ML & Climate - Project

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Abstract

Offshore Wind Farms (OWF) are gaining traction around the world as one of the best renewable energy sources due to their lack of interference with infrastructure and energy production potential. Despite this, OWF planning and configuration optimization has been a stale research area, with governments around the world opting to instead uniformly place the greatest number of turbines in the designated farm. Most work in the area deals with optimizing turbine placements in the farm to maximize the power production by account for the wake effect - the biggest contributor to OWF inefficiency. With a recent application of Genetic Algorithm (GA) to OWF configuration optimization using Wake Effect heuristics in mind, I propose a multi-objective GA model that defines heuristics for (1) Wake Effect and (2) Cable Length to define configurations. Here, Cable Length heuristic combines the Array-Cable length (approximated using Minimum Spanning Tree) and Export-Cable length (distance from Turbine placement's euclidean center to shore) to now incorporate all 3 changeable components within the OWF planning problem. My NSGA-II based approach achieves comparable results to the classical single-objective GA approach, however, it also presents increased computation costs. Potential methodology for real-world application of the approach is also presented.

1 Introduction and Prior Works

In the global push toward renewable energy production, Off-shore Wind Farms (OWFs) are gaining traction as one of the best alternative energy production methods for countries with significant shorelines. OWFs provide a comparably efficient energy production model to Land Wind Farms due to their ability to support larger turbines (those with larger blade diameters) and lack of interference with infrastructure Shen et al. (2021); Gualtieri (2019).

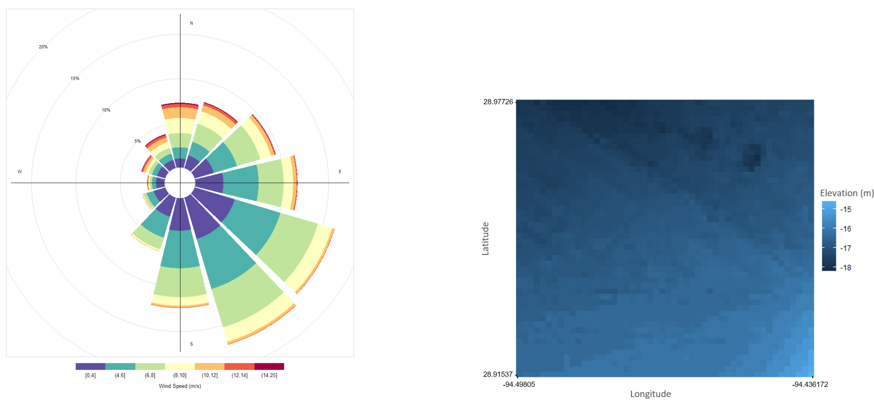
One of the main problems within OWF configurations stems from power loss caused by the wake effect generated by turbines on other turbines of the farm (here, the wake is assumed to contain turbulent winds that only reduce the power production of a given turbine. OWF configuration optimization research aimed to placing turbines that reduce this wake effect are abundant in academia Gualtieri (2019); Hou et al. (2015); Shakoor et al. (2016); Starke et al. (2020). With approaches that incorporate other OWF planning such as the array cable (cable that connects all the turbines to one or more off-shore substation that can process the power produced by the turbines) configuration and export cable (cable that connects the offshore substation to an onshore substation that connects the farm to the grid) solely taking a 2-phased approach - first configuring turbine placements to minimize power loss due to wake effect and second configuring the cables to reduce costs Wu et al. (2022).

In this paper, I explore a method for incorporating all 3 optimization requirements (wake minimization, export cable length minimization and array cable length minimization) in OWF planning when defining the Turbine placement locations.

2 Methods

2.1 Data

As the dataset for this work, I collected the required datapoints from an actual site currently being investigated as a potential OWF site by the Federal Government of US. While the actual area being considered is 546,645 acres large with an uneven shape, I truncated my test area to a 7km by 7km area within the space - (28.7726 N,-94.49805 W) to (28.91537 N, -94.436172 W). I used the wind speed/direction data for the area collected by a NOAA Buoy situated within the area (1.5m above sea level) - shown in Figure 1. I collected the elevation data for the site using Google Maps Platform API - shown in Figure Figure 1. Finally, I collected the distances to shore for the whole grid using Google Maps Platform API.



(a) Windrose Diagram

(b) Elevation Heat Map

Figure 1: (a) Windrose diagram of wind data in the selected area as provided by NOAA. Winds in the selected area tend to approach from the SE direction the most. (b) Elevation map of the selected area as provided by Google Maps Platform. There doesn't exist a large variance in the elevations, likely due to the smaller size of the selected area.

