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Offshore windmill and substation maintenance planning with Distance, Fuel consumption and Tardiness optimisation

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ABSTRACT

Despite a lot of research about predictive maintenance for onshore and offshore windmill farms, nearly no investigation has been performed to obtain the optimal sequence in which windmills are to be served in a predefined time frame. The higher fuel costs and the increasing time pressure on maintenance jobs urge the need for optimisation, so offshore windmills can be serviced at minimal costs and within a limited time frame. To minimise distance travelled, fuel consumption and average tardiness of all maintenance tasks to be carried out, a multi-objective, non-dominated sorting island model of genetic algorithms is used.

The following novel contributions are realised: (i) A multi-objective island model is used, where on each island a different genetic algorithm is used to minimise a separate cost function per island. (ii) A set of non-dominated maintenance sequences, shown as a Pareto plane, are computed and (iii) these optimal solutions can be used by the planner to select the route to be followed by the CTV when travelling from windmill to windmill during a maintenance sequence.

Tests on two of the islands have resulted in a relative improvement of around 65 to 70% on fuel consumption and distance in relation to a random sequence, while the third island has generated a relative gain of 69% in average weighed tardiness. The three islands combined have resulted in a set of Pareto optimal sequences for offshore windmill maintenance.

1. Introduction

In recent times, a lot of investigative work has been carried out to minimise maintenance costs [1,2], particularly to optimise the vessel planning and usage for performing maintenance on offshore windmill farms [3,4]. Knowledge about wave height, wind direction and strength, as well as many other weather parameters is decisive in determining whether a vessel can sail out and perform the planned maintenance. When a vessel is grounded during weather days, a standby fee is to be paid, amounting half of the price for a full maintenance day, except fuel consumption.

Companies managing offshore windmill farms, need to invest a significant amount of their time and money in the maintenance of the substations and windmills in these farms. Studies done by the Danish wind industry association have shown that older and thus smaller local wind turbines typically have annual maintenance costs around 3% of the original turbine investment. Contemporary turbines are significantly larger, but do not need more service. They thus show lower maintenance costs per kW installed power [5]. For newer machines, the same association postulates that these costs vary between 1.5 and 2% per year of the original turbine investment. This corresponds with 14%–30% of total Offshore Wind Farm (OWF) project life cycle expenditure [6]. Although investments have been made to lower OPEX by using more sustainable materials, later investigations pointed out that operation and maintenance (O&M) remain responsible for a big part of the costs of the offshore windmill farm. The reduction in O&M costs – typically around 20% to 25% of the total levelised cost of electricity (LCOE) of contemporary wind power systems as shown in the Guide to an Offshore Windfarm by of The Crown Estate and the Offshore Renewable Energy Catapult – and improved reliability have become major priorities in wind turbine maintenance strategies [4,7]. Taking into consideration the increasing importance of electric energy generated by wind turbines throughout the last two decades, as well as the influence of maintenance costs on the LCOE of the technology, this study will aim for a reduction of the maintenance costs of wind farms.

Maintenance performed is mostly preventive and consists of electrical and mechanical services on the substations, performed on a monthly, quarterly, half-yearly and yearly basis. Furthermore, there are yearly inspections and coating repairs, Health, Safety and Environment (HSE) maintenance – with check-ups of safety material – and finally summer campaigns, planned upfront. All these maintenance tasks need

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to be planned, considering the availability of the vessel and personnel, the weather conditions, the wave height and sea currents [8]. The complex planning – done in a non-automated manner on a daily basis – is subject to changes throughout the day and demands a lot of experience of planners and vessel captains. The goal of this paper is to optimise the sequence of all windmills maintained, by focusing on three parameters:

1. Minimisation of the distance travelled by the vessel when servicing all windmills based on the travelling salesman problem,
2. Minimisation of the average tardiness of all the maintenance tasks performed
3. Minimisation of the fuel consumption during maintenance travel.

2. Related work

This is the first paper to use a multi-objective island model with GA to determine an optimal schedule for servicing offshore windmills, according to the author's knowledge. No research has been found regarding the minimisation of the distance travelled and the fuel consumed during a maintenance run, in combination with Tardiness limitation. We applied the TSP on offshore windmill maintenance, in order to minimise the distance travelled and the fuel consumed, and extended it to a multi-objective problem in order to prioritise maintenance interventions. This resulted in non-dominated maintenance routes that combine minimisation of distance and prioritisation of maintenance interventions amongst these routes.

The island model can be used to run the same algorithm with similar objective on different CPU's in order to distribute calculation capacity. Ma et al. run a traditional GA on each island where the population is divided into sub populations per island. The GA are separately executed on each island, and individuals then undergo inter-island migrations [9]. Schuman et al. show in their work that parallel genetic algorithms are a way to accelerate optimisation by exploiting large-scale computational resources [10]. The use of various sub populations can help to retain genetic diversity. Hence, each island can possibly follow a different search trajectory through the search space. Furthermore Lapa et al. discussed the use of genetic algorithms for preventive maintenance to reduce the costs of repair, the downtime of the asset and overall cost reduction for a Pressurised Water Reactor in a Nuclear Power Plant. They have proven that the use of a GA leads to preventive maintenance policies that show high reliability and low costs [11].

