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TWO-STAGE SIMULATION OPTIMIZATION FOR OPTIMAL DEVELOPMENT OF OFFSHORE WIND FARM UNDER WIND UNCERTAINTY

Qing Li
Honggang Wang

Department of Industrial & Systems Engineering
Rutgers, the State University of New Jersey
CoRE Building, Room 201
96 Frelinghuysen Road
Piscataway, NJ 08854, USA

ABSTRACT

As one of the most promising renewable energy sources, wind energy reduces consumption of fossil fuels and becomes economically viable with significant environmental benefits. Offshore wind resources are abundant and more stable for sustainable clean energy production. In this paper, we propose stochastic models and optimization methods for optimal development of offshore wind farms. Wind uncertainty is studied by using probabilistic models with seasonal/time scenarios. A two-stage optimization framework is proposed to first determine the optimal number of turbines and then refine the turbine placement for most-productive layout under wind uncertainty. The method is tested using an offshore farm at the south New Jersey coast.

1 INTRODUCTION

As a fast growing renewable energy resource, wind power provides a sustainable energy alternative with lower operational costs and less environmental impact. Worldwide wind energy production and consumption increase steadily. As of 2014, the market volume for new wind projects was 40% bigger than in 2013. In the United States, wind power is a $10 billion per year industry, with the potential to generate 20% of national electricity by 2030.

Offshore wind, specifically, is known to be strong, steady and abundant. Since offshore wind is stronger during the middle of the day and evening when energy is consumed most, offshore wind power can play a significant role for peak hour energy supply. In Europe, there have been installed more than 2,000 offshore wind turbines, providing thousands of Mega-watts of electricity each year. Offshore wind projects in the States, however, is in the early stage. In 2014, the US Department of Energy initiated three pilot offshore wind projects, including the on-going one in south New Jersey. In this paper, an offshore wind farm located at south Jersey coast is considered and studied.

Offshore wind farm development project involves determining the number of turbines and their locations. Due to the uncertainty of wind directions and speeds, it is difficult to find the most productive locations for all turbines. Research on wind farm development faces the following three challenges: (i) Due to the dynamic nature of wind and complex interaction between turbines, accurate evaluation of power generation of the farm is subject to various sources of uncertainty. (ii) The system performance is highly nonlinear and stochastic. To find the optimal development plan, decision variables, such as the number of turbines and its corresponding placement, have to be considered simultaneously under wind uncertainty.

(iii) A mixed-integer stochastic programming model needs to be developed to account for integer variables, continuous variables, and stochastic wind parameters.

The wind farm layout problem is often studied as combinatorial problems. Extensive research in wind farm layout design includes both onshore wind farms (Mosetti et al. 1994; Ozturk and Norman 2004; Grady et al. 2005; Marmidis et al. 2008; Wan et al. 2009; Wan et al. 2009; Emami and Noghreh 2010; González et al. 2010; Kusiak and Song 2010; Li et al. 2010; Ituarte-Villarreal and Espiritu 2011; Chen and Agarwal 2012; Wan et al. 2012; Chen et al. 2013) and offshore farms (Pérez et al. 2013; Yuan-Kang Wu 2014; Gao et al. 2015; Peng Hou 2015; Rodrigues et al. 2015).

To accurately evaluate wind energy generated from wind turbines, wake loss models have been widely applied to count for turbine interactions. Analytical wake loss models characterize the wind speed under wake by the use of closed-form expressions. One of the most popular analytical models was developed by Jensen (Jensen 1983), which has been widely adopted in wind energy literature. Jensen's wake loss model assumes that the wake expands linearly, and the speed of turbine in a wake region can be calculated by a function of distance between turbines. Due to its simplicity and relative accuracy, Jensen's model is the most commonly used wake loss model in wind energy simulation; details are introduced in Section 2.3. There are other analytical wake loss models (Ozturk and Norman 2004; Ishihara et al. 2004; González et al. 2010). For instance, Ishihara's model (Ishihara et al. 2004) considers a turbulence's recovery rate; Ozturk's model (Ozturk and Norman 2004) develops a direction-based model in which linear reduction wake model is considered in cross wind interference and quadratic reduction wake model is used in prevailing wind interference.

