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RESEARCH ARTICLE

Wind Turbine Optimal Preventive Maintenance Scheduling Using Fibonacci Search and Genetic Algorithm

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Abstract: Maintenance scheduling is essential and crucial for wind turbines (WTs) to avoid breakdowns and reduce maintenance costs. Many maintenance models have been developed for WTs' maintenance planning, such as corrective, preventive, and predictive maintenance. Due to communities' dependence on WTs for electricity needs, preventive maintenance is the most widely used method for maintenance scheduling. The downside to using this approach is that preventive maintenance (PM) is often done in fixed intervals, which is inefficient. In this paper, a more detailed maintenance plan for a 2 MW WT has been developed. The paper's focus is to minimize a WT's maintenance cost based on a WT's reliability model. This study uses a two-layer optimization framework: Fibonacci and genetic algorithm. The first layer in the optimization method (Fibonacci) finds the optimal number of PM required for the system. In the second layer, the optimal times for preventative maintenance and optimal components to maintain have been determined to minimize maintenance costs. The Monte Carlo simulation estimates WT component failure times using their lifetime distributions from the reliability model. The estimated failure times are then used to determine the overall corrective and PM costs during the system's lifetime. Finally, an optimal PM schedule is proposed for a 2 MW WT using the presented method. The method used in this paper can be expanded to a wind farm or similar engineering systems.

Keywords: cost-based maintenance scheduling; genetic algorithm; hierarchical optimization; preventive maintenance; reliability modeling; wind turbine maintenance policy

I. INTRODUCTION

Wind energy is one of the growing sources of renewable energy worldwide. In recent years, the cost of wind energy has decreased significantly, making it more competitive with other sources of electricity. Wind turbines (WTs) are proven sources of energy, and they have continuously contributed to global energy production. However, they have also had issues with high failure rates and high maintenance costs. This paper aims to discuss various factors that affect the operation of WTs and their maintenance cost [1]. Having a proactive maintenance program can help reduce costs and prevent failures. Therefore, using historical data is beneficial in determining the right maintenance strategy. This is especially essential for large projects where the cost of maintenance is significant enough to make them uncompetitive.

There are different policies for WT maintenance, such as corrective, preventive, condition-based, and predictive maintenance [2]. When a failure occurs, corrective maintenance is used to return the machine to a working condition, such as the work done in [3]. Although corrective maintenance requires less monitoring and inspection effort, it is not usually used for critical systems or components. Condition-based maintenance reduces the cost of machine failures; however, it requires condition monitoring equipment installed on the system, which is commonly expensive. Predictive maintenance applies condition-based maintenance for fault prognosis and planning for replacing damaged subsystems, such as the methods presented in [4,5]. Predictive maintenance can minimize the time spent on maintenance, and it can also improve reliability. However, same as the condition-based method, it also needs test equipment. Validating the accuracy of the predictive maintenance method is also a challenge. When maintenance activities such as oil or bearings changes are scheduled before the operation, it is called preventive maintenance (PM) [2,6–11]. PM is generally intended to reduce the probability of failure in machines. In this study, we aim to improve the PM policy for a WT.

Regarding the mentioned policies and strategies for WT maintenance, scheduling optimal PM scheduling of WTs involves two main tasks: the prediction of the components' life (in the terms of probability) and the optimization of the maintenance schedule. The probabilistic approach for components' life estimation uses statistical models, such a method has been discussed in [11,12]. The deterministic approach uses physics-based models to estimate the life based on the degradation rate of the components such as the work done in [13]. The data-driven approach uses machine learning techniques to learn the degradation patterns from the sensor data [14]. Once the useful life probability is predicted, the maintenance schedule can be optimized. Several optimization methods have been proposed, including the heuristic approach, the mathematical programming approach, and the simulation-based approach. The heuristic approach generates feasible maintenance schedules based on a nature-inspired algorithm [15,16]. The mathematical programming approach formulates the optimization problem as a mathematical model and uses optimization algorithms to find the optimal solution. The simulation-based approach uses computer simulations to evaluate the performance of different maintenance schedules and selects the best one. For example, in [17], a mathematical programming approach was proposed for the

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optimization of the maintenance schedule of WTs. The proposed method achieved a considerable reduction in the maintenance cost and an improvement in the availability of WTs.

One of the most common approaches to optimizing the maintenance schedule is formulating the problem as a mathematical optimization problem, which can then be solved using optimization algorithms. For example, in [18], a mixed-integer linear programming (MILP) model was proposed for optimizing the maintenance schedule of a multi-component system. The model considered the trade-off between maintenance costs and system availability and was shown to be effective in reducing maintenance costs while maintaining high system availability. Another approach to optimizing the maintenance schedule is to use simulation-based techniques. Simulation involves creating a computer model of the system and using it to evaluate different maintenance schedules. For example, in [19], a discrete-event simulation model was developed for optimizing the maintenance schedule of a WT. The model considered the stochastic nature of the WT's operation and maintenance (O&M) needs and was used to evaluate different maintenance policies. Data-driven approaches have also been proposed for optimizing the maintenance schedule. These approaches involve using machine learning techniques to analyze data from the system and identify patterns that can be used to optimize the maintenance schedule. For example, in [20], a data-driven approach was proposed for optimizing the maintenance schedule of a manufacturing plant. The approach used machine learning techniques to analyze data from the plant and identify the optimal maintenance schedule based on cost and production requirements. In addition to these approaches, several other techniques have been proposed for optimizing the maintenance schedule, including heuristic approaches [16,21] and fuzzy logic approaches [22]. These approaches aim to find an optimal maintenance schedule while considering factors such as system reliability, cost, and safety.

Regarding the reviewed articles, the use of historical data can be beneficial when choosing the right maintenance strategy, which would reduce O&M costs. Historical failure data can be represented using probability distributions to simulate the failure using methods such as Monte Carlo simulation (MCS) [23]. Maintenance costs for WTs could be considerably greater because of the portion of unscheduled maintenance, which is hard to predict at the start of a project. Hence, a more optimized maintenance strategy is needed to reduce O&M costs [24]. In the reviewed studies on WT maintenance cost, researchers have only considered one or two factors (such as labor cost and downtime cost) in the cost structure. However, considering different costs and combining them for an optimization model can result in a more effective maintenance schedule. To the best of our knowledge, no published study has considered all unit maintenance costs, desired reliability, maximum availability, labor, and dismantling costs in their PM optimization method.