Since then, extensive research has been done about the application of this model using a different genetic algorithm on each island. A general overview of this method application was given by Konak et al. in their tutorial about multi-objective optimisation using genetic algorithms. In their study, both solution methods to solve multi-objective optimisation problems using GA are compared, being one single GA with a complex, combined objective function and secondly Pareto solutions from a multi-island, multi-objective GA method. They concluded that for most multi-island model implementations, it is not vital to find every Pareto optimal solution, but rather identify Pareto optimal solutions across the range of interest for each objective function. Each island works with a straight forward GA with a rather simple objective function, while working with one GA on one island requires a complex objective function to obtain good results [12]. Nyoman Gunantara and Qingsong Ai discussed an island model with a different objective function on each island, resulting in a Pareto plane of optimised solutions, as one of the methods to solve multi-objective optimisation problems [13], while Bejarano et al. applied the same method and studied the possible clustering of Pareto solutions [14].

Ma et al. applied the multi-island, multi-objective GA method with Pareto solutions to the optimisation of multifaceted maintenance strategies for wind farms [15]. This paper offers a method to simultaneously optimise three aspects of maintenance strategies for wind farms that can be conflicting. These aspects are: the reliability thresholds that announce when a component of the windmill needs maintenance, the priority of maintenance jobs if there are more jobs than vacant maintenance teams, and the use of strategic maintenance. When compared to this paper, there is a big difference. Hence, we optimise the route and schedule when it is already determined that maintenance will take place, while Ma et al. concentrate more on determining when maintenance will be necessary and prioritising in case of intervention overload. Additionally, researchers have studied routing and scheduling optimisation by using an island model with Ant Colony Optimisation (ACO). Zhang proposed a duo-ACO to improve the use of the maintenance vessels and workers, specifically the efficient scheduling and routing of the maintenance fleet to reduce the operation and maintenance cost [16]. In another paper the same author proposes a multi-ACO, keeping in mind the conditions in which offshore wind farms are operated [17]. Allal et al. more recently studied a multi-agent based simulation–optimisation of maintenance routing in offshore wind farms to optimise maintenance task routing. In their paper, another ACO is used – instead of a GA – to optimise the routing [18]. We opted to go for a multi-objective approach with Genetic Algorithms, because compared to ACO, the GA is fast, easy to implement and cost efficient in terms of computational resources. The ACO is more greedy but gives better results, especially with large problems, which is not the case in our research [19]. Finally, the study performed by Gölbasi introduces a discrete-event simulation for maintenance planning. The method proposes an algorithm that is capable of simultaneous evaluation and comparison of multiple maintenance scenarios for an operating system [20].

It has been the purpose of this paper to determine an optimal routing for offshore windmill maintenance vessels in order to reduce travel costs and downtime of the asset. Although some weather parameters have been directly or indirectly considered, like currents and wind, further research is absolutely necessary to study the significant influence of all weather conditions on offshore windmill maintenance planning. As mentioned above, multi-objective island models with GA have been extensively studied before, but never for routing and scheduling optimisation of a predefined set of windmills to be maintained. The novelties of this paper can be described as follows: the use of a multi-objective island model with genetic algorithms to minimise distance, fuel consumption and average total tardiness. Therefore it uses the calculation of a Pareto plane of non-dominated solutions. This then results in a collection of optimal maintenance sequences. Minimisation of distance travelled has been studied in several area's, both by using a genetic algorithm and known solvers [21–23]. Also the minimisation of average tardiness in a flow shop problem has been subject to vast research [24–26]. However, applying it to offshore windmill maintenance and combining both in an island model to find an optimal maintenance sequence – for minimal distance, fuel consumption and average tardiness – was not investigated before. The parameters of the genetic algorithm used, e.g. mutation and crossover rate, are optimised in order to calculate the best results as quick as possible, based on tests carried out for this paper.

3. Method

3.1. Problem formulation

As described above, high maintenance costs are still a huge problem when operating offshore wind farms. The distance covered and fuel consumed by the vessel should thus be minimised. On the other hand, an optimal time schedule needs to be determined to optimise labour time and prioritise jobs. The latter decreases labour cost and down time. Therefore the problem is how to schedule the preventive maintenance tasks for a set of windmills so that the cost, the delays, and the emissions are minimised.

