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Time-varying cost modeling and maintenance strategy optimization of plateau wind turbines considering degradation states

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HIGHLIGHTS

- A multi-objective optimization model for maintenance decision of plateau wind turbine.
- The time-varying properties of downtime, distribution costs are modeled.
- The constant cost assumption is changed by calculating the time for device degradation.
- The run time of each degraded state of the wind turbine is calculated.
- The maintenance intensity and frequency are determined according to the maintenance target.

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ABSTRACT

Plateau wind power has great potential in reducing carbon emissions; however, compared with other renewable energy, its economics still need to be improved. As an effective approach to enhance its economic feasibility, maintenance strategy optimization aims to reduce maintenance costs per kilowatt-hour and extend equipment lifespan. This paper proposes a multi-objective optimization model for the maintenance decision-making of plateau wind turbines that considers the degradation state. It incorporates: i) modeling the maintenance process of plateau wind turbines by combining time-based and state-based methods; ii) considering the time-varying maintenance costs in complex environments; and iii) employing a multi-objective optimization method to find the optimal strategy that meets maintenance requirements. The complexity considered in the model mainly includes the randomness of the operating duration for each equipment state, the temporal variability of equipment distribution and installation costs, and the uncertainty in maintenance effectiveness. The proposed optimization method is applied to a wind farm in the Yunnan-Guizhou Plateau, China.

The results indicate that traditional maintenance strategies underestimate maintenance costs and equipment lifespan losses. Compared with conventional maintenance strategies, this method can reduce equipment maintenance costs by 24.07 % and extend its operating life by 11.58 %. Additionally, this paper has conducted a series of parametric analyses to enhance the generalization performance of the model. The proposed method effectively addresses the economic issues of plateau wind turbine maintenance and provides a valuable decision-making tool for guiding the long-term maintenance of wind turbines in complex environments.

1. Introduction

In recent years, the global decarbonization trend has led to a rapid expansion of the share of renewable energy [1]. As nearly all suitable land for wind energy development in flatlands has been allocated, the focus of wind power development is shifting towards more complex environments such as oceans and plateaus [2–4]. Except for the Antarctic continent, plateaus account for 30 % of the total land area [5]. The plateau region has a fragile environment and outdated power facilities, and residents rely on burning biomass for energy for a long time, posing significant challenges to the local ecosystem [6]. However, the plateau contains abundant wind resources [7], offering hope to overcome this tremendous challenge and improve the living conditions of residents.

The availability of flatland wind power has reached a satisfactory

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Nomenclature

O&M	Operation and Maintenance
PSO	Particle Swarm Optimization
NSGA-II	Non-dominated Sorting Genetic Algorithm II
RUL	Remaining Useful Life
CM	Corrective Maintenance
PM	Preventive Maintenance
FFMS	Fixed Frequency Maintenance Strategy
FRRS	Fixed Resource Ratio Strategy
MOOS	Multi-objective Optimization Strategy
HFMS	High Frequency Maintenance Strategy
LFMS	Low Frequency Maintenance Strategy

Symbols

θ_1	Distribution to installation cost rate
φ_1	Corrective maintenance cost penalty factor
θ_2	Downtime cost rate
c_k	Maintenance resource ratio
η	Maintenance effect influence factor
ε_k	Maintenance effect
v_k	Rate of degradation
cdf_1	Cumulative distribution function of Gamma process
ρ	Preventive maintenance cost coefficient
N_k	The number of times the$k$th state is maintained
γ_k	Lifetime decay rate
f_k	The maintenance frequency of the$k$th state (times/year)
cdf_2	Cumulative distribution function of Exponential distribution
t_k	The running time of the$k$th state (month)
$\overline{C}_C$	Average transportation and installation costs ($)
$\overline{C}_S$	Average downtime cost ($)
$\overline{C}_I$	Regular maintenance cost ($)
C_E	Equipment acquisition cost ($)
T_S	Down time (month)

level (about 95 % to 97 %) [8]. If wind turbines (WTs) of the same type are installed on the plateau, their availability will significantly decrease, leading to a reduction in lifespan and an increase in maintenance costs. India, Denmark, China, and other countries have greatly tried to practice plateau wind energy development [9–11]. However, due to environmental complexities such as wind shear [12], turbulence [13], low temperature [14], the challenges of developing wind power on plateaus are immense. Operating and managing WTs is complex, and their lifespan will be significantly affected [15]. The cost of plateau wind power is mainly composed of construction costs and operation and maintenance (O&M) costs [16]. For wind farms that have been put into operation, improving the efficiency of operation and maintenance, and extending the service life of equipment are very important for enhancing their economic performance.

High operation and maintenance costs, coupled with limited service life of equipment, are among the main constraints facing the development of wind energy on the plateau [17].The optimization of maintenance strategies [18] aims to provide maintenance decision-making basis for wind farm operators to enhance the economic operation capacity of WTs [19].Maintenance strategy optimization aims to provide maintenance decisions for wind farm operators to improve the economic operation capability of WTs. A wind farm with a capacity of 100 MW has a fixed asset investment of 150 million US dollars [20], and the annual depreciation cost is very high. Optimizing the maintenance strategy could lead to cost savings of 30–40 %. Compared with a single goal [21–23], decision-makers often focus on multi-dimensional maintenance effects, such as minimizing maintenance costs [24] and maximizing economic benefits [25]. Due to the environmental complexity of the plateau environment, it is often difficult to find an optimal multi-objective maintenance strategy. For example, low temperatures lead to icing of roads and blades due to significant seasonal temperature differences in the plateau [26], which incurs high component transportation and installation costs [27]. In contrast, such time-varying costs are typically not a concern in plain regions.

Existing research mainly focuses on state-based [28] and time-based [29] maintenance decisions. The time-based strategy assumes that the equipment's lifespan follows distributions such as the Weibull or Gamma distribution, enabling the scheduling of periodic maintenance to improve equipment reliability [30]. Based on the "constant cost assumption," time-based maintenance strategies have yielded many useful conclusions [31]. However, as the environment faced by WTs becomes increasingly harsh, the applicability of this assumption has significantly decreased. Due to the progress of sensor technology and artificial intelligence technology, the state of WT components can be monitored quickly [32]. State-based strategies plan the resources required for equipment maintenance in advance according to real-time status [33], but this approach gives less consideration to time information. In the complex plateau environment, WTs require not only periodic maintenance schedules but also plans for the allocation of equipment when immediate failures occur [34]. This necessitates that operators conduct a comprehensive analysis that considers the degradation characteristics of the equipment and its status information. Addressing the issue of not considering time information in state-based methods during the process of breaking the "constant cost assumption" is crucial for plateau wind power maintenance modeling. Therefore, the maintenance strategy considering time and state information can more accurately describe the situation in the equipment O&M process, and it is necessary to consider the time-varying maintenance cost caused by a complex environment.

This paper comprehensively employs state-based and time-based periodic maintenance strategies to address the production losses and lifespan reduction of WTs caused by the complex environment of plateaus. It utilizes stochastic processes to describe equipment degradation characteristics and establishes a time-varying cost maintenance decision model. By optimizing resource ratios and maintenance frequencies during the maintenance process, the aim is to lower the maintenance cost and longer the operational lifespan.

In summary, the contributions of the paper are:

1. In response to the complexity of the plateau environment, this paper employs multiple interrelated objectives to represent the economic aspects of operation and maintenance for WTs.
2. Given the single angle of traditional maintenance modeling, this paper combines the state-based and time-based maintenance models to describe plateau WTs' degradation and maintenance process more accurately.
3. This paper models the time that equipment degradation states have experienced as a stochastic process, providing data for the time-varying nature of costs, thereby solving the problem that the "constant cost assumption" is not applicable to the study of the economic feasibility of wind power in complex environments.

The remainder of this paper is organized as follows: Section 2 identifies the contributions of the paper through a literature review and proposes the research question. Section 3 presents the methodology used to address the research question. Section 4 discusses the relevant parameters of the maintenance optimization decision model. Section 5 includes the analysis and discussion of results, using a wind farm in the

Yunnan-Guizhou Plateau of China for case analysis. Finally, Section 6 provides a summary and conclusion of this paper.

2. Literature review

2.1. Maintenance cost of plateau WTs

Almost all suitable land for wind energy development in flatlands has been incorporated into planning in recent years. In contrast, wind farms, as an infrastructure providing clean energy, must be expanded worldwide [35,36]. Plateaus account for 40 % of the world's land area, and the plateau wind farm has begun to provide electricity to the Qinghai-Tibet Plateau. Wind farms in the Pamir Plateau [37], Yunnan-Guizhou Plateau [38], and Pyrenees Mountains [39] have been operating for decades. In plateau, environmental factors such as low wind density, wind shear, and extreme temperatures [15] affect the O&M of WT units, resulting in higher O&M costs compared to flatlands. In terms of power supply, plateau WT have also encountered issues such as high downtime rates, unstable power supply, and low economic benefits. These problems have hindered the development of wind energy in plateau.

Due to the significant temperature difference between winter and summer, as well as the frequent freezing of roads and WT blades in winter, the maintenance cost of plateau wind power fluctuates considerably throughout the year [40]. Gyatso et al. [5] studied the operation performance of WTs on the Qinghai-Tibet Plateau but only considered maintenance decisions from the perspective of equipment selection. The load of wind power equipment changes with the wind conditions and market demand. Due to the spatial heterogeneity of wind power distribution [41], the load of the same type of WT in a wind farm may vary significantly throughout a year. However, most maintenance studies of WTs at sea or on the flatland rarely consider the characteristics of the environment and the equipment itself [25,42,43]. This paper integrates degradation states, runtime, and environmental factors such as freezing and wind speed fluctuations to establish a maintenance decision model for plateau wind power generation equipment. This aims to address the issue of current maintenance practices for plateau WTs neglecting environmental complexity.

2.2. Maintenance strategy

When wind power equipment begins to degrade, the decision regarding maintenance resources and maintenance frequency required can effectively reduce the cost of power generation [44]. In the early stage of equipment degradation, abandoning or directly replacing it will lead to higher costs. On-site maintenance can only formulate optimal maintenance strategies based on the degradation condition of each equipment, thereby reducing maintenance costs, and extending the equipment's lifespans. Many studies regard maintenance as a method that can improve the degree of degradation. Still, the evolution of the degradation state of most mechanical equipment is irreversible, such as cracks and defects will not heal automatically [45], such as WT gears [46], bearings [47], etc., so the operation life can only be prolonged by slowing down the degradation speed.