This study considers all critical subsystems in a WT for PM scheduling. Also, for optimizing the PM schedule, we consider the regulated major PM activities in WT industries to improve the application of our method for real operations [25]. We have also used different resources to find an accurate replacement cost for all components in our model. Therefore, our optimization of the PM schedule is performed based on actual replacement costs to minimize the summation of a WT's corrective and PM costs. MCS using lifetime distributions of WT components is also performed to estimate potential failure times of components and plan the PM activities. Moreover, labor costs, dismantling, and unavailability costs have also been considered in our study, providing a more general model than previous studies. As we are considering many components in our simulations, the MCS will be a timely process. Therefore, we need to utilize an efficient optimization framework for PM scheduling that guarantees the minimum need for MCS runs. Accordingly, we have used two layers of optimization to select the optimal number of PM activities and PM optimal times, respectively. In the first layer, we have used the Fibonacci search algorithm to optimize the number of maintenances in a given lifespan. In the second layer, the genetic algorithm (GA) is applied to determine the PM times and which component to maintain in each PM activity. In the end, we compare our results with other models from the literature to validate our results and show the effectiveness of our proposed method for PM schedule optimization considering the maintenance costs. The method presented in this paper is generic, and it can be used for other similar engineering systems.

II. SYSTEM CONFIGURATION AND RELIABILITY MODEL

A WT is a complicated system that includes many subsystems and components. Therefore, a reliability model is usually used for estimating the system lifetime and scheduling maintenance strategies. A reliability model helps with estimating the failure time of the system and its components for further use in PM scheduling. An adequate reliability model for a 2 MW WT is reported and is used directly in this study. Here, we briefly describe this model's reliability block diagram (RBD), which demonstrates different subsystems and components and how their failures cause a system failure.

A. RELIABILITY BLOCK DIAGRAM

Figure 1 represents RBD for a 2 MW WT. Each block represents a subsystem. The WT has six mechanical subsystems with a total of 28 components. Each component follows a specific lifetime distribution.

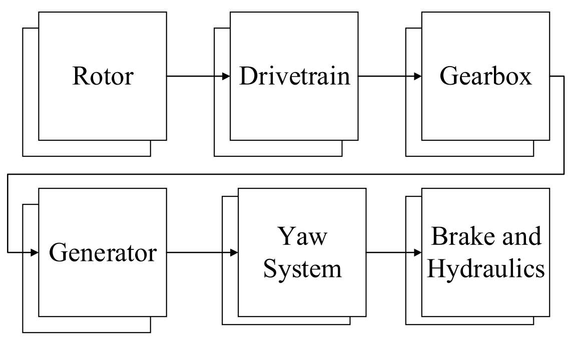

Fig. 1. RBD for the wind turbine.

B. DESCRIPTION OF SUBSYSTEMS

Each subsystem can be represented by another RBD with a set of components connected in series or parallel. A subsystem can also contain another subsystem with another RBD. In the following, the gearbox is briefly described as an example of a subsystem. Please refer to [2] for more details about the subsystems.

1) GEARBOX SYSTEM. The gearbox is a seven-block series system where two lube pumps and cooling fans are required. The repair of the gearbox gears and bearings blocks requires a crane (the first two blocks). Figure 2 shows the RBD of a gearbox.

Lifetime distributions of some gearbox components are provided in Table I [6]. The lifetime distributions for other components can also be found in [26].

These lifetime distributions are used to estimate the potential failure times of each subsystem and component. Each time the component replaces at the corrective or PM time, a new failure time will be estimated for the newly replaced component. In the next section, we consider those estimated failure times together with the time required to replace a component and the replacement cost to define and solve the PM optimization problem.

It is noted that in order to develop a PM model, the relations among components have been dealt with the following assumptions:

(1) we have used a verified RBD model. The system has 8 subsystems and 5 components with a total of 34 components. The RBD is used to represent the subsystems and components of the jet engine.

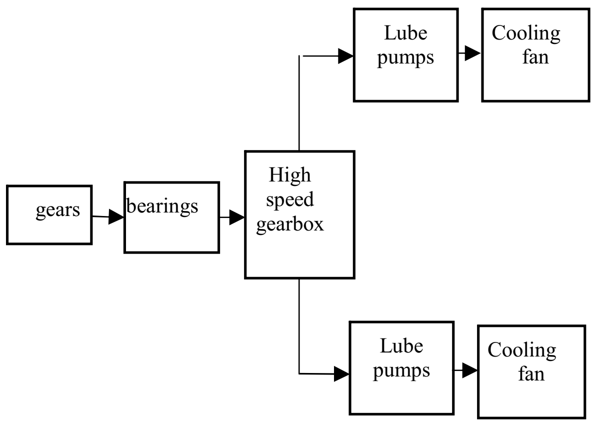

Fig. 2. RBD for the gearbox.

Table I. The lifetime distribution of the Gearbox system components

Component	Failure distribution	Exp. (λ)	Weibull	
			α	β
Gearbox gears	Exponential	14,600		
Gearbox bearings	Weibull		9490	3.5
High-speed gearbox	Weibull		9,490	3.5
Lube pumps	Weibull		4,380	3
Gearbox cooling fan	Weibull		6,935	1.1

(2) Regarding the block diagram, if a component fails, the system will stop working if it does not have any redundancies. Here, we assume that failure only stops the system and does not affect other components' performance unless otherwise concluded during the inspection.

(3) We have considered the regulated major PM activities in WT industries in our model and if there is a component major degradation, that will be replaced at that maintenance activity.

III. PM SCHEDULING OPTIMIZATION

A WT has a typical lifespan of 20 years; during this lifetime, the operators do multiple PM checks. The current industry policy indicates having one PM every 6 months for the WT.

A. PM MODEL PARAMETERS

The part costs of 28 components are given in Table II. They are directly used from the NREL report and maintenance delay cost in case of component failure. In addition to these expenses, every time the crew must go to the WT site for maintenance, a crew travel expense of $50,000 is incurred.