To find the optimal placement of turbines, exhaustive evaluation of all possible turbine placements in a field is not feasible, particularly for large-scale development problems. Mixed-integer programming (MIP) models, in this case, can be employed to search for optimal or practically good solutions. Methods developed in previous literature for such MIP problems can be classified by considering candidate turbine locations (Mosetti et al. 1994; Grady et al. 2005; Marmidis et al. 2008; Wan et al. 2009; Wan et al. 2009; Emami and Noghreh 2010; Li et al. 2010; Mittal 2010; Ituarte-Villarreal and Espiritu 2011), or by predetermining total numbers of turbines (Kusiak and Song 2010; Wan et al. 2012). For example, in Mosetti's (Mosetti et al. 1994), when the possible turbine locations are pre-defined (in the center of 10x10 discretized cells), the optimization process is applied to search all possible layout solutions for the number of turbines and their best placement. For placement optimization, evolution based global search algorithms, such as Genetic Algorithm (Mosetti et al. 1994; Grady et al. 2005; Emami and Noghreh 2010; Li et al. 2010; Chen et al. 2013; Gao et al. 2015), Gaussian Particle Swarm (Wan et al. 2012; Peng Hou 2015), virus based algorithm (Ituarte-Villarreal and Espiritu 2011), bionic algorithm (Song et al. 2013) are widely used to find the optimal placement. Wan (Wan et al. 2009) develops a two-stage Genetic Algorithm for wind farm development. In the first stage, it employs binary Genetic Algorithm to seek turbine locations for minimal cost per unit energy production. During the second stage, the positions of turbines are allowed to be adjusted within their cells to further improve the energy production. Wan's work (Wan et al. 2009) is different from the our work in this paper in that our two-stage framework optimizes the turbine placement inside the whole farm in the send stage optimization.

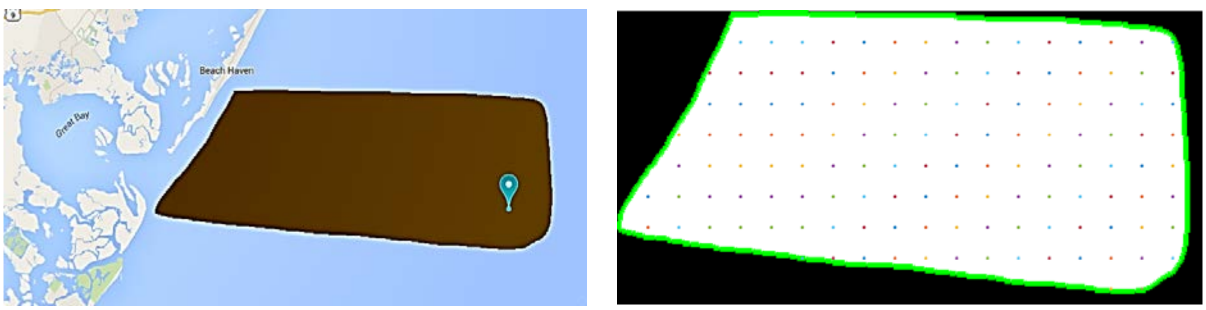
For the optimal development of wind farm under wind uncertainty, the proposed two-stage optimization framework couples a discrete model for the optimal number of turbines and a continuous model for a refined turbine placement solution. Probabilistic wind models are built based on real offshore wind data collected at the New Jersey coast. The contributions of this work include: (i) we consider uncertainty of wind based on real offshore wind data and perform simulation optimization for offshore wind farm development; (ii) We develop a two-stage simulation based optimization framework that can be used to determine both the number of facilities (turbines) and locations of these facilities. As a general framework, this method can be used for logistic, transportation, and facility planning problems under complex system uncertainty.

The remainder of this paper is organized as follows. Section 2 describes the problem formulation, including wind farm models, wind uncertainty model, wake loss model along with two-stage optimization methodologies. Section 3 presents computational studies and discusses the optimization results. Section 4 concludes this work.

2 PROBLEM FORMULATION

2.1 An Offshore Wind Farm at New Jersey Coast

The wind farm case studied in this paper is based on an on-going offshore wind power project in New Jersey. The considered region off the coast of New Jersey is shown in Figure 1(a). During the first stage, 132 candidate locations are pre-determined for possible turbines as shown in Figure 1(b). The farm is about 7km x 3km and adjacent turbine locations are about 400m apart. Different from onshore wind farm, offshore wind field (particular for wind speed) is heterogeneous; wind decreases significantly towards coastline due to change of tide and terrain conditions. To take this into account, a linear reduction term is added to the wind speed model. We assume a 20% reduction as wind flows through the farm from its east side (ocean) to west side (coastline).



