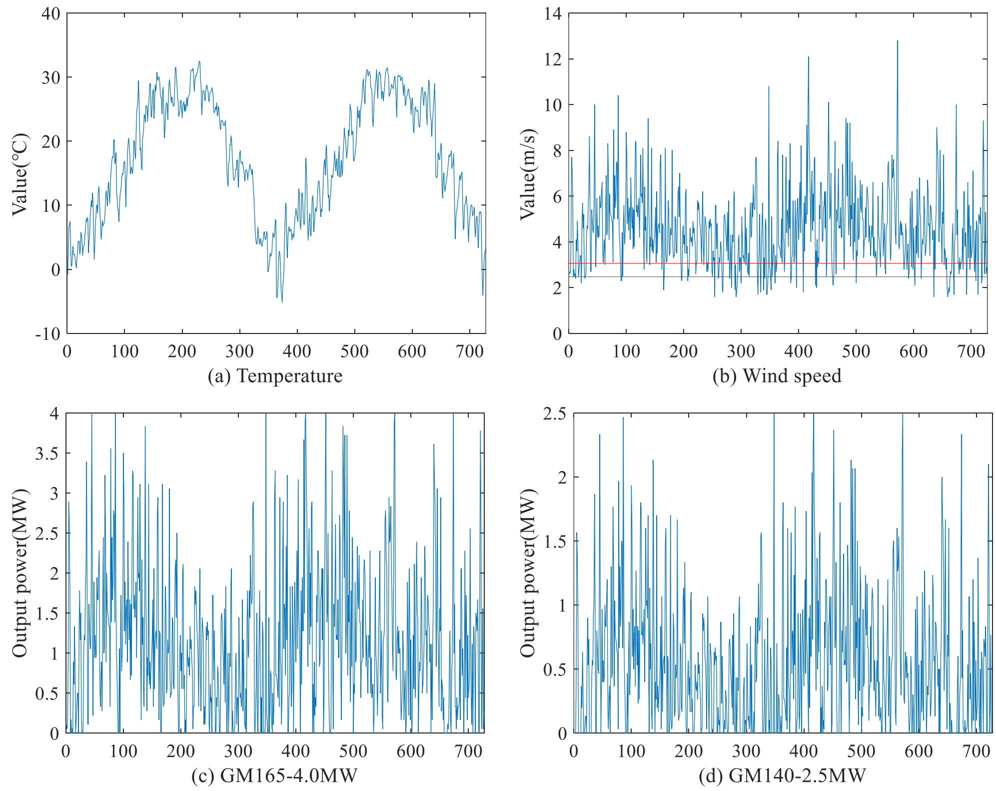

Figure 5. The changes in wind speed, temperature, and power in the wind farm.

The coordinates of 18 turbines for demonstration are shown in Table 5. The interval distance between turbines will affect their output power and power generation. The closer the distance, the stronger the influence, which is called the wake effect. The farther the distance, the less conducive for repairmen to implement maintenance behaviors. Therefore, this paper sets the interval between two turbines as [100, 3600] to reduce the wake effect and conform to the real wind farm. Assume that the x coordinate range of turbines is [1000, 5000], and the y coordinate range is [550, 3000]. In addition, assume that the wake effect has no effect on the output power of turbines.

Table 5. The coordinates of 18 turbines.

Number of Turbines	Position	Number of Turbines	Position
1	(1304, 2312)	10	(4177, 2244)
2	(4196, 1004)	11	(3712, 1399)
3	(2788, 1491)	12	(2370, 2075)
4	(1332, 695)	13	(3007, 1970)
5	(3639, 1315)	14	(3488, 1535)
6	(4312, 790)	15	(3326, 1556)
7	(2381, 1676)	16	(2562, 1756)
8	(3238, 1229)	17	(3715, 1678)
9	(2778, 2826)	18	(3918, 2179)

According to the turbine components' parameters in [32,35], the random generation functions of Weibull parameters are set and finally shown in Table 6. According to the parameters of components, the state transition probability of the turbine components is obtained. The probability of turbine components in different states is shown in Figure 6. The sum of probabilities in different states is 1.

