Multi-objective optimization of wind turbines maintenance using the Whale Optimization Algorithm

Tahar Benmessaoud[1]*, Abdelkader Rouibah[2], Ahmed Taibaoui[3]

[1]Renewable Energy Systems Applications Laboratory (LASER), Faculty of Science and Technology, Ziane Achour University, Djelfa 17000, Algeria.
* **Corresponding Author Email:** t.benmessaoud@univ-djelfa.dz - **ORCID:** 0000-0003-3129-9175
[2]Laboratory Applied Automation and Industrial Diagnostics of University of Djelfa (LAADI),
Djelfa 17000, Algeria.
Email: a.rouibah@univ-djelfa.dz - **ORCID:** 0009-0000-4854-5796

[3]Laboratory of Development in Mechanics and Materials (LDMM) - University of Djelfa, 17000, Algeria.
Email: ahmed.taibaoui@univ-djelfa.dz. - **ORCID:** 0009-0004-6799-4721

Abstract:

Wind energy is the most productive source of electricity in wind rich regions. The exploitation of this clean energy requires the establishment of Onshore / Offshore wind farms to meet national electricity needs. The wind stochasticity in these zones makes random the loads undergone by these wind turbines unlike the majority of industrial machines operating in more or less static conditions. Under these conditions, the establishment of an optimal maintenance plan becomes more of a necessity in order to reduce unexpected shutdowns and maintain the electricity production levels of the wind systems. In this paper, a new multi-objective optimization is proposed whose objective functions aim to improve the availability of wind turbines and reduce their maintenance costs. To do this, the Whale Optimization Algorithm is proposed to solve the present problem based on the various determined constraints.

1. Introduction

The continuous growth of global energy demand, combined with increasing environmental concerns and stringent regulations on greenhouse gas emissions, has accelerated the deployment of renewable energy technologies worldwide. Among these technologies, wind energy has emerged as one of the most mature, cost-effective, and widely adopted solutions for large-scale electricity generation. Modern wind turbines, particularly those installed in large onshore and offshore wind farms, contribute significantly to national energy mixes due to their high-power capacity and technological advancements in aerodynamics, materials, and control systems [1-3].

Despite these advantages, wind energy systems operate under harsh and highly stochastic environmental conditions. Wind speed variability, turbulence, temperature fluctuations, and mechanical fatigue generate random and dynamic loads on wind turbine components, leading to accelerated degradation and unexpected failures [4, 5]. Unlike conventional industrial machines that often function under relatively stable operating conditions, wind turbines are continuously exposed to uncertain and non-stationary stresses, which complicates reliability assessment and maintenance planning [6].

Operation and maintenance (O&M) activities represent a substantial portion of the total lifecycle cost of wind energy systems, accounting for up to 20–30% of the overall investment for onshore wind farms and even higher percentages for offshore installations [7, 8]. Unplanned shutdowns due to component failures not only increase corrective maintenance costs but also result in significant production losses, thereby reducing system availability and economic profitability [9]. Consequently, the development of optimal maintenance strategies has become a critical challenge for wind farm operators and decision-makers.

Maintenance policies for wind turbines generally include corrective maintenance, preventive

maintenance, and condition-based or predictive maintenance approaches. While corrective maintenance is associated with high downtime and unpredictable costs, preventive maintenance can reduce failure occurrences but may increase operational expenses if not optimally scheduled [10]. In recent years, condition monitoring systems and reliability-centered maintenance have been widely investigated to enhance maintenance effectiveness; however, their integration into comprehensive optimization frameworks remains complex due to the multi-objective and constrained nature of the problem [11, 12].

To address these challenges, optimization techniques have been increasingly applied to wind turbine maintenance planning. Classical mathematical programming approaches often face limitations when dealing with nonlinear, multi-objective, and highly constrained problems [13]. As a result, meta-heuristic and nature-inspired algorithms such as Genetic Algorithms, Particle Swarm Optimization, Ant Colony Optimization, and Bacterial Foraging Optimization have been successfully employed in wind energy applications[14-16]. These algorithms demonstrate strong capabilities in exploring large search spaces and identifying near-optimal solutions within reasonable computational times.

