



Optimal maintenance management of offshore wind turbines by minimizing the costs

Alfredo Peinado Gonzalo^a, Tahar Benmessaoud^c, Mani Entezami^a, Fausto Pedro García Márquez^{b,*,1}

^a School of Engineering, University of Birmingham, B15 2SA Birmingham, United Kingdom

^b Ingenium Research Group, Universidad Castilla-La Mancha, 13071 Ciudad Real, Spain

^c Ingenium Research Group, Djelfa university, Algeria

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ABSTRACT

Renewable and sustainable energy production systems offer promising perspectives for the future, as their production and maintenance prices decrease, and their efficiency and reliability increase, favouring the competitiveness of this industry. Thereby, wind energy is one of the most used and developed as renewable energy, since it is a cost-effective way to generate clean and sustainable energy. Wind energy is divided into onshore and offshore depending on the wind farm location. Offshore wind energy is increasing its use. However, the offshore industry requires more maintenance, which is also more complicated to do because of the environmental conditions. Setting the best maintenance strategy becomes a complicated optimization problem with several objectives and constraint functions. In this paper, a novel multi-objective optimization problem is defined and solved for real case studies by using Genetic Algorithms and Particle Swarm Optimization to minimize operational costs and maximize performance of the wind turbines. The results of both algorithms are compared considering several scenarios in a real case study. These results show a better performance of Particle Swarm Optimization for optimal cost achieved, and less computational cost to solve it. Finally, the influence of the model parameters is studied by performing a sensitivity study, that shows the importance of preventive maintenance and the reduction of corrective maintenance tasks.

Introduction

Wind power is one of the largest growing sectors in energy production as it is based on a non-pollutant energy production technology [1–3]. Wind power is divided into onshore and offshore based on the location of the wind farm. Generally, offshore wind farms generate more power, are less environmentally impactful, and have the possibility to be larger in size. They require larger initial investments and operation and maintenance costs [4,5]. Energy production using wind turbines shows an increasing trend, see Fig. 1, from less than 10 GW in the early 2000 s to more than 50 GW in 2018 [6] (in blue), with production predicted to be increased even more (in orange). More than 90% of the production is onshore, the rest being offshore [7].

Wind turbines are complex machines subjected to random environmental and mechanical loads that cause wear and damage in their

components, reducing their availability [8], leading to regular shut downs and inspections, and causing costs and power losses [4,9]. These costs can be reduced by applying maintenance optimization management, aimed at ensuring acceptable levels of energy production [10,11] and reducing false alarms [12,13]. Research on the applications of Artificial Intelligence (AI) for wind turbine maintenance has significantly increased in the last two decades [14–17], with an exponential growth in publications, mostly dedicated to modelling and optimizing management using methods such as statistical methods, trend analysis, time and frequency-domain and Fourier transforms [14,17]. In general, Maintenance Optimization Management using AI generally focuses on decision making, maintenance optimization and fault detection.

Decision making and maintenance optimization focus on minimizing maintenance costs and downtimes due to inspections and faults [18], with most faults and delays concentrated in the turbine gearbox, generator and blades. Optimization functions are usually associated

* Corresponding author at: ETSI Industrial, Universidad Castilla-La Mancha, Campus Universitario s/n, 13071 Ciudad Real, Spain. Tel.: +34 (9)26 295300 Ext.: 6230; fax: +34 (9)26 295361 - Ext. IBERCOM fax: 3801.

E-mail addresses: m.entezami@bham.ac.uk (M. Entezami), faustopedro.garcia@uclm.es (F.P. García Márquez).

¹ <https://blog.uclm.es/faustopedrogarcia>.

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Nomenclature			
GA	Genetic Algorithm	C_T	Total maintenance and production costs [€]
PSO	Particle Swarm Optimization	α_j	Duration of the preventive maintenance task [h]
ANN	Artificial Neural Network	C_j^{PM}	Hourly cost for performing preventive maintenance [€/h]
λ	Failure rate [-]	β_k	Number of corrective maintenance tasks [-]
r	Downtime [h]	C_{CMA}	Average cost for performing corrective maintenance [€]
A	Availability [-]	n_e	Supplementary hours of maintenance [h]
T_i	Time interval [h]	C_{pen}	Penalty cost of additional maintenance work [€]
N_i	Number of failures occurred during the time interval [-]	C_{el}	Cost of electricity production [€]
x_i	Number of turbines reported for the time interval [-]	E^{CMA}	Average energy loss due to corrective maintenance [kWh]
r_i	Productive hours lost during the time interval [h]	G	Number of generations [-]
C_{PM}	Cost of preventive maintenance tasks [€]	P_j^{PM}	Power loss due to preventive maintenance of task j [kW]
C_{CM}	Cost of corrective maintenance tasks [€]	P	Population [-]
C_{PE}	Penalty cost of additional maintenance work [€]	P_{ti}	Power generated by the wind turbine i [kW]
C_{Loss}	Cost due to production loss when the system stops [€]	r_i	Downtime of the turbine i [h]

with economic variables such as related costs due to power losses, power production income or fault occurrence, producing a large variety of models applied for this [18,19]. Hajej et al. [20] modelled the relationship between variation of energy production and failure rate of wind turbines considering a Weibull distribution for power production, aiming to optimize their maintenance strategy following their production policies. Nachimuthu et al. [21] proposed a statistical model assuming known fault occurrence probabilities by taking time spent on inspection and repairing into account for uncertainties in condition monitoring. They obtained cost savings above 80% compared to traditional practice. Other approximations to select a maintenance strategy include: component monitoring, considering the lifetime costs associated to maintenance, inspection and repair of each component [22]; Identification of the defect position and severity to evaluate the need for inspection and repair [23]; and Optimizing the relationship between preventive and corrective maintenance [10]. It is common to compare several maintenance strategies in order to obtain the most appropriate approach, [24,25], or to group individual component maintenance schedules to improve the general strategy [26]. In summary, most statistical methods applied for decision making consider fault probability and system availability to decide the best maintenance policy. This is the same approach carried out in this paper, but in this paper new variables and components of the system, employing methods based in AI, are introduced.