Time-based maintenance typically utilizes stochastic processes to describe the age of equipment [31], and maintenance is conducted based on the age and operational cycle of the equipment. Time-based maintenance strategies typically include the "constant cost assumption", which assumes that maintenance costs are fixed and unchanging, or that maintenance can restore the equipment to as good as new. Under the" constant cost assumption" [48], time-based maintenance decision optimization methods have yielded many interesting conclusions, such as the existence of an optimal maintenance interval within a finite horizon that minimizes the maintenance cost of the equipment [49]. However, changes in the environment have assumed of the "constant cost assumption" no longer applicable to real-world situations. For example, the change of seasons leads to different maintenance costs each month, and market prices cause fluctuations in the prices of WT spare parts, etc. Within a plateau wind farm, even if two WTs are of the same age, their degradation levels may differ due to different loads and operating conditions [50]. Regardless of the equipment's age, its degradation state is intuitive information that reflects the equipment's current condition, such as a high risk of teeth breakage caused by the fracture of the gear root. State-based maintenance [28] directly uses condition information to make maintenance decisions on equipment. Equipment degradation depends on the amount of maintenance resources invested [51], and investing appropriate maintenance resources in each state is beneficial to prolong the lifespan of equipment [52]. State-based maintenance typically does not consider maintenance cycles and performs maintenance on the equipment immediately when a failure occurs. However, for heavy equipment like WT units, a large amount of resource allocation and maintenance personnel preparation is required before scheduled maintenance can be carried out [22,53]. Maintenance that considers both time cycles and status information can accommodate the development of long-term maintenance plans for wind farms and determine response measures for immediate failures.

During the operation of plateau WTs, the inevitable cost incurred by equipment degradation failure can be mitigated by reasonable maintenance measures, extending the equipment's lifespan. However, relying solely on state-based or time-based maintenance strategies is no longer sufficient to meet the maintenance needs of wind power in complex environments. With the rapid development of artificial intelligence and detection technology [54], sensor signals from industrial sites can be transmitted promptly and rapidly. Many studies have achieved online real-time equipment condition diagnosis with artificial intelligence algorithms. This paper assumes that the operating time of each state follows a stochastic process and combines state-based and time-based strategies to study wind power maintenance issues in complex plateau environments.

2.3. Time-varying costs

In the research on equipment maintenance modeling, Barlow et al. [31] introduced an age replacement strategy, which means that PM is carried out if the equipment reaches a critical age. This result proved to be the best choice under constant cost rate and thus extended to many studies such as integrated maintenance [55], production [56], and scheduling [57]. Most later studies [58,59] focus on extending the applicable conditions and less on the variable cost rate problem. For example, Papadopoulos et al. [60], based on environmental changes and changes in maintenance time, windows can perform operations when maintenance opportunities arrive to reduce production losses caused by equipment downtime.

With the change in equipment maintenance conditions, the conclusion under constant cost rate no longer applies to the maintenance of WT under variable cost rates in complex environments. Schouten et al. [40] considered the time-varying maintenance cost of a single WT. Still, they ignored the real-time state of the equipment and only described the WT degradation as a component following a stochastic process. In the operating environment of WTs, wind speed and direction change very fast, and the operation state of each WT is complex and changeable due to the equipment's operation temperature, humidity, and power generation plan [61]. Compared with the constant cost rate, the time-varying cost [62] can more accurately describe the changes in the plateau wind power O&M environment.

3. System description and maintenance strategy

3.1. General assumptions

To make the assumptions more consistent with the operating characteristics of the plateau WT and, at the same time, reduce the model complexity, we consider a system that can be simplified by a single component, such as considering only the most essential elements. Assuming that the system's state at time t can be represented by an observable random variable X_t, for example, the evolution of a gear crack, the process $(X_t)_{t\geq 0}$ is an increasing stochastic process.

In addition, some assumptions are as follows:

(1) At the initial time, the device's state is x_0. The device is in a brand-new state, and each CM replaces the previous component with an intact one.
(2) The state detection is perfect and does not occupy the running time; that is, it can accurately and quickly detect the working state of the equipment. The degradation state is self-alarming; that is, the sensor detects the degradation state of the equipment all the time.
(3) The failure of equipment can have significant consequences, and CM should be performed immediately upon occurrence of such failure.

3.2. Degradation modeling

During their operation, plateau WT units are often affected by freezing, squalls, and hail. These influencing factors are not continuously applied to the WTs but gradually cause damage to them over time.

The gamma process, which has been widely used to describe the degradation process of various industrial systems, is strictly monotonically increasing, which is in line with the degradation behavior of most devices. In addition, the gamma process [63] is the accumulation of countless small shocks, that is, discontinuity, and this characteristic is well in line with the degradation process of the mechanical structure of the plateau WT [64]. We assume that the degraded state between the kth state and the $k+1$th state follows a gamma stochastic process $(X_t)_{t\geq 0}$, which has the following characteristics:

(1). $X_0 = 0$, $(\widetilde{X}_t)_{t\geq 0}$ is monotonically increasing.

(2). The independent increment $\widetilde{X}_{k+1} - \widetilde{X}_k$ of the degradation state between the kth state and the $k+1$th state follows a gamma probability density function with shape parameter α_k and scale parameter β, as shown in Eq. (1).

$$f_{\alpha_k,\beta}(x) = \frac{1}{\Gamma(\alpha_k)}\beta^{\alpha_k}x^{\alpha_k-1}exp(-\beta x)I_{\{x\geq 0\}} \tag{1}$$

here, $\Gamma(\alpha_k) = \int_0^{\infty}\omega^{\alpha_k-1}exp(-\omega)d\omega$, $\alpha_k,\beta > 0$, $I_{\{x\geq 0\}}$ is an indicative variable, $\alpha_k = \nu_k/\beta$, and ν_k is the rate of degradation between state k and state $k+1$ at state x_k. The degree of PM can determine ν_k, that is, there is a functional relationship between the degree of PM and the rate of degradation. This paper argues that the degree of PM can change the average degradation rate; that is, PM with more resources can improve the average degradation degree, and cheap PM will even increase the degradation rate of equipment.

3.3. Maintenance strategy

Mechanical equipment will experience a variety of defect states during its life cycle. If the defect is repaired immediately, it will incur high costs. Advanced fault diagnosis methods often classify equipment degradation states into limited types [65], and corresponding maintenance decisions to limited kinds of degradation states can reduce the difficulty of maintenance decisions [66]. Fig. 1 illustrates the degradation paths of a WT gearbox.

The corresponding maintenance strategy is as follows:

In this study, finite degradation states are considered, and the degradation states are defined according to the actual industrial problems. Let the degradation state $x_k \in \{x_1, x_2, x_3, \cdots, x_M\}$, equipment degradation develops in subscript order, such as gear crack change.

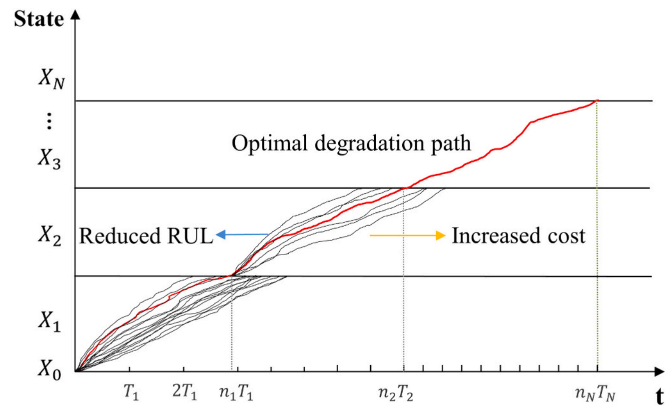


Fig. 1. Case of gearbox degradation path.

1. The climatic conditions and local load on the plateau are analyzed. It is found that when the wind speed is too high or the demand is low, the WTs cease operation.
2. When $x_k < x_1$, the equipment is in a healthy state and does not need too much maintenance. It only needs to be inspected according to the daily work content.
3. When $x_m \leq x_k \leq x_n$, $m < n$, $m \geq 1$, the equipment is in a defective state, and PM with frequency f_k and maintenance intensity c_k is required according to the corresponding degradation state. The routine inspection currently is included in the PM process.
4. When $x_k \geq x_N$, the equipment is in a failure state, and CM needs to be performed immediately, otherwise the failure will cause permanent damage to the whole system.

Fig. 2 is the decision-making flowchart for this paper, which is mainly divided into two parts based on the results of the status check. If the equipment is in a healthy state, perform routine maintenance. If the equipment has entered a degradation phase, use the methods of this paper to make decisions on the resources and maintenance frequency required for the maintenance process. Then execute this maintenance strategy until the equipment fails.

4. Model formulation

This section describes the formulation of the proposed model, which was developed from the research of Phuc Do et al. [67] and Schouten et al. [40]. The purpose of the maintenance model is to minimize the maintenance cost per kWh and maximize the operation time of the equipment. The decision variables are the maintenance frequency and resource input ratio at each stage of the WT maintenance. The maintenance cost depends on the stochastic preventive and time-varying CM costs. CM costs, including maintenance resource deployment, lifting equipment, and labor costs; PM costs, including replacement parts, labor costs, downtime costs, and downtime costs refer to the loss of revenue caused by WT replacement equipment.

4.1. Time-varying cost rate

As the road of the plateau wind farm is often relatively poor, it is prone to freezing in winter [68], which is an enormous challenge for the transportation of maintenance resources and causes varying resource distribution costs over time. In addition, the downtime cost needs to consider the plateau climate change, which has similarities with the resource distribution cost, and the downtime cost rate can be obtained according to the seasonal patterns of the wind field.

