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A Response Surface-Based Cost Model for Wind Farm Design

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ABSTRACT

A *Response Surface-Based Wind Farm Cost* (RS-WFC) model is developed for the engineering planning of wind farms. The RS-WFC model is developed using Extended Radial Basis Functions (E-RBF) for onshore wind farms in the U.S. This model is then used to explore the influences of different design and economic parameters, including number of turbines, rotor diameter and labor cost, on the cost of a wind farm. The RS-WFC model is composed of three components that estimate the effects of engineering and economic factors on (i) the installation cost, (ii) the annual Operation and Maintenance (O&M) cost, and (iii) the total annual cost of a wind farm. The accuracy of the cost model is favorably established through comparison with pertinent commercial data. The final RS-WFC model provided interesting insights into cost variation with respect to critical engineering and economic parameters. In addition, a newly developed analytical wind farm engineering model is used to determine the power generated by the farm, and the subsequent *Cost of Energy* (COE). This COE is optimized for a unidirectional uniform "incoming wind speed" scenario using Particle Swarm Optimization (PSO). We found that the COE could be appreciably minimized through layout optimization, thereby yielding significant cost savings.

1. Introduction

Wind energy is becoming an increasingly important source of renewable energy, particularly when we seek to reduce the emission of greenhouse gases and to mitigate the effects of climate change. Over the past five years, the global installed wind capacity has been growing at an average rate of 27.8% per year (BTM, 2011).

In recent years, the U.S. has emphasized the nation's need for greater energy efficiency and for a more diversified energy portfolio (Snyder and Kaiser, 2009; Berry, 2009). This plan has laid the path for a national effort to explore an energy scenario in which wind would provide 20% of U.S. electricity by 2030 (Lindenberg, 2008).

Efficient planning and resource management are likely to play important roles towards the success of an energy project. Wind can be viewed as one of the most potent alternative energy resources. However, the economics of wind energy does not yet place it at a competitive advantage over coal or natural gas (fossil fuels). The cost models of wind projects developed in this paper are intended to help investors better plan their projects, as well as to provide valuable insight into the areas of the project that require further development to improve the overall economics of wind energy.

The cost of developing a wind farm has received considerable attention both in academia and industry. As discussed in the European publication *Wind Energy–The Facts* (Morthorst et al., 2009), the primary factors governing wind farm economics include: (i) the installation cost, (ii) the Operation and Maintenance (O&M) cost, and (iii) the electricity production. Fig. 1 illustrates a typical breakdown of the total cost for an offshore wind farm in shallow water, which includes: (i) wind turbine purchase, (ii) onshore utility connection, (iii) O&M cost, and (iv) decommissioning (Musial et al., 2006). The installation costs generally include those of the wind turbine purchase, support structure, and grid connection. It is observed that the installation cost and the O&M cost account for 95% of the total cost.

1.1. Cost analysis review

Several models have been developed to estimate the cost for both onshore and offshore wind farms in Europe (Cockerill et al., 1998; Cockerill, 1998; Herman, 2002b, 2003). A *Geographical Information System* (GIS) based cost model for the estimation of the COE is presented in the publication *Structural and Economic Optimization of Bottom-Mounted Offshore Wind Energy Converters*

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Nomenclature

N	Number of wind turbines in a farm
P_0	Rated power of a wind turbine (kW)
C_t	Total annual cost per kilowatt installed of a wind farm ($/kW)
n	Wind turbine lifetime (year)
C_{in}	Installation cost per kilowatt installed of a wind farm ($/kW)
C_{ma}	Cost of material ($)
$C_{O\&M}$	Operation and maintenance cost per kilowatt installed of a wind farm ($/kW)
D	Wind turbine rotor diameter (m)
H	Hub height of a wind turbine (m)
LPC	Levelized production cost ($/kWh)
n_{fi}	Years financed
ϕ	Percentage financed
η	Interest rate
C_{LC}	Wage per hour for construction labor ($/h)
C_{LM}	Wage per hour for management labor ($/h)
C_{LT}	Wage per hour for technician labor ($/h)
n_p	Number of data points evaluated
n_u	Number of coefficients in the RS-WFC model
m	Number of design variables
U	Wind profile
P_{farm}	Power generated by a wind farm (kW)
C_p	Power coefficient of a wind turbine
a	Induction factor of a wind turbine
COE	Cost of energy ($/kWh)
AEP_{net}	Net annual energy production (kWh)
$RMSE$	Root mean squared error
RAE	Relative accuracy error

(OWECS) in 1998 (Cockerill et al., 1998; Cockerill, 1998). The model allowed rapid evaluation of the economic viability of certain OWECS concepts over a large geographic area, and the identification of economically suitable sites for locating OWECS. The *Energy Research Centre of the Netherlands* (ECN) has developed a computer program named *Offshore Wind Energy Costs and Potential* (OWECOP). This program can evaluate the COE for offshore wind energy, using a GIS database. A probabilistic analysis was implemented into the OWECOP cost model to form the OWECOP-Prob (Herman, 2002b). An investigation of the transport and installation cost in offshore wind farms was carried out and implemented in the OWECOP II model of ECN (Herman, 2002a).