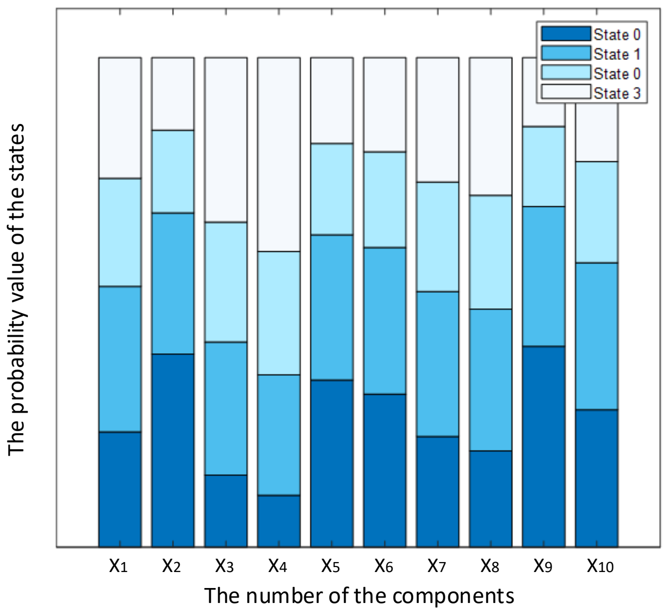

Figure 6. The probability of turbine components in different states.

Table 7 shows the cross-section data of the integrated importance measure (IIM). These data are obtained by Equations (16) and (17). The four kinds of states of a component in a turbine are obtained. Table 7 only shows the cross-section data, and the dynamic data of IIM over time are not shown because of too much data. According to Table 7 and Equation (14), the dynamic data of recovery importance measure (RIM) is obtained in the submitted form. RIM is used to select the optimal maintenance behavior of a faulty component, rather than to select the preferred maintenance component from several faulty components. Equation (13) is the improved turbine performance by correction maintenance. Equation (18) is the improved performance by replacement. Comparing the ΔU_m and ΔU_r, selecting the optimal maintenance behavior. Based on the above, the dynamic grouping failure modes of 18 turbine systems are obtained in Figure 7.

Table 6. The parameters of components in turbine systems.

Parameters	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
γ	466	771	1052	772	488	543	755	538	561	780
	696	638	897	803	525	563	656	782	617	904
	516	569	802	787	789	646	747	604	721	1138
	611	844	742	755	524	778	840	544	599	715
	584	859	975	568	778	451	784	735	781	1078
	628	794	873	619	564	413	663	587	384	661
	445	857	875	664	404	563	733	632	459	1108
	449	706	899	767	524	645	607	712	542	727
	601	598	926	627	462	781	794	740	384	1089
	415	699	848	580	798	518	644	598	429	1061
	642	783	912	879	580	624	541	501	408	670
	409	762	742	623	618	723	628	556	631	1170
	684	822	802	879	505	533	627	727	474	711
	603	787	849	756	753	435	519	774	686	1044
	397	745	1008	637	441	581	579	654	574	1064
	649	642	949	726	729	407	846	774	430	866
	676	661	992	790	571	679	766	664	638	1131
	547	811	1030	641	768	442	844	790	347	614
β	1.35	0.49	0.54	1.05	1.08	1.21	0.77	0.83	0.91	0.54
	0.84	0.77	0.55	0.64	0.69	0.58	0.53	0.51	0.75	1.25
	1.14	1.15	1.18	1.10	1.28	0.51	1.25	1.44	0.88	1.10
	0.65	1.30	0.80	1.14	1.28	1.12	0.84	1.11	0.75	0.90
	0.51	0.95	1.03	0.90	0.90	0.93	1.10	0.67	0.72	0.98
	1.07	1.44	0.74	0.60	0.84	0.94	1.01	0.54	0.58	0.97
	1.13	0.87	1.16	0.87	1.41	0.76	0.45	0.69	0.61	1.07
	0.74	0.71	0.80	1.04	0.45	0.77	1.10	1.35	0.94	1.09
	1.02	0.92	1.16	0.77	0.84	1.35	0.76	0.66	0.53	0.64
	0.76	0.61	1.44	1.28	0.93	0.89	0.71	0.92	1.37	1.25
	1.25	0.60	0.53	0.57	1.06	1.19	0.90	1.35	0.59	0.64
	0.81	0.71	0.91	0.70	0.51	0.63	1.07	0.64	0.60	0.86
	1.14	1.20	0.54	1.38	0.59	0.53	1.25	0.89	1.16	0.68
	1.08	1.05	1.17	1.10	1.10	0.65	1.01	1.06	1.12	0.72
	1.41	1.41	1.36	1.20	0.66	1.00	0.47	1.04	0.80	0.45
	0.65	1.22	0.53	1.26	0.56	1.11	1.24	1.11	0.53	1.37
	1.04	1.02	0.96	0.49	0.49	1.38	0.72	0.71	0.45	0.96
	0.53	0.89	1.00	0.86	0.61	0.48	1.27	0.87	0.82	0.91