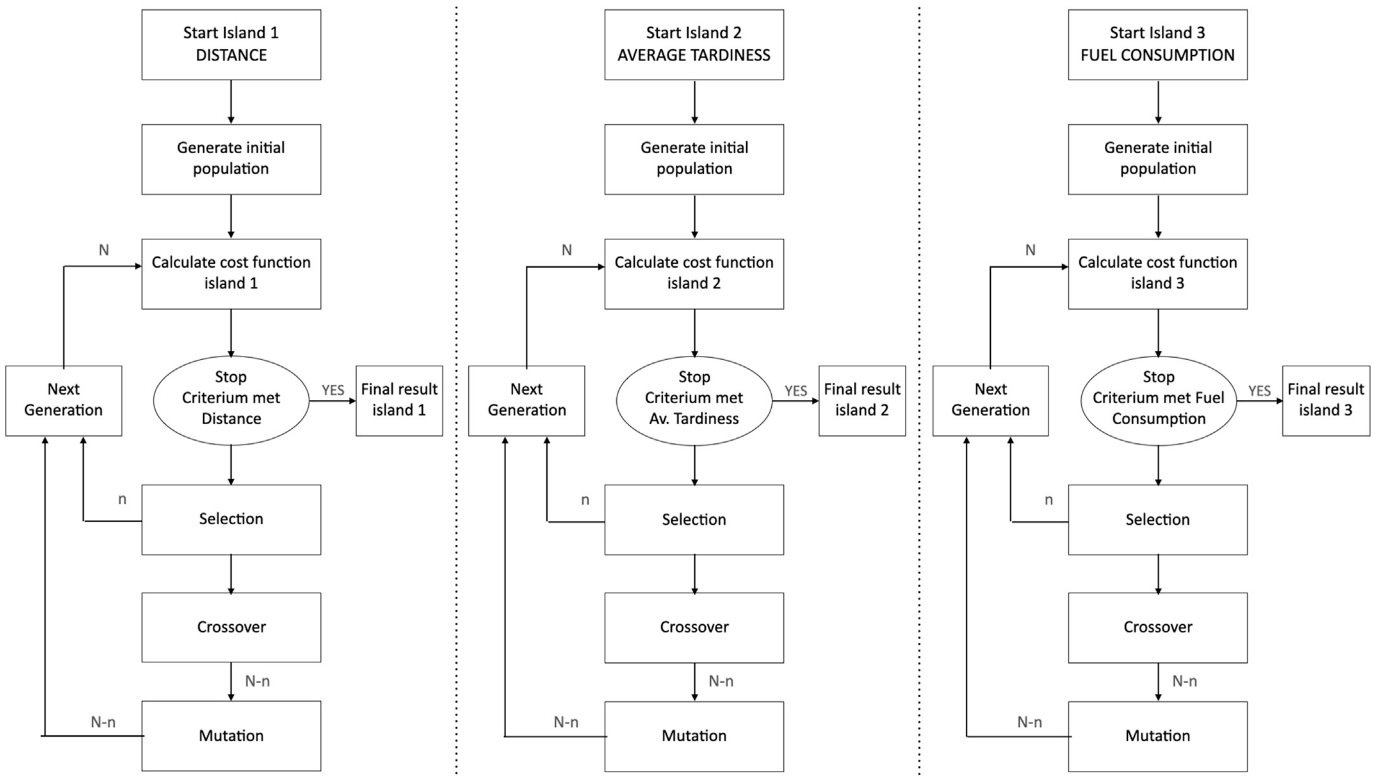

Fig. 1. Multi objective island model.

Reducing the amount of fuel used by a maintenance vessel can easily be done by solving the TSP and taking into account currents and wind direction. In addition distance and travel time are minimised. However, introducing maintenance scheduling to reduce average tardiness can lead to service sequences requiring high travel time and fuel consumption. This paper offers solutions that fulfil all three objectives in the best possible way, meaning a Pareto plane of non-dominated maintenance routes.

Fig. 1 shows a flow graph of the multi-objective island model, where a genetic algorithm is run on three different islands, each with a different cost function. On the first island, a GA is used to solve the NP-hard travelling salesman problem (TSP), applied to the maintenance of windmills at sea. Solving the TSP by using a genetic algorithm is a heuristic optimisation method, minimising the distance travelled [21, 27]. The TSP can also be resolved by applying other heuristic methods, like e.g. the Ant Colony Optimisation [28], and by solvers such as the one developed by OR tools [22]. The use of a GA has important advantages over other methods. The algorithm can find solutions to problems that are nearly impossible to solve using traditional methods. Furthermore, it is less probable that it gets stuck in local minima. Finally, it often finds better solutions than traditional methods.

In this particular case, the problem can be defined as finding the shortest possible route for the maintenance vessel that visits each windmill exactly once and returns to the dock at the end. The second island uses a different genetic algorithm to optimise the average tardiness of the maintenance sequence. This can be described as an m-machine, no-wait flow shop scheduling problem, [24] in which the windmills are seen as machines and one maintenance job immediately follows the previous one. Finally the third island uses a similar algorithm as island one to reduce the fuel consumed.

The objective of the first island is thus reducing the distance travelled between the dock and the different windmills needing maintenance. On the second island, a genetic algorithm is used to define the optimal route in such a way that the average tardiness of the maintenance jobs is minimised. The third and final objective is obtained by using a similar GA as for the TSP, with extra constrains to search for the route with minimal fuel consumption (Fig. 1). All three genetic algorithms are run on a different island, resulting in separate maintenance sequences, each minimising a predefined objective: distance, average tardiness and fuel consumption. Fig. 2 then shows schematically how the solutions of each island are fed to the GA's of the other two islands, resulting in a set of three-dimensional coordinates. The latter are finally used to calculate and plot a plane of Pareto solutions. These contain the non-dominated solutions, corresponding to the ideal maintenance sequences. A solution is called Pareto optimal, if none of the objective functions can be improved without degrading the other objective values. Each of the sequences on this plane, can be seen as a best solution to the problems formulated. The importance of each objective can be incorporated by using a weight factor. However, in this case, each objective is considered to be equally important.