Approximate analytical expressions, which represent the cost of a wind farm as functions of various contributing factors, have also been explored in the literature. In the paper (Kaldellis and Gavras, 2000), a complete cost-benefit analysis model, adapted for the Greek market, was presented to evaluate the pay-back period and the economic efficiency for lifetime operation (10 to 20 years). The results showed (i) that the profitability is particularly sensitive to changes in the capital cost, the capacity factor, the electricity escalation rate, and the initial installation cost; (ii) that the profitability is slightly less sensitive to changes in the O&M cost; and (iii) that the impacts of the turbine rated power and of the inflation rate are limited. Kiranoudis et al. (2001) evaluated the parameters of the proposed *short-cut* wind efficiency model, using an approximate mathematical expression to represent the installation cost and the annual O&M cost of a wind farm. This cost formulation was later used as the objective function by Sisbot et al. (2009). Genetic algorithm was employed to obtain the optimal layout of a wind farm by maximizing the power production capacity.

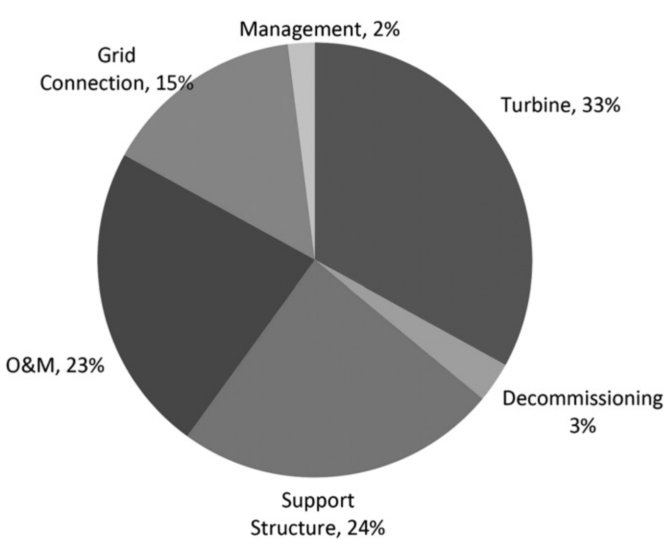


Fig. 1. Typical cost breakdown for an offshore wind farm in shallow water (Musial et al., 2006).

The *Response Surface-Based Wind Farm Cost* (RS-WFC) model developed in this paper evaluates the cost of a wind farm in terms of various critical design and economic factors. The Cost of Energy (COE) is determined from the RS-WFC model, and subsequently minimized to obtain optimal wind farm layouts.

1.2. Development of RS-WFC model

The RS-WFC model presented in this paper builds on the E-RBF cost model introduced in the paper by Zhang et al. (2010b). A power generation model (Chowdhury et al., 2010a) has been incorporated in this paper to formulate a framework for evaluating wind farm economics. The COE is evaluated by integrating the cost model and the power generation model. The basic steps of this framework are summarized as follows:

- *Step* 1: This step formulates the wind farm cost model using a response surface method. The Extended Radial Basis Functions (E-RBF) method is adopted to develop the RS-WFC model in this paper. Importantly, the RS-WFC model also has the flexibility to use other response surface methods. The RS-WFC model is composed of three components that estimate: (i) the installation cost per kilowatt installed, (ii) the annual Operation and Maintenance (O&M) cost per kilowatt installed, and (iii) the total annual cost of a wind farm per kilowatt installed. The inputs for the RS-WFC model include the following five parameters: (i) the turbine rotor diameter, (ii) the number of wind turbines in a farm, (iii) the cost of construction labor, (iv) the cost of management labor, and (v) the cost of technician labor. The response surface is trained using data from the *Energy Efficiency and Renewable Energy Program* at the *U.S. Department of Energy* (Goldberg, 2009). The accuracy of the model is then illustrated through comparison with pertinent commercial data.
- *Step* 2: This step incorporates a power generation model with the RS-WFC model. The power generation model proposed in the *Unrestricted Wind Farm Layout Optimization* (UWFLO)