B. OPTIMIZATION MODEL

A WT with 28 components is considered, and the components follow their specific lifetime distribution. The maintenance of the 28 components is performed based on the failure times generated using their specific lifetime distributions. Whenever a failure occurs in the wind farm, the maintenance team is sent onsite to perform corrective maintenance and takes this opportunity to simultaneously perform PM on multiple turbines and their components which show relatively high risks. The industry uses a fixed remaining useful life threshold of the component to trigger a replacement of the component. The threshold limit can be determined based on the working conditions and the environment of the WT. For the case study, a constant threshold limit is not implemented because the purpose of the study is to find the optimal PM times for the replacement of multiple components before their failure, which results in minimal maintenance costs. If a constant threshold limit is considered, multiple components will only be replaced when they are close to their end of life and meet the threshold limit. This will increase maintenance instances.

The lifetime distributions generate random failure times, and the total cost generated in each realization is not the same. For this purpose, the MCS is used to find the average total costs of 100 realizations. This total maintenance cost can help the WT industry estimate maintenance budgets and develop plans for PM.

1) OBJECTIVE FUNCTION. The objective function of the current optimization problem is to minimize corrective and PM costs. The considered optimization problem is a MILP problem with some variables constrained to be integers while other variables are non-integers. Whenever a component fails, corrective maintenance is performed, and PM is performed at intervals generated by the optimization. Every maintenance occasion, preventive or corrective, involves a constant crew travel cost. Also, we have part cost, labor cost, mobile crane per-use cost, and downtime losses.

Table II. Spare part replacement cost

Components	Component cost ($) [25]	Labor cost ($) [25]	Crane cost ($) [3]
Subsystem: rotor			
Blade structure	87,500	23,000	105,260
Blade non-structure	12,700	4,000	
Pitch cylinder	13,000	1,000	
Pitch bearing	13,100	4,000	105,260
Pump and hydraulics	3,300	1,000	
Pitch position x-direction	1,800	500	
Pitch motor	8,400	500	
Pitch gear	8,300	2,000	
Subsystem: drive train			
Main bearing	23,700	13,000	105,260
High-speed coupling	7,700	1,000	
Subsystem: gearbox			
Gearbox gears	282,000	18,000	105,260
Gearbox bearings	196,300	8,000	105,260
High-speed gearbox	183,300	3,000	
Lube pumps	3,000	500	
Gearbox cooling fan	2,300	500	
Subsystem: generator and cooling			
Generator – rotor	198,300	6,000	105,260
Generator – bearings	2,200	500	
Full converter	36,000	500	
Generator cooling fan	2,300	500	
Contactor generator	11,700	500	
Partial converter	17,000	1,000	
Subsystem: brakes and hydraulics			
Brake caliper	7,300	1,000	
Brake pads	5,700	500	
Accumulator	2,200	500	
Hydraulic	6,000	500	
Subsystem: yaw system			
Yaw gear	9,700	800	
Yaw motor	2,200	800	
Yaw sliding pads	800	800	

Corrective maintenance means the replacement of a single component (i) when it fails. PM can be the replacement of one or more components of the system simultaneously. Eqs. 1–3 represent the maintenance costs of the system that is also used as our optimization cost function [15].

$$\mathrm{Min}(f) = \mathrm{CMC} + \mathrm{PMC} \quad (1)$$

where CMC is the corrective maintenance costs, and PMC is the preventive maintenance costs.

$$\mathrm{CMC} = \sum_{i=1}^{N} (C_i + L_i + R_i + J + D_i) \times (Z_i) \quad (2)$$

$$\mathrm{PMC} = \sum_{t=1}^{P} \left(\left(\sum_{i=1}^{N} (C_i + L_i + R_i) \times (X_{it}) \right) + J \right) \quad (3)$$

The symbols used in the above equations are explained below:

N	The number of components: 28
C_i	Cost of component i
L_i	Labor cost, component i
R_i	Cost of mobile crane, if applicable
J	Crew travel cost to wind turbine site, USD 50,000
D_i	Operational downtime cost due to component failure
P	The optimal number of preventive maintenances obtained from the Fibonacci search algorithm. The preventive maintenance time is given by $[m_1, m_2, m_3 \ldots\ldots m_P]$ that gives the minimum total maintenance cost. $[m_1, m_2, m_3 \ldots\ldots m_P]$ are obtained from optimization
X_i	Binary decision variable of whether to perform replacement of component i at preventive maintenance t (0 = No replace, 1 = Replace)
Z_i	The number of corrective maintenances of component i during the life span

The number of corrective maintenances for a component i is dependent on the number of PMs (P) and PM times for the system $[m_1, m_2, m_3 \ldots\ldots m_P]$. The number of corrective maintenance increases the number of overhauls and total maintenance costs (f). The optimal number of PM (P) and PM times [m_1,m_2,m_3 . . . . .m_P] that result in minimal total maintenance costs, and corrective maintenance (z_i) for a component i are obtained from the optimization method.

2) CONSTRAINTS AND FACTORS CONSIDERED. The constraints of the proposed optimization model are described below:

- Service life: Each component must be replaced before the end of its service life (PM) or upon the end of its service life – failure (corrective maintenance). Here, the service life is the random failure times of probabilistic components generated by their specific lifetime distribution.

The factors considered for the case study are explained below:

- Labor cost: This is the cost associated with the old component's disassembly and installation of the replacement component. Each component has its own specific associated labor cost based on the data provided in.
- Component cost: This is the cost of the replacement part from the crane cost: This is the cost of a mobile crane use for components that require a mobile crane for replacement.
- The time duration for repair: This is the time duration for maintenance of a component. Every component considered has its specific repair duration. The data are based on [6].
- Crew travel cost to the WT location: Every time the maintenance crew travels to the WT location, there is a logistic and admin cost associated, and it is a fixed cost per visit. The costs are extracted from [25].
- Delay in maintenance due to failure: Based on the literature, critical components of the WT have a very long lead time. Whenever one of those components fails, the WT is out of commission for months.
- Operational loss due to failure and maintenance: This is the cost associated with the downtime of WTs caused due to component failure and maintenance. The operational loss can be calculated by using the equation below:

$$\text{Loss of electricity (kWh)} = (\text{Days}) \times (\text{hours}) \times (\text{wind turbine capacity (kW)}) \times (\text{capacity factor})$$

For a 2 MW WT with a 33% capacity factor, the loss of electricity in a year is 5.7×10^6 kW h.