2.2 Wake Objective

There are many potential methods for accounting for power-loss caused by the wake effect in OWFs. One of the easier approaches simply refrain from placing turbines close to each other - Dhoot et al. (2021) constraint their approach to not place turbines within 5 rotor-diameter lengths from each other. Similarly, in defining methods for calculating wind-flow within land wind farms, Starke et al. (2020) utilize a Voronoi Diagram based approach.

The most widely used wake effect calculation methods utilize Jensen's wake model Shakoor et al. (2016). Jensen's wake model defines the deficit caused by wake created from turbine i upstream to the given turbine j by scaling the overlap between the turbine i's wake and turbine j's rotor swept area by factors related to the distance between the turbines, the wind speed and wake decay.

I implemented the interaction-matrix based approach from Dhoot et al. (2021) to Jensen's Wake model by utilizing a grid view of the OWF area. In this, a binary matrix X is devised such that it defines the configuration of the OWF: 1 indicates existence of a turbine in the given location and 0 indicates non-existence. I used the 7km by 7km area mentioned above in Section 3.1 and divided the area into a 50-by-50 matrix with cells of size 140m by 140m; $X \in R^{50,50}$. A constraint is then placed on X that requires every configuration to contain the same number of turbines N - allowing more accurate comparison between configurations and incorporating the fact that N is almost always fixed by law-makers prior to configuration definition due to budget/logistical reasons (N=50 for this work). The optimization problem formulation is defined in equation (1).

$$\text{minimize} \sum_{i \in V^{WT}} W_i \circ X \tag{1}$$

$$\text{subject to} \sum_{i \in V^{WT}} x_i = N$$

For matrix W_t, each element $w_{i,j}$ is calculated using equation (2) below for $i, j \in V^{WT}$. Where V^{WT} is a set of all potential locations of turbines (combination of Longitudes and Latitudes per matrix above).

Essentially, I store an interaction matrix W_t for each potential turbine location wherein each element of those matricies is calculated using Jensen's Wake model for our available wind speed/direction data above. This formulation allows us to simply element-wise multiply the binary matrix X to each of those interaction matricies; and summing those per-turbine wind deficit values will stand as the configuration-wide wind deficit value (referred to in the rest of the paper as "Wake Objective"). This objective value can now be calculated for potential configurations X to define preferences within a population of different configurations (smaller objective value is preferred as it indicates smaller power loss to wake).

$$w_{i,j} = \begin{cases} \sum_{d \in D} P_d V_{i,j}^d & ,i \neq j \\ 0 & ,i = j \end{cases} \tag{2}$$

$w_{i,j}$ calculates the total deficit caused by turbine i on turbine j by proportionally summing up the wake deficits for all potential wind-directions D. Here, the deficit in a given direction d, $V_{i,j}^{\text{d}}$, uses the average wind speed in the given direction v_d (used in calculation for C_i^T in equation (3)) and is normalized by the probability of winds blowing from that direction P_d. The wake decay constant, κ, which is used to consider the turbine's height and surface roughness into the wake's decay as it travels is fixed at 0.04 as recommended by Shakoor et al. (2016) for off-shore wind turbines. Turbine heights were all fixed to 170m - potential future work can be made by also varying turbine heights Abdulrahman (2017).

$$V_{i,j}^{\text{d}} = 1 - \frac{V_i}{V_{i,j}} = \left(1 - \sqrt{1 - C_i^T}\right) \left(\frac{R_j^W}{R_j^W + \kappa D_{i,j}}\right)^2 \frac{A_{i,j}^{\text{overlap}}}{A_i^R} \quad i, j \in V^{WT} \tag{3}$$

Details for the definition of the Jensen's Wake deficit model shown in equation (3) can be found in Wu et al. (2022). To summarize, the first component in the calculation, $\left(1 - \sqrt{1 - C_i^T}\right)$, defines the wind-based scaling that takes into account the wind-speed and wake decay constant κ. The second component in the calculation, $\left(\frac{R_j^W}{R_j^W + \kappa D_{i,j}}\right)^2$, defines the distanced-based scaling that takes into account the distance between turbines i and j. Finally, the third component, $(\frac{A_{i,j}^{\text{overlap}}}{A_i^R})$, simply calculates proportion of overlap between turbine j and wake created by turbine i. Code for calculating the Wake deficit value above is provided in the $make\_data\_wake$ file.