In this paper, the assumption is made that the planning of the windmill maintenance for a day is determined and not subject to any changes. The weather conditions and wave height are suitable for landings at the windmills. These assumptions are made for this paper in order to make a route planning and maintenance schedule for a day during which on sea maintenance is feasible. If these thresholds are not met, the vessel cannot sail and maintenance is simply not possible. Although this will also lead to additional costs for standby vessels, there is no need to optimise the route or fuel consumption of a vessel that will not be able to leave the dock. Other weather parameters like wind speed and weather induced parameters, like the sea currents are taken into consideration when calculating and minimising the fuel consumption of the vessel. Hence, carried by the wind and by the current, a vessel will consume lesser fuel than when both are opposite to the sailing direction. More about the influence of these parameters will be discussed in paragraph 4.3. Additionally, all the permits of work (POW) are approved plus the vessel and personnel are available for the whole day.

Finally, we assume that windmills at several farms can be serviced in one day and that the maintenance time and due time are known for

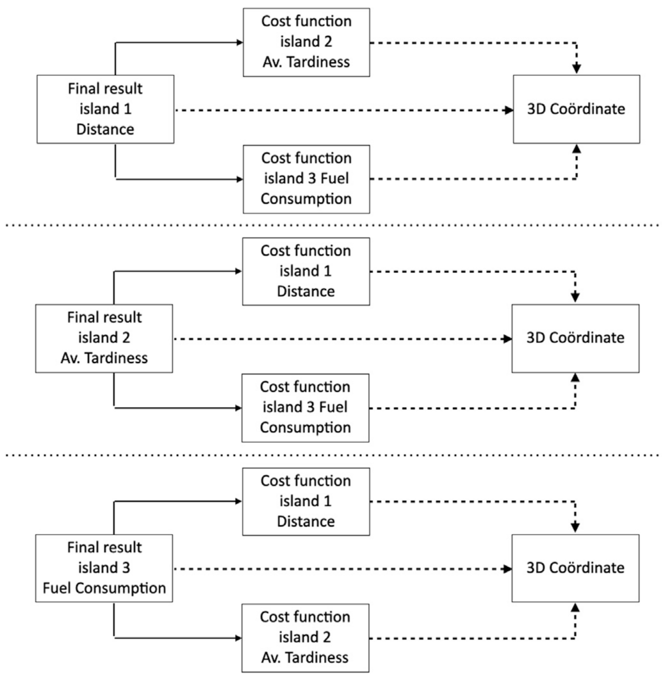

Fig. 2. Pareto coordinates calculation.

each job. In real operating circumstances, there always needs to be a vessel present in a farm when repairmen are working on a substation or windmill in this park. This implies that a crew transport vessel (CTV) can only be used to operate in one farm at the time, except if there is a hotel ship nearby. In order to obtain more significant results, tests are carried out with windmills belonging to separate windmill parks, since distances between the turbines in the same park are very small. Translating the above made assumptions, the following parameters, conditions, decision variables and objectives are defined and categorised.

3.2. Parameters

Input parameters.

n, number of maintenance jobs, number of windmills to be serviced
$W = (w_1, w_2, \dots, w_k)$, set of windmills
$M = (m_1, m_2, \dots, m_n)$, set of maintenance jobs
P_w^m, processing time of maintenance job m on windmill w
D_w^m, due time of maintenance job m on windmill w
i_x^y, distance between two windmills or between windmill and dock
E_v, fuel consumption per vessel (= e_v * transfer time)
e_v, fuel cost per unit time of the vessel
a_v, average fuel consumption per kilometre of the vessel v
j_x^y, fuel consumption change due to currents between two windmills or between windmill and starting point
k_j^q, fuel consumption change due to wind between two windmills or between windmill and starting point
v, cruising speed of the vessel, considered a constant
$w(m)$, weight of the maintenance job m
C_m, completion time of maintenance job m
x_n, x-coordinate windmill n in radians
y_n, y-coordinate windmill n in radians
R, earth radius (=6373 km)
W_v, weight of vessel v

Landing and sailing conditions.

h_w, wave height at windmill w, considered acceptable
l_w, landing window at windmill w, considered open
d_w, direction of wind at windmill w, considered acceptable for landing
f_w, speed of wind at windmill w, considered acceptable for landing

Availability.

a_v, availability of vessel v (boolean), considered available
b_o, availability of worker o (boolean), considered available
z_m, availability of work permit for maintenance job m (boolean), considered available
g_m, spare parts availability for maintenance jobs m (boolean), considered available
h_m, interference with production planning (boolean), considered non-existent

Decision variables.

M_S, a sequence of maintenance jobs
C_D, Total distance
C_E, Total vessel fuel cost
C_A, Average Tardiness

Objectives.