The cost of electricity is assumed to be \$0.096/kW h. Whenever the WT is not operating, it losses \$63.36/hr. Table III gives a breakdown of downtime and maintenance delay costs for each component.

3) DECISION VARIABLES. The optimization decision variables are listed below:

- The number of PM (P) required for the system for a given lifespan.
- PM times [m_1,m_2,m_3 . . . . .m_P].

Table III. Component maintenance delay cost

Components	Maintenance delay cost ($)
Subsystem: rotor	
Blade structure	286,675
Blade non-structure	286,675
Pitch cylinder	1,592
Pitch bearing	1,592
Pump and hydraulics	1,592
Pitch position x-direction	1,592
Pitch motor	1,592
Pitch gear	1,592
Subsystem: drive train	
Main bearing	33,445
High-speed coupling	33,445
Subsystem: gearbox	
Gearbox gears	191,116
Gearbox bearings	191,116
High-speed gearbox	191,116
Lube pumps	1,592
Gearbox cooling fan	1,592
Subsystem: generator and cooling	
Generator – rotor	95,558
Generator – bearings	95,558
Full converter	95,558
Generator cooling fan	1,592
Contactor generator	95,558
Partial converter	1,592
Subsystem: brakes and hydraulics	
Brake caliper	1,592
Brake pads	1,592
Accumulator	1,592
Hydraulic	1,592
Subsystem: yaw system	
Yaw gear	1,592
Yaw motor	1,592
Yaw sliding pads	1,592

- Replacement decision of components (whether to perform the replacement or not) at those PM times x_{it}.

IV. NUMERICAL SOLUTION TO THE OPTIMIZATION MODEL

The optimization problem in this study is a MILP problem, and a combination of the Fibonacci search algorithm and GA is used. We use a GA, since it has been successfully implemented in solving some of the maintenance problems of the WT. The first step of the method is to find the total maintenance costs of the system using GA based on the inputs from the Fibonacci search algorithm. Fibonacci inputs the total number of PM required for the system (p) to GA. Through this input from Fibonacci, GA generates an initial population and finds the total maintenance costs. The next step is to find the optimal number of PM required for the system using a Fibonacci search algorithm by successively providing inputs to GA and also obtaining

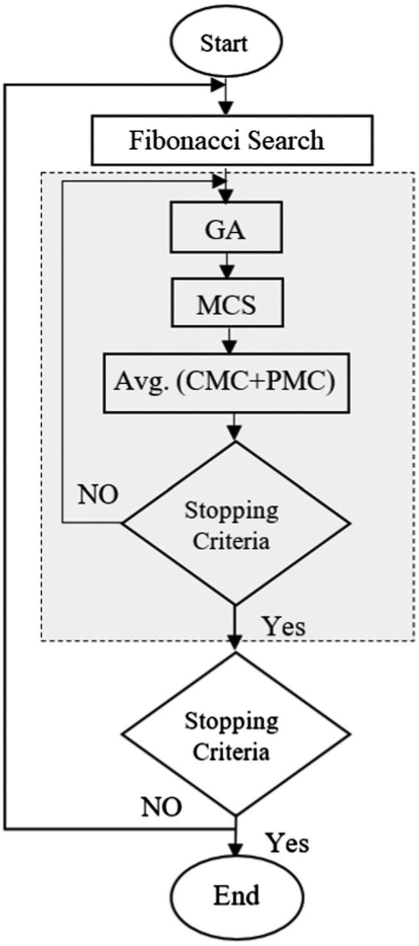

Fig. 3. Flowchart of the genetic algorithm.

the output (total maintenance cost according to the input) from GA. The flowchart in Fig. 3 explains how GA and Fibonacci are used together in our study to solve the explained optimization problem.

A. APPLICATION OF GA

GA is used to optimize the total maintenance costs and to obtain the optimal PM times and optimal selection of components to be maintained. The chromosome for the GA consists of both real and binary values. The real values are the PM times of the system, while binary values represent whether to do replacement of component i at those PM times or not. The initial population is in the form of a matrix X with $N \times 2P$ elements. The matrix of the decision variables for the maintenance schedule is shown below.

$$\begin{bmatrix} 1 \\ 2 \\ \vdots \\ \vdots \\ \vdots \\ N \end{bmatrix} = \begin{bmatrix} m_1 & \cdots & \cdots & m_p & x_{11} & \cdots & \cdots & x_{1P} \\ m_1 & \cdots & \cdots & m_p & x_{21} & \cdots & \cdots & x_{2P} \\ m_1 & \cdots & \cdots & m_p & \vdots & \ddots & \ddots & \vdots \\ m_1 & \cdots & \cdots & m_p & \vdots & \ddots & \ddots & \vdots \\ m_1 & \cdots & \cdots & m_p & \vdots & \ddots & \ddots & \vdots \\ m_1 & \cdots & \cdots & m_p & x_{N1} & \cdots & \cdots & x_{NP} \end{bmatrix} \tag{4}$$

The left side of the above equation represents the number of components ($i = 1,2,\ldots.N$); a total of 28 components are considered in the case study. The elements in the row and column matrix on the right side of the Equation represent the number of PM times ($[m_1,m_2,m_3\ldots\ldots. m_P]$,$(0 < m_1 < m_2 < m_3 \ldots\ldots. < m_p < T)$) of the system. The binary decision variables $[x_{N1},x_{N2},\ldots.x_{NP}]$, $x_{Nm_p} \in [0,1]$, represent whether to perform PM on component N at PM time m_P.

The PM times $[m_1,m_2,m_3\ldots\ldots.m_P]$ and replacement decisions $[x_{N1},x_{N2},\ldots.x_{NP}]$ of the initial population (chromosomes) are generated randomly by GA for the input P (P is the number of PM) from Fibonacci. The GA evaluates the objective functions f (total maintenance costs) for the initial population.

The next step involves selecting crossover and mutation to generate the next generation and calculating the objective function for the population of the new generation. The GA uses the current population to create children that make up the next generation. The algorithm selects a group of chromosomes in the current population, called parents; parents contribute their genes, that is, the elements of their vectors to their children, which is the next generation for GA.

The tournament model scheme is used for the selection of parents in chromosomes. Chromosomes having lower total maintenance costs have a higher chance of getting selected for the reproduction population. Each selection after mutation and crossover generates two sets of new children. The selected parents are randomly paired in the crossover.