In recent years, the use of AI for both maintenance optimization and

early fault detection has been increasing due to the advantages of these systems, especially cost reduction, reliability, and versatility [14,27,28]. Configurations based on Artificial Neural Networks (ANN) are the most common, applied for both short term maintenance considering different types and components [29], long term planning for maintenance and life cycle scheduling and costs [30] and wind turbine positioning [31,32], and production forecasting [33–35], producing notable cost and inspection time reductions [36,37]. Fault tree analysis is also applied for decision making [38,39]. Fuzzy logic is commonly applied for decision making considering costs and failure modes [40,41], and preventive maintenance for early fault detection and prediction [42–44]. Genetic Algorithms (GA) and Particle Swarm Optimization (PSO) are discussed in Section 2.

Fault detection using AI is frequently combined with Supervisory Control and Data Acquisition (SCADA) systems. García Márquez et al. [45] showed the use of ANN to detect gearbox faults using bearing temperature and wind speed, as well as machine learning [46] for early ice detection using ultrasounds and EMATs [47–49]. Marugán et al. [12] presented a new approach based on ANN to detect false alarms and prioritize alarms for wind turbines maintenance focused on reliability, where principal component analysis is employed for filtering the signals [50]. Benmessaoud et al. [51] applied fuzzy logic to evaluate the state of a wind farm based on big data and a SCADA system. Their approach reduced false alarms, and hence led to an optimization of the wind farm. False alarms were also studied by Peco et al. [52] on the main bearing of

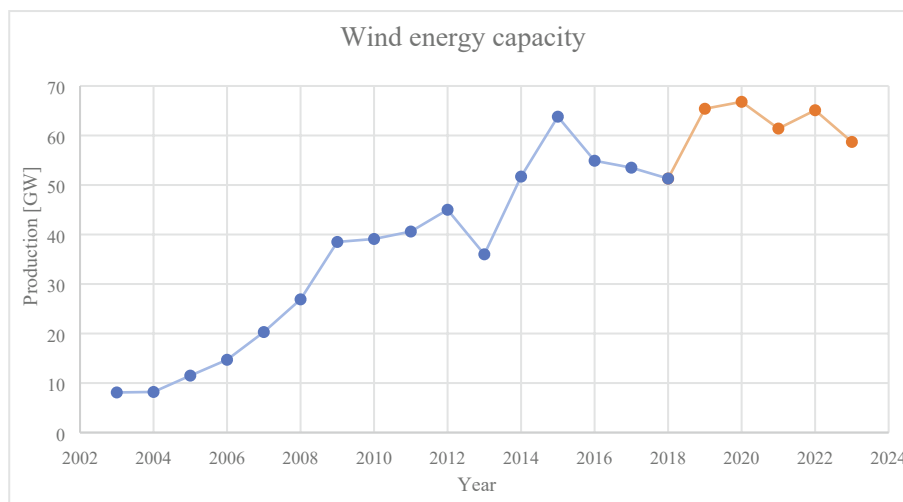


Fig. 1. Evolution of wind energy capacity (blue) and its projection (orange) [6].

the wind turbines. They modelled the temperature of the gearbox bearing versus wind speed to study false alarms by data partitioning and data mining centres. In summary, the combination of SCADA systems with AI makes up a robust method to detect and evaluate false alarms in wind power systems.

In this paper the use of GA and PSO is proposed to optimize maintenance tasks of a wind turbine, which is not a scientific novelty. The novelty of this research lies in the application of a real case study using the failure rate of different components from an offshore wind turbine to optimize the scheduling and defining of maintenance regimes, considering both preventive and predictive maintenance. Therefore, reliability and costs are also taken into account for a new complex and robust model. This optimization is carried out by using component failure rate and availability, the costs associated to perform preventive and corrective maintenance tasks, and costs due to production losses. The response of the model is evaluated using both PSO and GA, in order to assess their advantages and disadvantages and to validate the results. Furthermore, a sensitivity study is performed to evaluate the influence of the model parameters in the costs.

The rest of the paper is structured as follows: Section 2 explains the background of GA and PSO for wind turbine maintenance management; The cost model is presented in Section 3 by applying component availability and costs derived from maintenance and downtime; Section 4 shows the real case study; The cost model is then evaluated in Section 5 with a case study and a comparison between GA and PSO in several scenarios, as well as a sensitivity study; Statistical analysis of GA and PSO is done in Section 6; Finally, Section 7 presents the conclusions of this research.

Genetic algorithms and Particle Swarm optimization backgrounds

This section presents the fundamentals of the algorithms applied in the research, both GA and PSO, as well as their applications for wind energy condition monitoring.

Genetic algorithms

GA are proposed as one of the most common approaches used for wind turbine maintenance optimization problems. GA are evolutionary algorithms that use a technology inspired by evolutionary biology such as selection, reproduction, mutation, crossover and hybridization, which gives them the ability and the robustness to find optimal solutions, i.e., fitness function [53]. GA adapt to the environment initiating a modelling of the collective evolution process of the individuals. The state of each individual is schematized by a point in the space [54]. Each successive generation is generated by selecting a percentage of the existing chromosomes based on the preference of the optimization function, by a process named reproduction. This process is finalized with the occurrence of one of the finishing causes producing the fitness function [55]. The main objective of GA is to improve the robustness and to balance performance and costs required for survival in many different environments [54]. Fig. 2 presents the structure of a GA, adapted from [56].