$\text{Min}(C_D, C_E, C_A)$

3.3. Island model solution

In artificial intelligence (AI) and computing, a genetic algorithm (GA) is defined as a meta-heuristic search method that belongs to the group of evolutionary algorithms [10,29]. It is used for finding optimised solutions to search problems based on the theory of evolutionary biology and natural selection. Genetic algorithms are perfect for searching through large and complex data sets in order to find decent solutions to complex issues as they are particularly capable of solving (un)constrained optimisation issues. A schematic overview of how the GA works, is shown in Fig. 3. It shows that starting from an initial population, and by applying crossover and mutation, solutions are searched that minimise a predefined cost function until the stop criterion is reached. The logical structure of the used genetic algorithm, can be written as follows [23]:

Start Generate a random population of n suitable solutions for the TSP.
Fitness Evaluate the fitness function of each individual in the selected population. The Fitness is defined as the unit fraction of the route.
New population Create a new population by repeating the next 4 steps until the new population is complete.

- **Selection** Select two parents from the population.
- **Crossover** Cross over the parents to form new children (offspring), with a crossover operator. The latter combines the genetic information of two parents to generate new offspring.
- **Mutation** Mutate the new offspring (mutation probability). This implies a small random change in the chromosome, to get a new solution in order to avoid local minima.
- **Accepting** Place the new children in a new population.

Replace Use the newly generated population for a further execution of the algorithm.
Test If the end condition is met, stop, and return the best solution in the current population.

$\boxed{\textbf{Loop}}$ Go back to the **Fitness** step.

Island models genetic algorithms can be divided in two major classes. In the first class, the same GA is run on several parallel islands to avoid local minima. The initial population is divided in subpopulations each fed to another island and migration of solutions is possible via a predefined migration criterion [9]. The second class contains islands models in which a different GA is run on each of the islands. Each island is looking for solutions to minimise separate cost functions and the results obtained are handed to the cost functions of the other islands. The case studied in this paper, exists of a model with three islands, and every test result of one island is fed to the other two, resulting in coordinates with three dimensions, being distance, tardiness and fuel cost. All coordinates are finally offered to a Pareto algorithm in order to calculate the plane of non-dominated solutions, containing sequences of windmills that are Pareto optimal. The next paragraphs will discuss every single island and coupled test results separately, to conclude with the calculation and visualisation of the Pareto optimal maintenance sequences.

4. Results

4.1. Island one — TSP

On the first island, the cost function to be minimised is the distance travelled. Fig. 3 shows that the trajectory miles covered in a maintenance sequence – the order in which the wind turbines are visited – is the sum of the distance from the dock to the first windmill, the distance between the different wind turbines to be serviced and finally the distance from the last windmill back to the dock. The blue arrows represent a random sequence, the red is an optimal solution after the algorithm is run. This is a variant of the NP hard travelling salesman problem. In the TSP, a n × n distance matrix I = (i_x^y) is calculated. The algorithm then looks for a cyclic permutation p of the set 1,2, …, n that minimises the function:

$$c(p) = \sum_{i=1}^{n} c_{ip(i)} \tag{1}$$

The value c(p) is called the length of the permutation p. The items in p are usually called nodes, in this paper windmills, and we will only focus on the symmetric TSP, where $i_x^y = i_y^x$ for all windmills [30]. When calculating the minimal fuel consumption (see subsection Island Three — Fuel Consumption), the distance matrix will still be symmetrical. However, the fuel consumption travelling from windmill x to windmill y can differ from the amount used when sailing in the opposite direction, due to currents and wind direction.

Tests are carried out with the following GA parameters: a population size of 100, a mutation rate of 0.01, a crossover rate of 1 and 500 iterations as stop criterion of the algorithm. These parameters were chosen based on a grid search in the parameter space and have proven to be optimal, since modification of the parameters did not lead to significantly better results. A higher number of iterations led to a higher amount of calculation time, while the distance calculated remained almost the same. Simultaneously, we carried out tests with the OR tools TSP solver as can be found on [22]. This way of solving the TSP is called constraint optimisation or constraint programming (CP). CP is based on finding a feasible solution rather than identifying an optimal solution. It concentrates on the constraints and variables, less on the objective function, if there even is one. The goal may simply be to narrow down a significantly large set of possible solutions to a more controllable subset by adding constraints to the problem.

As discussed earlier, all tests are carried out with a group of 26 windmills divided over three farms in order to get significant gain in distance reduction, since distances between turbines in the same farm are too small. To calculate these distances travelled between two windmills, or between the dock and a windmill, we apply the following formulas for distance calculations between sphere coordinates, after converting the coordinates to radians, see parameters in section 2.2 [10, 31]:

$$d_1 = |\sin^2(\frac{d_x}{2}) + \cos(x_1)\cdot\cos(x_2)\cdot\sin^2(\frac{d_y}{2})| \tag{2}$$

$$d_2 = 2\cdot\arcsin\sqrt{d_1}\cdot R \tag{3}$$

$$d_x = x_2 - x_1 \tag{4}$$

$$d_y = y_2 - y_1 \tag{5}$$

The algorithms found in literature to solve the TSP are working with Euclidean distances [23]. Our tests have been carried out with distances calculated with above equations. Our algorithm calculates the route travelled for every wind turbine maintenance sequence in the initial population and then determines the fitness function, computed as the inverse of the total route distance. From the ranked routes – according to the best fitness result – an elite population is selected and completed by mutation and crossover to a full population. This is done for every iteration until the predefined number of iterations is reached and then the route with the best fitness result is proposed as a final solution (see Fig. 1).