In the model, a set of parents using scattered crossover produce two children. A random binary vector (a vector of [0,1] randomly) equal to the length of the pair of parents is created. Based on the elements in a random binary vector, the elements from the parents are selected. If the element in a random binary vector is 1, it selects the elements from the first parent, and if the element in a random binary vector is 0, it selects the elements from the second parent. A parent's mutation is done by replacing the parents' elements with a random number satisfying the constraints. The elements of binary bits are changed from 0 to 1 and vice versa [27].

The GA is a global optimization technique. It can be used to calculate the globally optimal set of variables. However, as our computational power was limited, we also limited the number of generations to 100,000. Therefore, we can say our solution is close to the global optimum values, but we cannot say that it is exactly the global optimal solution. We believe that increasing the number of generations may result in a better answer but at a higher computational cost.

For every generation generated, the objective functions f (total maintenance costs) are evaluated until the stopping criteria are met. The stopping criteria for the current model are the maximum number of generations; for the case study, it is 100,000. GA is used to find the optimal PM times $[m_1,m_2,m_3\ldots\ldots m_P]$ and replacement decision of components to be maintained $[x_{N1},x_{N2},\ldots\ldots x_{NP}]$ at those PM times. The flowchart of the applied GA algorithm is presented in the Appendix (Fig. A1).

B. APPLICATION OF FIBONACCI SEARCH ALGORITHM

The Fibonacci search algorithm's purpose in the model is to find the optimal number of PMs required for the system.

The Fibonacci search algorithm finds an extremum (maximum or minimum) of a function within a specified interval. The algorithm operates by successively reducing the range of values on the specified interval and finally finding the interval locating the function's extremum. The ratio of the remaining length to the initial length of the range of values at each iteration is the ratio between two consecutive Fibonacci numbers, and the ratio approaches the golden ratio. Reducing a range of values is terminated when the difference between the range of values is less than the specified value. Currently, the WT industry does PM every 6 months, and manufacturers recommend at least one maintenance annually so based on these numbers. A WT operating for 20 years must have at least 20 PMs; however, currently, most WTs perform about 40 PMs in 20 years. The initial values is used as it covers a broader range to give the optimal result.

The steps involved in the Fibonacci search algorithm are as follows [28]:

(1) Evaluate the functions $f(a_y), f(b_y)$ at the point $[a_y,b_y]$ of first iteration y w.r.t initial range of interval values $[a_0,b_0] \in a_0 < b_0$, $a_y = b_0 - \frac{F_N}{F_{N+1}} * L$, $b_y = a_0 + \frac{F_N}{F_{N+1}} * L$, $L = b_0 - a_0$, $[a_y,b_y] \in a_y < b_y$, where F_N is the nth Fibonacci number.

(2) If $f(a_y) > f(b_y)$, reduction of the interval will be $a_0 = a_y$, and $b_0 = b_0$ and the function is evaluated at a new point of the next iteration $a_{y+1} = b_y$, and $b_{y+1} = a_0 + \frac{F_{N-1}}{F_N} * L$. If $f(a_y) < f(b_y)$, reduction of an interval will be $a_0 = a_0$, $b_0 = b_y$ and the function is evaluated at a new point $b_{y+1} = a_y$, and $a_{y+1} = b_0 - \frac{F_N - 1}{F_N} * L$.

(3) The steps are repeated until the difference in the range of values is less than or equal to the specified value of termination.

All outputs from the Fibonacci are rounded to the closet integer as it is the number of PM and can only be integers. Values with first decimals larger than 0.5 are rounded up, and below are rounded down.

The initial length $[a_0,b_0] = [5,60]$ is the range for the Fibonacci. Then, the reduced interval for the first iteration $[a_y,b_y]$ of the initial length $[a_0,b_0]$ is evaluated using the procedure discussed above. Every point generated by Fibonacci is used as an input for GA to select the next range for Fibonacci iteration. The objective functions (total maintenance costs) $f(a_y)$ and $f(b_y)$ are evaluated at the point $[a_y,b_y]$ (the number of PMs $M = a_y, M = b_y$) using GA. In the next step, the total maintenance costs obtained from $f(a_y)$ and $f(b_y)$ are compared. Then the new reduced interval for the next iteration will be evaluated. The difference between the range of values of a new interval is evaluated. If the difference is greater than 0 (specified value of termination), evaluate objective functions f for the new reduced interval, and compare them to evaluate the next reduced interval. Else if the difference is less than or equal to 0 (specified value of termination), then the optimization is terminated. The above steps are repeated until the specified value of the termination condition is met. The flowchart of the working of a Fibonacci search algorithm is given in the Appendix, Fig. A1.

In Table IV, the interval [9,9] is the final interval and clarifies that 9 is the optimal number of PM. The trend from the figure shows the total cost of maintenance for the WT is decreasing as we decrease the number of PM but below 9 the maintenance cost starts increasing again.

Table IV. Results of the Fibonacci search algorithm to find the optimal number of preventive maintenances

Iteration	a_y	b_y	$f(a_y)$ \$	$f(b_y)$ \$	Interval
0	5	60	1.20 M	4.24 M	
1	26	39	1.68 M	2.61 M	[5–60]
2	17	26	1.45 M	1.68 M	[5–39]
3	12	17	1.14 M	1.45 M	[5–26]
4	10	12	1.09 M	1.45 M	[5–17]
5	8	9	1.12 M	1.032 M	[5–12]
6	9	11	1.032 M	1.13 M	[8–12]
7	9	9	1.032 M	1.032 M	[8–11]

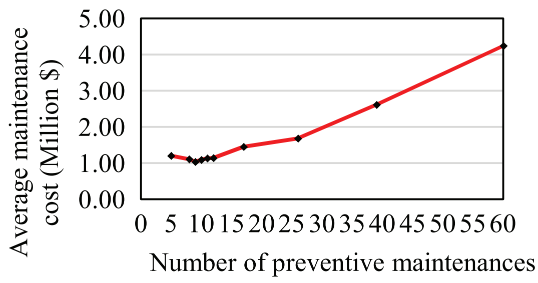

Fig. 4. Average maintenance costs for all output from Fibonacci.