This paper determines the CM cost rate function and the downtime cost rate function. According to the relationship between the risk of extreme weather and time, considering the relatively high cost caused

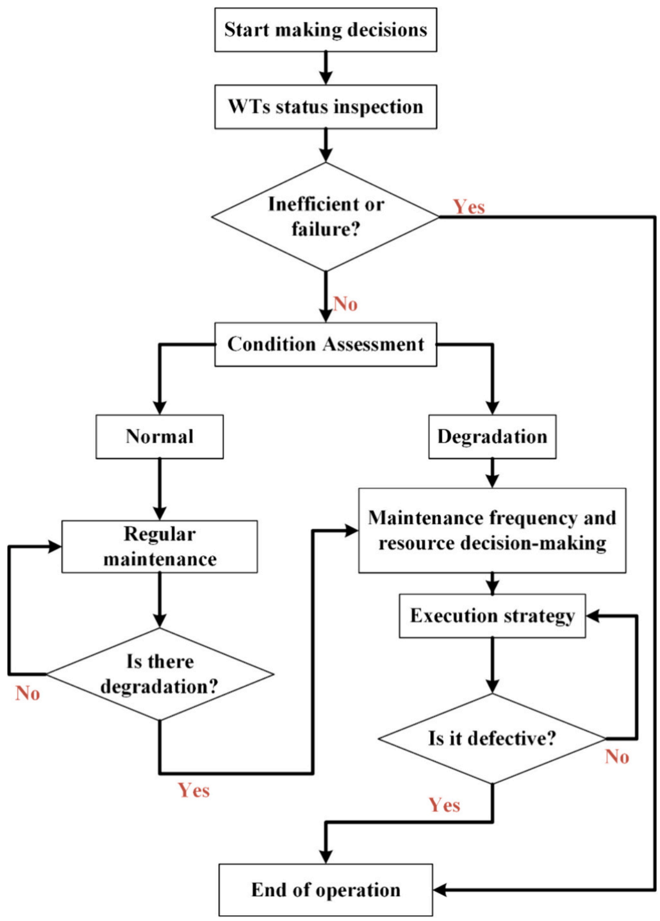


Fig. 2. Decision-Making Flowchart.

by distribution and installation in the CM process, the cost rate function of distribution and installation is given by Eq. (2).

$$\begin{matrix} \varphi_1, t \in PeriodofFreezing \\ 1, other \end{matrix} \tag{2}$$

The CM cost multiplier during the freezing period is set to φ_1, $\varphi_1 > 1$, while the resource distribution cost rate is 1 at other times. Winter is a high-incidence season for road icing, and the cost of maintaining resource distribution and installation is very high. As a penalty, we set a very high delivery and installation cost rate during the freezing period to avoid major component replacements during this time.

The characteristics of wind speed change in plateau areas may differ from those in flatlands. Firstly, the wind speed in the plateau area is generally lower compared to coastal regions. Secondly, the peak-to-valley variation trend of wind speed also differs from that in flatlands. The peak-to-valley variation of wind speed changes in the plateau area is affected by terrain, altitude, longitude, and latitude. Accurate fitting of the variation patterns can be achieved by utilizing local wind measurement station data.

According to the study of Schouten et al. [40], the wind change can generally be fitted as the following function, and the downtime cost rate can be obtained by simply fitting the parameters based on field data.

The change rate of downtime cost is given by Eq. (3),

$$\theta_2 = A\sin(\omega t + \varphi_2) + B \tag{3}$$

where t is the downtime, A, B, and φ_2 are used as correction parameters, which are determined by the wind speed variation rule at the study site. According to the equipment degradation cycle length and inspection law, using a month as the maintenance time unit is more appropriate.

4.2. Preventive maintenance cost

When the equipment is in a particular state, the decision variables are the ratio of resources invested in each maintenance and the maintenance frequency of this state. The ratio of resources invested in each maintenance determines the degradation speed, where a higher resource allocation ratio leads to a reduced degradation rate. The maintenance frequency determines the state's running time, with an appropriate maintenance frequency prolonging the continuation time of the state, while a lower maintenance frequency reduces the running time [64].

4.2.1. Quality of maintenance

The cost of PM is usually determined by the level of resources allocated to the operation. The cost of maintenance increases with the increase of resources, and the quality of maintenance also improves. The degradation rate depends on the degree of maintenance, and the maintenance behavior may only sometimes improve the system. As evidenced by numerous cases in practice indicate that low-quality maintenance may accelerate the deterioration of equipment [69,70].

The maintenance quality depends on the resource ratio c_k invested in each maintenance in the state x_k stage. According to the actual application, it can be set to the maintenance tool level, worker level and other factors that affect the maintenance effect.

When the equipment is in state k, the impact of each maintenance input resource ratio c_k on maintenance quality can be described by variable ε_k, which satisfies Eq. (4),

$$\varepsilon_k = 2(c_k)^\eta - 1 \tag{4}$$

here, c_k is the ratio of resources invested in each maintenance at the state $x \in (x_k, x_{k+1})$, whose value ranges from $(0, 1)$. The value ε_k is in the range $(-1, 1)$, indicating whether the maintenance was of low or high quality. η is the correlation factor, which describes the nonlinear relationship between maintenance resource ratio and maintenance quality and takes a nonnegative real number.

If the maintenance action of state k is CM, then the degradation rate after maintenance is reset to $v_0 = \alpha_0/\beta$. Here, α_0 refers to the shape parameter of the gamma process when the WT is in a healthy state, and β is the scale parameter of the process. If the maintenance is PM, the degradation rate after maintenance is Eq. (5).

$$v_k = v_{k-1}(1 + \varepsilon_k) \tag{5}$$

Eq. (5) represents the impact of maintenance quality on the degradation rate, and in the subsequent description, the degradation rate is used to model the maintenance cost, the slower the degradation after maintenance, the higher the cost of maintenance. Based on the degradation rate, the cost of PM can be evaluated as a function of the degradation rate. According to Eq. (5), we can obtain the recursive formula for the shape parameter α_k when the WT is in state x_k, which is $\alpha_k = \beta \nu_k$.

We assume that the degradation state between the kth state and the $k+1$th state follows a gamma stochastic process $(X_t)_{t \geq 0}$, $cdf_1(x)$ is the cumulative distribution function of the degradation state x, and the probability of the device being in state $x \in (x_k, x_{k+1})$ is given in Eq. (6).

$$P_k(x) = P\{x_k < x < x_{k+1}\} = cdf_1(x) - cdf_1(x_k), (\mathrm{k} = 1, 2, \cdots) \tag{6}$$

The cost of the PM phase is C_P,

$$C_P = N_k \sum_{k=1}^{M} \rho c_k P_k(x) \tag{7}$$

ρ is the cost coefficient of the PM phase, which is determined by the actual situation of the wind farm. N_k is the maintenance number of the kth state, $N_k = t_k f_k$, f_k is the maintenance frequency at state k, and M is the number of degraded states that are divided.

PM strategy optimization can be applied to decision-making processes such as long-term maintenance resource procurement and optimal staff scheduling to determine the optimal maintenance strategy and resource allocation strategy.

4.2.2. Frequency of maintenance

To simulate the effect of maintenance frequency on the operation time of each state of the equipment, this paper assumes that the operation time of each state is determined only by the maintenance frequency of that state. This can be found in many practical studies [71]. For example, adding lubricating oil to the bearing at an appropriate frequency can keep the pitting area of the bearing rolling element unchanged. In contrast, the pitting area of the rolling component will become more prominent when the frequency is low, and the operation time of the equipment under the pitting defect state will be shortened.

When the equipment state $x \in (x_k, x_{k+1})$, the impact of the maintenance frequency f_k at stage k on the reduction in the running time of the equipment at this state can be expressed by a nonnegative continuous random variable y, which follows the exponential distribution with probability density function as in Eq. (8).

$$h(y) = \gamma_k exp(-\gamma_k y) I_{\{c_k \geq 0\}} \tag{8}$$

f_k is the maintenance frequency of the device at phase k, and a different maintenance frequency is used in each state. Since the maintenance frequency is constant in a state, it is assumed that the equipment degradation rate is constant in this state, and the reduction in the running time of this state relative to the previous state due to degradation is determined by γ_k, γ_k as in Eq. (9).

$$\gamma_k = log_a(f_k) \tag{9}$$

a is used as the basic unit of maintenance time, meaning that the year a is divided into equal parts. Due to the limitation of maintenance resources, wind farms often use a fixed duration as the basic maintenance unit to ensure wind power benefits. When $a = 12$, then the basic unit of maintenance time is one month, and if $f_k = 2$ currently, it means that maintenance is performed twice a year. $f_k \in \mathbb{Z}^+$. Here, a must be greater than 1 to ensure that the equipment gets more than one maintenance opportunity per year.

At a certain frequency f_k, the probability of the reduction of the running time of a state x_k relative to the previous state x_{k-1} is given by Eq. (10).

$$\vartheta_k = cdf_2(x_k) - cdf_2(x_{k-1}) \tag{10}$$

$cdf_2(x_k)$ denotes the cumulative probability function of $x \in (x_k, x_{k+1})$. The duration of the device in state $k-1$ is t_{k-1}. After the maintenance of frequency f_k, the duration t_k in state k is given by Eq. (11).

$$t_k = t_{k-1}(1 - \vartheta_k) \tag{11}$$

That is, when the equipment is in a certain state x_k, the higher the maintenance frequency of this phase, the longer the duration of this phase. Since the device degradation is more severe than the previous state, we assume that the current state will not run longer than the previous state.

4.3. Corrective maintenance costs

Maintenance operations require corresponding resource allocation, and the seasonal turnover in the plateau region causes varying maintenance cost rates over time. When a fail-down event occurs, CM is necessary.CM requires deploying maintenance resources from external sources and assigning workers, which involves the remote movement of heavy equipment, which is highly costly due to the extreme temperatures in the plateau. Therefore, regarding equipment replacement costs, it is crucial to not only account for the equipment purchase cost but also factor in the changing equipment transportation cost [72]. Because it takes more time for maintenance resources and personnel to arrive at the wind farm in winter, and the wind in winter is not conducive to maintenance operations, CM will cause extended downtime and incur huge downtime costs.

The equipment replacement cost of plateau wind power includes the equipment purchase cost and the maintenance equipment assembly cost. The rise and fall of equipment acquisition cost is slight, and the acquisition cost of equipment in the whole life cycle is assumed to be a constant value C_E.