Table 1 list the result of twenty tests, presenting a relative gain in distance – from random to best – of around 70% when running the GA with the above indicated parameters. Also the furthest first option is added to the table, in which the vessel first sails to the furthest windmill to avoid return issues when the weather changes.

Table 2 shows the statistical parameters and their values after running the algorithm for 20 times. These results show a significant gain in route distance after only 500 iterations and a calculation time of a little less than 23 s on a MacBook Pro from 2021 with the new Apple M1 chip and 8Mb RAM. Nor the augmentation of the number of iterations, nor a higher mutation rate or lower crossover rate lead to an important improvement of the results and thus all further tests were carried out with the indicated parameters.

Finally, Table 3 shows the results of the OR tools solver on the same set of windmills. Every run of the solver results in the same optimal distance travelled. We can conclude that, compared to the random value (Mean Rand), the relative gain is more or less the same. However, when comparing the final result (Result) of both methods, there is a difference of a little under 10% in favour of the Genetic Algorithm.

The results show clustering around the different windmill farms. Since distances between windmills in the same farm are rather small

Table 1
GA Results for all 3 islands.

Island	Mean rand	Mean final	Furthest 1st	Rel. gain
Distance (km)	4450,98	1333,86	1385,74	70%
Tardiness (min)	2319,65	1475,16	2077,23	64%
Fuel Consumption ($\frac{l}{ton}$)	731,29	227,16	231,58	69%

Table 2
Statistical Results for all 3 islands.

Parameter	Result (km)	Tardiness (min)	FC ($\frac{l}{ton}$)
Mean	1333,87	1475,16	227,16
Standard Deviation	2,6554	93,53	1,2093
Confidence level (0,975)	1,1638	40,99	0,5300
Confidence level (0,95)	0,9797	34,51	0,4462
Confidence level (0,9)	0,7660	26,98	0,3488

Table 3
GA vs OR-Tools.

Method	Result (km)	Mean Rand (km)	Rel gain (%)
GA	1333,87	4450,98	70
OR Tools	1433	4450,98	68

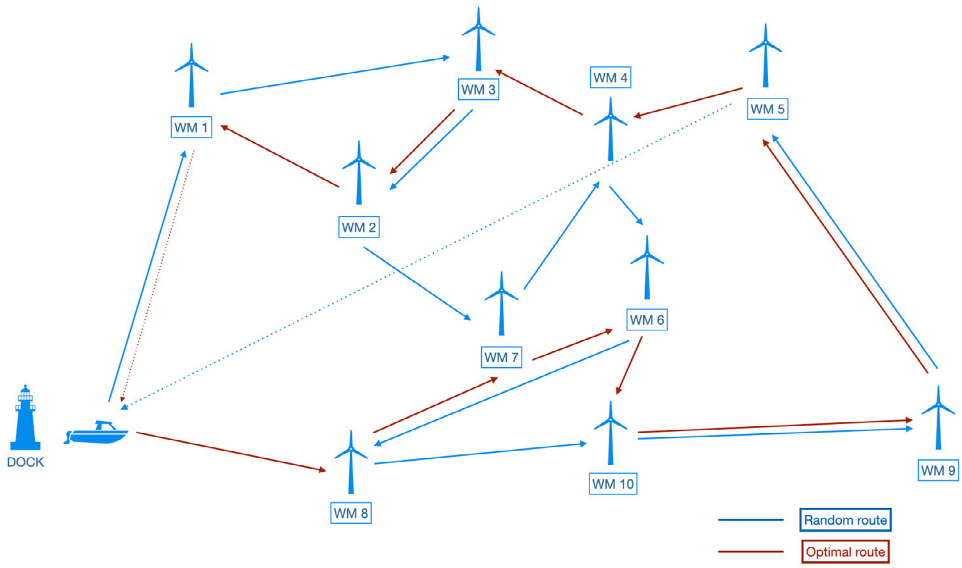

Fig. 3. Maintenance sequences: Random and Optimal.

(less than 1 kilometre), while travel routes between windmill farms are much longer (up to 600 km), it is obvious that a vessel will first address all windmills in one farm and then move to the other. As a second conclusion we can conclude that running the GA over and over again will not lead to large differences in the outcome, due to the clustering. Hence, the sequence followed within a farm can vary without resulting in significant changes in distance, but the overall distance is mainly determined by the order in which the farms are addressed.

4.2. Island two — average tardiness

If we should chose to minimise the total makespan of the maintenance sequence, this can be seen as single machine system with n jobs subject to sequence dependent setup times. Immediately the analogy is shown to solving the TSP. However we opt to use this island to minimise the total average tardiness, which takes into account due times by which maintenance jobs need to be handled and weight factors. These factors prioritise certain maintenance jobs, making the problem more complex and the analogy with the TSP less likely.