Offshore wind farm in New Jersey. (b) Wind farm with 132 candidate turbine locations.

Figure 1: An NJ coast offshore wind farm.

2.2 Modeling Wind Uncertainty

The wind uncertainty along the NJ coast is studied and historical wind speed and direction data in this area is collected. The wind speed data is collected once every 10 minutes at the measuring location. The 2014's one year wind data is used to fit the wind probabilistic models.

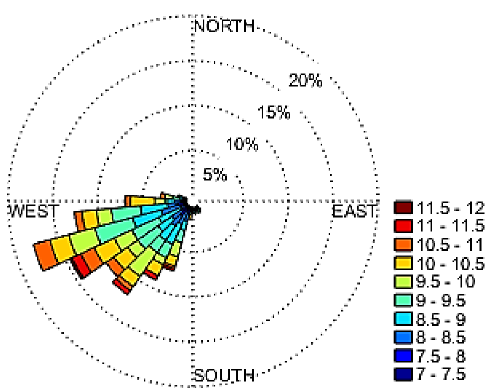


Figure 2: A rosemap for stochastic wind modeling.

Based on the wind rosemap shown in Figure 2, historical data indicates wind blows in the direction mainly from 162° to 267°, with higher probabilities falling in the range of (181°,267°). With some distribution analysis, the wind direction θ_0 at measuring location can be estimated by a lognormal distribution $\log(\theta_0) \sim N(5.3566, 0.1184^2))$. Wind speed changes significantly at different times of a day.

Thus, we use different wind speed models considering two dayparts scenarios: (12pm,22pm], (22pm,12pm]. Figure 2 indicates the wind speed is mostly in the range of 8 m/s-11 m/s. With some simple statistical fitting analysis, two Weibull distributions are determined for the two scenarios respectively with parameters shown in Table 1.

Table 1: Weibull models for stochastic wind speed considering two dayparts scenarios.

	T(1) (22:10pm~12pm)	**T(2) (12:10pm~22pm)**
Shape Parameter	3.0523	2.5042
Scale Parameter	10.5787	9.6388

2.3 Modeling Wake Loss among Turbines

Wind energy captured by a turbine in the farm varies by locations and wind dynamics. To model such stochastic interaction between turbines, a wake loss model is needed to estimate the varying speed captured by different turbines. Jensen's model is used to quantify the wake effects among turbines. Under assumptions, the vertex vortices effect is neglected in the near field where wind speed right behind the rotor is reduced to one third of original speed, thus the wake model is better applied in the remote wake region. The wake radius expands linearly behind the turbine and the wake deficit is obtained by assuming linearized momentum conservation. In Jensen's wake loss model, the speed at a turbine is mainly affected due to wake loss caused by upwind turbines. Figure 3 shows the wake shadow behind an upwind turbine in the wind direction.

The wake region of an upwind turbine can be simply defined by a cone centered at its rotor centroid expanding along the wind direction d of an angle γ=arctan(κ), where κ is the speed entrainment constant. If a downwind turbine j is inside the wake cone of an upwind turbine i, the speed reduces from u_0 to u, where u_0 is the upwind speed at i; otherwise j has the same speed u_0 as i if j is not in the wake of i.

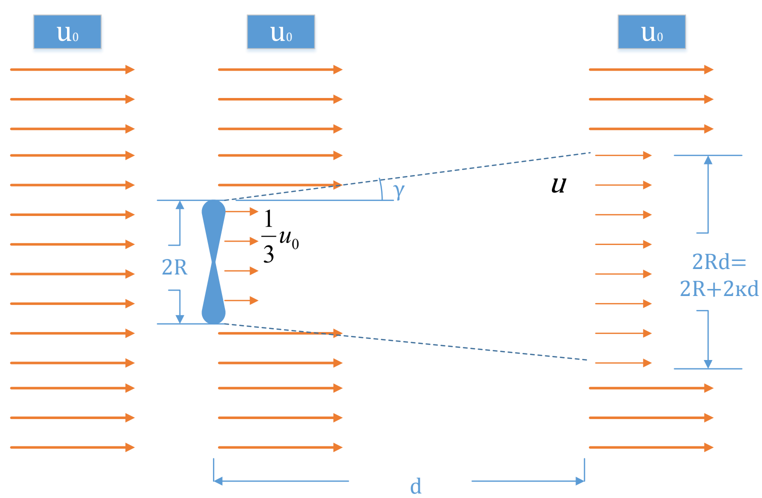


Figure 3: Jensen's Wake Loss Model.