GA for wind turbine monitoring are generally oriented towards maintenance optimization, defining an objective function to balance Operation and Maintenance costs and component availability. As each optimization problem is unique, there are different optimization approaches, and authors often compare them to obtain the most appropriate one for their requirements [57]. Researchers generally convert operations into economical terms to homogenise the optimization problem, considering also scheduling and availability into the formulations [58,59]. Other approaches consider aspects such as the Levelized Cost of Energy [60], environmental aspects, or even personality traits of inspectors [59]. The application of GA to optimize scheduling has proven beneficial for both energy production [61] and cost reduction

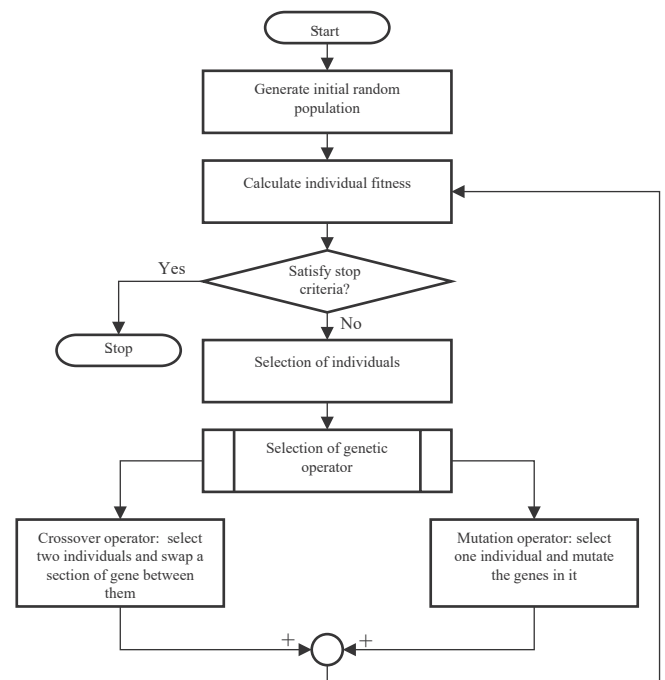


Fig. 2. Flow chart of a Genetic Algorithm, . adapted from [56]

[62], hence the utility of this technique to optimize wind farm monitoring and maintenance. This paper applied GA to solve the novel and robust problem presented in Section 3, which has not been studied in the literature yet.

Particle Swarm optimization

PSO follows a similar approach to GA, in which a group of particles, named population, is located at random positions, that are updated aiming to optimize a given problem. PSO simulates animal social behaviour cooperating to find food, where each member of the swarm changes the search pattern considering its own experience and other members as well [63]. The group behaviour is based on five principles (proximity, quality, diverse response, stability and adaptability) that make the guiding principles to establish the swarm life system [64]. Fig. 3 presents the schematics of a PSO, adapted from [63].

PSO is frequently merged with other AI techniques, and aimed at optimizing different aspects of WT design and maintenance management such as power dispatch [65,66], maintenance planning [67,68], and gearbox condition monitoring using temperature [69] or vibration signals [70]. Microgrid size optimization is another recurrent application of PSO, considering both economic [71,72] and environmental aspects [73,74]. Researchers have shown that the combination of GA and PSO is currently one of the most powerful algorithms [65,73,75]. Other combinations are with fuzzy logic [76] and Monte Carlo methods [77]. Similar to GA, PSO is used to solve the novel and robust problem considered, which is new according to the state of the art. The validation of this research lies in the comparison between GA and PSO for the case study presented in Section 4 in terms of objective optimization and time required for convergence, as well as other aspects presented in the discussion of results.

Model approach

Maintenance parameters

The model approach is based on the main maintenance parameters given for offshore wind turbines: failure rate (λ), downtime (r) and

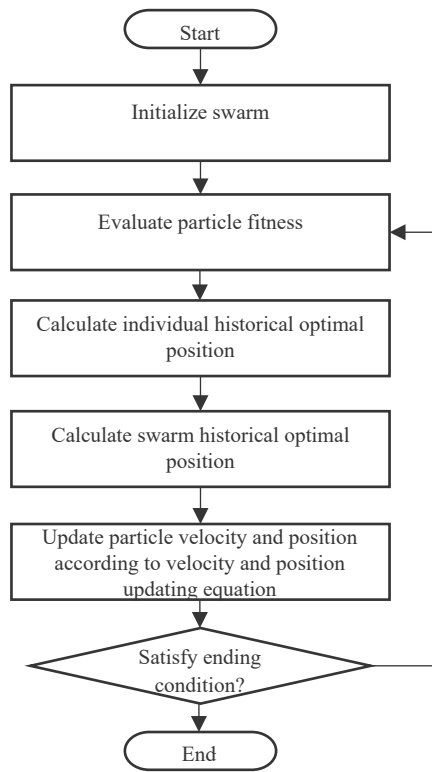


Fig. 3. Schematics of a Particle Swarm Optimization algorithm, adapted from [63]

availability (A), given by equations (1), (2) and (3) respectively.

The failure rate λ is understood as a measure of the occurrence of turbine failures along time. It is expressed as the number of failures per turbine per year and defined by equation (1).

$$\lambda = \frac{\sum_{i=1}^I N_i}{\sum_{i=1}^I x_i T_i} \quad (1)$$

where N_i is the number of failures occurred during the time interval; x_i is the number of turbines reported for the time interval, and; T_i is the time interval. The downtime r is understood as the average amount of hours lost due to failures, defined by equation (2).

$$r = \frac{\sum_{i=1}^I r_i}{\sum_{i=1}^I x_i T_i} \quad (2)$$

where r_i is the amount of productive hours lost during the time interval T_i due to failures. The average availability A is understood as the mean time between failures and the total time of operation of the wind turbine. It is defined by equation (3), this parameter combines λ with r to give an estimation of the availability of the wind turbine.