Table 7. The cross-section data of the integrated importance measure under states 0, 1, 2, and 3.

Turbine	States	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
1	0	0.5368	0.3915	0.1691	0.5533	0.8395	0.0655	0.0202	0.0066	0.6875	0.4245
	1	0.1706	0.1372	0.0683	0.1264	0.1492	0.1813	0.0636	0.0520	0.7290	0.1166
	2	0.0710	0.0902	0.0470	0.0995	0.1223	0.0431	0.0324	0.0318	0.1276	0.0910
	3	0.4283	0.3271	0.1780	0.2909	0.3430	0.3085	0.1391	0.1416	0.9049	0.2691
2	0	0.0057	0.3112	0.0339	0.2453	0.0122	0.0362	0.3078	0.0021	1.1814	0.0931
	1	0.0054	0.0816	0.0147	0.0505	0.0063	0.0789	0.1121	0.0149	0.2303	0.0247
	2	0.0042	0.0307	0.0231	0.0284	0.0071	0.0141	0.1046	0.0079	0.0687	0.0142
	3	0.1454	0.3734	0.1150	0.3198	0.1698	0.2368	0.2301	0.1289	0.7927	0.1668

Table 7. *Cont.*

Turbine	States	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
3	0	0.0536	0.6591	0.1996	0.1843	0.4278	0.1327	0.0146	0.0460	0.0773	0.1841
	1	0.0671	0.4072	0.1449	0.1086	0.1773	0.2125	0.0467	0.1576	0.0920	0.1241
	2	0.0318	0.1661	0.0824	0.0831	0.1305	0.1017	0.0359	0.1024	0.0574	0.0930
	3	0.3457	0.9056	0.3549	0.3621	0.5145	0.5951	0.2097	0.3225	0.4964	0.3986
4	0	0.2459	0.0302	1.0941	0.0078	0.4781	0.0467	0.4694	0.0016	0.0056	0.0591
	1	0.0811	0.0171	0.2308	0.0063	0.0866	0.1164	0.6084	0.0173	0.0134	0.0221
	2	0.0269	0.0147	0.1268	0.0061	0.0362	0.0261	0.1485	0.0083	0.0072	0.0120
	3	0.3522	0.1502	0.4659	0.1326	0.3492	0.2432	0.4083	0.1197	0.1634	0.1399
5	0	0.9886	0.9801	0.2211	0.0329	0.7554	0.0145	0.1871	0.2791	0.0136	0.0334
	1	0.1917	0.1970	0.0718	0.0182	0.1322	0.0201	0.0804	0.6157	0.0072	0.0205
	2	0.1261	0.1402	0.0623	0.0243	0.1051	0.0201	0.0842	0.2920	0.0115	0.0285
	3	0.5528	0.5129	0.1635	0.1197	0.3273	0.1684	0.1905	0.4486	0.1861	0.1432
6	0	0.0159	0.0881	0.0331	0.0040	2.0305	0.8529	0.0661	0.0137	0.0206	0.0035
	1	0.0128	0.0441	0.0167	0.0037	0.2503	0.7867	0.0863	0.0615	0.0279	0.0033
	2	0.0045	0.0120	0.0089	0.0034	0.0654	0.0771	0.0206	0.0136	0.0100	0.0026
	3	0.1674	0.2614	0.1331	0.1510	0.8606	0.8367	0.1955	0.1940	0.2086	0.1075
7	0	0.2124	1.7268	0.7097	1.1137	0.0243	0.1339	0.1131	0.0162	0.4928	0.0141
	1	0.0756	0.3756	0.1671	0.2093	0.0155	0.2311	0.1815	0.0767	0.3317	0.0098
	2	0.0412	0.2600	0.1164	0.1375	0.0197	0.0797	0.0794	0.0461	0.1010	0.0130
	3	0.3519	0.7954	0.3164	0.5776	0.1929	0.4566	0.2334	0.1995	0.6432	0.1198