A graph plotted for the average maintenance costs obtained at the number of PM (P) is given in Fig. 6. The points in Fig. 6 represent the variation of average maintenance costs with the number of PM P in each iteration of Fibonacci. From Table III and Fig. 4, the optimal number of PM required for the system is 9, and minimal maintenance costs of \$ 1.032 M are obtained.

V. RESULTS OF THE GA TO FIND THE OPTIMAL MAINTENANCE TIMES AND THE OPTIMAL COMPONENTS FOR MAINTENANCES

This section describes the working of a GA to find the optimal PM times and replacement decisions for components at those PM times. Based on the number of PMs, P obtained from the Fibonacci search algorithm. GA generates the initial population of random values of PM times $[m_1,m_2,m_3 \ldots \ldots .m_P]$ and replacement decisions $[x_{N1},x_{N2},\ldots .x_{NP}]$ of components at those PM times (components to be considered for replacement at those PM times) satisfying the constraints discussed in Section 4.1. for the first generation (iteration) and evaluates the objection function f. If the component fails before the PM time, a corrective maintenance event is used for the replacement of the failed component.

The next generation populations are created using crossover and mutation. The PM is done on the system at these specific intervals generated in each generation of GA. GA evaluates the objective function until the stopping criteria are met.

The evaluation of objective functions $f(a_y)$ and $f(b_y)$ (average maintenance costs) for the inputs of start and end values of intervals $[a_y,b_y]$ of each of Fibonacci (the number

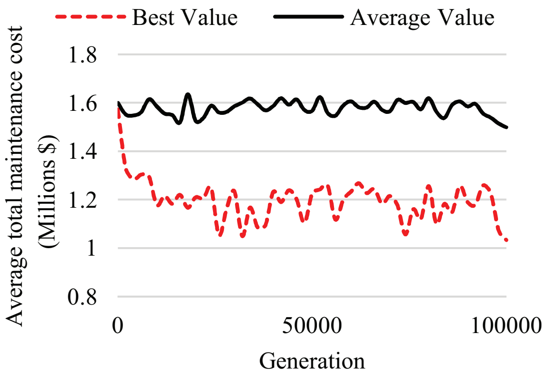

Fig. 5. Average total maintenance cost at nine preventive maintenances.

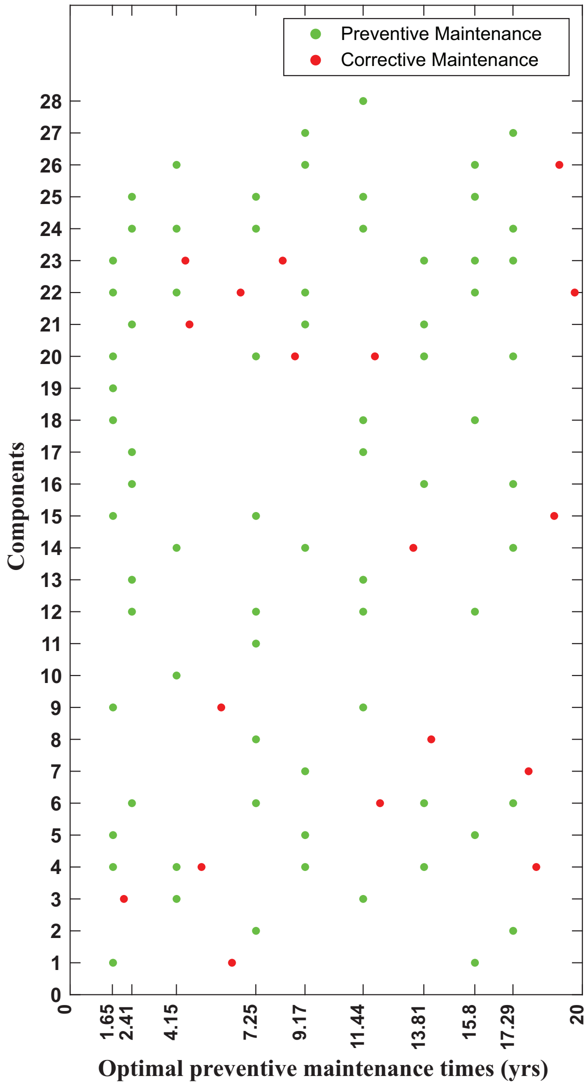

Fig. 6. Optimal preventive maintenance times and the components to be chosen for replacement at those preventive maintenance times.

of PMs M) using GA is given in Table III. In Table III, the interval [26,39] is the first interval in the first iteration of Fibonacci for the initial length [5,60]. This interval is obtained using the procedure described in Section 4.2. The objective functions (average maintenance costs) $f(26)$ and $f(39)$ are evaluated by GA. The intervals for the next iterations of Fibonacci are evaluated using the Fibonacci, and for all the start and end values of intervals (number of PM P) average maintenance costs are obtained using GA. In Table III, the last interval of Fibonacci is [9,9]. Since the change in the length of reduced intervals is equal to the specified value of termination (zero), the optimization is terminated here. The average total maintenance costs obtained at the number of PM $P = 9$ is the minimum. Therefore, the required optimal number of the PM for the system is 9, and the optimal average maintenance costs are obtained at $P = 9$. The average maintenance costs obtained in each generation (iteration) of GA at the number of PM are given in Fig. 6. The average maintenance costs obtained in each generation (iteration) of GA for other Fibonacci inputs (number of PM) are not presented.

In Fig. 5, the black line represents the individual best of average maintenance costs in every generation (iteration) population, and a line with an "o" marker represents the mean value of average maintenance costs in every iteration. The stopping criteria for the current optimization problem is a specific number of generations 100000. In this study, we have obtained minimal costs at the number of PM $P = 9$. But the PM obtained at this point in our first experiment is not satisfactory.

Moreover, the goal of the optimization algorithm is to find the global optimal solution. We used GA, which is known as a global optimization technique and as a technique that can calculate the globally optimal set of variables. However, as our computational power was limited, the number of generations has been limited to 100,000 as such, and we did not use a tolerance limit to prevent the algorithm from getting stuck in local optima. Therefore, we can say our solution is close to the globally optimum values, but we cannot say that it is exactly the global optimal solution. We believe that increasing the number of generations or decreasing the tolerance limit may result in a better answer, but at a higher computational cost.

The optimal PM times and components to be chosen for replacement at those PM times ($P = 9$) are given in Table III.