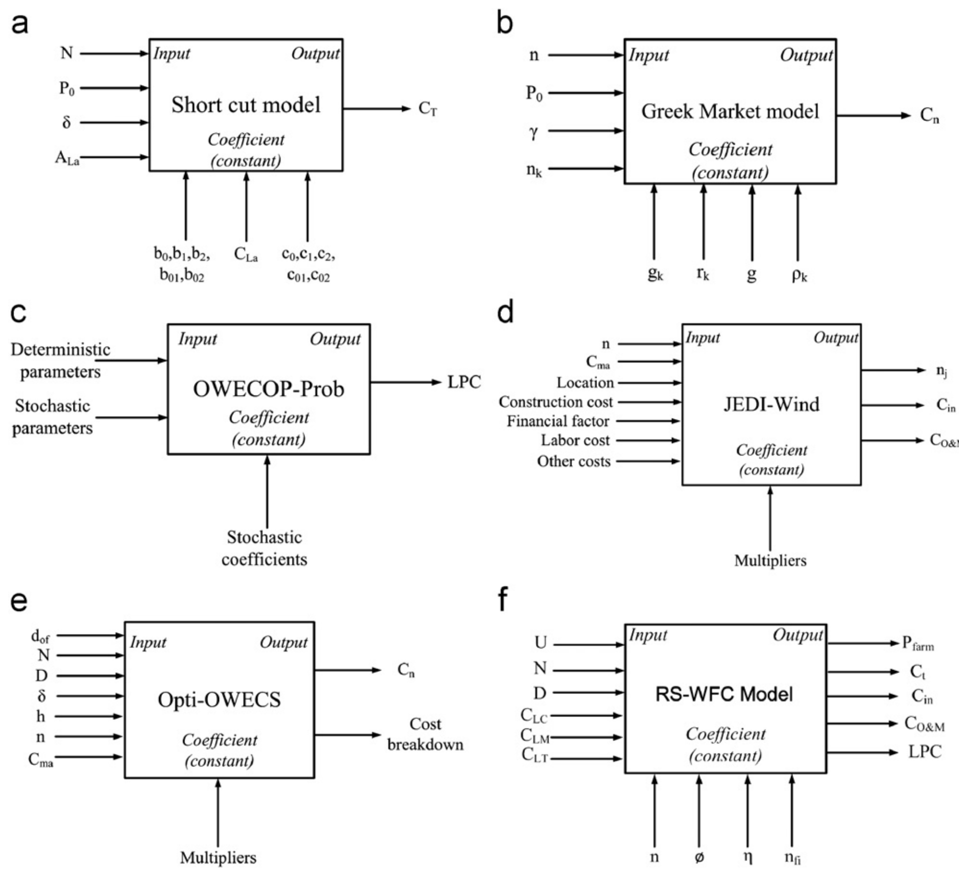
model, recently developed by Chowdhury et al. (2010a), is adopted in this paper. This model uses a standard analytical wake model (Frandsen et al., 2006) to determine the growth of wakes and the velocity deficit in the wake.

- *Step* 3: The COE is evaluated and optimized using the Constrained Particle Swarm Optimization (PSO) algorithm. The COE used in this model is measured by the *Levelized Production Cost* (LPC), which is defined as the total annual cost divided by the energy produced by a wind farm in one year.

The primary objective of this paper is to provide a cost model which accounts for a broad set of parameters that play important roles in the engineering planning of wind farms. In addition, a wind farm economics evaluation framework is presented by integrating a comprehensive cost model and an analytical power generation model of wind farms. The RS-WFC model is developed for the purpose of wind farm design. In its current form, the cost model is more advanced in engineering than in financial areas. Indeed, one of the key contributions of this paper is to exploit the synergism between these two areas, which will bring forth new possibilities. The following assumptions are made in the development of the overall RS-WFC framework in this paper:

1. The cost model is developed particularly for onshore wind farms in the U.S.
2. The cost of grid connection is not within the scope of this paper.
3. The total installation cost is divided by the wind turbine's lifetime to estimate the annual installation cost of a wind farm. Therefore, cost factors that do not remain constant over the lifetime of a farm are not accounted for in this initial study.
4. The incoming wind is assumed to be unidirectional and approaching with a fixed speed.
5. The designed wind farm is assumed to have a rectangular shape.

This paper consists of seven sections. In Sections 2 and 3, the RS-WFC model is developed and validated. Section 4 presents a synopsis of the power generation model developed by Chowdhury et al. (2010a). Section 5 presents the determination and optimization of the COE. A case study on the development of a 25 turbines



N - number of turbines; P_0 - rated power; δ - the relative distance between turbines; A_{La} - farm land area; C_T - total annual cost ($); C_{La} - cost of unit farm land area ($\$/m^2$); n - turbine lifetime (year); γ - the subsidy percentage by government; n_k - the lifetime for certain major part; g_k - mean annual change of the price for the k^{th} major component of a turbine; r_k - replacement cost coefficient; g - annual increase of the operation and maintenance cost; ρ_k - the corresponding level of technological improvements; C_n - total investment cost (€); LPC - levelized production cost (€/kWh); C_{ma} - cost of material; n_j - jobs affected by the whole project; d_{of} - distance to shore (km); D - turbine rotor diameter (m); h - support structure height (m); U - wind profile; C_{LC} - wage per hour for construction labor ($/h); C_{LM} - wage per hour for management labor ($/h); C_{LT} - wage per hour for technician labor ($/h); ϕ - percentage financed; η - interest rate; n_{fi} - years financed; P_{farm} - power generated by a wind farm (kW); C_t - total annual cost per kilowatt installed of a wind farm ($/kW); C_{in} - installation cost per kilowatt installed of a wind farm ($/kW); and $C_{O\&M}$ - operation and maintenance cost per kilowatt installed of a wind farm ($/kW)

Fig. 2. Input and output structure of each cost model: (a) Short-cut model (Kiranoudis et al., 2001). (b) Greek market model (Kaldellis and Gavras, 2000). (c) OWECOP-Porb cost model (Herman, 2002b). (d) JEDI-wind model (Goldberg, 2009). (e) OPTI-OWECS cost model (Cockerill, 1997). (f) RS-WFC model.