Considering wake effects from multiple upwind turbines, a downwind turbine can have wake loss caused by more upwind turbines. For example, as shown in Figure 4, when the wind blows from west to east, both turbines T1 and T2 are upwind without any wake effect between each other; turbine T5 has the wake interaction solely from T2; and T4 is located in the combined wake loss region of T1, T2 and T3. On the other side, T3 is outside of both wake cones of its upwind turbine T1 and T2; therefore, there's no wake loss of wind power for T3, given this wind direction.

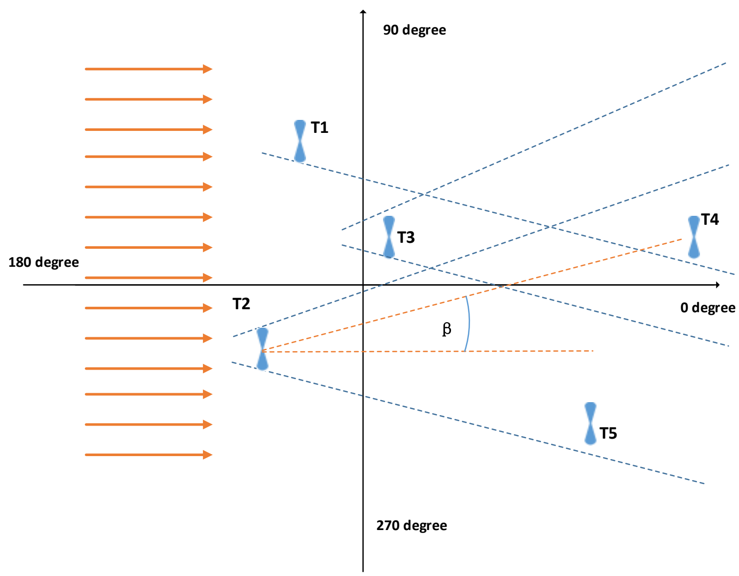


Figure 4: Turbines under the Wake of Multiple Turbines (top view).

Wind power generation at a time instant for a turbine is often modeled by equation (11) with the wind speed U at the turbine. Accurate evaluation of wind power generated from a turbine also needs to offset the power from wake loss caused by upwind turbines. As the wind direction and speed are highly dynamic, the wake loss zones in the farm changes in time.

Considering the wake loss between a pair of identical turbines i and j, the Jensen's model quantifies the reduction of wind speed. As indicated with equation (1), the reduced wind speed u at the downwind turbine j can be calculated by equation (2).

$$Def = 1 - \frac{u}{u_0} = \frac{2\alpha}{\left(1 + \frac{\kappa d}{R}\right)^2} \tag{1}$$

$$u = u_0\left[1 - Def\right] = u_0\left[1 - \frac{2\alpha}{\left(1 + \frac{\kappa d}{R}\right)^2}\right] \tag{2}$$

Where u_0 is the wind speed at turbine i, u is the reduced wind speed at turbine j, d is the distance between turbines i and j in the wind direction, and R is the radius of turbine rotor. The entrainment constant κ, which indicates how quickly the wake decays in distance, can be quantified with a simple model (3):

$$K = \frac{0.5}{\ln\left(\frac{Z}{Z_0}\right)} \tag{3}$$

Where Z is the hub height of wind turbine, and Z_0 is the surface roughness of the terrain. In this study, identical wind turbines and a flat farm land spans with homogeneous obstructions are considered, therefore Z_0 and Z are assumed to be constant throughout the field.

In equation (1), α is the axial induction factor around a turbine, specifying the reduction rate of wind speed when the wind passes through the upwind turbine. The factor α can be calculated using the thrust coefficient C_T:

$$\alpha = \frac{1}{2}\left(1-\sqrt{1-C_T}\right) \tag{4}$$

Where C_T is a characteristic parameter of the turbine. Let R_d be the radius of wake cone, R_d can be calculated by equation (5).

$$R_d = R\sqrt{\frac{1-\alpha}{1-2\alpha}} \tag{5}$$

By equations (3) and (4), the reduced wind speed u in the wake zone (equation (2)) is a function of the distance d between turbines i and j. When a turbine j locates within multiple turbines' wake regions, due to the multiple wake loss effects, the total energy loss for j can be computed by equation (6) based on the kinetic energy balance. After a simple transformation by equation (1) and (6), the wind speed for turbine j can be computed by (7).