It is worth mentioning in this study that the failure times of components are generated from a lifetime distribution, and they are random, causing fluctuations in the best fitness value. To reduce randomness, in our study, 100 simulations are used. But we still can see fluctuations. If more number of simulations were used in the future, the fluctuation will become smaller. It should also be noted, to further evaluate the GA's efficiency to solve our optimization problem, we have also used the particle swarm optimization (PSO) algorithm to compare our results. PSO is a popular algorithm for optimization problems, and it has been shown to perform well in some cases. The PSO resulted in the best fitness of 1.77E + 06 after 99000 iterations. Where GA has resulted in the best fitness value of 1.032E + 6 after similar number of iterations, showing that the GA algorithm outperformed the PSO in finding an optimal value for our problem. The PSO results are presented in Table A2 in the Appendix.

The maintenance schedule is also presented in Fig. 6. In Fig. 6, the X-axis represents the optimal PM times

Table V. Optimal preventive maintenance times and replacement decisions

Optimal preventive maintenance times (years)	Components selected for replacement at optimal preventive maintenance times (x_{it})
1.65	1,4,5,9,18,19,20,22,23,
2.41	6,12,13,16,17,21,24,25
4.15	1,3,4,10,14,22,24,26
7.25	2,4,5,6,8,11,12,15,20,21,23,24,25,26
9.17	4,5,7,9,14,21,22,23,25,26,27
11.44	3,4,9,12,13,17,18,24,25,28
13.81	1,4,6,12,13,16,20,21,22,23
15.80	1,2,4,5,12,18,22,23,25,26
17.29	2,6,14,16,20,23,24,26,27

$[m_1,m_2,m_3 \ldots \ldots m_P]$ and Y-axis represents components ($i = 1,2,3,4 \ldots$ N) to be chosen for replacement at those PM times. The component i to be chosen for PM at times $[m_1,m_2,m_3 \ldots \ldots m_P]$ is represented by a green dot. Corrective maintenance done on components is represented by a red dot. The red dot represents the time at which corrective maintenance is done on the components. The values of optimal PM times $[m_1,m_2,m_3 \ldots \ldots m_P]$ and components to be chosen for replacement at those times are given in Table V.

VI. COMPARISON OF MAINTENANCE COSTS OF THREE MODELS

In this section, the proposed PM model's total maintenance costs are compared with the two conventional models: Model 1 (corrective maintenance model) and Model 2 (fixed interval PM model with threshold limit). The two models are described below.

A. MODEL 1: CORRECTIVE MAINTENANCE MODEL

In Model 1, only a corrective maintenance strategy is used in the system. In this strategy, whenever a component fails, it is replaced. The total maintenance cost is the sum of the corrective maintenance costs of the components. A total of 10000 simulations have been used to estimate the average maintenance costs. The total maintenance cost for the corrective maintenance model is 3.5 million $.

B. MODEL 2: FIXED INTERVAL PM MODEL WITH THE THRESHOLD LIMIT

In Model 2, the WT has a PM check on the system every 6 months. For a WT with an expected life span of 20 years, a total of 38 PMs are required on the WT. A PM replacement is done on a component during a PM check if the remaining reliability of a component is less than 0.05.

If the component fails before the PM time, corrective maintenance is done on it. The model's total costs are the sum of the corrective and PM costs of the components like the proposed model. A total of 10000 simulations have been used to estimate the average maintenance costs. The total maintenance cost calculated for model 2 is 2.4 million $.

The maintenance costs obtained from the above two models are compared with the proposed model (Model 3) which finds the optimal number of PM intervals required, the optimal PM times, and the components to be chosen for replacement at those PM times.

The comparison between the maintenance costs generated in all three models is given in Fig. 7. From Fig. 7, the minimal maintenance costs of 1.032 M are obtained from the proposed model. The maintenance costs obtained from the proposed PM model are 57% lower than the fixed PM model and 70% lower than the corrective maintenance.

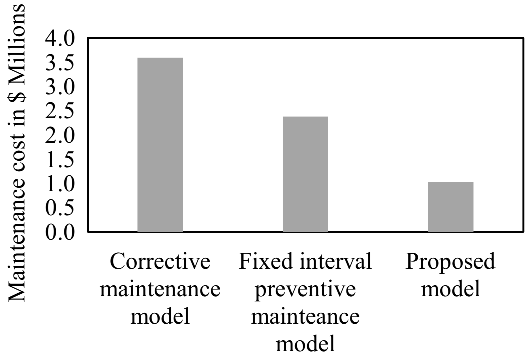

Fig. 7. Total maintenance cost for three models.

VII. CONCLUSIONS

WT maintenance is of great importance and acquires considerable costs. The proposed optimization model identifies the optimal number of PM and their times, and components to be chosen for replacement at those PM times for a 20-year maintenance plan. This plan results in minimized costs for WT maintenance. The total maintenance cost obtained from the proposed optimization model is 57% lower than the common industry-used fixed PM plan. The proposed model generates the PM times based on random failure times of components and their lifetime distributions and finds the optimal PM times for multiple component replacement and resulting in minimized maintenance costs. The Fibonacci search algorithm and GA are used together to solve the optimization problem. The proposed method can be further improved by adding more lower-level components and including multiple WTs in a wind farm. Factors like poor maintenance and weather conditions can also be added to the maintenance plan.

Acknowledgements

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

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Appendix A

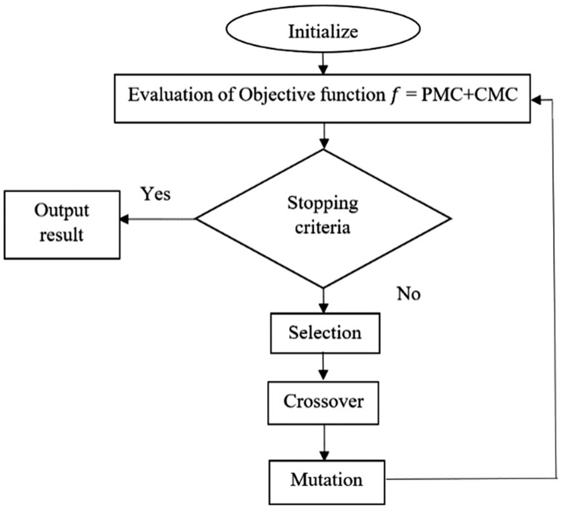

Fig. A1. Flowchart of the GA algorithm used in this study.