$$A = \frac{1}{1 + \lambda \hat{A} \cdot r} \quad (3)$$

Total cost model and optimization function

The total cost of the model (C_T) is calculated using the following costs: cost of preventive maintenance tasks (C_{PM}); Cost of corrective maintenance tasks (C_{CM}); Penalty cost of additional maintenance work (C_{PE}); and Cost due to production loss when the system stops (C_{Loss}). C_{PM} is the total cost derived from performing each preventive maintenance task, and is given by equation (4),

$$C_{PM} = \sum_{j=1}^J \alpha_j \hat{A} \cdot C_j^{PM} \quad (4)$$

where α_j is the duration of the preventive maintenance task in hours

[h], and C_j^{PM} is the hourly cost for performing preventive maintenance [€/h]. C_{CM} is the cost derived from performing corrective maintenance tasks, expressed in equation (5).

$$C_{CM} = \beta_k \cdot C_{CMA} \quad (5)$$

where β_k is the number of corrective maintenance tasks, and C_{CMA} is the average cost for performing corrective maintenance [€]. C_{PE} is the cost due to losses associated to corrective maintenance tasks, given by equation (6),

$$C_{PE} = n_e \hat{A} \cdot C_{pen} \quad (6)$$

where n_e are the hours supplementary of maintenance at time t and C_{pen} is the penalty cost of additional maintenance work [€/h]. C_{Loss} is the production loss cost due to the wind system stops, given by equation (7).

$$C_{Loss} = \left(\sum_{j=1}^J \alpha_j \hat{A} \cdot P_j^{PM} + \beta_k \hat{A} \cdot E^{CMA} \right) \hat{A} \cdot C_{el} \quad (7)$$

where C_{el} is the electricity cost [€/kWh]; P_j^{PM} is the power loss due to preventive maintenance of task j [kW], and; E^{CMA} is the average energy loss due to corrective maintenance [kWh]. This equation can be simplified, obtaining equation (8):

$$C_{Loss} = \sum_i P_{ii} \hat{A} \cdot r_i \hat{A} \cdot C_{el} \quad (8)$$

where P_{ii} is the power generated by the wind turbine i and r_i is the downtime of the turbine i .

The total cost equation is obtained as the sum of costs presented in equations (4), (5), (6) and (8). This cost results in given by equation (9).

$$C_T = \sum_{j=1}^J \alpha_j \hat{A} \cdot C_j^{PM} + \beta_k \cdot C_{CMA} + n_e C_{pen} + \sum_i P_{ii} \hat{A} \cdot r_i \hat{A} \cdot C_{el} \quad (9)$$

Considering the variables and functions previously stated, the cost minimization given by equation (9) is the objective function. Hence, the optimization objective is given by equation (10).

$$\min \left\{ C_T = \sum_{j=1}^J \alpha_j \hat{A} \cdot C_j^{PM} + \beta_k \cdot C_{CMA} + n_e C_{pen} + \sum_i P_{ii} \hat{A} \cdot r_i \hat{A} \cdot C_{el} \right\} \quad (10)$$

Equation (10) is to be optimized given the constraints (11–14), in which the limits for each constraint are explained in [78,79], and in Section 4:

$$\alpha_j \geq 8; 1 \leq j \leq J; j \in J \quad (11)$$

$$\beta_k \geq 1; 1 \leq k \leq K; K > 1 \quad (12)$$

$$n_e \geq 0 \quad (13)$$

$$r_{min} \leq r_i \leq r_{max} \quad (14)$$

The variables presented in this section are summarized in Table 1, and also described in the nomenclature. These are the variables to be optimized so as to minimize the total cost.

The application of the cost model and optimization function through a real case study and discussing the results are presented in Section 4 Table 2.

Case study

Wind turbines are formed by four major systems: foundation and tower, blade system, electrical components (generator and related components), and power train [80,81]. The tower supports the nacelle, which generates energy via the rotation of the blades caused by the wind. This rotation is transformed into electricity in the generator by the power train and transferred to the network. These components are subject to faults and, therefore, need to be regularly inspected and

Table 1
Variables considered for the optimization problem.

Variable	Description	Type	Units
λ	Failure rate	Continuous	[-]
r	Downtime	Continuous	[h]
A	Availability	Continuous	[-]
T_i	Time interval	Continuous	[h]
N_i	Failures occurred during T_i	Discrete	[-]
x_i	Turbines reported for the time interval	Discrete	[-]
r_i	Productive hours lost during the time interval	Continuous	[h]
C_{PM}	Cost of preventive maintenance tasks	Continuous	[€]
C_{CM}	Cost of corrective maintenance tasks	Continuous	[€]
C_{PE}	Penalty cost of additional maintenance work	Continuous	[€]
C_{Loss}	Cost due to production loss when the system stops	Continuous	[€]
C_T	Total maintenance and production costs	Continuous	[€]
α_j	Duration of the preventive maintenance task	Continuous	[h]
β_k	Number of corrective maintenance tasks	Discrete	[-]
n_e	Supplementary hours of maintenance	Continuous	[h]
C_{pen}	Penalty cost of additional maintenance work	Continuous	[€]
C_{el}	Cost of electricity production	Continuous	[€]
P_{ti}	Power generated by the wind turbine i	Continuous	[kW]
r_i	Downtime of the turbine i	Continuous	[h]

Table 2
Failure rate and downtime for each turbine component over 24 months.

Component	Failure rate [-]	Downtime [h]	Risk factor	Normalized risk factor
Gearbox	0.625	136.925	85.578125	0.419
Generator	0.4	101.625	40.65	0.199
Electrical System	0.7	33.907	23.7349	0.116
Blade	0.617	36.9	22.7673	0.111
Hydraulic System	0.5	19.075	9.5375	0.0467
Control System	0.507	12.567	6.371469	0.0312
Pitch System	0.375	11.175	4.190625	0.0205
Sensors	0.327	11	3.597	0.0176
Others	0.433	7.2	3.1176	0.0153
Wind Measurement	0.217	11.725	2.544325	0.0124
Mechanical Brake	0.5	2.5	1.25	6.12e-3
Yaw System	0.15	5.5	0.825	4.04e-3
Shaft/Bearing	0.1	2	0.2	9.79e-4
Tower	0.02	1	0.02	9.79e-5

repaired when necessary.