8	0	0.0084	0.8105	0.0057	0.0026	0.0034	0.1812	0.2135	0.6623	0.1668	0.0877
	1	0.0092	0.1881	0.0070	0.0037	0.0045	0.2008	0.1605	1.1016	0.0700	0.0371
	2	0.0095	0.0869	0.0111	0.0065	0.0077	0.0700	0.0863	0.3281	0.0440	0.0299
	3	0.1616	0.4601	0.1005	0.1032	0.1313	0.4268	0.2398	0.7838	0.4219	0.1867
9	0	0.6217	0.5513	0.2361	0.2804	1.3659	0.0334	0.5170	0.0096	1.0883	0.5725
	1	0.2361	0.2410	0.0836	0.0890	0.2711	0.0863	0.7375	0.0586	0.8313	0.1337
	2	0.0589	0.1162	0.0588	0.0418	0.1040	0.0343	0.2325	0.0312	0.2570	0.0491
	3	0.4740	0.4473	0.1885	0.3095	0.6992	0.2360	0.5783	0.1843	1.2668	0.2906
10	0	0.1023	0.0276	1.0319	0.0108	0.2033	0.0230	0.7332	0.2772	0.0233	0.1663
	1	0.0369	0.0167	0.2302	0.0116	0.0682	0.0316	0.3777	0.4134	0.0146	0.0643
	2	0.0434	0.0259	0.1421	0.0200	0.0754	0.0319	0.2218	0.2262	0.0199	0.0729
	3	0.2013	0.1361	0.3353	0.1190	0.2360	0.1865	0.4073	0.3378	0.2525	0.2245
11	0	0.0385	0.0041	0.1653	0.3278	0.0118	0.3427	0.0104	0.0018	0.7066	0.2548
	1	0.0211	0.0044	0.0544	0.0768	0.0079	0.4619	0.0335	0.0174	0.4468	0.0613
	2	0.0100	0.0039	0.0268	0.0355	0.0075	0.0741	0.0139	0.0085	0.1120	0.0263
	3	0.1891	0.1288	0.2089	0.3291	0.1683	0.4923	0.1548	0.1289	0.8937	0.2262
12	0	0.0097	0.0339	0.7115	0.2935	0.0075	0.0208	0.0047	0.0182	0.0094	0.0651
	1	0.0061	0.0153	0.1450	0.0697	0.0075	0.0533	0.0174	0.0775	0.0217	0.0241
	2	0.0085	0.0161	0.0729	0.0337	0.0066	0.0259	0.0132	0.0369	0.0119	0.0151
	3	0.1643	0.2039	0.3486	0.2967	0.1532	0.2243	0.1335	0.1986	0.2102	0.1563
13	0	0.0060	0.1746	0.0306	0.5201	0.0100	0.1163	0.0312	0.3515	0.4812	0.5233
	1	0.0155	0.1552	0.0336	0.1966	0.0104	0.2224	0.0778	0.8143	0.3469	0.2134
	2	0.0065	0.0345	0.0265	0.0561	0.0074	0.0500	0.0421	0.2013	0.1117	0.0538
	3	0.1504	0.3192	0.1215	0.3856	0.1295	0.3616	0.1567	0.5615	0.5580	0.3400
14	0	1.2753	0.0108	0.1423	0.0525	0.0226	0.1297	0.1703	0.0134	0.1787	0.4047
	1	0.4130	0.0138	0.0610	0.0273	0.0164	0.2392	0.2982	0.0695	0.2077	0.1123
	2	0.1056	0.0159	0.0519	0.0172	0.0130	0.0782	0.1274	0.0399	0.0757	0.0467
	3	0.7913	0.1353	0.1592	0.1649	0.1807	0.4184	0.3160	0.1596	0.4947	0.2800
15	0	0.0377	1.1247	0.7361	1.7565	2.8807	0.7807	0.0481	0.0056	2.2264	0.0110
	1	0.0191	0.2240	0.1567	0.2748	0.3886	0.8830	0.0989	0.0352	0.7570	0.0089
	2	0.0176	0.1943	0.1152	0.1768	0.2269	0.2168	0.0513	0.0318	0.2706	0.0123
	3	0.1995	0.5695	0.2969	0.6968	1.0156	0.8819	0.1725	0.1480	1.5347	0.1187