Table 1
Cost models comparison.

Location	*Short-cut* model	Greek model	OWECOP-Prob model	JEDI-Wind model	Opti-OWECS model	**RS-WFC model**
	Onshore	Onshore	Offshore	Onshore	Offshore	Onshore
Input of the cost model						
N	✓		✓	✓	✓	✓
P_0	✓	✓	✓			
D			✓		✓	✓
U			✓			✓
δ	✓				✓	
n		✓			✓	✓
γ		✓				
Tax				✓		
Financing				✓		✓
Cost of labor			✓	✓	✓	✓
Output of the cost model						
Total cost	✓	✓	✓		✓	✓
Installation cost				✓	✓	✓
O&M cost				✓		✓
P_{farm}			✓			✓
LPC			✓			✓
Pros and Cons						
Pros	P_1,P_{10}	P_1,P_2,P_9,P_{10}	P_8,P_{11},P_{12}	$P_3,P_6,P_7,P_8,$	P_2,P_8	$P_1,P_2,P_4,P_5,P_6,P_7,P_8,P_{10},P_{11},P_{12}$
Cons	$C_2,C_3,C_5,C_6,C_7,C_8,C_9,C_{11},C_{12}$	$C_3,C_5,C_6,C_7,C_8,C_{11},C_{12}$	$C_1,C_2,C_3,C_4,C_6,C_7,C_9,C_{10}$	$C_1,C_2,C_4,C_9,C_{10},C_{11},C_{12}$	$C_1,C_3,C_4,C_6,C_7,C_9,C_{10},C_{11},C_{12}$	C_3,C_9

P_1: *Analytical model available*	C_1: *Analytical model not available*
P_2: *Considering life cycle cost*	C_2: *Not considering life cycle cost*
P_3: *Considering tax*	C_3: *No tax consideration*
P_4: *Appropriate input parameters*	C_4: *Too many input parameters*
P_5: *Appropriate output parameters*	C_5: *Too few input parameters*
P_6: *Financing parameters available*	C_6: *Neglecting financing parameters*
P_7: *Considering rotor diameter effect on cost*	C_7: *Not including the rotor diameter effect on cost*
P_8: *Including cost of labor*	C_8: *Neglecting cost of labor*
P_9: *Considering subsidy*	C_9: *Not considering subsidy*
P_{10}: *No parameters difficult to determine*	C_{10}: *Including input parameters difficult to determine*
P_{11}: *Evaluating the power generation*	C_{11}: *Not evaluating the power generation*
P_{12}: *Evaluating the COE*	C_{12}: *Not evaluating the COE*

wind farm is provided in Section 6. Concluding remarks are given in the last section.

2. Cost model development

2.1. Cost models comparison

While we develop an advanced wind farm cost model for the U.S. wind energy market, the benefits and drawbacks of the existing cost models are also explored in this paper. Five representative cost models are presented in this section. They are (1) the *short-cut* model (Kiranoudis et al., 2001); (2) the cost model for the Greek market (Kaldellis and Gavras, 2000); (3) the OWECOP-Prob cost model (Herman, 2002b); (4) the JEDI-wind cost model (Goldberg, 2009); and (5) the Opti-OWECS cost model (Cockerill, 1997). A detailed comparison of existing cost models can be found in the previous paper by Zhang et al. (2010b).

The input and output structure for each model is shown in Fig. 2. The comparison between the RS-WFC model and the existing models is given in Table 1. From Table 1, it is seen that the RS-WFC model: (i) evaluates the *Cost of Energy* (COE), (ii) evaluates the power generation, (iii) includes the life cycle cost, (iv) considers financial parameters, (v) uses appropriate input and output parameters, and (vi) provides analytical expressions for efficient use in design and/or optimization.

In addition, note that the data used to develop and test the RS-WFC model is obtained from the *Energy Efficiency and Renewable Energy Program* at the *U.S. Department of Energy* (Goldberg, 2009). Note also that the Nomenclature provides required definitions.

2.2. Extended radial basis functions (E-RBF) approach

Typical response surface methods include (Zhang et al., 2011a): (i) Quadratic Response Surface Methodology (QRSM), (ii) Radial Basis Functions (RBFs), (iii) Extended Radial Basis Functions (E-RBF), and (iv) Kriging. The E-RBF approach, which has been shown to be a robust response surface technique by Mullur and Messac (2005, 2006), is adopted in this paper. The E-RBF approach uses a combination of radial and non-radial basis functions, which possesses the appealing properties of both types of basis functions: (i) the effectiveness of the multiquadric RBFs and (ii) the flexibility of the Non-Radial Basis Functions (N-RBFs) (Mullur and Messac, 2005).