The wind turbines used in this case study are three 1.65 MW Vestas V66 types. The SCADA data employed corresponds to the European project OPTIMUS. The data were collected every 10 min in the period of 24 months. There are twelve preventive maintenance tasks to be performed on each wind turbine, with an approximate duration of 8 h each [78,79]. In this case, maintenance work can be performed without stopping the system. The simulation parameters are assumed as follows: $C_j^{PM} = 85\text{€}/h$; $C_k^{CM} = 1500\text{€}/h$; $C_{el} = 0.83\text{€}/MWh$; $C_{pen} = 20\text{€}/h$; $P_{ti} = 1.65\text{MW}$; $J = 36$. The failure rate and downtime of each wind turbine component over 24 months are shown in Table 1, where the limit values extracted from it are $\lambda_{min} = 0.02$; $\lambda_{max} = 0.625$, $r_{min} = 1h$; $r_{max} = 136.925h$.

Fig. 4 shows these variables in a Pareto chart to demonstrate the relative importance of the main components.

Table 3 and Fig. 4 show that the gearbox is the component with the highest risk factor, more than 40% of the total. It is followed by the generator, focusing almost 20% of the total, and the electrical system and blade, being 11% each. These four main components concentrate more than 80% of the risk factor and associated downtime, therefore, they should be monitored and inspected with a higher frequency than the others.

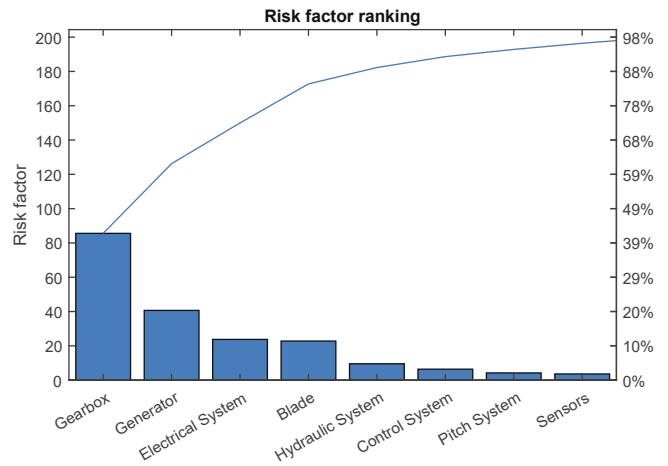


Fig. 4. Pareto chart ranking component risk factors.

Table 3
GA and PSO parameters considered for the optimization problem.

Parameter name	Description	Range	Type	Units
P	Population	5–500	Discrete	[-]
G	Number of generations	1–1000	Discrete	[-]
α_j	Duration of preventive maintenance task	8–50	Continuous	[h]
β_k	Duration of corrective maintenance task	1–6	Continuous	[h]
n_e	Supplementary hours of maintenance	1–20	Continuous	[h]
r_i	Turbine downtime	1–137	Continuous	[h]

Results and discussion

This section shows the results obtained from the optimization process using GA and PSO. This optimization has been carried out using: non-defined fitness limit; Limited maximum number of iterations; Fixed population size; Constraint tolerance equal to zero; Termination tolerance equal to zero; and Lower and upper bounds to define variable intervals. The results are obtained by optimizing equation (10), varying the maximum number of iterations and population size for both GA and PSO ranging from 5 to 500 particles, and 1 to 1000 iterations, with higher resolution at the lower end of both ranges. The parameters used for approaching the problem are presented in Table 3.

A comparison between these two algorithms is presented after the best selection is decided for each of them. Finally, a sensitivity study is carried out to evaluate the variation of the cost model respect to the parameters composing it.

Results for Genetic algorithm

Fig. 5 shows the optimization results using GA given the conditions stated above. Top subfigures show, respectively in a heatmap, the minimum cost obtained in 1000x [€] (a), and the time required in seconds (b) to reach that cost given certain population size and maximum iterations. Bottom left shows a normalized value combining both cost and time (c), in which an increasing value means a worsening result. Thus, the blue zones correspond to better results and the yellow ones to worse, respectively. Bottom right shows the evolution of cost results and time required (d), using darkening tones of blue to represent the increasing population size of each test.

The main findings extracted from the results are:

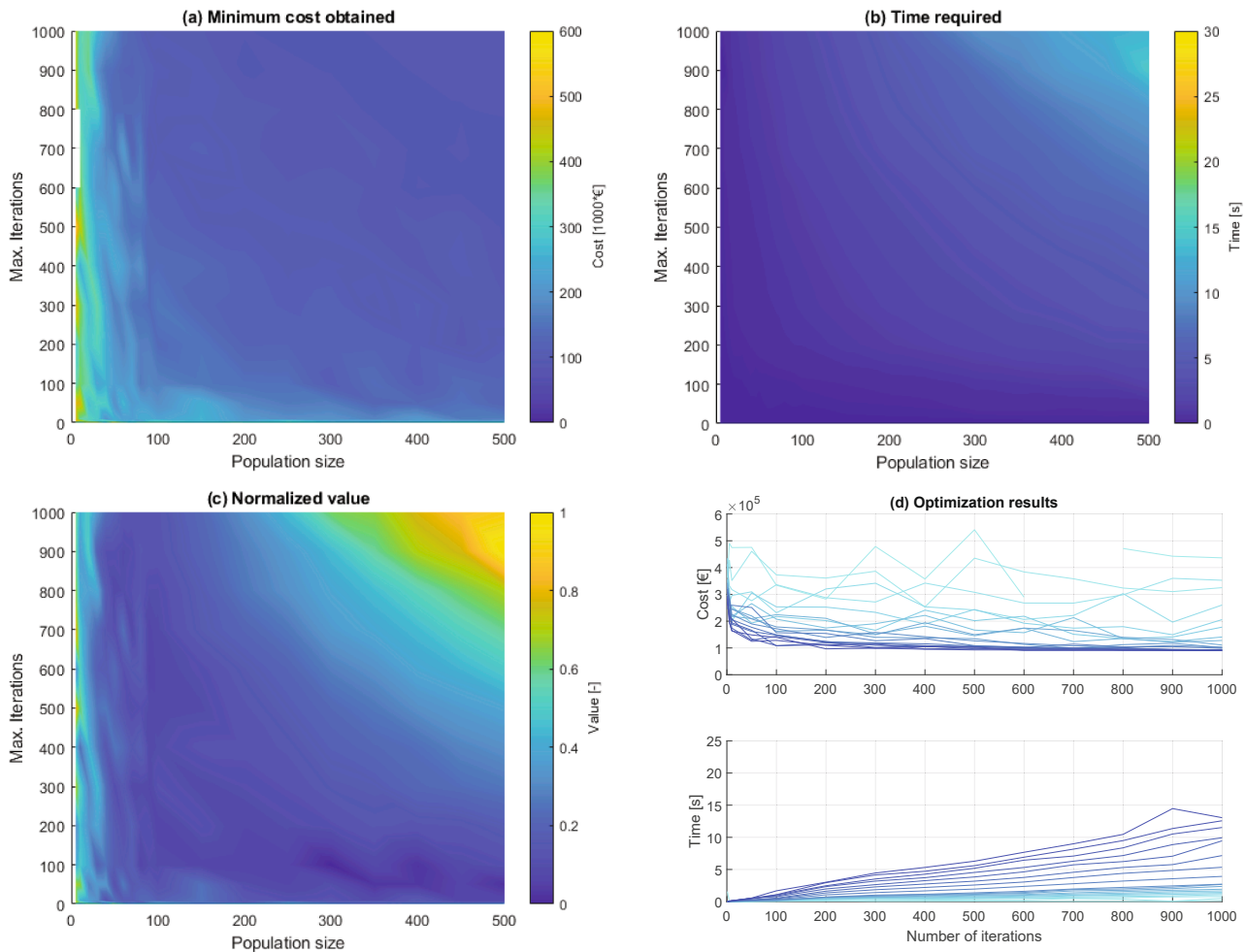


Fig. 5. Results for problem optimization using GA. Minimum cost obtained (a), time required (b), normalized value (c) and optimization results (d).

- Costs do not show convergence to the minimum value until the population is high enough, above 100 individuals, showing the low accuracy of GA for the optimization problem.
- The time required to reach the final result for each population size and maximum iteration number is relatively low, less than 15 s in the most requiring case, showing the high speed of the algorithm.
- The normalized values show that a configuration with relatively high population and low number of iterations is preferable to others, as the results already converged but the computation time increases.
- Population values beyond 300 individuals show few changes in cost evolution, although computational time tends to increase. Hence, a value beyond that would imply higher computational costs and below would imply less convergence to minimum, meaning that a population size close to 300 individuals is optimal for the problem.
- Results beyond 400 iterations do not show significant reductions in cost, but increase time required to finish the process. Hence, this value can be considered as optimal for the problem.

Considering the aforementioned findings, it can be concluded that a population size of 300 individuals with a maximum of 400 iterations is the optimal combination for the problem. This combination obtains a minimum total cost of 108,600 € approx.

Results for Particle Swarm optimization

Fig. 6 presents the optimization results using PSO in the same manner as Fig. 5.

The main findings from Fig. 6 are:

- Costs quickly converge before 100 iterations to the optimal value of 90,628 €, independently from the population size, showing the high accuracy of PSO for this problem.
- The increment in computation time for a higher population is more noticeable than for GA, showing higher computational requirements compared to it.
- The best normalized values are in low population ranges, independently from the maximum number of iterations. Even so, a low number of iterations is preferable to reduce computational costs and resolution time.
- With a population size above 40 there is low variation of optimal costs but increment computational time. Therefore, there is no need to increase population beyond that point.
- For any population size, most results reach the optimum point at 600 iterations or before. Therefore, there is no need to advance beyond that point.

Hence the best combination is a population size of 40 particles and a maximum of 600 iterations, obtaining an optimal result of 90,628 €.

Validation of results

This section presents a validation of the results employing the two best population sizes of GA (300 particles) and PSO (40 particles) in terms of computational time required, convergence, and optimal value