Table 7. *Cont.*

Turbine	States	X_1	X_2	X_3	X_4	X_5	X_6	X_7	X_8	X_9	X_{10}
16	0	2.1837	0.9268	0.0234	0.8848	0.0428	0.0270	0.6021	0.1792	0.0061	0.0060
	1	0.7491	0.3515	0.0283	0.2639	0.0308	0.0459	0.4568	0.2769	0.0154	0.0099
	2	0.2255	0.1509	0.0142	0.0876	0.0160	0.0306	0.1314	0.1151	0.0166	0.0071
	3	0.9929	0.4278	0.1314	0.4695	0.1554	0.1707	0.3951	0.3375	0.2063	0.1011
17	0	0.1112	0.0739	0.5703	0.0086	0.3113	0.0314	0.0062	0.1950	0.9640	0.5763
	1	0.0465	0.0327	0.1460	0.0087	0.0760	0.0658	0.0149	0.4540	0.2337	0.1420
	2	0.0493	0.0356	0.0985	0.0155	0.0702	0.0417	0.0200	0.2369	0.1024	0.1333
	3	0.2714	0.1780	0.2449	0.1099	0.2369	0.2280	0.1221	0.4071	0.6235	0.3729
18	0	1.4503	0.1910	0.0155	0.0585	1.5790	0.0389	0.9647	0.4400	0.0640	0.1018
	1	0.3447	0.0799	0.0127	0.0295	0.2772	0.1172	1.2646	1.1655	0.1103	0.0438
	2	0.1416	0.0475	0.0170	0.0271	0.1560	0.0378	0.3956	0.3513	0.0325	0.0343
	3	0.6908	0.2853	0.1025	0.1832	0.6751	0.2845	0.7439	0.7814	0.3318	0.1928

The total number of turbine systems failures is 49 times. Its grouping modes 1, 2, 3, and 4 appear 7, 27, 34, and 35 times. Among them, grouping mode 4 appears the most frequently. The number of simultaneous failures of seven turbine systems is two times. The number of simultaneous failures of four turbine systems is five times. The number of simultaneous failures of three turbine systems is six times. The number of simultaneous failures of 2 turbine systems is 14 times. Twenty-seven times simultaneous failures of two or more turbines occurred. Table 8 shows the maintenance optimization based on the improved SA algorithm. Considering that more turbine failures at the same time would increase the diversity of maintenance sequences, Figure 8 shows the maintenance optimization when seven turbine systems fail at the same time.