More recently, the Whale Optimization Algorithm (WOA), inspired by the bubble-net hunting strategy of humpback whales, has attracted significant attention due to its simplicity, fast convergence, and strong balance between exploration and exploitation phases [17]. Several studies have reported the effectiveness of WOA in solving complex engineering optimization problems, including power systems, renewable energy integration, and scheduling applications [18]. However, its application to wind turbine maintenance optimization, particularly in a multi-objective context considering availability maximization and cost minimization simultaneously, remains relatively limited.

In this context, the present paper proposes a multi-objective optimization model for wind turbine maintenance planning using the Whale Optimization Algorithm. The proposed approach aims to determine the optimal number and scheduling of preventive maintenance tasks over a predefined planning horizon while minimizing total maintenance costs and maximizing system availability. The model incorporates realistic operational constraints, failure rates, repair times, and production loss costs, making it suitable for practical wind farm applications. A real onshore wind farm case study is used to validate the

effectiveness and robustness of the proposed method.

2.Whale optimization algorithm

Whale optimization algorithm (WOA) is a recently developed swarm-based meta-heuristic algorithm by Mirjalili & Lewi [17], The algorithm simulates the bubble-net hunting maneuver technique—of humpback whales. During hunting, the whales create typical bubbles along a circle path while encircling prey. Simply, the hunting behavior could be described as follows at a depth of about 12 m, the whales create the bubble in the form of a spiral around the prey, and then rise to the surface following the bubbles. Mathematically, in the WOA hypothesis model, the current best candidate solution is the target prey. The remaining whales try to update their position to the best solution according to equation (1):

$$D = |C. X^*(t) − X(t)| \qquad (1)$$
$$X(t + 1) = X^*(t) − A. D \qquad (2)$$

Where:

X^* : represents the position vector of the best solution,
X : is the position vector,
t: represent the current iteration,
$A \; and \; C$: are coefficient vectors. A and C values are calculated as follows:

$$A = 2. a. r − a \qquad (3)$$
$$C = 2. r \qquad (4)$$

Where:

a : is a control parameter and it is linearly decreased from two to zero over iterations,
r: is a random number [0,1].
The exploitation phase of the bubble net strategy is a hybrid of two combined approaches that can be mathematically modeled as follows:

    a. Shrinking Encircling Mechanism
obtained by decreasing a value according to Equation (4). Noting that a is a random value in [−a, a].

    b. Spiral Updating Position
To simulate the whale's helix-shaped movement, a spiral equation is created between the position of the whale and the prey as follows:

$$X(t + 1) = D'. e^{bl}. cos(2πl) + X^*(t) \qquad (5)$$
$$D' = |X^*(t) − X(t)| \qquad (6)$$

Where:
b: is the parameter space (fixed number),

l: is a random number in $[-1, 1]$.

Indeed, the whales swim at the same time along a spiral-shaped trajectory and in a constricting circle. To choose either the spiral or the shrinking circle mechanism model, a 50% probability is assumed as follows:

$$X(t+1) = \begin{cases} X^*(t) - A.D & if\ p < 0.5 \\ D^l.e^{bl}.cos(2\pi l) + X^*(t) & otherwise \end{cases} \quad (7)$$

Where:

p : is a random number in a uniform distribution, Similarly, to almost all meta-heuristic algorithms, in the bubble net method the position of the optimal model is not known, so humpback whales search for their prey randomly. Furthermore, in the exploration phase, $1 \prec A \prec -1$ is used to force the agent to move away from this location.