2.3 Single Objective Genetic Algorithm

Genetic Algorithms are meta-heuristic algorithms aimed at optimizing an arbitrarily defined objective by performing random changes to a randomly generated initial population-set of candidates. In this, the algorithm tries to mimic the natural DNA chain changes from generation to generation Deb et al. (2002); Kizhakkan et al. (2019). It continually generates children by selecting the best candidates from a given population to then potentially incorporate into the next generation based on their objective performance. While there are approaches to usage of real-number GAs, the formulation for the OWF above restricts implementations based only using binary arrays (wherein we flatten the X matrix defined above). Here, we further restrict implementation to only those that keep the same number of 1's in the binary array (=N) throughout. The psuedo code for GAs is shown below in Algorithm 1.

To fully explore the implementation of single Objective GA, I defined definitions for popular Selection Procedures (Rank Selection, Roulette Selection, Tournament Selection), Crossover Procedures (One-point Crossover, Two-point Crossover, Segment Crossover, uniform Crossover) and Mutation Procedures (Inversion Mutation, Random Mutation, Scramble Mutation, Swap Mutation) all configured to keep the number of 1's constant per the constraint.

```
Data: P,Cn=P/2,I,m=0.1
Pop = Generate P candidates with randomly placed turbines;
while best candidate improvements encountered in I previous iterations do
    Select Parent Pairs to generate children using SelectionProcedure();
    C = {};
    for {P1,P2} in Parent Pairs do
        C1,C2 = perform crossover with P1 and P2 using CrossoverProcedure();
        C1 = perform mutation with probability m using MutationProcedure();
        C2 = perform mutation with probability m using MutationProcedure();
        add C1,C2 to C
    end
    nextPop = {};
    add Cn children with best Objective() performance from C to nextPop;
    add (P-Cn) parents with best Objective() performance from P to nextPop;
    Pop = nextPop;
end
Return Best candidate in the first population
```

Algorithm 1: Single Objective GA

2.4 Multiple Objective Genetic Algorithm

2.4.1 Cable Length Objective

In prior works that take a two-step process to OWF planning, the approaches can incorporate accurate but expensive computations for Array Cable configurations and Substation placements. For example, Wu et al. (2022) use Ant-Colony Optimization to define Array cable configurations such that the power-flow between each segment of the cables is normalized. Dutta and Overbye (2012) propose a k-means clustering approach to defining Substation placements by testing multiple values for k in each iteration until the power-flow directions for each clusters to their assigned Substations are consistent.

In use of cable length as a GA heuristic, I looked to instead simplify the approaches such that the computations costs are feasible in the context of calculating them for even candidates with randomly generated turbine placements. Hou et al. (2015) use Prim's Algorithm to define a Minimum Spanning Tree (MST) using a network view of the candidate's configuration where the turbines are nodes and the edges are array cables to find optimal array cable configurations. Furthermore, they test multiple approaches to substation placements such as the center of the area, center of turbines, etc. The MST approach here removes the potential for cross-cabling and finds an approximation of the smallest possible cabling length required for a given candidate. I chose to use their MST based approach to define the Cable Length Objective such that for each candidate, a single substation is configured to be added as a node to the MST in the center of Turbine node locations. I also added cabling lengths for connecting cables to each turbine from the ground (calculated by adding up the distance to seabed/elevations for each turbine). Finally, I also added the Export Cable length for each candidate, calculated as the distance from the substation to a destination on the shore.

Visual for the Cable Length Objective mentioned above is shown in Figure 2.

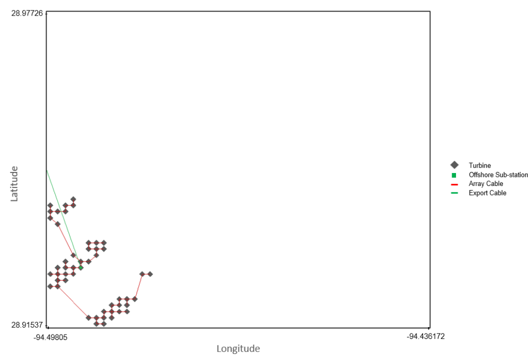


Figure 2: Visualization of the Cable Length objective calculations for an arbitrary OWF configuration.

2.4.2 Scaled Composite Single Objective Approach

An obvious incorporation of the extra heuristic into GA is through scaling the normalized values for the two objective values for a given candidate. In this, the heuristic performances of the candidate population is used to rank the candidates by combining averaging/scaling the ranks for the separate objectives.