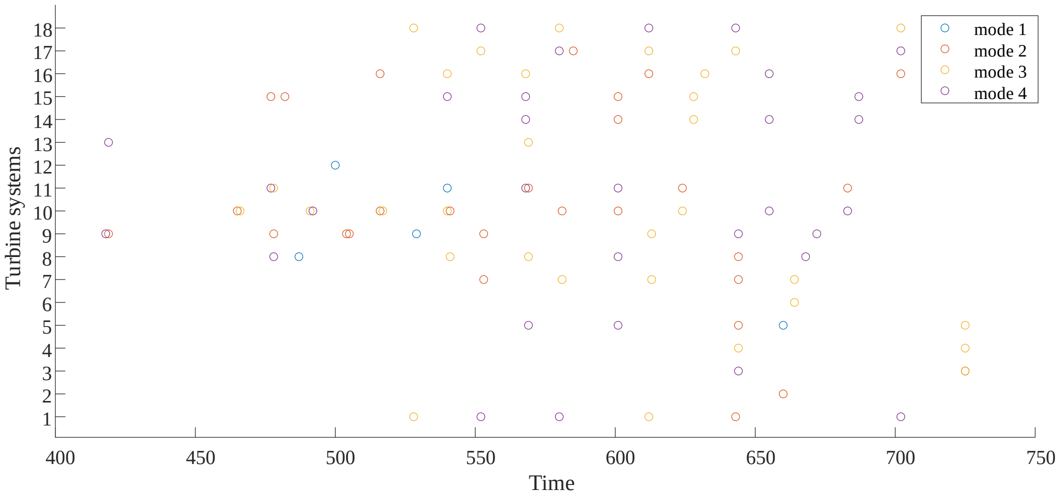

Figure 7. The dynamic grouping failure modes of 18 turbine systems.

In Figure 8a, the position coordinates of the seven turbines are [1304 2312], [3639 1315], [4177 2244], [3712 1399], [3488 1535], [3326 1556], and [3238 1229]. In Figure 8b, the position coordinates of the seven turbines are [2370 2075], [2778 2826], [1332 695], [2381 1676], [2788 1491], [3639 1315], and [3238 1229]. Figure 9 is the fitness evolution curve of optimizations. It shows the process of the improved SA algorithm searching for the optimal maintenance sequence. In Figure 9a,b, the optimal solutions are obtained when the number of iterations is not more than 500 and not more than 300. This shows that the improved SA algorithm is suitable for maintenance sequence optimization.

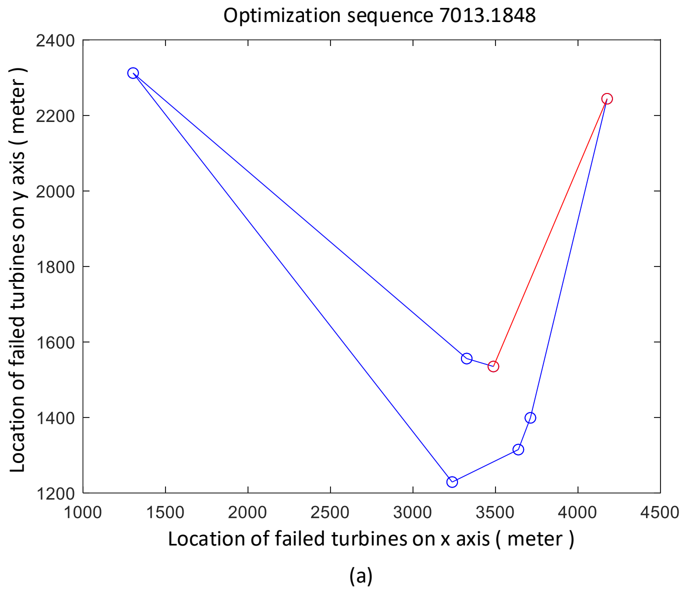

Figure 8. The maintenance optimization when 7 turbine systems fail at the same time. (**a**) The maintenance sequence for turbines is 10, 11, 8, 5, 1, 15, and 14. (**b**) The maintenance sequence for turbines is 12, 9, 5, 8, 3, 4, and 7.