The change of maintenance equipment assembly cost rate with time is expressed by Eq. (12).

$$C_C(t) = \overline{C}_C \theta_1(t) \tag{12}$$

$\overline{C}_C$ is the average assembly cost generated by the primary equipment replacement of the important components of the plateau WT, and $\theta_1(t)$ is the resource distribution cost rate of the plateau wind farm. t is the time that the equipment needs to be replaced, depending on the total time of operation of the equipment and the month in which the equipment was just put into operation. Generally, when the equipment fails, the purchase demand is sent to the manufacturer immediately, and the manufacturer can ship the equipment to the wind farm in time.

The downtime cost mainly focuses on the loss of power generation due to wind loss during the downtime and is related to the specific time when the downtime occurs. The downtime cost during the equipment replacement period is given by Eq. (13).

$$C_S(t) = T_S \overline{C}_S \theta_2(t) \tag{13}$$

T_S is the average downtime duration and $\overline{C}_S$ is the average downtime cost per unit time. t is the moment when the device is replaced.

Regardless of downtime or CM costs, operators do not want downtime when extreme cold occurs. Through the previous analysis, we can decide the degree of PM each time, which will change the degradation state experience time, which makes it possible to change the WT downtime. Specifically, we need to control the maintenance degree in the PM process and try to control the downtime at other times except the freezing period.

4.4. Regular inspection of costs

General industrial equipment will conduct regular inspections, whether in a defective or normal state. Although the regular inspection cycle is relatively long, it will still produce non-negligible costs. The difference between conventional and PM costs is that conventional maintenance considers the cost of transportation and personnel arrangement in the process of regular inspection. In contrast, PM cost is the cost of maintenance resources used in the maintenance process because PM requires maintenance resources that are more expensive than conventional maintenance.

Each inspection looks for the moment of lower wind speed in the future to reduce the impact of downtime. The inspection cost of the whole life cycle is given by Eq. (14).

$$C_I = \overline{C}_I N_I \tag{14}$$

Among them, N_I is related to the wind field environment and WT characteristics, $N_I = T/T_I$, and T_I is the routine inspection cycle. According to the maintenance regulations of the wind field, the unit needs to carry out routine maintenance of the WT within a fixed time. $\overline{C}_I$ represents the average downtime, resource consumption, and labor cost incurred during routine maintenance.

4.5. Maintenance objectives

To evaluate the performance of the maintenance strategy, this paper takes minimizing the total maintenance cost of the life cycle and maximizing the operation time as the goal and finally obtains the maintenance frequency f_k and the resource investment ratio c_k when the optimal decision parameter state is k.

The total maintenance cost of the key equipment of the WT from operation to failure replacement is given by Eq. (15), which includes both preventive maintenance costs and corrective maintenance costs.

$$C_{all} = C_P + C_C + C_S + C_I + C_E \tag{15}$$

H is the running time of the equipment, as shown in Eq. (16).

$$H = \sum_{k=1}^{M} t_k \tag{16}$$

The maintenance requirement of the wind farm is to minimize the maintenance cost per kWh and maximize the operation time. The optimization objectives and constraints are as follows,

$$min\ C = \frac{C_{all}}{H \cdot E} = \frac{\sum_{k=1}^{M} C_k P_k(x) + \overline{C}_C \theta_1(t) + T_S \overline{C}_S \theta_2(t) + \overline{C}_I N_I + C_E}{H \cdot E} \tag{17}$$

$$max\ H = \sum_{k=1}^{M} t_k \tag{18}$$

$E$is the amount of electricity generated per unit time, which can be obtained by consulting the wind farm operation log.

$t = (H + initial\ time)//12$in objective$C$means that the*initial time*passes through the total life length$H$and the specific month of shutdown (the remainder is taken to represent the month). $H \cdot E$represents the total amount of electricity generated during the equipment's life cycle.

If the expected maintenance cost of the equipment at a certain stage exceeds the average CM cost, then CM is the more economical choice, so a constraint$\rho c_k N_k + t_k \overline{C}_S < \overline{C}_C + T_S C_S$needs to be introduced, That is, the sum of the PM cost and the subsequent generation revenue at a certain stage needs to be less than the average CM cost$\overline{C}_C + T_S C_S$, otherwise it directly enters the CM procedure.

Therefore, the constraints are as follows,

$$\begin{cases} f_k \in \mathbb{Z}^+ \\ 0 < c_k \le 1 \\ \rho c_k N_k + t_k \overline{C}_S < \overline{C}_C + T_S C_S \end{cases} \tag{19}$$

According to Eqs. (17)–(18), the model has two objectives, with decision variables being the maintenance frequency for each state and the maintenance resource ratio. For the multi-objective optimization model, this paper employs the NSGA-II algorithm for solving, while for the single-objective optimization problem in the comparative experiment, this paper utilizes the PSO algorithm for solving.

5. Numerical example

5.1. Scenario set-up

The wind farm studied in this paper is in western Guizhou Province, China, at an altitude of 2700 m. Since the wind farm has been in operation for a considerable period, it has experienced various mechanical and electrical failures in a typical plateau environment. Among them, the fault with the most enormous single economic loss is attributed to the gearbox. To achieve the above maintenance objectives, the WT of the wind farm is taken as the research object, and the field data from the wind farm are collected to conduct a case study.

A WT has many components, but the mechanical components determine its maintenance costs. In addition to the gearbox, other components, such as generators, bearings, etc., choose the WT's maintenance cost. The method of the text can also be used as a module to construct a maintenance decision model for multiple components. Because other essential components can also divide their degradation states by monitoring techniques, this paper's method of combining state and time is still valid. Therefore, the case study part of this paper only considers the WT component that causes the most significant single economic loss –the gearbox.

Fig. 3 shows the monthly average wind speed change curve of the wind farm studied in the past 10 years [73]. Observing the ten-year wind data obtained in this paper, it can be found that the wind speed of the Yunnan-Guizhou Plateau wind farm studied in this paper has a trend of sinusoidal variation. To model concisely while also describing the characteristics of the data, we have also chosen the sine function for modeling.

It can be seen from the figure that the average wind speed is the maximum in March and the minimum in September. Using the fitting method to fit the scatter plot, Eq. (20) can be obtained,

$$\theta_1(x) = 0.7sin\left(\frac{\pi}{6}x - \frac{\pi}{12}\right) + 2.99 \tag{20}$$

The wind farm icing cycle occurs from the middle of December to the middle of February, a total of 2 months, during which there are many snow and freezing days. Due to the long CM cycle of the equipment, it is entirely possible to fall within this span, so it is necessary to avoid CM in this period [74]. This paper uses the penalty factor method to prevent the WT replacement event from occurring in the freezing period. Fig. 4 shows the monthly average weekly freezing days in the wind farm area in the last ten years. (See Fig. 5.)

Due to the progress of prediction technology, the rotating machinery of the plateau WT has been able to predict its operation stage roughly, and the average downtime caused by failure has been shortened from 2 to 3 months to half a month [75]. Although the equipment replacement cycle is significantly reduced, if the replacement occurs in the freezing season, it is still necessary to perform road and tower blade deicing, which will bring considerable time and economic costs.

The following are some parameters from the wind farms under study, Table 1 shows the cost coefficient versus the moment of commissioning of the equipment, $\overline{C}_C$is equipment transportation and installation cost, $\overline{C}_S$is downtime cost, $\overline{C}_I$is routine.

maintenance cost, and$C_E$is equipment acquisition cost. The units of the above costs are thousands of dollars (k$),$T_S$downtime time is taken as maintenance unit in months.

The initial time here means that the WT was installed and put into operation in November. According to the reference [67], the shape parameters and scale parameters are selected as Table 2.

Given the highly nonlinear nature of the objective function, averaging can mitigate the impact of random fluctuations in individual experiments on the outcomes, leading to a more balanced set of solutions. Consequently, this paper employs a method of averaging results from multiple experiments for each experimental setup.

5.2. Results of fixed maintenance frequency

This section optimizes the policy using a fixed maintenance frequency. The fixed maintenance frequency data were collected from the wind farm described in the previous.

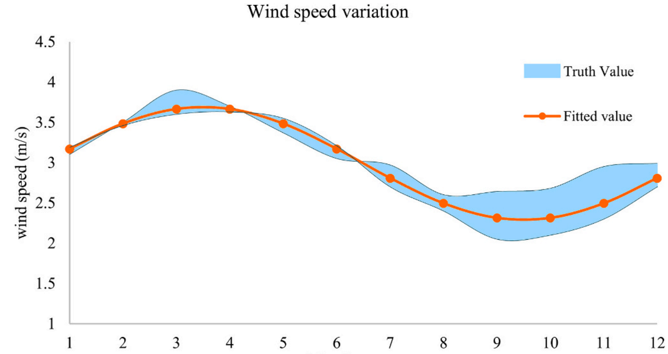


Fig. 3. Fitted plot of monthly mean wind speed.

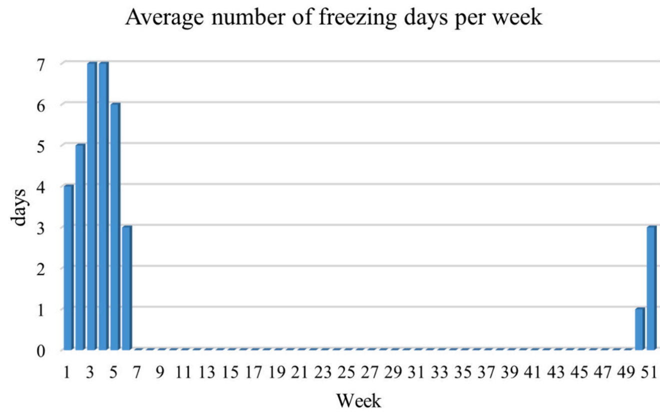


Fig. 4. Period of Freezing.

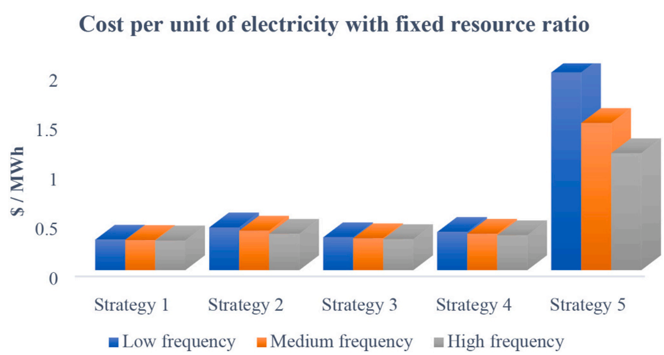


Fig. 5. Comparison of maintenance cost per kWh for fixed input resource ratio.