2.4.3 NSGA II-Pareto-based Approach

Deb et al. (2002) define the NSGA II approach to incorporating multiple objectives into GAs that I implemented for the OWF optimization problem. The NSGA II approach restricts the selection method to Tournament Selection. I chose to implement the Random Mutation and Uniform Crossover.

In the approach aimed at promoting exploration, the model first ranks the candidates by iteratively defining Pareto Fronts - the current best rank is given to candidates with performances in the two objectives such that there do not exist any other candidate in the population with better performances in both objectives. The candidates and then either selected into the next population based on their given ranks (smaller selected first) or larger "crowding distances". The crowding distance metric is calculated by finding the normalized euclidean distance between the given candidate and its neighboring candidates with the same rank in the Pareto Front connection line - candidates with best performances in either objectives for a given rank are automatically selected when choosing between those with same ranks. Through this crowding distance metric, the algorithm promotes exploration of the objective space in that it promotes candidates with higher likelihood of containing unique information (different from other candidates in the same rank).

3 Results and Discussion

3.1 Single Objective Genetic Algorithm Exploration

In my testing and recreation, I confirmed the potential of use of GA to OWF turbine location optimization for minimizing the power loss caused by the wake effect. As shown in the Figure 3, the GA algorithm is able to quickly make strides in improving the wake-effect objective value in early iterations to the initial randomly generated population. The algorithm then makes slower improvements to the objective until converging (not finding better candidate from the previous generation for I consecutive iterations). Looking directly at the actual configuration output shown in Figure 7, the turbines tend toward the North-East corner of the area - likely naturally to reduce the search space; that said the same configuration translated to any space should provide the same actual power-loss minimization. Furthermore, the turbine locations seem to form lines perpendicular to SE, likely to capture the dominating wind speed/direction in the dataset.

In the exhaustive look at the Single Objective Selection/Crossover/Mutation combination approaches shown in Figure 4, the Random Mutation method is consistently best performing mutation method, with Segment Crossover method mostly showing best results for the different selection methods. The Selection methods don't show a clear front-runner.

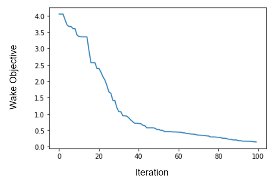


Figure 3: By-iteration Wake Objective performance of the best candidate

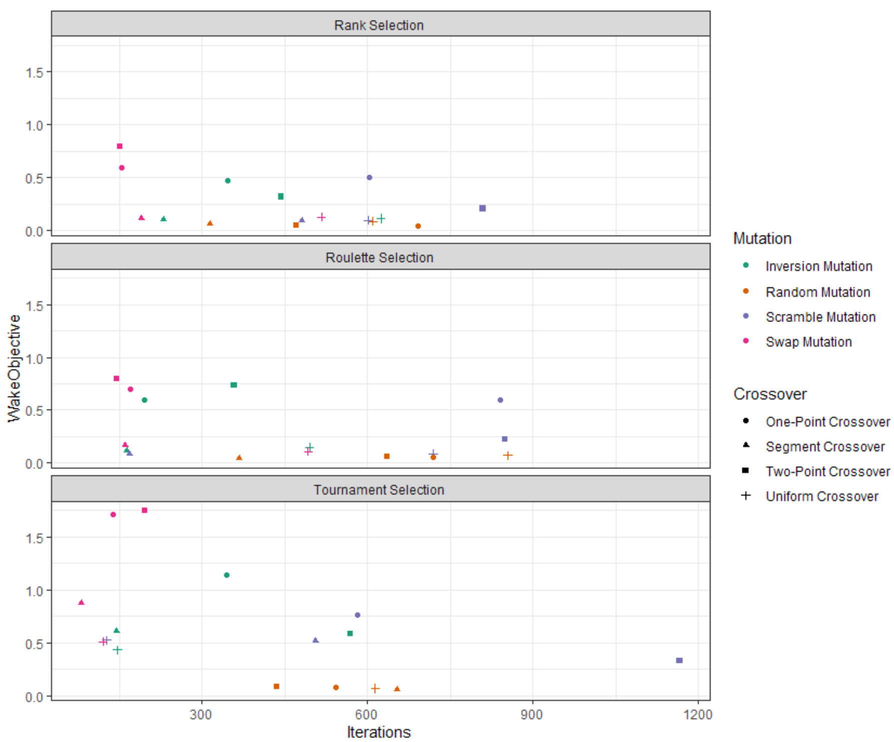


Figure 4: Wake Objective Performances for all combinations of Mutations, Crossovers and Selection methods. In each case, the algorithm completed processing when reaching a point of convergence - when the best candidate does not see objective improvements for 100 consecutive iterations. Mutations occurred for a given child with a probability of 0.1. Generally GA configurations across the board end with better objective performances for higher convergence iterations. Random Mutations are consensus best performing mutations.