The exploration phase is represented mathematically in equations (8) and (9) as follows:

$$D = |C.X_{rand} - X(t)| \quad (8)$$
$$X(t+1) = X_{rand} - A.D \quad (9)$$

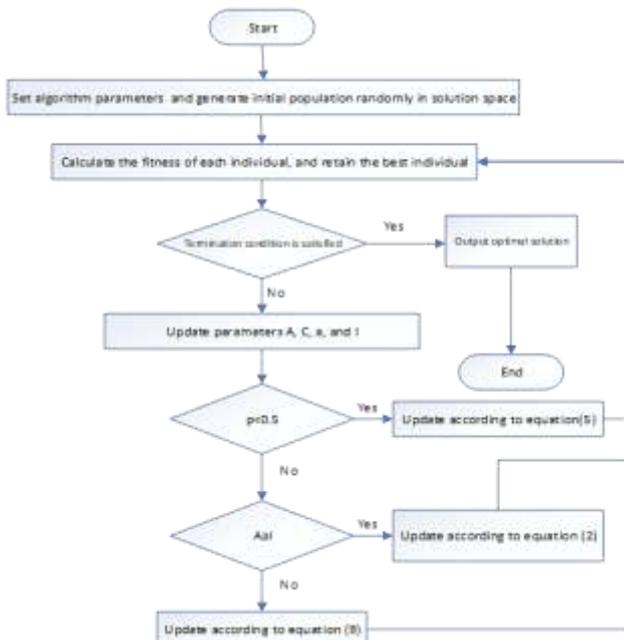Figure.1, shows the flowchart of standard Whale Optimisation Algorithm (WOA).

Figure 1. *Flowchart of standard Whale Optimisation Algorithm (WOA)*

3.Model Approach

3.1 Maintenance Parameters

To determine the mathematical optimization models, several maintenance parameters responding to the problem in question are necessary such as:

❖ Availability A: The availability of an industrial system is given by the equation:

$$A = \frac{MTBF}{MTBF + MTTR} \quad (10)$$

With:

MTBF: Mean time between failures.
MTTR: Mean time to repair.

❖ Failure rate λ: The failure rate is inversely proportional to MTBF, it is given by:
$$\lambda = \frac{1}{MTBF} \quad (11)$$

❖ Repair rate: The repair rate is the inverse of the MTTR, it is expressed by:
$$\mu = \frac{1}{MTTR} \quad (12)$$

Applying equations (11) and (12) to equation (10), the expression of availability will be:
$$A = \frac{\mu}{\mu + \lambda} \quad (13)$$

Availability can be given by the following expression:
$$A = \frac{1}{1 + \lambda.MTTR} \quad (14)$$

3.2 Total Cost Model

Total cost is the sum of costs spent on equipment maintenance plus production costs lost due to system downtime, it is expressed by:

$$C_T = C_{PM} + C_{CM} + C_{pen} + C_{loss} \quad (15)$$

With:

C_{PM}: Preventive maintenance costs.
C_{CM}: Corrective maintenance costs.
C_P: Cost of additional work carried out by the maintenance team.
C_{loss}: Cost lost due to system downtime.

The total cost of i turbines can be expressed by equation (7):

$$C_T = \sum_{j=1,i=1}^{J,I} \alpha_{ji} C_{CMh} + \sum_{i=1}^{I} \beta_i\ C_{PMa} + \sum_{i=1}^{I} n_i\ C_{pen} + \sum_{i=1}^{I} P_i.r_i.C_{el} \quad (16)$$

Where:

α_{ji}: is task j duration for corrective maintenance in wind turbine i [h].

If preventive maintenance is carried out without stopping the system, α_{ji} can be given by equation (9):

$$\alpha_{ji} = \frac{1}{\lambda_{ji}}.\frac{[1 - (1 + n_{ji}\ \lambda_{ji})A_i]}{A_i} \quad (17)$$

With:

λ_{ji}: is failure rate j in wind turbine i [1/h].

n_{ji}: is supplementary hours for corrective maintenance task j in wind turbine i.

A_i: Availability of wind turbine i.

β_j: is the number of preventive maintenance tasks.

C_{CMh} : is the hourly cost for performing corrective maintenance [€/h].