Table 1
Cost coefficient and initial time.

$\overline{C}_C$(k$)	T_S(months)	$\overline{C}_S$(k$)	$\overline{C}_I$ (k$)	C_E (k$)	Initial time
20	0.5	45	1	200	November

Table 2
Model parameters.

α_0	β	η	ρ
1	2	2	0.1

section, and the input parameters are provided in Section 5.1. The FFMS focuses on the maintenance resources required for the equipment in each state and can be considered as a state-based maintenance strategy.

The unit of the above strategy is the number of maintenances per year. In the current practice of wind farm maintenance, the influence of maintenance frequency on the unit is rarely considered. Therefore, this section summarizes the two maintenance frequencies shown in Table 3 according to the actual situation of the wind farm to verify the influence of frequency on the maintenance effect.

Because the maintenance frequency is fixed, the service age of WT components depends entirely on the maintenance frequency through the analysis model; an objective has been fixed here, so it is converted into a single objective optimization problem. Using the PSO algorithm [76] with the particle number of 100 and 200 iterations, when the low-frequency maintenance strategy is used in the maintenance of the WT components, the cost of kWh can be reduced to 4.687$/MWh by optimizing the maintenance resource ratio, and the life of the equipment is 261.7 months. When using the high-frequency maintenance strategy, the kWh cost can be reduced by optimizing the maintenance resource ratio to 3.352$/MWh, which is 278 months of life. The above conclusions show that the strategy of higher maintenance frequency in the early degradation stage will not only increase the cost of electricity per unit but can also prolong the service life of the equipment.

Table 3
Fixed maintenance frequency strategy.

Strategy	x_1	x_2	x_3	x_4	x_5
HFMS	6	7	8	9	12
LFMS	2	3	4	6	12

5.3. Results for fixed resource ratios

Currently, most wind power airports do not consider the impact of the change in input resource ratio on equipment life and production costs when performing maintenance. To compare the effects of different maintenance resource ratios on the life and production costs of the WTs, this section uses different maintenance resource ratios to optimize the maintenance of the plateau WTs. FRRS mainly optimizes the variable of maintenance frequency, which is consistent with the time-based maintenance strategy, and therefore can be regarded as an optimization of the time-based maintenance strategy.

According to the maintenance resource input ratio of each state of the WT gear, five maintenance strategies are designed, as shown in Table 4. The number represents the input resource ratio, which is distinguished according to the specific equipment. For example, the quality of maintenance supplies, workers' technical proficiency, and the condition monitoring level can be considered when maintaining the gearbox. The maintenance of fixed maintenance resource ratio is a multi-objective optimization problem. Here, the NSGA-II algorithm [77] with 100 particles and 300 iterations is adopted to optimize the problem, and the results are as follows. The NSGA-II algorithm incorporates an elitist strategy and a method for calculating crowd distance, thereby enhancing the efficiency and quality of solutions. It possesses strong robustness and effectiveness when dealing with multi-objective problems.

Where the ordinate is the maintenance cost per kWh, the unit is $/MWh. Combined with Table 3, we can see that during the healthy and slight wear of the equipment, maintenance with a low resource ratio can reduce the kWh cost of the equipment life cycle to a greater extent. Maintenance using a large resource ratio may not be worth the loss in the early stage of equipment operation. Combined with the conclusion of the previous section, in the early stage of equipment operation, operation, and maintenance personnel need to maintain the equipment a small number of times, and the maintenance frequency can be higher. Still, it can use low-maintenance resources. In the middle and late stages of equipment operation, increasing the maintenance frequency and improving the resources invested in maintenance is necessary.

5.4. Model validation

To verify the validity and credibility of the model, this section studies the maintenance strategy of the WT in the plateau wind farm when it is put into operation at different times. The model considers equipment

Table 4
Five fixed maintenance resource ratio strategies.

Strategy	x_1	x_2	x_3	x_4	x_5
Strategy One	0.01	0.05	0.6	0.8	0.9
Strategy Two	0.1	0.15	0.6	0.8	0.9
Strategy Three	0.1	0.2	0.6	0.8	1.0
Strategy Four	0.2	0.4	0.6	0.8	1.0
Strategy Five	0.6	0.7	0.8	0.9	1.0

distribution and installation costs over time, and the primary input parameters have been given in Section 5.1. Table 1 shows the parameter settings used by the NSGA-II algorithm to obtain the optimal solution. The population size of the algorithm is 100 individuals, the iteration is 300 generations, and everyone's fitness value is evaluated by the given calculation formula for the running time and the calculation formula for the maintenance cost of per MWh.

Fig. 6 shows the obtained Pareto front, which demonstrates the non-dominated solutions for the device's expected lifetime and the cost per MWh. (See Figs. 7 and 8.)

Due to the high cost of distribution and installation, the high risk of abnormal climate, the wind farm studied in this paper does not carry out the loading and unloading operation of significant components from December to February of the following year. So, this paper chooses March, June, September, and November as the initial months for the WT to be put into operation. The resulting Pareto fronts are shown in Fig. 6 (a), 6(b), 6(c), and 6(e). Analysis of Fig. 6 shows that different operational times will lead to different optimal maintenance strategies for WTs. Putting the WT into operation in March can make it run longer, but the maintenance cost will increase in the optimization strategy. The reasons for the jump are analyzed in the parameter analysis section. Commissioning in June may shorten the WT's life but will not significantly impact maintenance costs. The service life of the WTs put into operation in September is reduced even more, and the maintenance cost is not significantly affected. For the WTs put into operation in November, using the maintenance strategy developed in this paper may extend the WT's life, but it will increase the maintenance cost. Table 5 shows the four Pareto-optimal strategies with the operational time of March, June, September, and November.

This paper selects four typical installation moments for WT equipment to optimize the O&M strategy. Combined with Fig. 6, the WT maintenance must be carried out at a high frequency in the early stage of equipment degradation, requiring a small investment in maintenance resources, but this is very effective for WT gearbox maintenance.

Table 6 compares the maintenance strategies and their effects. Combining the results of Sections 5.2 and 5.3, it can be found that when using the FFMS, which is equivalent to using a state-based method, even if the optimal state-based strategy results in a maintenance cost of \$4.02/MWh, the multi-objective optimization method in this paper can still reduce the maintenance cost by 24.07 %. At the same time, by comparing the operating time, it can be found that in the settings of this paper, using the state-based maintenance strategy will result in a loss of 11.58 % of the lifespan. When using the FRRS, i.e., the time-based maintenance strategy, the optimal maintenance frequency results in an average lifespan of 289.3 months, while the multi-objective optimization method in this paper can increase the operating time by 3.69 %. This also means that using the time-based maintenance strategy will result in an economic loss of 18.21 %. After comparing with FFMS and

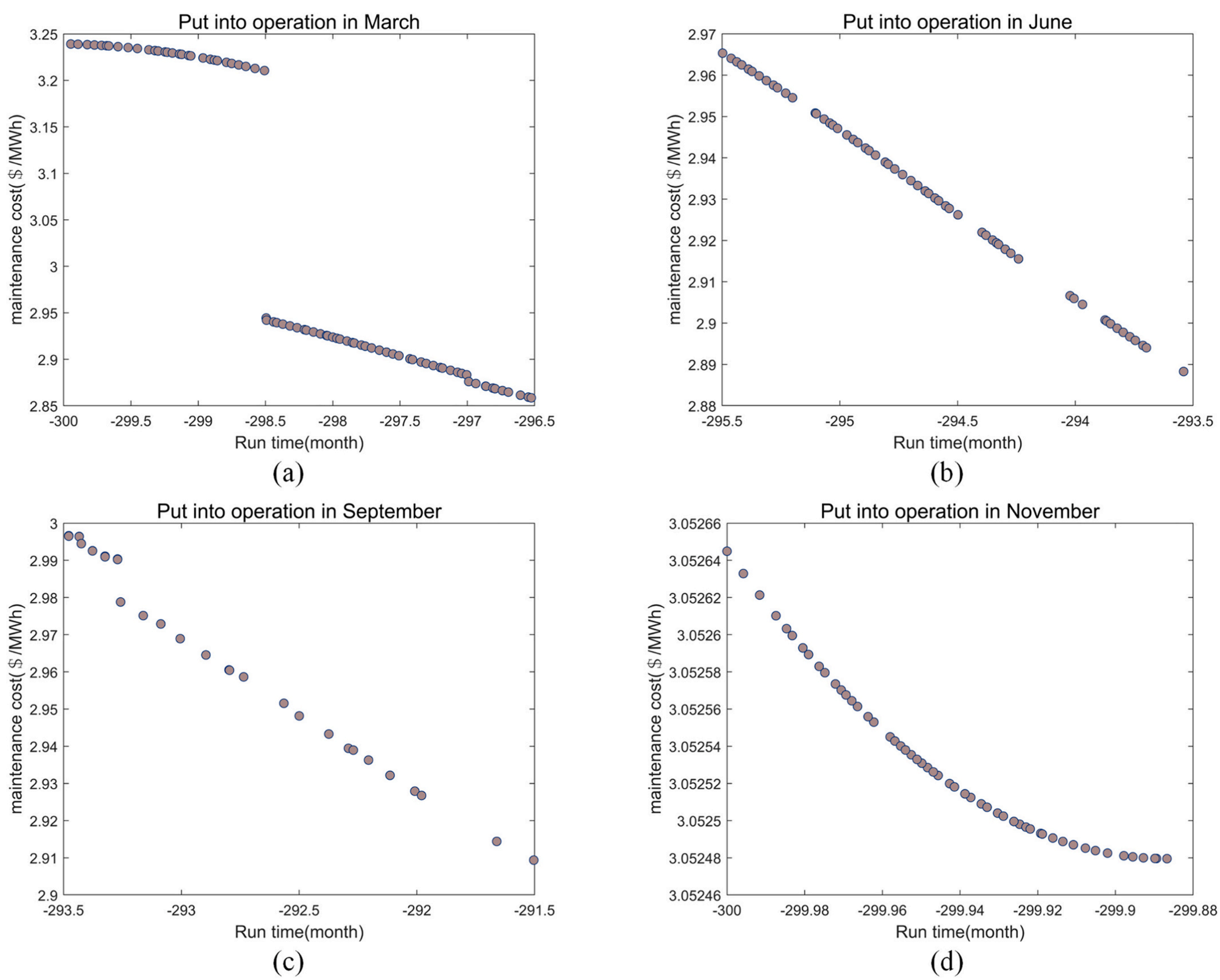


Fig. 6. Time-varying costs considering time and state maintain the optimization results.