2.2.1. Radial basis functions (RBFs)

The idea of using *Radial Basis Functions* (RBFs) as approximation functions was first proposed by Hardy (1971), where he used the multiquadric RBFs to fit irregular topographical data. Since then, RBFs have been used for numerous applications that require global approximations of multidimensional scattered data (Jin et al., 2001; Cherrie et al., 2002; Hussain et al., 2002).

The RBFs are expressed in terms of the Euclidean distance, $r=\|x-x^i\|$, of a point x from a given data point, x^i. One of the most effective forms of RBFs is the multiquadric function (Cherrie et al., 2002; Hardy, 1971), which is defined as

$$\psi(r)=\sqrt{r^2+c^2} \tag{1}$$

where $c>0$ is a prescribed parameter. The final approximation function is a linear combination of these basis functions across all data points, as given by

$$\tilde{f}(x)=\sum_{i=1}^{n_p}\sigma_i\psi(\|x-x^i\|) \tag{2}$$

where σ_i is the generic coefficient to be determined, and n_p denotes the number of prescribed data points. The number of coefficients is equal to the number of sample points, n_p.

Table 2
Non-radial basis functions.

Region	Range of ξ_j^i	ϕ^L	ϕ^R	ϕ^β
I	$\xi_j^i \le -\lambda$	$(-t\lambda^{t-1})\xi_j^i+\lambda^t(1-t)$	0	ξ_j^i
II	$-\lambda \le \xi_j^i \le 0$	$(\xi_j^i)^t$	0	ξ_j^i
III	$0 \le \xi_j^i \le \lambda$	0	$(\xi_j^i)^t$	ξ_j^i
IV	$\xi_j^i \ge \lambda$	0	$(t\lambda^{t-1})\xi_j^i+\lambda^t(1-t)$	ξ_j^i

λ,t, prescribed parameters.

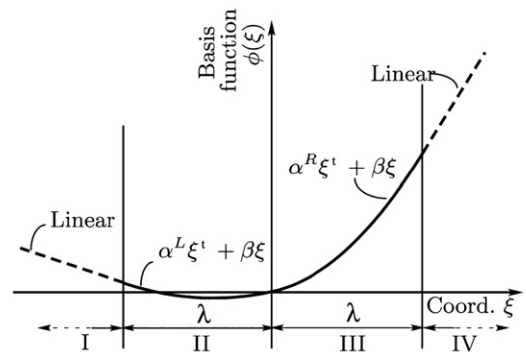


Fig. 3. Non-radial basis functions (Mullur and Messac, 2006).

2.2.2. Non-radial basis functions (N-RBFs)

The *Non-Radial Basis Functions* (N-RBFs) are not functions of the Euclidean distance, r. Instead, they are functions of individual coordinates of generic points x relative to a given data point x^i, in each dimension separately. We define the coordinate vector as $\xi^i=x-x^i$, which is a vector of m elements, each corresponding to a single coordinate dimension. Thus, ξ_j^i is the coordinate of any point x relative to the data point x^i along the jth dimension. The N-RBFs for the ith data point and the jth dimension is denoted by ϕ_{ij}. It is composed of three distinct components, as given by

$$\phi_{ij}(\xi_j^i)=\alpha_{ij}^L\phi^L(\xi_j^i)+\alpha_{ij}^R\phi^R(\xi_j^i)+\beta_{ij}\phi^\beta(\xi_j^i) \tag{3}$$

where α_{ij}^L, α_{ij}^R and β_{ij} are coefficients to be determined for a given problem.

From Table 2 and Fig. 3, it is seen that the N-RBFs are linear in regions I and IV, and that they are a sum of tth degree monomials and the linear terms in regions II and III.

2.2.3. Extended radial basis functions (E-RBF)

The E-RBF approach incorporates both the RBFs and the N-RBFs, and the approximation function takes the form:

$$\tilde{f}(x)=\sum_{i=1}^{n_p}\sigma_i\psi(\|x-x^i\|)+\sum_{i=1}^{n_p}\sum_{j=1}^{m}\{\alpha_{ij}^L\phi^L(\xi_j^i)+\alpha_{ij}^R\phi^R(\xi_j^i)+\beta_{ij}\phi^\beta(\xi_j^i)\} \tag{4}$$

where ϕ^L, ϕ^R and ϕ^β are components of the N-RBFs. The vectors α^L, α^R and β, defined above, contain mn_p elements each, and the vector σ contains n_p coefficients. Thus, the total number of coefficients to be determined is given by $(3m+1)n_p$. Two methods that can be used to solve Eq. (4) are linear programming and pseudo-inverse. In some cases (even if the original function is convex), it is possible that the linear programming approach might not yield a feasible solution. In this paper, the pseudo-inverse approach is adopted to solve the coefficients. The pseudo-inverse (A^+) of a matrix (A) is a generalization of the inverse matrix. It is commonly used to compute a best fit solution to a system of linear equations that lacks a unique solution (Ben-Isreal and Greville, 2010). Mullur and Messac (2005) describe the development of the E-RBF approach.