C_{CMa} : is the average cost for performing preventive maintenance [€].

C_{pen}: Penalty cost of additional maintenance work [€ / h].

P_i: is the power of electricity generated by the wind turbine i [kW].

r_{ji}: is the downtime j of wind turbine i [h].

The number of overtime hours in each repair j is given by the following inequation (18):

$$n_i \leq r_{ji} - \alpha_{ji} \qquad (18)$$

C_{elec}: Electricity Cost [€ / kWh].

3.3 Objectives Functions of Optimisation Model

The objective is to determine the optimal number of preventive maintenance tasks which corresponds to better availability (Amax) with minimal maintenance cost (Cmin).

Minimize equation (16)

$$C_T = \sum_{j=1,i=1}^{J,I} \frac{1}{\lambda_{ji}} \cdot \frac{[1 - (1 + n_{ji}\,\lambda_{ji})A_i]}{A_i} \cdot C_{CMh}$$
$$+ \sum_{i=1}^{I} \beta_i\, C_{PMa} + \sum_{i=1}^{I} n_i\, C_{pen}$$
$$+ \sum_{i=1}^{I} P_i \cdot r_i \cdot C_{el}$$

Maximize equation (14)

$$A_i = \frac{1}{1 + \lambda_{ji} \cdot (\alpha_{ji} + n_{ji})}$$

Subject to:

$$[(1 + \lambda_{ji} \cdot (n_{ji} + 1)] \cdot A_{ji} - 1 \leq 0; \quad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (19)$$

$$-r_{ji} + \alpha_{ji} + n_{ji} \leq 0 \; ; \qquad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (20)$$

$$n_{ji} = L_{ji} - 8; \quad L_{ji} \geq 8; \qquad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (21)$$

$$2783. \lambda_{ji} - 1 = 0; \qquad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (22)$$

$$4 \leq \beta_i \leq 12 \; ; \qquad i \in I \; ; \; 1 \leq i \leq 3 \qquad (23)$$

$$n_{ji} \geq 0 \; ; \qquad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (24)$$

$$r_{min} \leq r_{ji} \leq r_{max} \; ; \qquad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (25)$$

$$\lambda_{min} \leq \lambda_{ji} \leq \lambda_{max} \; ; \qquad 1 \leq i \leq 3; \; 1 \leq j \leq 3 \qquad (26)$$

$$0.9 \leq A_i \leq 0.98 \qquad 1 \leq i \leq 3 \qquad (27)$$

4. Real case study and results

In this case study, it was considered the onshore wind farm Vestas V66 with three 1.65 MW wind turbines[18]. It is assumed that this wind turbine experiences up to three failures, i.e., 1 to three corrective maintenance tasks to be performed over a period of one year. The cost per hour is assumed to be the same for all corrective interventions. The maintenance team works within the limit of 8 hours per day. Exceeding this hourly limit, we start counting overtime. Preventive maintenance tasks are supposed to be scheduled at least every three months and at most every month in the year with an average cost estimated at 65 euros for each task. All preventive maintenance tasks are supposed to be carried out without shutting down the wind system. Table 1 shows the failure rate and downtime for each component of the wind turbine.

***Table 1.** Failure rate and downtime of each turbine component [18].*

| Component	Failure rate (x10⁻³) (1/h)	Downtime (h)
Blades	0.617	36.9
Tower	0.02	1
Pitch System	0.375	11.175
Mechanical Brake	0.5	2.5
Shaft/bearing	0.1	2
Gearbox	0.625	136.925
Generator	0.4	101.625
Hydraulic system	0.5	19.075
Yaw System	0.15	5.5
Wind Measurement	0.217	11.725
Control system	0.507	12.567
Sensors	0.327	11
Electrical system	0.7	33.907
Others	0.433	7.2

The simulation parameters are assumed as follows: $C_{PMa} = 65\,€$; $C_{CMh} = 45\,€/h$, ; $C_{el} = 0.83\,€/$KWh, ; $P_i = 1.65\,MW$; $C_{pen} = 20\,€/h$.