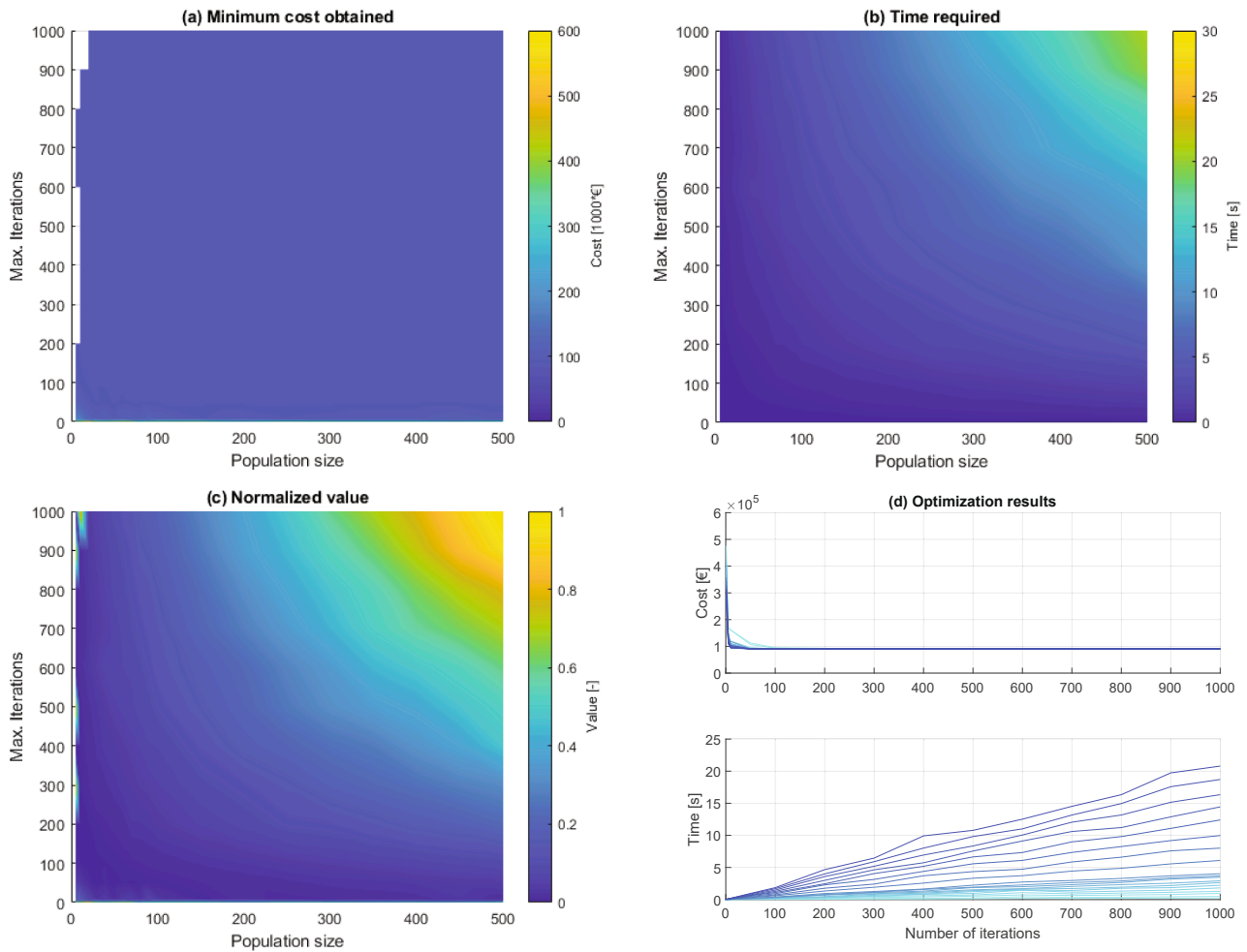


Fig. 6. Results for problem optimization using PSO. Minimum cost obtained (a), time required (b), normalized value (c) and optimization results (d).

obtained. Fig. 7 shows the comparison between GA and PSO for both optimal cost (top), and computational time required (bottom) for the optimal population size.

Fig. 7 shows that PSO is clearly superior to GA in both convergences: optimization costs and computational time. After only 100 iterations, it

already converged to a result close to the optimal (90,628€) in less than a second. However, GA needed 600 iterations to approach that value and, even after 1000, it did not reach it, requiring a relatively higher computational time than PSO.

This section shows that, though GA generally requires less computational time than PSO for the same population size, it requires larger population size and iterations, and thus more computational resources to reach to the optimal value. Hence, PSO is concluded to be the best suited algorithm for this optimization problem. As it requires lower population size, iterations and thus computational time to reach the optimal value.

The maintenance strategy for each wind turbine consists then of 12 scheduled preventive maintenance tasks of 8h each and one corrective maintenance task of 1h, with an overall cost of 20,190 € per wind turbine.

Sensitivity study

A sensitivity study has been carried out to evaluate the response of the cost model to a $\pm 10\%$ variation of the following parameters: $\min(\alpha)$, $\min(\beta)$, $\min(n)$, $\min(r)$, C_{pmh} , C_{emas} , C_{el} and C_{pen} on the following model parameters: α , β , n , r and C_T .

Table 4 shows the results as follows: the columns show the variable variation respect to the $\pm 10\%$ variation of the value of the row variable (e.g., the range of values of $\min(\alpha)$ is $8 \pm 10\%$, which is equal to [7.2, 8.8]). Results are shown in percentage values.

The observations extracted from the results are as follows:

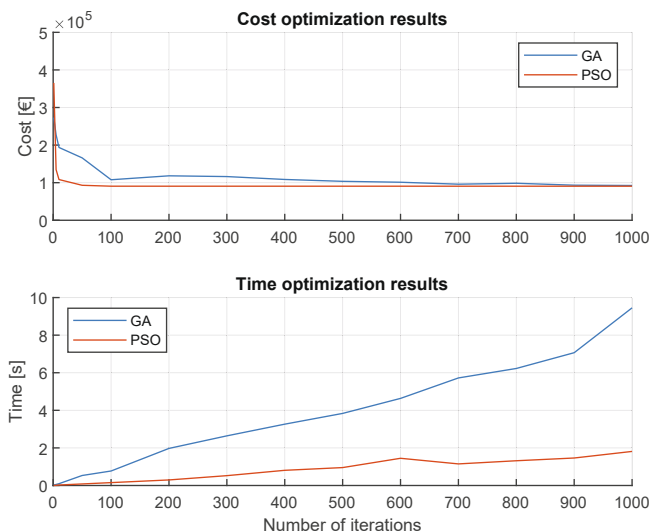


Fig. 7. Result comparison between GA and PSO.

Table 4
Relative parameter variation for sensitivity study.