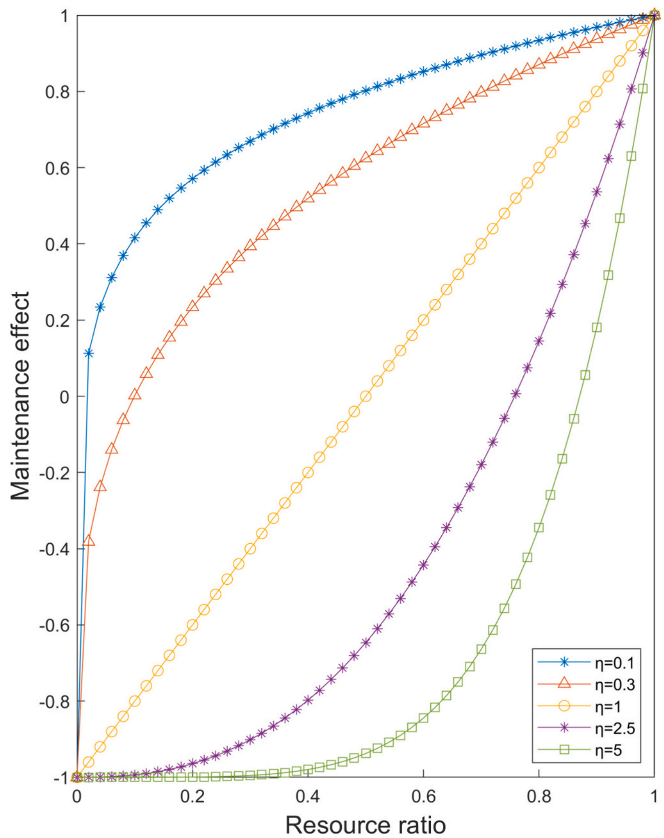


Fig. 7. PM effects for different η.

FRRS, the results show that the multi-objective maintenance strategy in this paper can make the plateau WT have a longer lifespan with lower maintenance costs.

Furthermore, the optimization results also indicate that the FRRS adopted by traditional wind facilities, which means that the maintenance resources in the early and later stages of equipment operation are the same, affecting later-stage performance of the equipment. It is necessary to invest in maintenance with lower resource ratios in the early stages of equipment operation and then transition higher ones in the last stages. Only with such a maintenance strategy can minimize the cost of electricity consumption during operation. Unlike previous findings, the maintenance party needs to employ a higher maintenance frequency in the early stage and maintain a higher maintenance frequency in the later stage to maximize the equipment's operational lifespan. Considering all factors, during the maintenance process of plateau WTs, low resource ratios but multiple maintenance are required in the early stage of equipment operation. While in the later stage of equipment operation, high-level resources and higher frequency maintenance are necessary to optimize kilowatt-hour maintenance cost and operational lifespan.

5.5. *Applicability analysis*

To demonstrate that the maintenance strategy considering both time and state information can accurately represent the actual operation and maintenance process of equipment under the complex operating environment of the plateau, this section simulates the maintenance process of WTs in different scenarios by changing model parameters. Since plateau wind power has a relatively poor economic performance compared to plain wind power, the main comparison object in this section is plain wind power.

The air density on the plateau is low, and when the wind force is small, it does not meet the starting conditions for WTs at all. Most plain wind farms do not have this problem, and their WTs can almost always meet the power generation conditions throughout the year. Therefore, in plain areas, no matter when equipment maintenance and replacement are carried out, there will be downtime costs. However, in plateau, if maintenance plans are executed when there is no wind, it is possible to avoid huge downtime costs. Therefore, this paper uses the annual

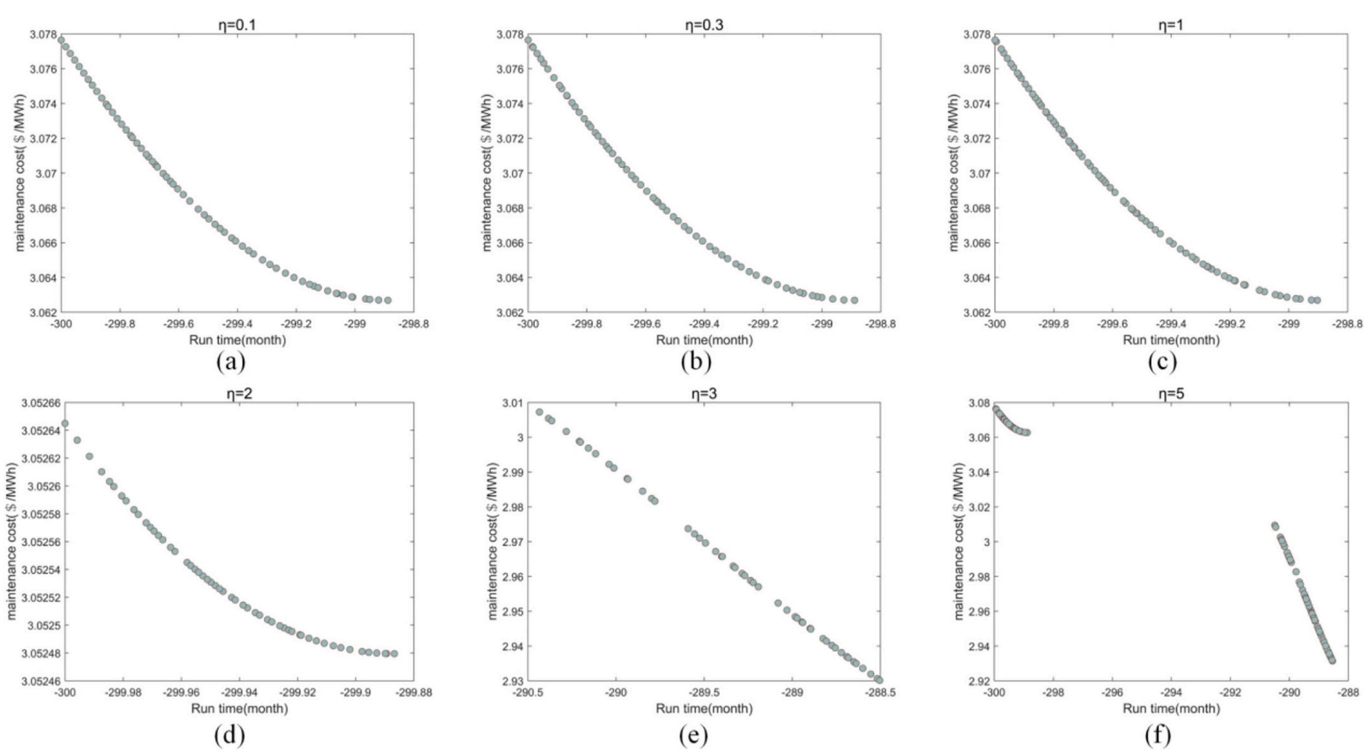


Fig. 8. Non-dominated solutions for different η.

Table 5
Pareto strategies for different input running times.

Time	Variable	x_1	x_2	x_3	x_4	x_5
March	c_k	<0.1	<0.1	0.1–0.63	0.1–0.54	0.8–1
	f_k	6–9	6–12	6–10	8–10	9–12
June	c_k	<0.1	<0.1	0.8–1	0.4–0.6	0.6–1
	f_k	6–8	6–9	6–12	8–12	9–12
September	c_k	<0.1	0.2–0.25	0.6–0.93	0.5–0.81	0.6–0.77
	f_k	7–9	7–11	5–9	4–10	4–8
November	c_k	<0.1	<0.1	0.6–0.9	0.16–0.44	0.57–0.74
	f_k	8–12	9–12	8–12	9–12	8–12

Table 6
Comparison of maintenance strategies.

Strategy	Maintenance cost($/MWh)	Run time(months)
FFMS	4.02	268.85
FRRS	3.7324	289.3
MOOS	3.0525	299.97

average wind speed to replace the downtime cost change rate function of the plateau environment, indicating that the plain area can meet the power generation conditions throughout the year. Since the phenomenon of road icing rarely occurs in plain, and even in winter, effective maintenance of wind power equipment can be carried out, the assembly cost rate is set to 1, indicating that there is no additional assembly cost generated by environmental changes.

Table 7 presents the optimal solutions obtained using this model under different scenarios. In the scenario settings, two scenarios are set for the plain: the first is where the wind is relatively stable and can meet the power generation conditions throughout the year; the second is where there are slight wind fluctuations within a year, but the fluctuations are small, and the assembly cost rate for both scenarios is set to 1. According to surveys, on the Qinghai-Tibet Plateau, the wind fluctuations are relatively small throughout the year, but the freezing period is longer, resulting in higher equipment assembly costs; while on the East African Plateau, there are larger wind fluctuations throughout the year, but the freezing time is shorter; on the Yunnan-Guizhou Plateau, there are larger wind fluctuations throughout the year, and the time of freezing is also longer. Implementing the maintenance strategy proposed in this paper under extreme conditions can demonstrate the applicability of the method presented.

From the table, the plain with stable wind power can obtain the highest benefit, including the lowest maintenance cost per kWh and the longest lifespan. As the environment deteriorates, the cost per kWh gradually increases, and the lifespan of the equipment also gradually shortens. In the plateau scenarios, the data from the extreme environment comes from a wind farm in the western part of Guizhou Province, where the monthly average wind speed fluctuations are significant, and the freezing period is also relatively long. At the same time, we designed maintenance experiments for several other wind farms, studying the impact of different environmental factors on the maintenance effect of plateau wind farms by controlling variables. The experimental results show that during the execution of the maintenance strategy provided in this paper, compared to scenarios with larger wind speed fluctuations, scenarios with longer freezing periods will have a greater maintenance cost per kWh, and the lifespan of WTs will be shortened. This indicates that freezing periods has a greater impact on the economic performance of plateau wind power, while the impact of monthly average wind speed fluctuations is slightly lower.