The genetic algorithm ran on the second island in the model, minimises the average tardiness of a maintenance sequence. Each of the n maintenance jobs (numbered 1, …,n) is to be processed without interruption on a sequence of windmills that can handle no more than one job at a time. Therefore, we make a link between maintenance jobs and windmills, on which jobs need to be carried out in sequence (analogy with a sequence of jobs on one machine: one cannot start before the previous one has finished) [25,26] This assumption is made to counter for the fact that we visit windmills in different windmill farms. In other words, we keep the vessel at the location until the job is done.

To calculate the average tardiness of a sequence of maintenance jobs, we assume that the maintenance job m (m = 1, …,n) becomes available for processing at time zero. This job requires an uninterrupted positive processing time P_m^w, uses a positive weight w(m) and has a due date D_m by which it should ideally be finished (see parameters in section 2.2). For a given processing order of the jobs, the earliest completion time C_m is defined as the sum of the completion times of all jobs prior to job m. For example, C_2 is the sum of production times of jobs 0, 1 en 2. The tardiness (T) of a job m, the total weighed tardiness (TWT) of all jobs up to n included and the average tardiness (AT) are computed as:

$$T(m) = \max(C_m - D_m, 0) \tag{6}$$

$$TWT = \sum_{m=1}^{n} w(m)T(m) \tag{7}$$

$$AT = \frac{TWT}{n} \tag{8}$$

Table 1 shows that the algorithm again results in a high gain of tardiness reduction of the job sequence – up to 64% from random to best – when it is executed with the following parameters: a population size of 30, a mutation rate of 0.1, a crossover rate of 0,9 and 2000 iterations as stop criterion of the algorithm (see Fig. 2). As for the TSP problem, tests have been done with other values of these parameters – e.g. a lower mutation rate of 0.01, a higher mutation rate of 0.5, a higher crossover rate of 0.99 or a lower crossover rate between 0.5 and 0.8 – and again the ones above have proven to be optimal.

For the TSP problem, we detected a clustering of the windmills visited, meaning that the optimal route is going from one windmill farm to another. In every farm, the sequence of the windmills changes the distance travelled only in a minimal way. This explains that the optimal route is only slightly different in all tests. The results of the Tardiness algorithm show much more diversity in sequence than the ones resulting from the first and third island. Hence, the total tardiness is solely dependent on due dates, completion times and weight factors. Since windmills close together in distance can have a completely different weight factor and a significant divergence in tardiness, the minimisation can lead to vessels travelling from farm to farm in order to attain all time objectives.

4.3. Island three — fuel consumption

The genetic algorithm used to minimise the fuel consumption is in many ways similar to the one used on the first island to solve the TSP of section 3.1. As tests with this algorithm have proven in the TSP, the parameters to obtain the best results are: a population size of 100, a mutation rate of 0.01, a crossover rate of 1 and 500 iterations as stop criterion of the algorithm (see Fig. 1). While on the TSP island, the attitude and longitude of the dock and wind turbines are the only input parameters, there are extra factors that have an important influence on the fuel consumption of the CTV, used to move technicians from one windmill to another. First, the sea-currents need to be taken into account. These currents vary in speed and direction over time, but to make calculations feasible, the assumption is made that the current parameters are constant for the trajectory between windmills and the dock [32]. Secondly, the wind at sea will play an important role. Again for the purposes of this paper, we consider the wind direction and speed to be the same over the whole region and the time-frame in which all maintenance is carried out [33].

Calculations for this paper have been done with wind blowing to the east at such a speed that they change the fuel consumption by 10%. In the formula, the fuel consumption (FC) is multiplied by 0.9 when the vessel is travelling from west to east and multiplied by 1.1 when sailing in the opposite direction. Currents are presumed to move in the same directions as the wind and for the purpose of this paper, running at 5 kilometres per hour. Hence, the fuel usage for a vessel travelling from one windmill to another with wind and current in favour, over a distance x is (see parameters section 2.2):

$$FC = \frac{0,9 \cdot x \cdot W_v \cdot a_v \cdot (\frac{v}{v+5})}{1000} \tag{9}$$

For a vessel moving in the opposite direction over a distance x, the fuel consumption is calculated as follows:

$$FC = \frac{1,1 \cdot x \cdot W_v \cdot a_v \cdot (\frac{v}{v-5})}{1000} \tag{10}$$

Tables 1 and 2 list the results for this island, which are similar to the ones found on island one, with a large gain in fuel consumption reduction (round 69% on average). The algorithm used is comparable to that of the TSP and thus – because of the grouping of the windmills and the small distances between turbines in one farm – the optimal sequences are clustered around these farms. The total final consumption for all tests is comparable and adjacent to the minimum. As to be expected, the maintenance sequences are interchangeable with the ones that resulted from the GA on island one. To conclude, we also calculated the fuel consumption linked to the maintenance sequence obtained in paragraph 3.1 by using the OR tools solver. The result differs only 1% from the optimal obtained by using a GA, but again the GA gives the better absolute value.

As for the first island, the same conclusions about windmill clustering can be made. To reduce fuel consumption, a vessel will first address all windmills in one farm, before moving to the next farm. The fuel consumption is only significantly influenced by the sequence in which the farms are addressed and the direction of wind and current on the route between the farms.