Variable	Variation	α	β	n	r	C_T
min(α)	+ 10%	10	0	0	0	2.7
	-10%	-10	0	0	0	-2.7
min(β)	+ 10%	0	10	0	10	7.3
	-10%	0	-10	0	-10	-7.3
min(n)	+ 10%	0	0	10	10	0.0022
	-10%	0	0	-10	-10	-0.0022
min(r)	+ 10%	0	0	0	0	0
	-10%	0	0	0	0	-2.7
P_{ti}	+ 10%	10	0	0	0	6.8
	-10%	0	0	0	0	-6.8
C_{pmh}	+ 10%	10	0	0	0	2.7
	-10%	0	0	0	0	-2.7
C_{cma}	+ 10%	0	0	0	0	0.5
	-10%	0	0	0	0	-0.5
C_{el}	+ 10%	0	0	0	0	6.8
	-10%	0	0	0	0	-6.8
C_{pen}	+ 10%	0	0	0	0	0.0022
	-10%	0	0	0	0	-0.0022

- Variations of min(α), min(β) and min(n) cause variations of the final values of α , β and n , respectively. This occurs because of these values already reach the lower boundary for the optimization problem, independently of the constraint. Opposite to them, variation of min(r) causes no variation on the final value of r , because this value did not reach the lower boundary of the optimization problem.
- All cost parameter variations (C_{pmh} , C_{cma} , C_{el} , C_{pen}) cause only symmetrical variations in C_T of a larger or smaller magnitude. The other parameters, however, show interactions between them, such as β and n , causing r to change in the same magnitude as them.
- Variations in C_T are mostly due to β causing a 7.3% variation of costs when their value change at 10%. The second most important source of variation are P and C_{el} , causing a 6.8% variation. The rest of parameters cause variations lower than 3% in the total costs. r is remarkable as its variation does not cause symmetrical changes in total costs, as occurring with the rest of parameters. α and C_{pmh} cause exactly the same variation, most likely due to the localization of these parameters in the same term of the cost model. This happens as well with n and C_{pen} , and P and C_{el} .
- The results show the importance in reduction of corrective maintenance activities, as they cause large increments of costs when performed. It would be then possible to increase preventive maintenance time without increasing total costs as much.
- Although power output is not likely to show large variations by design, a larger production means larger maintenance costs, but these can be mitigated by the incomes generated by the power generated itself.

This section presented the main results and observations of this study. Previous research already addressed maintenance optimization considering parameters such as costs, energy output, and environmental variables [65,72,73]. This work addressed these parameters by converting them to costs, thus simplifying the optimization problem and accelerating the obtention of the optimal results. Combinations of GA and PSO with other AI techniques proved their use for power dispatch optimization, and for hybrid system configuration [66,71,74,75]. Compared to them, this study demonstrated how both GA and PSO are good methods to optimize maintenance scheduling formulated as optimization problems, being PSO superior to GA in computational cost and obtainment of the best results. The sensitivity study, not found in the literature, highlighted the usefulness of preventive maintenance, as it can be increased without causing as much cost increments as corrective maintenance.

Statistical analysis of GA and PSO

Non-parametric analysis such as Quade and Friedman Test [82,83] were conducted based on the results shown in Section 5. For these tests, it is started by preparing an average error. It has been done by deducting the minimum value of the superior algorithm, i.e., in this case PSO, from the mean values of GA. It was named a hypothetical situation H_0 , according to which there is no difference between the algorithms used and they are all one and the same. A contradictory hypothetical situation H_1 states that there are distinct differences between the algorithms used, PSO and GA. If the p-value generated by the non-parametric statistical tests is more than significance level, i.e., 0.05, the hypothesis H_0 is discarded. As per the data generated by Quade test, the lowest of the sum of the ranks is gained by proposed PSO making it the best among the rest of the algorithms. Also, the Q-statistic value is greater than the critical value as mentioned in reference [84], and p-value of Quade test less than 0.05, all points towards the elimination of the null hypothesis H_0 . Similar observations were made from the Friedman ANOVA test.

The least ranks were maintained by the proposed algorithm for all the scenarios thus making it the superior among the rest. The Chi-Square value obtained from Friedman ANOVA test is less than the critical value mentioned in reference [85], and the p-value is less than 0.05, thus proving the null hypothesis obsolete.

Conclusions

This paper has presented the context of wind turbines maintenance management using Artificial Intelligence (AI) techniques to optimize the maintenance scheduling of wind turbines. A case study based on the scheduling optimization of three wind turbines has been presented, which used preventive and corrective maintenance, as well as the costs due to these activities, formulating the system as a cost minimization problem to be solved by Genetic Algorithms (GA) and Particle Swarm Optimization (PSO). The results show the benefits and disadvantages of each technique, as well as a comparison between them. The conclusions of the research are summarized as follows:

- GA and PSO are already settled as a common practice to assess maintenance in wind farms, as well as other AI-based techniques discussed in the introduction. GA is generally less computationally expensive, but it provides less optimal results compared to PSO. The use of one or other technique should be discussed depending on the application, complexity and objective of the problem.
- PSO is selected as the best algorithm as it, in comparison, reaches the optimal solution faster and with less computational cost. The maintenance strategy achieves an optimal cost of 141,050 € for the whole system. This strategy considers 12 preventive maintenance tasks and one corrective maintenance task as the optimal solution.
- The sensitivity study shows how preventive maintenance time can be increased with minimal increased costs as compared to corrective maintenance. Power production also causes cost variation, but it is naturally mitigated by the incomes from the power generated itself.
- The novelty of this research lies in the application of a real case study considering several wind turbines, and mainly the comparison between GA and PSO, two AI-based techniques applied to optimize a large range of problems, as well as the use of a sensitivity study to evaluate the variability of the optimization problem.

This study compared the performance of two of the most applied AI techniques for maintenance optimization. Both the population size and maximum number of iterations have been used to optimize the formulated problem, as well as the constraints for the sensitivity analysis. However, there are other parameters that could be analysed to improve the efficiency of the algorithms, such as the variables considered, the number of preventive and corrective maintenance tasks, or changes over time, such as energy prices and maintenance costs, or component wear.

Furthermore, different AI techniques could be applied to evaluate the problem, e.g., artificial neural networks. Future research works would be oriented towards considering a wider range of variables or different optimization algorithms. Advantages and disadvantages of the combination of different algorithms would also need to be considered when comparing them.

CRedit authorship contribution statement

Alfredo Peinado Gonzalo: Conceptualization, Methodology, Software. **Tahar Benmessaoud:** Data curation, Writing – original draft. **Mani Entezami:** Visualization, Investigation. **Fausto Pedro García Márquez:** Supervision, Software, Validation, Writing – review & editing.

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 paper.

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