Table 7
Applicability Analysis under Different Scenarios.

Scenarios		Maintenance cost ($/MWh)	Run time (months)
Plain	Wind stability	2.8182	302.17
	Low wind fluctuations	2.8324	301.46
Plateau	The wind is choppy	3.0350	300.86
	Long freezing period	3.0436	300.37
	Extreme environment	3.0525	299.97

5.6. Sensitivity analysis

The parameters and data analyzed above are from a plateau wind farm in the west of Guizhou, China, and the selected parameters may deviate from other plateau wind farms. This section analyzes the crucial parameters in the model to analyze the generalization performance of the model.

5.6.1. Maintenance effect influence factorη

$\eta$is a parameter that influences the ratio of maintenance input resources on the quality of PM. Different operators have different operation levels. To simulate the maintenancelevels of varying wind power operators or maintainers, this paper uses Eq. (4) to describe this relationship, and its characteristics are shown in Fig. 7.

To study the change ofηon the maintenance effect, this section sets up five control experiments with different values ofη. Fig. 8 (d) is the non-dominated solution obtained in the previous section, which is put into Fig. 8 for the convenience of comparison.

Here, the values of$\eta$are chosen as 0.1, 0.3, 1, 2, 2.5, and 5.

ηrepresents the impact of maintenance input resources on maintenance quality, which generally depends on the workability of the maintainer. Wind farms with higher performance can convert maintenance resources into corresponding maintenance quality, while wind farms with lower performance have difficulty converting invested maintenance resources into corresponding maintenance quality. Since the value of the input resource ratio is a decimal between 0 and 1, and the input resource ratio is very high in the later stage of maintenance, the larger$\eta$is, the faster the transformation efficiency changes, and the WT maintenance effect is more affected by the resource ratio, which leads to the jump of the solutions in Fig. 8 (e) and Fig. 8 (f). When$\eta$is between 0.1 and 2, it is more convenient to use this model for maintenance decision making, when$\eta > 2$, the non-dominated solution will produce some jumps, which is unfavorable for the decision process.

5.6.2. Sensitivity analysis of PM cost ratioρ

This section studies the impact of varyingρon the maintenance effect. As the scaling factor of the cost of the PM phase in the maintenance cost of the whole equipment life cycle, the value ofρcan be adjusted according to the actual situation of the wind farm. The wind power equipment selected in this paper does not consider the most extreme situation in the plateau environment, and the value of$\rho$of this equipment in the PM stage is 0.1. Due to the change in environment and the selection of model parameters, we consider the scaling factor$\rho \in (0, 0.25)$to comprehensively show the change in the maintenance cost of wind power equipment in the complex plateau environment.

Table 8 shows the impact of the change inρon the two objectives.

When$\rho$is small, it means that the cost of the PM stage is relatively small, and the influence of the local environment on the degradation of the WT is not significant, while when$\rho$is large, it means that the impact of the environment on the WT is enormous. From the perspective of electricity cost, it can be found that when the environment is more complex, the electricity cost will also rise, but due to the optimization of the strategy, the trend of the equipment operation time changing with$\rho$is not obvious.

5.6.3. Rationality analysis of assembly cost rate

This section analyzes the rationality of the assembly cost rate. Fig. 3 can be regarded as showing that the number of freezing days per week follows a gaussian distribution. The above text simply summarizes the freezing cost rate as a staircase distribution function, with the intention of penalizing activities such as the transportation of equipment and personnel allocation during the freezing period. This section considers the weekly average freezing dates in the plateau environment to follow a normal distribution, thereby verifying the rationality of the step assembly cost rate distribution function.

Fig. 9 (a) presents the optimization results of the assembly cost rate distribution function used in this paper, which is a staircase distribution function. Fig. 9 (b) shows the assembly cost rate distribution function obtained by fitting the original data with a gaussian.

distribution. It can be observed from the figures that the solutions obtained using both the gaussian distribution and the staircase distribution functions are similar, with maintenance costs being $3.05/MWh and operation duration being 299.95 months, which are basically consistent with the solutions in Section 5.4. This indicates that the staircase distribution function used in this paper is reasonable. At the same time, when using the gaussian distribution function, the initial convergence speed of the algorithm is relatively slow. The algorithm was implemented in MATLAB® using a computer equipped with a 12th Gen Intel Core CPU at 2.0 GHz and 64 GB of RAM. When using the gaussian distribution function, the running time was about 2 h, while when using the staircase distribution function, the running time was reduced to 1.5 h. This demonstrates that using a staircase distribution function to approximate the assembly cost rate distribution function is both reasonable and efficient.

5.6.4. The impact of technological advancement on maintenance

The technological iteration and commercialization of wind power generation are progressing very rapidly worldwide. To balance the technological iteration with ongoing maintenance, this section analyzes the impact of technological advancements on the maintenance process of WTs. With the progress of artificial intelligence technology, the fault diagnosis of gearboxes has evolved from initial manual identification to current intelligent diagnosis, which has not only improved diagnostic accuracy but also reduced the cost of diagnosis. Therefore, this paper primarily models the impact of technological iteration as a decrease in maintenance costs over time.

As technology advances over time, almost all costs associated with equipment maintenance will gradually decrease, such as preventive maintenance costs, corrective maintenance costs, regular inspection costs, and equipment purchase costs [78]. The reduction of these costs can essentially be seen as the depreciation of maintenance technology costs. With the rapid development of the wind power market, the cost of maintenance will become increasingly lower [16]. Therefore, we add a depreciation factor to the numerator of Eq. (19), and the new maintenance cost function is shown as Eq. (21).

$$min\ C = \frac{C_{all}R}{H \cdot E} \tag{21}$$

In the equation,$R = \frac{1}{(1+\delta)^{g(H)}}$, where R is the depreciation factor, andδrepresents the depreciation rate. Since the technological iteration process is relatively long, it is set as$g(H) = H/12$to characterize the gradual progress of technology. The number 12 here indicates that technological iteration occurs once a year, but it can also be set to other appropriate values. However, the focus of this paper is not on how much this value should be set, but on the changes in maintenance strategies under the condition of technological progress. Fig. 10 shows the trend of changes in maintenance objectives as the depreciation factor varies.

The discount on maintenance costs due to technological progress is usually low, as a revolutionary change in an industry typically requires decades or even centuries of technological accumulation. In this paper, three discount rates are selected to explore the impact of technological progress on the economic viability of maintenance. From Fig. 10, we can see that as the discount rate increases, the cost of electricity from wind power gradually decreases, but the reduction is relatively small and tends to show a saturation trend. The results indicate that the usual means for wind power companies to improve economic viability is not to adopt more advanced maintenance technologies, as the effect on reducing maintenance costs is limited. Of course, if companies are willing to make appropriate investments in updating maintenance equipment or developing innovative maintenance technologies, they can still reduce some costs.

6. Conclusion

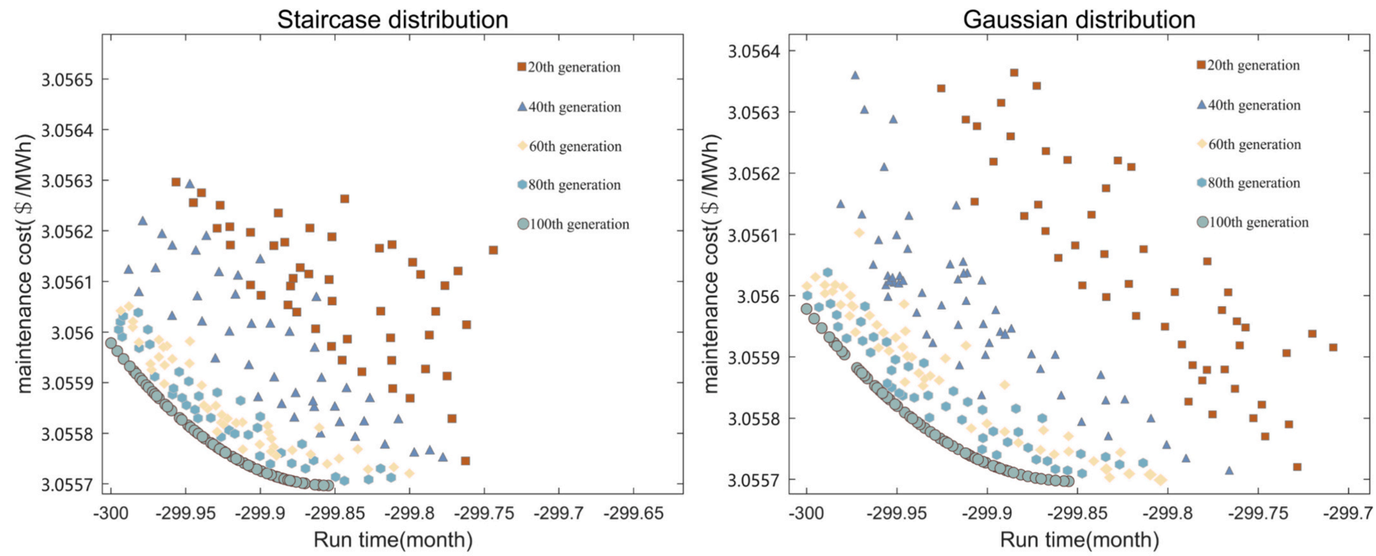
To solve the problem of low economic efficiency and more complex performance degradation of WTs in complex operating environments on high plateaus compared to flatlands, a maintenance strategy is proposed for plateau WTs that considers degradation states and time-varying maintenance costs. This paper models the life decay of each state of the equipment as a random process that follows an exponential distribution, establishing a model for the time-variant maintenance costs of WTs. A case study was conducted on a plateau wind farm in Guizhou, China, optimizing the maintenance cost per unit of electricity and operational lifespan, thereby determining the optimal level of maintenance resource input and maintenance frequency for each state.