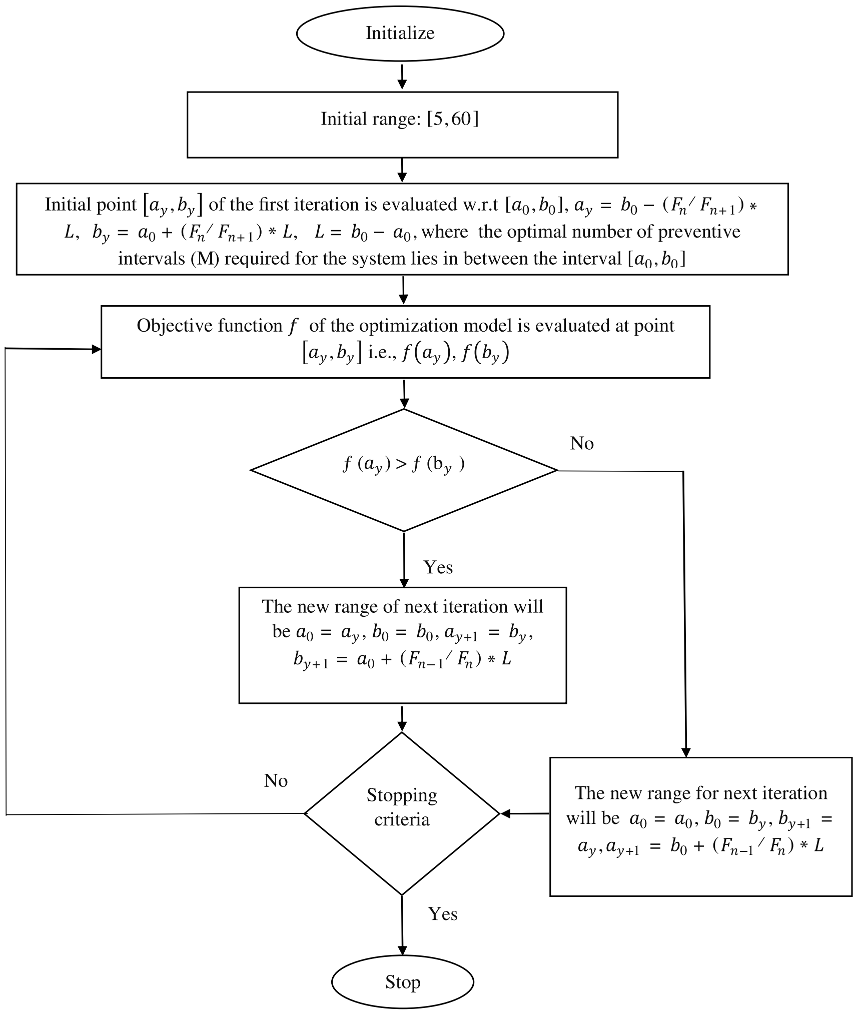

Fig. A2. Flowchart of the Fibonacci algorithm used in this study.

Table A1. Wind turbine components' and failure data [6,25]

Component	Failure distribution	Exponential (λ in days)	Weibull	
			Scale (α in days)	Shape (β)
Subsystem: rotor				
Blade structure	Exponential	146,000		
Blade non-structure	Exponential	36,500		
Pitch cylinder	Weibull		3,650	3.5
Pitch bearing	Weibull		18,250	3.5
Pump and hydraulics	Weibull		4,380	3.5
Pitch position x-direction	Weibull		4,380	2
Pitch motor	Weibull		5,475	1.1
Pitch gear	Weibull		4,380	3.5
Subsystem: drive train				
Main bearing	Weibull		14,235	3.5
High-speed coupling	Weibull		9,125	3.5
Subsystem: gearbox				
Gearbox gears	Exponential	14,600		
Gearbox bearings	Weibull		9,490	3.5
High-speed gearbox	Weibull		9,490	3.5
Lube pumps	Weibull		4,380	3
Gearbox cooling fan	Weibull		6,935	1.1
Subsystem: generator and cooling				
Generator – rotor	Exponential	73,000		
Generator – bearings	Weibull		6,205	3.5
Full converter	Weibull		5,475	2
Generator cooling fan	Weibull		6,935	1.1
Contactor generator	Weibull		7,300	2
Partial converter	Weibull		5,475	2
Subsystem: brakes and hydraulics				
Brake caliper	Weibull		3,650	2
Brake pads	Weibull		3,650	2
Accumulator	Weibull		2,190	3
Hydraulic	Weibull		4,380	3
Subsystem: yaw system				
Yaw gear	Exponential	146,000		
Yaw motor	Weibull		3,650	2
Yaw sliding pads	Weibull		3,650	3.5
Yaw bearing	Weibull		3,650	3.5

Table A2. Results of PSO algorithm for the PM planning

Iterations	Best	Mean
0	1.91E+06	2.01E+06
3000	1.91E+06	2.37E+06
6000	1.81E+06	2.05E+06
9000	1.81E+06	2.13E+06
12000	1.81E+06	2.07E+06
15000	1.81E+06	2.09E+06
18000	1.80E+06	2.06E+06
21000	1.80E+06	2.06E+06
24000	1.80E+06	2.05E+06
27000	1.80E+06	2.05E+06
30000	1.80E+06	2.03E+06
33000	1.78E+06	1.99E+06
36000	1.77E+06	2.00E+06
39000	1.77E+06	1.99E+06
42000	1.77E+06	1.98E+06
45000	1.77E+06	1.98E+06
48000	1.77E+06	1.98E+06
51000	1.77E+06	1.97E+06
54000	1.72E+06	1.91E+06
57000	1.68E+06	1.90E+06
60000	1.67E+06	1.89E+06
63000	1.61E+06	1.88E+06
66000	1.56E+06	1.88E+06
69000	1.56E+06	1.89E+06
72000	1.56E+06	1.90E+06
75000	1.56E+06	1.90E+06
78000	1.56E+06	1.90E+06
81000	1.56E+06	1.90E+06
84000	1.56E+06	1.91E+06
87000	1.56E+06	1.91E+06
90000	1.56E+06	1.91E+06
93000	1.56E+06	1.91E+06
96000	1.56E+06	1.90E+06
99000	1.56E+06	1.90E+06