3.2 Scaled Composite Single Objective Genetic Algorithm Exploration

In tests using the scaled composite calculation mentioned approach, I found that the algorithm is unable to converge - likely due to being unable to properly identify the minute improvements following the creations of the children. In this, I tested both equal(50-50) scaling for the two objectives and unequal(75-25) scaling favoring the Wake Objective; with both approach outputs showing only showing small improvements from the randomly generated Population in either objectives. This convergence dynamic is depicted in the Figure 6a by plotting the performances of the total populations in different iterations.

3.3 NSGA 2 Based Multiple Objective Genetic Algorithm Exploration

In tests using the NSGA2 based approach to Multi-Objective Genetic Algorithm, I found promising results - with Wake Objective minimization comparable to the classical Single Objective. The by-iteration objective performance of the best candidate is shown in Figure 5 - keep in mind that the best candidate in this case can be any candidate with rank-1; I chose to pick the best Wake Objective performing candidate.

Compared to the scaled Composite method to incorporating the new objective function, the NSGA2 based approach is able to correctly converge in terms of minimizing both Wake Objective and Cable Length Objective. This can be seen in the plots of all candidates in a given iteration shown in Figure 6b, as all candidates reach toward the bottom-left area of the objective performance graph.

Finally, to compare the classical Single Objective GA and my approach, I show the final results from the two methods in Figure 7. Single Objective GA is able to naturally produce candidates with turbines close to each other in this case as the winds speeds/directions in the data set are not even and dominated by those from arriving from SE. As seen in the graph, the final outputs are very much similar to each other with minute differences in some of the turbine placements - reflected in the closeness of objective value performances.

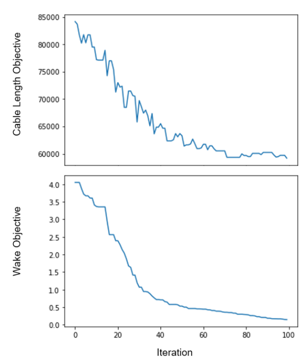
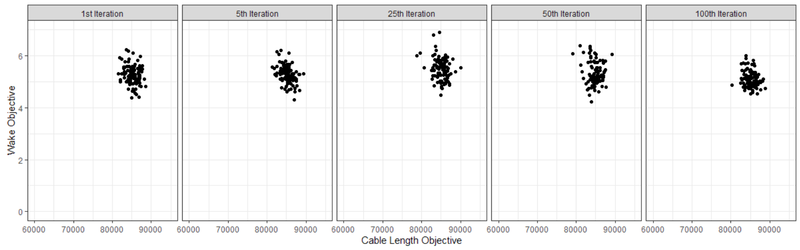


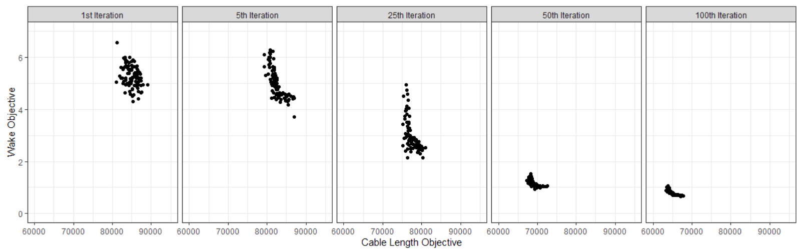
Figure 5: By-iteration performance of NSGA-2 multi-objective GA

4 Conclusions

In this work, I explored the application of Genetic Algorithms(GAs) in Offshore Wind Farm (OWF) turbine location planning. As the objective for the GAs, I defined an interaction-matrix Wake model based on Jensen's Wake model to account of power loss caused by Wake effects created by turbines Dhoot et al. (2021); Shakoor et al. (2016); Wu et al. (2022). I then explored the different approaches to single objective GA in the OWF context by considering all combinations of Parent Selection methods (Rank Selection, Roulette Selection, Tournament Selection), Pair Crossover methods (One-point Crossover, Two-point Crossover, Segment Crossover, Uniform