2.3. RS-WFC model

The RS-WFC model is divided into three parts to estimate (i) the installation cost per kilowatt installed, C_{in}, (ii) the annual O&M cost per kilowatt installed, $C_{O\&M}$, and (iii) the total annual cost of a wind farm per kilowatt installed, C_t. As discussed above, the number of coefficients of the RS-WFC model, $n_u=(3\,m+1)n_p$, is based on the number of data points. Table 3 shows the number of coefficients for each part of the RS-WFC model. C_{LC}, C_{LT} and C_{LM} represent the wage per hour for construction labor, technician labor and management labor, respectively; N is the number of turbines in a farm and D is the rotor diameter. Thus, although the RS-WFC model presents an explicit mathematical expression, the many numerical coefficients (n_u) have not been listed in this paper.

Table 3
Function list of the RS-WFC model.

Model expression	Number of variables, m	Number of data points, n_p	Number of coefficients, n_u
$C_{in}=f(C_{LC},C_{LT},C_{LM})$	3	40	400
$C_{O\&M}=f(N,C_{LT},C_{LM})$	3	500	5000
$C_t=f(N,D)$	2	101	707

Table 4
Parameter selection for the RS-WFC model.

Parameter	λ	c	t
Value	4.75	0.9	2

Table 5
Sample data for creating the installation cost model.

State	C_{LC} (\$/h)	C_{LT} (\$/h)	C_{LM} (\$/h)	C_{in} (\$/kW)
California	20.70	30.97	49.56	2107
Colorado	18.32	25.00	40.00	2043
Iowa	16.16	22.05	35.28	2011
Kansas	16.26	22.18	35.49	2012
Minnesota	19.62	26.77	42.83	2062

The current cost model is limited by the availability of data pertaining to wind farm cost factors. For example, the available data only allows the use of labor cost information to differentiate the installation costs between each state in the U.S. The influences of other parameters (e.g., the number of turbines, the rated power, and the rotor diameter) remain the same for all states. Therefore, the installation cost model is developed as a function of labor costs. However, when pertinent turbine data and required/existing infrastructure data become available, the underlying response surface methodology in the RS-WFC framework can be readily used to include these key factors influencing the wind farm cost.

2.3.1. Parameter selection for RS-WFC model

The values of the prescribed parameters are shown in Table 4. Mullur and Messac (2005) have reported these values to be appropriate for a broad range of problems.

2.3.2. Installation cost

Installation costs consist of the following five parts: (i) the cost of wind turbines, (ii) the support structure cost, (iii) the equipment cost, (iv) the material cost, and (v) the construction labor cost. The installation cost is based on the national average cost adjusted for geographic differences in the construction labor cost. The installation cost model is developed using data from 40 different states of the U.S. Selected sample data (Goldberg, 2009) of several states is shown in Table 5. In general, the model is expressed as

$$C_{in}=f(C_{LC},C_{LT},C_{LM}) \tag{5}$$

2.3.3. Annual O&M cost

The input parameters for the subject model include three components: (i) the number of turbines in a wind farm, (ii) the management labor cost, and (iii) the technician labor cost of all states in the U.S. (except the state of New York). The output of the subject model is the corresponding annual O&M cost per kilowatt installed. The data for the state of New York is used as test data. Table 6 lists the sample data from the states of California and Colorado (Goldberg, 2009). In general, the model is expressed as

$$C_{O\&M}=f(N,C_{LT},C_{LM}) \tag{6}$$

2.3.4. Total annual cost

This subsection develops a model that estimates the total annual cost of a wind farm based on the number and the wind turbine rotor diameter. The model is expressed as (Table 3)

$$C_t=f(N,D) \tag{7}$$

Table 6
Sample data for developing the annual O&M cost model.

California				Colorado			
N	C_{LT} (\$/h)	C_{LM} (\$/h)	$C_{O\&M}$ (\$/kW)	N	C_{LT} (\$/h)	C_{LM} (\$/h)	$C_{O\&M}$ (\$/kW)
10	19.82	49.56	26.58	10	16	40	25.00
20	19.82	49.56	26.58	20	16	40	25.00
30	19.82	49.56	25.90	30	16	40	24.31
40	19.82	49.56	25.23	40	16	40	23.64
50	19.82	49.56	24.58	50	16	40	22.99
60	19.82	49.56	23.95	60	16	40	22.36
70	19.82	49.56	23.31	70	16	40	21.75
80	19.82	49.56	22.71	80	16	40	21.15
90	19.82	49.56	22.08	90	16	40	20.57
100	19.82	49.56	21.58	100	16	40	20.00

The total annual cost per kilowatt installed data, C_t, is obtained from the sum of annual installation cost and O&M cost:

$$C_t = \frac{1}{n} C_{in} + C_{O\&M} \tag{8}$$

where n is the lifetime of a wind turbine. It is assumed that the annual installation cost of a wind farm is equal to the total installation cost divided by the wind turbine's lifetime. Inflation or derating is not taken into account in this paper. Future work should address this assumption.