$$Vel\_def_j = \sqrt{\sum_{i=1, i\neq j}^{N_j} Vel\_def_{i,j}^2} \tag{6}$$

$$u_{\mathrm{j}} = u_0\left[1-\sqrt{\sum_{i=1}^{N_j}\left(1-\frac{u_{ij}}{u_i}\right)^2}\right] \tag{7}$$

In equation (7), N_j is the total number of upwind turbines that generate wake effect $Vel\_def_{i,j}$ at turbine j. Note that N_j may vary continuously as the wind direction and speed change through the time and at different locations in the farm. Here u_{ij} represents the reduced speed at turbine j affected by upwind turbine i.

2.4 Optimal Development of Offshore Wind Farm

The objective of wind farm development projects considers to minimize the Cost per Expected Power Production (CEPP). The total development costs and expected annual energy production are evaluated and analyzed. Distance constraints for turbine layout design are included in the proposed turbine placement optimization models.

2.4.1 Costs of Wind Turbines

The costs for offshore wind farm development include the capital investment of equipment, cable and devices installation, as well as labor cost. In this paper, it aims to minimize such development cost. The average installation cost for each turbine can be reduced by installing more turbines in the field. As discussed in Mosetti's and Grady's work (Mosetti et al. 1994; Grady et al. 2005), the total cost of a wind farm project (K$) can be estimated by N, the total number of turbines installed in the wind farm.

$$C_{ins}(N) = N\left(\frac{2}{3}+\frac{1}{3}e^{-0.00174N^2}\right) \tag{8}$$

From equation (8), if N is large enough, the average installation cost of each turbine can be reduced approximately by $\frac{1}{3}$.

The farther a turbine installed from the coast, the more it will cost due to increasing consumption of cable materials and associated installation cost. Such cable cost can be estimated by a linear cost function:

$$C_{cable}(D_i) = c_0 + c_d * D_i \tag{9}$$

Where D_i is the distance of a turbine away from the coast, c_0 is fixed cost for major cable structure installation and c_d is the cable installation cost per unit distance from the shoreline. The total wind farm cost is modeled as:

$$C(N, D_i) = C_{ins}(N) + \sum_{i=1}^{N} C_{cable}C(D_i) \tag{10}$$

2.4.2 Expected Annual Energy Production

The potential energy P_{wind} in the wind of speed U is commonly modeled by equation (11). Considering the energy loss in power generation, a turbine can produce $P_{turbine}$ at a certain time with wind speed U and efficiency coefficient C_p, as described by equation (12).

$$P_{wind} = \frac{1}{2}\rho A U^3 \tag{11}$$

$$P_{turbine} = \frac{1}{2}C_p \rho A U^3 \tag{12}$$

Where ρ is the air density 1.25kg/m3 at the sea level. A is the rotor swept area and U is the wind speed. The power coefficient C_p varies depending on aerodynamic and mechanical losses. According to Betz's law, the maximum energy captured by a turbine can be no more than 59.3% of the kinetic energy in wind; that is $C_p \leq 0.593$. A simple power function at turbine i is applied as the function of wind speed u_i:

$$P_{turbine\ i}(u_i) = 0.3u_i^3 \tag{13}$$

In general, the power generated from a turbine is not always related to wind speed u_i by (13) when u_i is outside a certain range. The model (13) is only applied to a certain range of wind speed $[u_{in}, u_{out}]$ for a designated turbine. The minimum effective speed u_{in} is called the cut-in speed for a turbine to start generating power, while the maximum effective speed u_{out} is called the cut-out speed. When $u \geq u_{out}$, turbines will terminate operation to avoid damage. In this study $u_{in} = 3\ m/s$, $u_{out} = 22m/s$. For any speed u in between u_{in} and u_{out}, a turbine generates energy estimated by (13).

2.4.3 Objective Model

We use Weibull probabilistic models $f_{u_0}(u_0)$ and Lognormal probabilistic model $f_{\theta_0}(\theta_0)$ respectively for modeling wind speed and direction. The expected total wind power produced from a wind farm with N turbines' placement can be computed as follows.

$$E_{\theta_0,u_o}(u_0,\theta_0) = \sum_{i=1}^{N} \int_0^{360} \int_{u_{in}}^{u_{out}} P_i(u_i; u_0, \theta_0) f_{u_0}(u_0) f_{\theta_0}(\theta_0) du_0\, d\theta_0 \tag{14}$$

Where u_0 is the speed at which the wind enters the farm, and u_i is the actual wind speed captured by turbine i taking into account the wake loss from upwind turbines.