Failure rate and downtime of each turbine component are shown in Table 1, where: $\lambda_{min} = 0.02$; $\lambda_{max} = 0.625$; $r_{min} = 1\,h$; $r_{max} = 136.925\,h$.

The optimization results of equation 8 by the

***Table 2.** Results of problem optimization.*

	A_i	β_i	n_i(h)	r_i(h)	λ_1(1/h)	λ_2(1/h)	λ_3(1/h)	C_T(€)	C_M (€)
WT 01	0.98	7	42	175.5	3.5025e-04	3.4993e-04	3.4958e-04		8465.7
WT 02	0.98	7	42	175.5	3.4949e-04	3.4945e-04	3.4948e-04	763031.56	8465.7
WT 03	0.98	7	42	175.5	3.4947e-04	3.4948e-04	3.4950e-04		8465.7
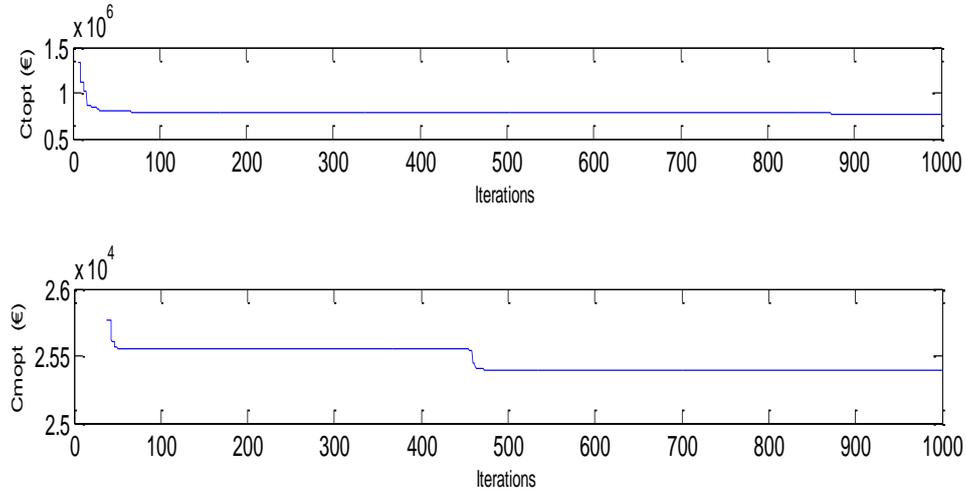
***Figure.2** Wind farm total and maintenance costs optimized by Whale Optimisation Algorithm (WOA).*

technique of Whale optimization algorithm are summarized in Table 2. Table 02 shows that the minimum number of preventive maintenance tasks necessary to reduce failures is 7 tasks per turbine for a period of one year. The distribution of these tasks over equal 52-day intervals can help avoid unexpected failure of several wind turbine components with a failure rate greater than 0.00035, such as: Gearbox, Blades, Mechanical Brake, Electrical system, Control system and Others. The duration of unnecessary wind system shutdown can be reduced from 175.5 h to 66 h if the intervention of the maintenance team is immediate after each failure, hence a significant profitability of electricity production. The simulation results by the whale algorithm also show an optimal availability of the wind farm of 98% and an optimal maintenance cost of 8465.70 € for each turbine without taking into account the production loss costs. Figure 2, represents the evolution of the maintenance cost (Cmopt) and total cost (Ctopt) including the production losses costs according to the number of iterations which is limited by 1000 iterations in this simulation.

5.Conclusion

In this paper, the whale algorithm is proposed as a new approach for solving the wind farm maintenance optimization problem. The robustness, efficiency and rapid convergence of this approach compared to other methods reported in the literature has shown its superiority and ability to solve the problem in question.