The rotor diameter, which is directly related to the rated power and the power generated by a wind farm, is a key factor of a wind turbine (with respect to its performance). In order to investigate the effect of the rotor diameter on the cost of a wind farm, a survey of leading wind turbines was performed. The survey data has been reported by Zhang et al. (2010b). It is noted that commercially available wind turbines with the same rated power may have different rotor diameters and different capacity factors, depending on the local wind profile. Here, for every specific rated power, an average rotor diameter value is selected, which is given in Table 7.

The input parameters to the total annual cost model are (i) the number and (ii) the rotor diameter of wind turbines installed in a wind farm; and the output is the total annual cost of a wind farm. All the 101 sets of data points are obtained for the state of New York (Goldberg, 2009), and the selected sample data is shown in Table 8.

Table 7
Relationship between rotor diameter (D) and rated power (P_0) of a wind turbine (Zhang et al., 2010b).

D (m)	49.00	55.00	59.20	65.00	80.50	82.00
P_0 (MW)	0.60	0.85	1.00	1.25	1.50	1.65
D(m)	84.25	88.00	92.13	100.00	101.00	
P_0 (MW)	2.00	2.10	2.30	2.50	3.00	

Table 8
Sample data for developing total annual cost model.

D (m)	P_0(MW)	N	C_t ($/kW)	D (m)	P_0(MW)	N	C_t ($/kW)
55	0.85	10	132.01	80.5	1.5	10	131.48
55	0.85	20	132.01	80.5	1.5	20	131.26
55	0.85	30	131.63	80.5	1.5	30	129.65
55	0.85	40	131.05	80.5	1.5	40	128.85
55	0.85	50	130.49	80.5	1.5	50	127.93
55	0.85	70	129.41	80.5	1.5	70	126.46
55	0.85	80	129.14	80.5	1.5	80	126.41
55	0.85	90	128.36	80.5	1.5	90	126.36
55	0.85	100	127.82	80.5	1.5	100	126.39

In the RS-WFC model, the wind turbine lifetime (n), the number of years financed (n_{fi}), the percentage financed (ϕ), and the interest rate (η) are specified as 20 years, 10 years, with 80% and 10%, respectively.

3. Cost model validation

In this section, we validate the RS-WFC model and present the estimated installation cost, annual O&M cost and total annual cost of a wind farm.

3.1. Performance criteria

The overall performance of the RS-WFC model is evaluated using two standard performance metrics: (i) Root Mean Squared Error (RMSE) (Jin et al., 2001; Forrester and Keane, 2009), which provides a global error measure over the entire design domain, and (ii) Relative Accuracy Error (RAE), which is indicative of local deviations. The RMSE is given by

$$RMSE = \sqrt{\frac{1}{n_t} \sum_{k=1}^{n_t} (f(x^k) - \tilde{f}(x^k))^2} \tag{9}$$

where $f(x^k)$ represents the actual function value for the test point x^k, $\tilde{f}(x^k)$ is the corresponding estimated function value. The parameter n_t is the number of test points chosen for evaluating the error measure. The RAE is evaluated at each test point, as given by

$$RAE(x^k) = \frac{|\tilde{f}(x^k) - f(x^k)|}{f(x^k)} \tag{10}$$

3.2. Cross-validation

Cross-validation is a technique that is used to analyze and improve the robustness of a surrogate model. Cross-validation error is the error estimated at a data point, when the response surface is fitted to a subset of the data points not including that point (also called the leave-one-out strategy). A vector of cross-validation errors, $\tilde{e}$, is obtained, when the response surfaces are fitted to all other $p-1$ points. This vector is also known as the prediction sum of squares (the PRESS vector).

The leave-one-out strategy is computationally expensive for a large number of points, which can be overcome by the q-fold strategy. The q-fold strategy involves (i) splitting the data randomly into q (approximately) equal subsets, (ii) removing each of these subsets in turn, and (iii) fitting the model to the remaining $q-1$ subsets. A loss function L is computed to measure the error between the predictor and the points in the subset that

Table 9
Installation cost estimated by the RS-WFC model.