4.4. The Pareto plane

To calculate the Pareto plane with non-dominated solutions, tests were run on the three separate islands and each result was then offered to the other islands. An example to demonstrate: the GA on the first island resulted in a maintenance sequence with minimal travelling distance. For this windmill sequence, the corresponding fuel consumption and average tardiness are calculated by using the calculation formulas in the other algorithms. By carrying out twenty test runs on each island, a total of 60 three-dimensional coordinates are created, corresponding with 60 maintenance sequences. Fig. 4 shows the Pareto plane.

As shown in the diagram above, the plane of non-dominated solutions contains coordinates that are far apart in one of the dimensions, values varying from an average tardiness of around 1400 to 2500 min and of distance from 1300 to 6300 km. In other words, when the distance travelled and the fuel consumption is minimal, the average tardiness is relatively high (almost double the value) in comparison to the minimal values resulting from the second island. The second group of solutions is on the opposite side of the spectrum, i.e. sequences with minimal tardiness, but relatively high distances and fuel consumption. Table 4 shows the values related to the coordinates of the points that form the Pareto plane.

Our research has led to a group of Pareto optimal maintenance sequences as a result of the multi-objective island model. Nevertheless it has proven to be very difficult to find a maintenance sequence that is

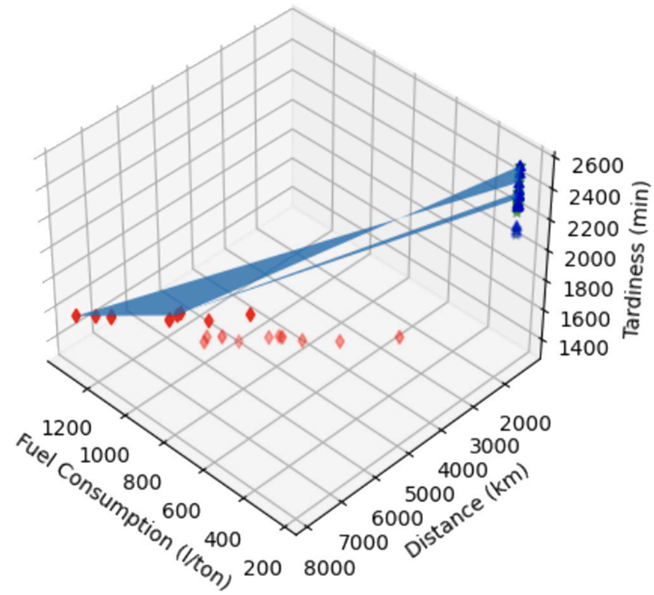

Fig. 4. Pareto plane for WM maintenance sequences using a multi-objective island model.

Table 4
Pareto points of the multi-objective island model.

Coordinates –	FC (l/ton)	Distance (km)	Tardiness (min)
1	227.45	1336.38	2545.92
2	1075.89	6331.68	1577.08
3	1333.52	7843.39	1576.92
4	227.11	1339.70	2442.15
5	227.59	1340.84	2439.19
6	228.73	1346.87	2377.85
7	1065.9	6288.18	1594.77
8	230.75	1379.38	2336.35

optimal for all three cost functions, since due dates of maintenance jobs are not at all correlated with proximity of the consequent windmills. For example, the first and third most important maintenance jobs to be carried out can be far away from the dock while the second most important is nearby, resulting in a distance to be covered twice as the one calculated when the optimal distance route is followed. Tests resulted in paths that either have a low average tardiness and a high distance and fuel consumption, or have a low distance and fuel consumption, but a high average tardiness. When determining the optimal sequence, the planner thus has to decide which parameter is most important when making the choice. From the 60 maintenance sequences, a list of 8 non-dominated solutions are calculated and proposed to the planner. Four of the solutions offer a path with a relative gain in distance and fuel consumption of 60 to 70%, while the 3 remaining offer a relative gain in average tardiness of around 70%. None of the tests resulted in a path with low values for the cost functions on all three islands.

5. Conclusions

The increasing number of windmills, both onshore and offshore, and the continuously increasing fuel costs resulted in rising maintenance costs for wind turbine operators. With a multi-objective island model, we managed to find non-dominated sequences in which the maintenance of several windmills can be carried out in such a way that the distance travelled, the fuel consumed and the tardiness of the jobs are optimal. It is then the task of the planner to choose a sequence that is part of the non-dominated solutions.

Looking at each island separately, we can list the results of the key performance indicators of each island as follows:

1. On island one, the use of a genetic algorithm for maintenance scheduling has led to a reduction of 70% of the total distance to be travelled, compared to that of a random sequence.
2. On island two, the result obtained for the minimisation of the average tardiness of a maintenance sequence is 64% less than the random value.
3. Island 3 shows similar results as Island one, meaning a cutback of 69% of the fuel needed for a random maintenance sequence.

The results obtained can be further discussed and compared with the outcome of a genetic algorithm with time constraints. The latter does not require a three-island model for multi-objective optimisation, but has a more complex objective function, due to time constraints. In future work, we will further dive into the maintenance planning, then taking into account multiple vessels (vehicle routing problem) to fulfil rigid time constraints.

Data availability

Data will be made available on request.

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