The study demonstrates that compared to FFMS, our strategy can reduce the maintenance cost per unit of electricity by 24.07 %, while extending the operational lifespan of the equipment by 11.58 %. In contrast to FRRS, our strategy can reduce the maintenance cost per unit of electricity by 18.21 % and extend the operational lifespan of the equipment by 3.69 %. When making maintenance decisions for wind farms, the optimization strategy proposed in this paper eliminates the need to focus on when equipment failures will occur; instead, it requires deciding on the resources needed for each maintenance and the frequency of maintenance. Compared to opportunistic or state-based maintenance strategies, our approach requires only condition monitoring at any time after a WT is put into operation, followed by optimizing decisions on the ratio of maintenance resources and maintenance frequency. Furthermore, the optimization results indicate that the FRRS traditionally adopted by wind farms, where the maintenance resources are the same in the early and late stages of equipment operation, affects the operational condition of the equipment in the later stages. In the long term, during the maintenance of plateau WTs, a low level of resources but frequent maintenance is required in the early stages of operation, while a high level of resources and higher frequency of maintenance is needed in the mid-to-late stages.

This work primarily focuses on the maintenance costs and operational lifespan of the equipment, without considering the efficiency changes of WTs during operation and equipment depreciation. In

Table 8
Range of nondominated solution strategies for differentρ.

ρ	Maintenance cost($/MWh)	Run time(months)
0.05	2.892–2.916	285.7–289.5
0.1	2.837–2.974	284.1–288.6
0.15	2.923–3.006	288.6–292.5
0.2	2.952–3.105	286.3–289.8



(a) (b)

Fig. 9. Optimization results of different assembly cost rate distribution functions.

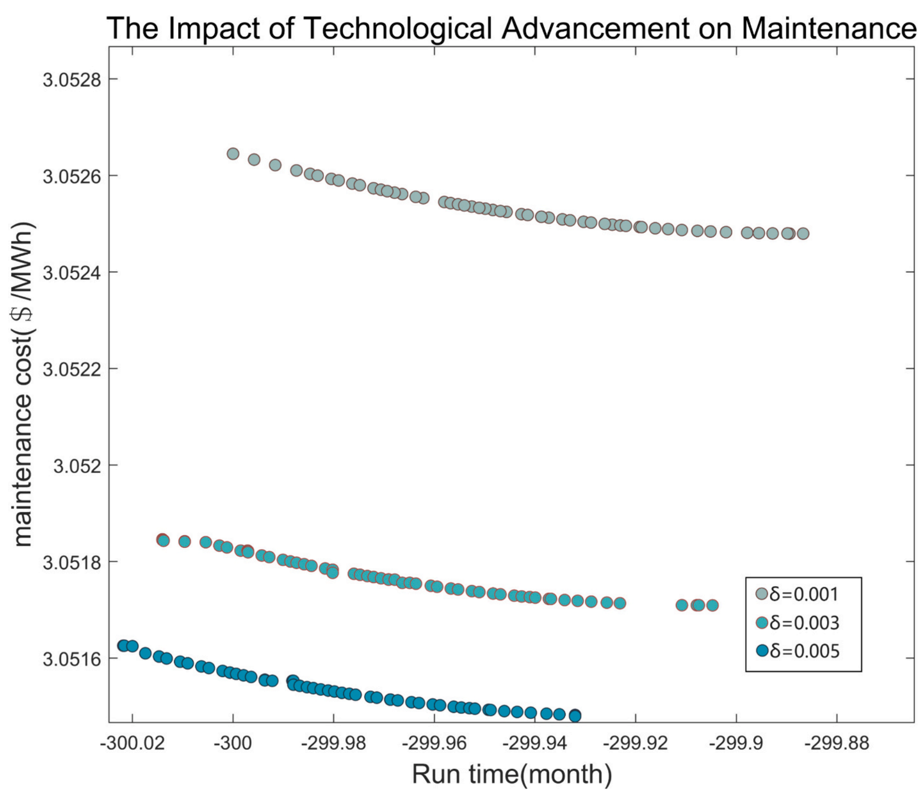


Fig. 10. The impact of technological advancement on maintenance.

practice, improving the efficiency of WTs can better enhance the economic viability of wind power, while equipment depreciation affects the utility of the maintenance plan. Therefore, our future research can revolve around these key points, improving the model from a broader perspective to adapt to more complex situations. Additionally, conducting experiments in wind farms will also be a focus of our next phase of work.

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CRediT authorship contribution statement

Huakang Tang: Writing – original draft, Methodology, Data curation, Conceptualization. **Honglei Wang:** Writing – review & editing, Visualization, Supervision, Investigation. **Chengjiang Li:** Writing – review & editing, Visualization, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this study.

Data availability

No data was used for the research described in the article.

Appendix A. Optimization results of operation at other times

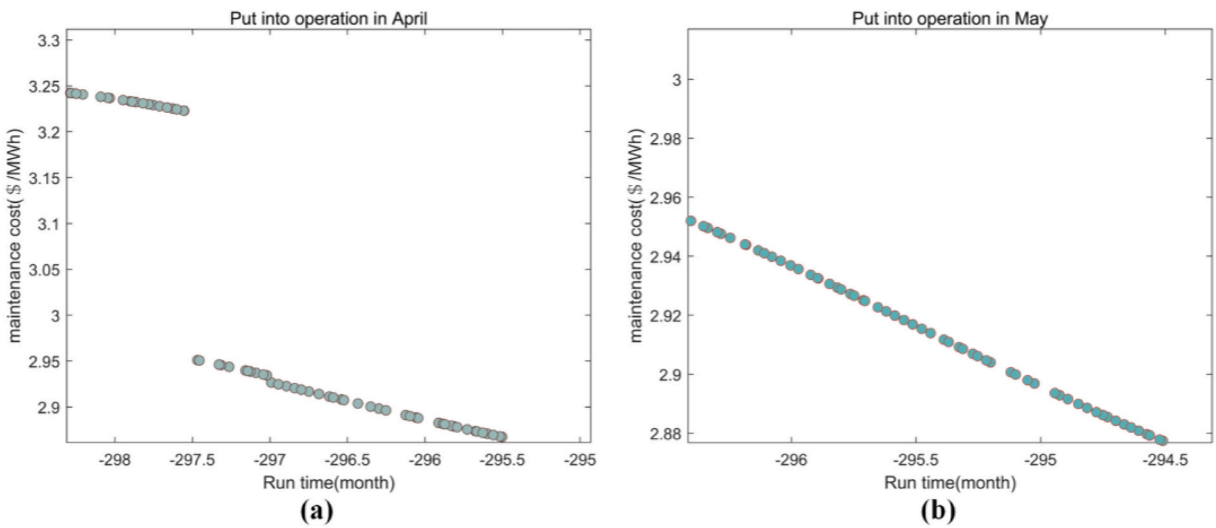

Fig. A1. Optimization results when put into operation in April and May.

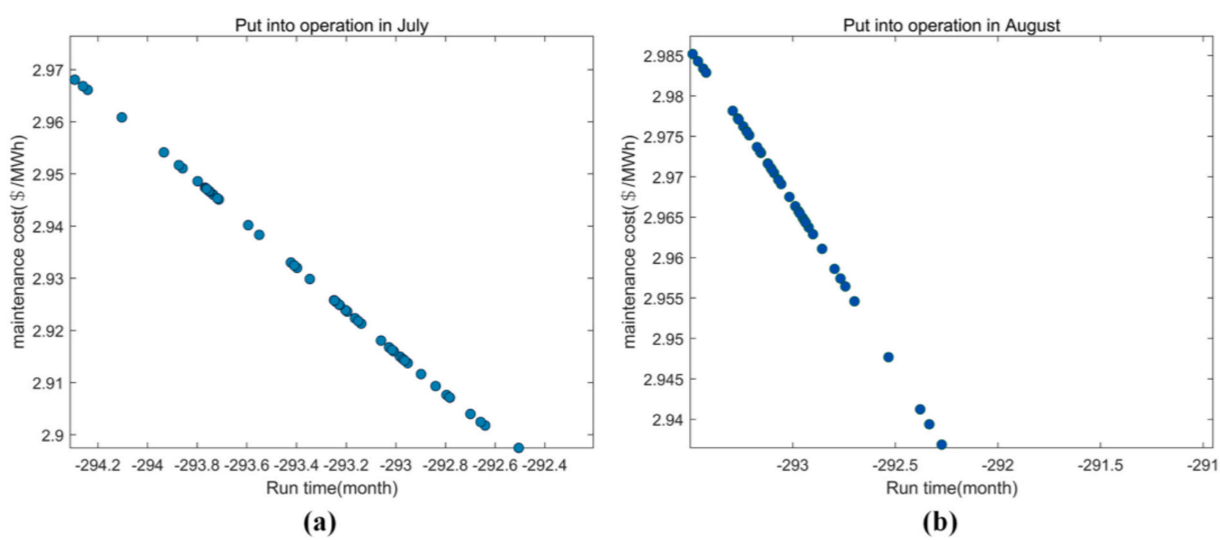

Fig. A2. Optimization results when put into operation in July and August.

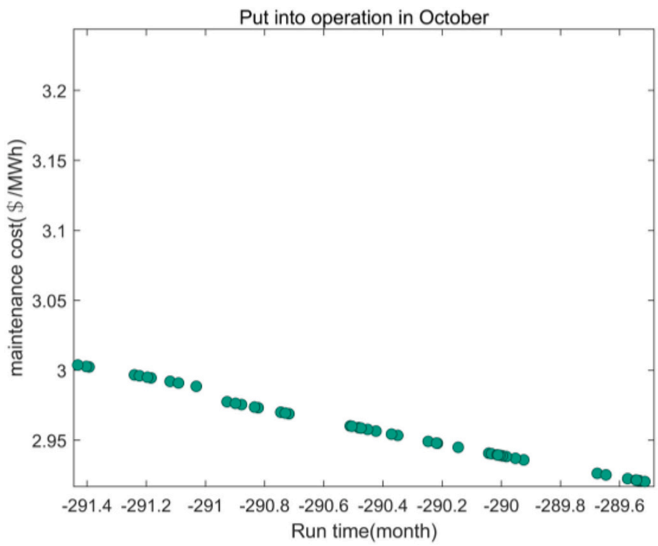

Fig. A3. Optimization results from the operation launched in October.

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