(a) Composite Single Objective (equal preference to Wake Objective and Cable Length Objective)



(b) NSGA-2 Based Multi-Objective

Figure 6

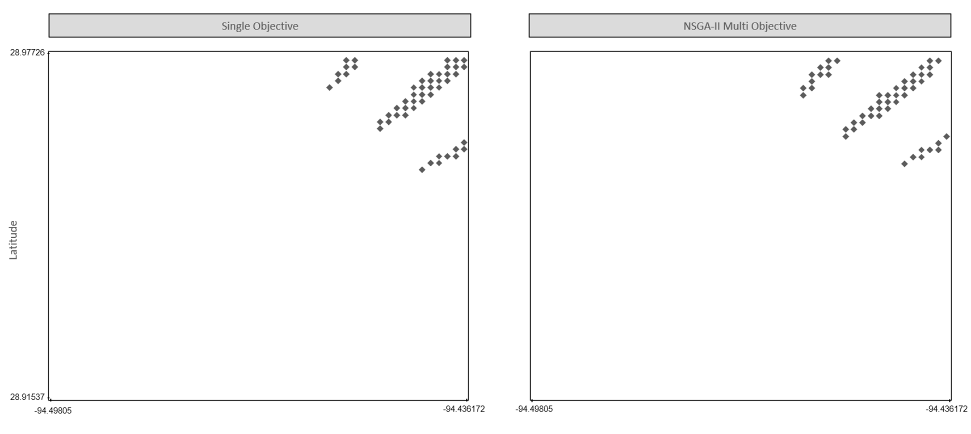


Figure 7: Configuration outputs for the two methods: (1) Classical Single Objective Genetic Algorithm with Random Mutations, Uniform Crossovers and Roulette Selection processed until 200 consecutive iterations without best candidate improvements and (2) NSGA2 Multi-Objective Genetic Algorithm aimed at both minimizing the Wake Objective and Cable Length Objective with Random Mutations, Uniform Crossovers and Tournament Selection processed for 1000 iterations. The above-depicted final best candidates have objective performances for Wake Objective and Cable Length Objective respectively as follows: (0.03669,60393.8) for Classical and (0.0451,60020.9) for Multi-Objective

Crossover) and Child Mutation methods (Inversion Mutation, Random Mutation, Scramble Mutation and Swap Mutation). I empirically show the results for each combination using collected data from a real-world potential OWF site.

Finally, I explored the potential incorporation of an extra objective to GAs to account for the final two configurable components to OWF planning. I defined a MST-based Cable Length Objective that calculates the minimum possible cabling length required to operate a given turbine configuration Hou et al. (2015). Using empirical results, I show that combining the two objectives into a Scaled Composite objective leads to improper GA formulation. And finally, I defined a NSGA-2 based approach to Multi-objective GA that correctly explores the objective space and converges to define results competitive with Single Objective GA. In empirical testing of the approach, I found that my model barely improves the cabling length naturally reached by Single Objective GA while hindering the power production potential.

5 Future Improvements

One potential mode of improving the NSGA-2 based approach is through defining a different Cable Length Objective function. The current approach simply calculates the minimum cabling length required to operate a given OWF, and therefore it is not likely indicative of actual cabling configuration that must adhere to constraints from power-loss and power-flow. A more efficient equivalent to Ant Colony Optimization model as defined by Wu et al. (2022) can lead to incorporating more accurate cabling length calculations into the multi-objective GA.

6 Real-World Application

Throughout the study, I simplified the problem statement of OWF planning by only considering a small area of the actual potential OWF site actually defined by the US Government. In this, I only consider a square shape area that does not account for the fact that most OWF sites are irregular shapes with potential for restricted spaces within those areas (turbines may be barred from being placed in a given location due to wild-life preservation efforts under the location).

To account for this irregularity, a potential work around for potential irregular sites is by first defining a square/rectangular area overlaying the actual site. This square/rectangular area can then be used to define the interaction matricies for the wake calculations. Finally, one can remove the restricted cells from the matricies (removing them from the search space for the GA in the future) and define a map from its flattened view to the actual site to then be used for cabling length objective calculations. One other potential augmentation for use in real-world scenario is through incorporating a k-means approach to MST calculations such that turbines are divided into k clusters (with the centers standing as the k substation locations and MST length calculated separately for each cluster) Dutta and Overbye (2012).

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