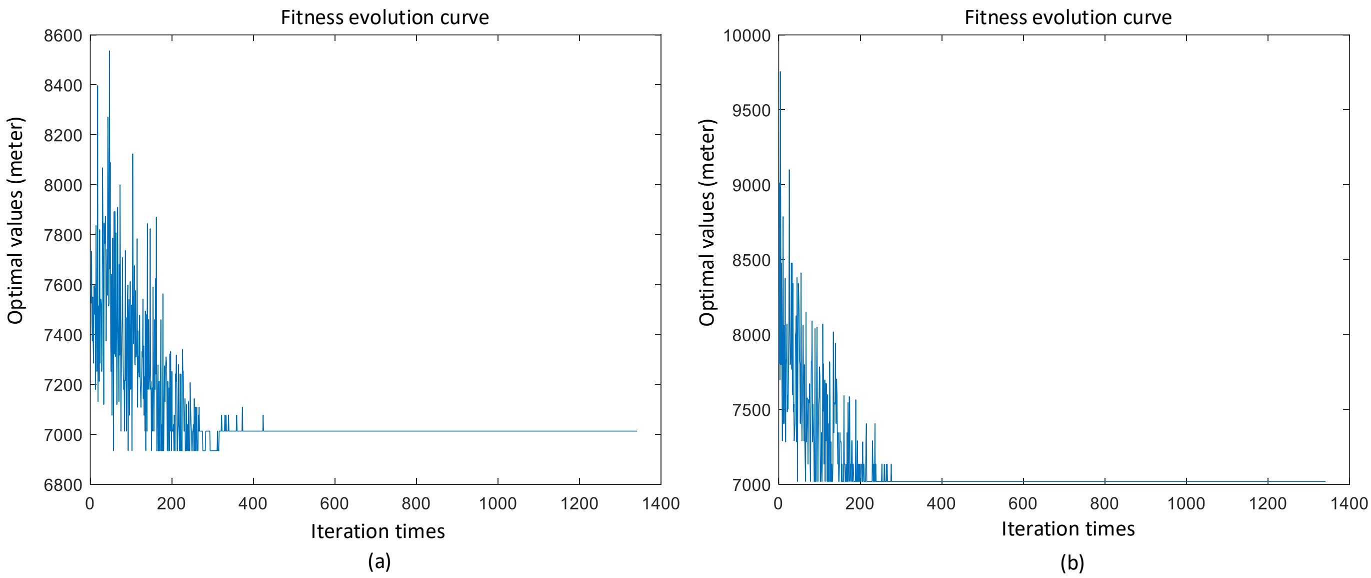

Figure 9. The fitness evolution curve of optimizations. (**a**) The maintenance value of turbines 10, 11, 8, 5, 1, 15, and 14 is 7013.1848. (**b**) The maintenance value of turbines 12, 9, 5, 8, 3, 4, and 7 is 7019.3644.

Assuming that in the baseline plan and the GM-VC plan, the operating environment of the wind farm, the initial parameters of the components, and the number of days required for maintenance behaviors are the same. According to [34], the current maintenance plan applicable to the wind farm is the baseline maintenance, including regular maintenance and corrective maintenance. Regular maintenance is the maintenance of all turbines every six months, and its cost is C_{rm}. Corrective maintenance is performed when a component fails, and its cost is C_{cm}. Based on the above, the turbine maintenance time series and maintenance cost under the baseline plan are obtained. Based on Equations (6)–(12) and Figure 7, the cost of the grouping maintenance plan is obtained. Finally, Figure 10 is obtained.

Table 8. The maintenance optimization based on the improved SA algorithm.