Given a layout X=[X_1, X_2, X_3, …, X_i,…,X_N], $u_i = u_0$ if turbine i is located at a place without any upwind turbines given the wind direction θ_0; otherwise, $u_i < u_0$ can be quantified by considering the wake loss from related upwind turbines:

$$u_i(X; u_0, \theta_0 \mid T(s), s) = u_0 \left(1 - \sqrt{\sum_{j=1}^{N_i(X; u_0, \theta_0 | T(s), s)} \left(\frac{2\alpha}{\left(1 + \frac{\kappa d_{ij}(X; u_0, \theta_0 \mid T(s), s)}{R}\right)^2} \right)^2} \right) \tag{15}$$

Where T(s) is time scenario index as specified in Table 1.

The objective function of optimization is to minimize the annual total development costs per expected power production (CEPP). It can be formulated as follows.

$$argmin_{(N,X)}\ CEPP = \frac{Annual\ Total\ Cost}{Expected\ Power\ Production}$$

$$= \frac{C\ (N, D_i)}{E_{\theta_0,u_o}} = \frac{N\left(\frac{2}{3} + \frac{1}{3}e^{-0.00174N^2}\right) + (c_0 + c_d * D_i)}{\sum_{i=1}^{N} \int_0^{360} \int_{u_{in}}^{u_{out}} P_i(u_i; u_0, \theta_0) f_{u_0}(u_0) f_{\theta_0}(\theta_0) du_0\, d\theta_0}$$

$$u_0 \geq u_i$$

$$\|X_i - X_j\| \geq 200, \forall\, i \neq j \in \{1,2 \ldots N\} \tag{16}$$

Since f_{u_0} is a Weibull density function, and f_{θ_0} is a Lognormal density function, there is no closed form solution (N^*, X^*) for this model. Monte Carlo methods can be applied to sample wind data (u_0, θ_0) and to estimate CEPP with a sample mean.

To account for significant variations during a day, two daypart scenarios s ($s \in \{1,2\}$) are considered: (22pm,12pm], (12pm,22pm]: s=1 when wind energy is produced during (22pm,12pm]; s=2 otherwise. One Weibull model is used for each of the two scenarios as discussed in 2.2. To approximate (16), twenty data points from each scenario s are randomly sampled, resulting in 40 wind data points for (u_0, θ_0). In this case, by equations (1)(2)(6)(7), CEPP in model (16) can be approximated by the sample mean:

$$\widehat{CEPP} = \frac{N\left(\frac{2}{3}+\frac{1}{3}e^{-0.00174N^2}\right) + (c_0 + c_d * \sum_{i=1}^{N} D_i)}{\sum_{i=1}^{N}(0.25\sum_{s=1}^{2}(0.1\sum_{T(s)=1}^{20} 0.3(u_i(X;u_0,\theta_0|T(s),s))^3))} = \frac{N(\frac{2}{3}+\frac{1}{3}e^{-0.00174N^2}) + (\$10{,}000 + \$500 * D_i)}{0.0075\sum_{i=1}^{N}\sum_{s=1}^{2}\sum_{T(s)=1}^{20} u_i(X;u_0,\theta_0|T(s),s)^3} \quad (17)$$

Where building the cable structure has a fixed cost c_0 \$10k and installation associated cost \$500/m.

2.5 Two-stage Optimization Framework

Genetic algorithm (GA) is a population based random search method, which has been widely applied to wind turbine layout design. GA is general as it does not require computing gradient of the objective functions. GA, however, is often slow and in some cases fails to converge.

In order to seek both the optimal number of turbines and their most productive locations, a two-stage optimization framework is proposed. In the first stage of optimization, the wind farm field is discretized to a number of candidate locations for turbines placement. A GA based binary global search optimization model is used to find the optimal number of turbines and their locations. As shown in Figure 5, the optimization in first stage searches solutions K=[K_1, K_2, K_3, …, K_i,…,K_M] where $K_i \in \{0,1\}$ and M is the total number of candidate locations (i.e. in this case M=132), $K \in \{0,1\}^M$. $K_i = 1$ indicates a turbine installed at location i and $K_i = 0$ when no turbine built at i. Thus, GA returns a solution K^* specifing a layout design for the wind farm development. $\sum_{i=1}^{M} K_i = N$ is the optimized number of turbines needed.