The results obtained from the simulation using the WOA algorithm showed that the appropriate number of preventive maintenance tasks corresponding to 3 failures in a reference period of one year is 7 tasks. Correct scheduling of these tasks versus corrective maintenance tasks can help prevent future unexpected shutdowns. The immediate intervention of the maintenance team after the occurrence of each failure can reduce the cost of lost production from 254,340 € to 90387 € for each wind turbine. The maintenance cost and the availability of each wind turbine are optimized at 8465.7 € and 98% respectively.

Author Statements:

- **Ethical approval:** The conducted research is not related to either human or animal use.
- **Conflict of 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 paper
- **Acknowledgement:** The authors declare that they have nobody or no-company to acknowledge.
- **Author contributions:** The authors declare that they have equal right on this paper.
- **Funding information:** The authors declare that there is no funding to be acknowledged.
- **Data availability statement:** The data that support the findings of this study are available on request from the corresponding author. The data

are not publicly available due to privacy or ethical restrictions.

management of offshore wind turbines by minimizing the costs. *Sustainable energy technologies and assessments*, *52*, 102230.

References

[1] Ackermann, T. (2012). *Wind power in power systems*. John Wiley & Sons.

[2] Burton, T., Jenkins, N., Sharpe, D., & Bossanyi, E. (2011). *Wind energy handbook*. John Wiley & Sons.

[3] Council, G. W. E. (2023). Boston Consulting Group. 2023. *Mission Critical: Building the global wind energy supply chain for a*, *1*.

[4] Tavner, P. J. (2012). *Offshore Wind Turbines-Reliability, Availability & Maintenance*. Institution of Engineering and Technology (IET).

[5] Ribrant, J., & Bertling, L. (2007). Survey of failures in wind power systems with focus on Swedish wind power plants during 1997-2005. 2007 IEEE power engineering society general meeting,

[6] Yang, W., Tavner, P. J., Crabtree, C. J., & Wilkinson, M. (2009). Cost-effective condition monitoring for wind turbines. *IEEE Transactions on industrial electronics*, *57*(1), 263-271.

[7] Carroll, J., McDonald, A., & McMillan, D. (2016). Failure rate, repair time and unscheduled O&M cost analysis of offshore wind turbines. *Wind energy*, *19*(6), 1107-1119.

[8] Shafiee, M. (2015). Maintenance strategy selection problem: an MCDM overview. *Journal of Quality in Maintenance Engineering*, *21*(4), 378-402.

[9] Benmessaoud, T., Mohammedi, K., & Smaili, Y. (2013). Influence of maintenance on the performance of a wind farm. *Przegląd Elektrotechniczny*, *89*(03a), 174-178.

[10] Moubray, J. (2001). *Reliability-centered maintenance*. Industrial Press Inc.

[11] Márquez, F. P. G., Tobias, A. M., Pérez, J. M. P., & Papaelias, M. (2012). Condition monitoring of wind turbines: Techniques and methods. *Renewable energy*, *46*, 169-178.

[12] Lu, B., Li, Y., Wu, X., & Yang, Z. (2009). A review of recent advances in wind turbine condition monitoring and fault diagnosis. *2009 IEEE power electronics and machines in wind applications*, 1-7.

[13] Coello, C. A. C., Lamont, G. B., & Veldhuizen, D. A. V. (2007). *Evolutionary algorithms for solving multi-objective problems*. Springer.

[14] Márquez, F. P. G. (2020). *Maintenance Management of Wind Turbines*. MDPI.

[15] Benmessaoud, T., Marquez, F. P. G., Mohammedi, K., & Marugan, A. P. (2021). Wind Farms Predictive Maintenance Based on Condition Monitoring System. *International Journal of Advanced Studies in Computers, Science and Engineering*, *10*(5), 1-6.

[16] Yang, X.-S. (2010). *Nature-inspired metaheuristic algorithms*. Luniver press.

[17] Mirjalili, S., & Lewis, A. (2016). The whale optimization algorithm. *Advances in engineering software*, *95*, 51-67.

[18] Gonzalo, A. P., Benmessaoud, T., Entezami, M., & Márquez, F. P. G. (2022). Optimal maintenance