Failure Number	The Number of Turbines	Maintenance Sequence
1	2	(2778, 2826) (3007, 1970)
2	2	(3712, 1399) (3326, 1556)
3	3	(3238, 1229) (3712, 1399) (2778, 2826)
4	2	(4177, 2244) (2562, 1756)
5	2	(1304, 2312) (3918, 2179)
6	4	(4177 2244) (2562 1756) (3326 1556) (3712 1399)
7	2	(3238, 1229) (4177, 2244)
8	3	(1304, 2312) (3715, 1678) (3918, 2179)
9	2	(2381, 1676) (2778, 2826)
10	4	(3712, 1399) (3488, 1535) (3326, 1556) (2562, 1756)
11	4	(3007, 1970) (3238, 1229) (3639, 1315) (3712, 1399)
12	3	(1304, 2312) (3715, 1678) (3918, 2179)
13	2	(2381, 1676) (4177, 2244)
14	7	(4177, 2244) (3712, 1399) (3238, 1229) (3639, 1315) (1304, 2312) (3326, 1556) (3488, 1535)
15	3	(1304, 2312) (2562, 1756) (3715, 1678)
16	2	(2381, 1676) (2778, 2826)
17	2	(4177, 2244) (3712, 1399)
18	2	(3488, 1535) (3326, 1556)
19	3	(1304, 2312) (3715, 1678) (3918, 2179)
20	7	(2370, 2075) (2778, 2826) (3639, 1315) (3238, 1229) (2788, 1491) (1332, 695) (2381, 1676)
21	3	(2562, 1756) (4177, 2244) (3488, 1535)
22	2	(4196, 1004) (3639, 1315)
23	2	(4312, 790) (2381, 1676)
24	2	(4177, 2244) (3712, 1399)
25	2	(3488, 1535) (3326, 1556)
26	4	(1304, 2312) (2562, 1756) (3715, 1678) (3918, 2179);
27	4	(3639, 1315) (2788, 1491) (1332, 695) (4196, 1004)

Figure 10 shows the maintenance cost comparison between the baseline plan and the proposed GMP-VC. In the baseline plan, corrective costs and preventive costs accounted for 44% and 51%. In the GMP-VC, they accounted for 34% and 46%. The latter saves 10% and 5% than the former. This shows that the proposed GMP-VC is feasible.

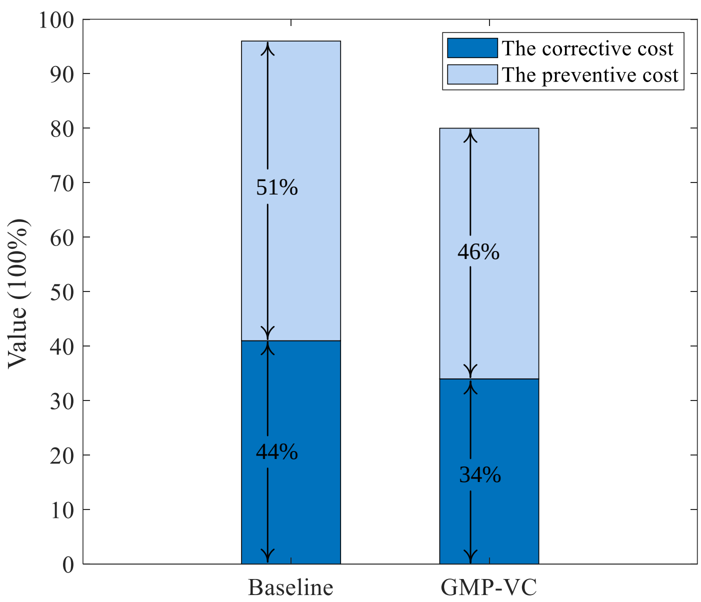

Figure 10. The maintenance cost comparison between the baseline plan and the GMP-VC.

5. Conclusions and Future Work

In this paper, a GM-VC policy is applied to a wind turbine system. According to the system characteristics, the four kinds of grouping modes divide the critical and noncritical into groups to reduce maintenance costs. The RIM-VC index improves turbine performance by selecting the optimal maintenance behavior. In the case, the optimized fault-maintenance time series is obtained through the input values of temperature, wind speed, and Weibull parameters. The result shows that corrective costs and preventive costs accounted for 44% and 51% of the baseline plan. In the GM-VC plan, they accounted for 34% and 46%. The proposed plan saves 10% and 5% than the baseline.

Nowadays, with the development of communication technology, the reliability monitoring of turbine systems through the Internet of Things is helpful to find faults and make maintenance decisions in a timelier manner. Therefore, a smart wind turbine system will be our next research work.

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