The second stage optimization takes the initial solution $\overrightarrow{X_0}$ that is the corresponding coordinates for turbines determined by $\vec{K}^*$. The continuous model with decision variables (x_i,y_i) will be solved by a local search optimization method for an improved layout design solution $\overrightarrow{X^*}$ that specifies the most-productive energy production locations for the N turbines in the field. In this work, a Pattern Search algorithm is employed to find $\vec{X}^*$.

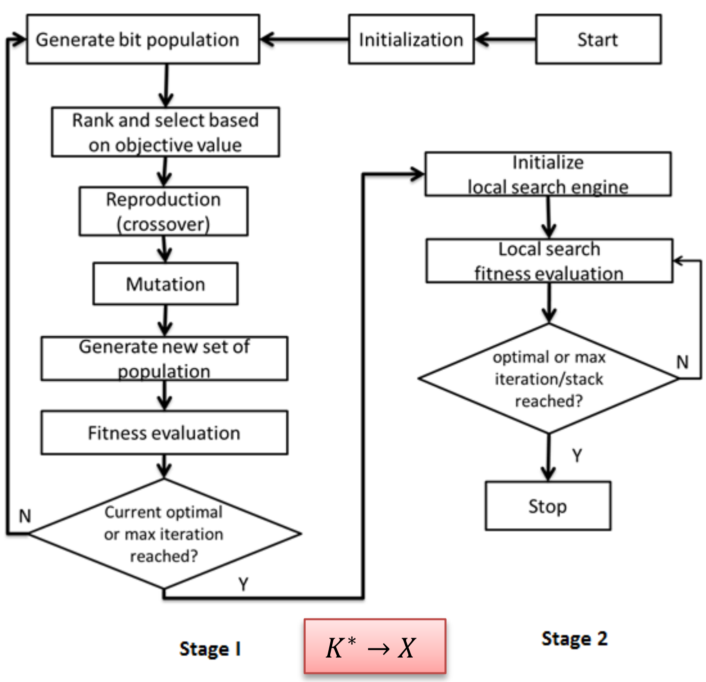


Figure 5: Two-stage optimization model.

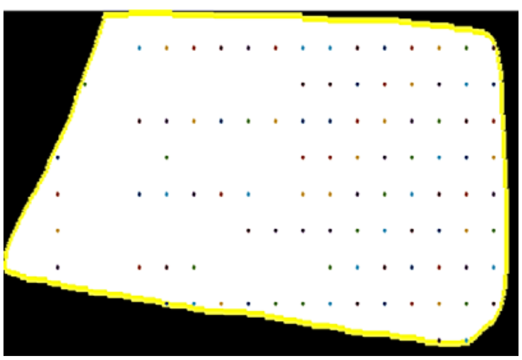
3 NUMERICAL ANALYSIS ON AN OFFSHORE WIND FORM

To demonstrate the proposed two-stage optimization framework, we consider an offshore wind farm at the NJ coast. Wind uncertainty is studied using probabilistic models by considering stochastic speed/direction scenarios with Monte Carlo sampling.

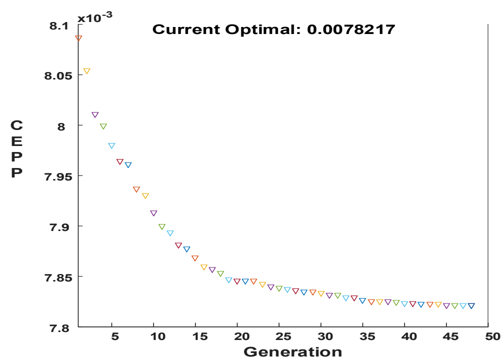
Identical turbines are considered with parameters: the hub height Z = 60m, the thrust coefficient C_T = 0.88, the surface roughness length Z_0 = 0.3m, and the rotor radius R = 20m. For the first stage, the field has total of 132 candidate locations with 400m apart. In the second stage of optimization, the N turbines are allowed to be located anywhere with a minimum distance of 200m between adjacent turbines. By equations (3) and (4), the values of entrainment constant κ and the axial induction factor α can be computed: κ=0.0944, α=0.3268.

Based on the one-year wind data at a measurement location, the wind direction is modeled with a Lognormal distribution $\log(\theta_0) \sim N(5.3566, 0.1184^2)$, and the wind speed is modeled with Weibull distribution with parameters shown in Table 1. Figure 2 shows that the wind directions lie mostly in the range of (181°, 267°) and the wind speeds are mainly between 8m/s and 11m/s. The offshore wind often blows from the ocean towards the coast and the speed reduces when it approaches the coastline. A 20% linear reduction of wind speed is used when wind hits coastline.

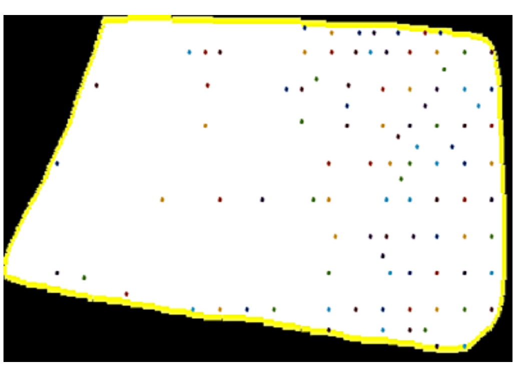
We apply the two-stage simulation optimization to this case. The optimized layouts in Figure 6 show that turbines tend to locate at farthest places from the coast where the wind is strongest, even though the cable costs will be higher. Figure 6(a) presents the optimized layout by the first stage of optimization, where the 98 turbines are located at the predetermined cells.



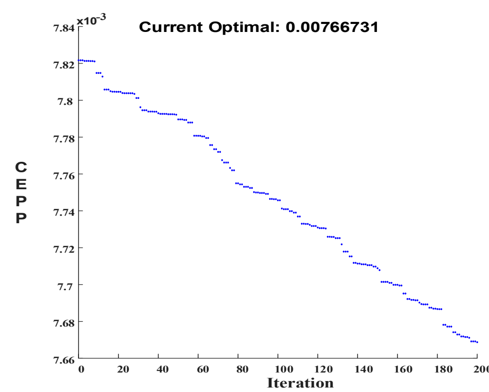
(a) Stage 1 Layout.



(b) Stage 1 Convergence.



(c) Stage 2 Layout.



(d) Stage 2 Convergence.

Figure 6: Optimal layouts and optimization progresses.

The optimization results of this case are summarized in Table 2. The first stage optimization determines that 98 turbines to be built in the farm with objective value CEPP=$\$7.8217 \times 10^{-3}$ /kW.year. The second stage further reduces CEPP by changing the locations of those 98 turbines; the CEPP value is decreased to $\$7.6673 \times 10^{-3}$ /kW.year.

Table 2: Optimization results for developing the NJ offshore wind farm.

	Stage 1 (discrete location-based search)	Stage 2 (continuous coordinates-based search)
Number of turbines	98	98
Expected power (kW/year)	18,550	20,319
Total Cost	\$145,092	\$155,792
Objective value CEPP (\$/kW.year) x10-3	7.8217	7.6673

4 CONCLUSION

In this study, a two-stage optimization framework is presented to optimize offshore wind farm layout design. Wind uncertainty is analyzed using probabilistic models based on one-year wind measurement data. The expected wind energy generation is estimated with sample means using Monte Carlo simulation. In the first stage, GA optimization is used to search candidate locations for the optimal number of turbines and their corresponding placement. In the second stage, a pattern search algorithm is applied to further improve turbine placement by searching continuous location variables so that CEPP is minimized.

In the future work, more realistic cost functions such as maintenance and failures will be considered. Multiple criteria decision making for the project including costs, revenues, and carbon emission control will be analyzed. Further work also includes development of new optimization solvers used in the two-stage optimization framework for large-scale wind farm development and other energy production systems.

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AUTHOR BIOGRAPHIES

QING LI is a Ph.D. candidate in the department of Industrial and Systems Engineering at Rutgers, the state university of New Jersey. Her research interests include multiple objective optimization, simulation-based nonlinear optimization solving real world renewable (wind, solar, biofuel) & nonrenewable energy (oil & gas) production and management problems. Her email address is ql78@rutgers.edu.

HONGGANG WANG is an Assistant Professor in the department of Industrial and Systems Engineering at Rutgers, the state university of New Jersey. He holds a Ph.D. in Industrial Engineering at Purdue University. His research interests include discrete stochastic optimization via simulation, system uncertainty modeling and analysis, operation research and their applications in oil-gas exploration and production, shale gas production, carbon sequestration and geothermal resources. His email address is hw260@rci.rutgers.edu.