State	N	C_{LC} ($/h)	C_{LT} ($/h)	C_{LM} ($/h)	n	n_{fi}	ϕ (%)	η (%)	C_{in} ($/kW) Reference	RS-WFC	RAE %
New York	50	22.77	31.07	49.71	20	10	80	10	2108	**2107.2**	0.04
South Dakota	50	13.33	18.19	29.10	20	10	80	10	1970	**1969.7**	0.02
Tennessee	50	13.31	18.44	29.51	20	10	80	10	1972	**1954.5**	0.89
Texas	50	17.59	24.01	38.41	20	10	80	10	2032	**2031.3**	0.03
Utah	50	16.86	23.01	36.81	20	10	80	10	2021	**2022.0**	0.05
Vermont	50	12.44	16.97	27.16	20	10	80	10	1956	**1955.9**	0.01
Virginia	50	18.86	25.74	41.19	20	10	80	10	2051	**2050.7**	0.01
Washington	50	21.86	29.83	47.73	20	10	80	10	2095	**2092.7**	0.11
West Virginia	50	17.42	23.78	38.04	20	10	80	10	2030	**2030.1**	0.01
Wisconsin	50	18.70	25.52	40.83	20	10	80	10	2048	**2047.9**	0.00
Wyoming	50	17.61	24.04	38.46	20	10	80	10	2032	**2031.7**	0.01

we set aside at each iteration; the contributions to L are then summed up over the q iterations.

More formally, when the mapping $\zeta : 1,\ldots,n \to 1,\ldots,q$ describes the allocation of the n training points to one of the q subsets and $\hat{f}^{-\zeta(i)}(x)$ (of the predictor) is obtained by removing the subset $\zeta(i)$, the cross-validation measure is given by (Zhang et al., 2011b)

$$PRESS_{SE} = \frac{1}{n}\sum_{i=1}^{n}[y^{(i)} - \hat{f}^{-\zeta(i)}(x^{(i)})]^2 \tag{11}$$

Hastie et al. (2001) recommended compromise values of $q=5$ or $q=10$. Using fewer subsets generally has an additional advantage of reducing the computational cost of the cross-validation process by reducing the number of models that have to be fitted.

In this paper, the number of subsets (q) is specified to be 10 for all three cost models. Both the training points and test points are used during the cross-validation evaluation.

3.3. Estimated installation cost

The estimated installation costs per kilowatt installed for eleven states in the U.S. are shown in Table 9. The actual reference installation costs are obtained from the *Energy Efficiency and Renewable Energy Program* at the *U.S. Department of Energy* (Goldberg, 2009).

The installation cost model is developed using 40 data points, which is sufficient to ensure the accuracy of the model. From Table 9, it is seen that all the estimated installation costs are nearly equal to the reference values. For the state of Tennessee, the RAE (0.89%) is somewhat larger than that in other states. However, it is still less than 1%. The RMSE value is 5.3561 and the PRESS value is 1.8420 (Table 10). The average installation cost of all the 51 states is estimated to be 2038.4 \$/kW. The RMSE and the root of PRESS values are approximately 0.26% and 0.07% of the average installation cost, respectively. The low values of the three performance metrics (RAE, RMSE and PRESS) indicate how the RS-WFC model adequately estimates the installation cost of a wind farm with reasonable accuracy.

Table 10
The root mean squared error (RMSE) and the prediction sum of squares (PRESS) for the RS-WFC model.

Component	Installation cost	Annual O&M cost	Total annual cost
RMSE (\$/kW)	5.3561	0.0728	0.3328
PRESS ((\$/kW)^2)	1.8420	0.4145	0.4124

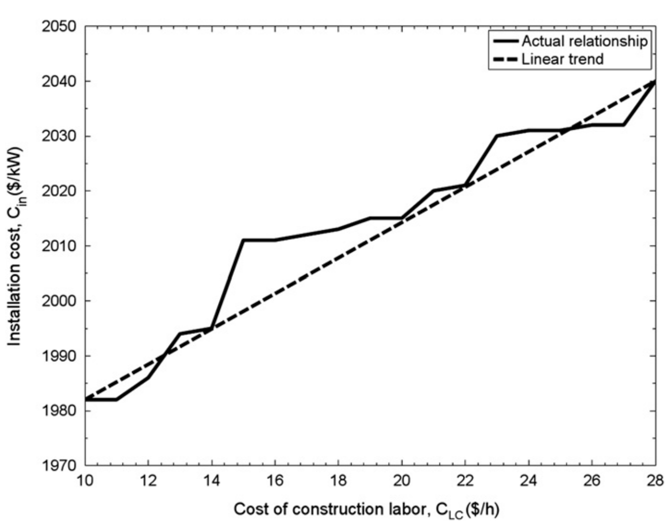


Fig. 4. Relationship between the installation cost and the labor cost.

Table 11
O&M cost estimated by the RS-WFC model for New York state.

N	C_{LT} (\$/h)	C_{LM} (\$/h)	n	n_{fi}	ϕ (%)	η (%)	$C_{O\&M}$ (\$/kW)		RAE
							Reference	RS-WFC	
10	31.07	49.71	20	10	80	10	26.61	**26.67**	0.23
20	31.07	49.71	20	10	80	10	26.61	**26.56**	0.19
30	31.07	49.71	20	10	80	10	25.92	**25.91**	0.03
40	31.07	49.71	20	10	80	10	25.26	**25.23**	0.13
50	31.07	49.71	20	10	80	10	24.61	**24.58**	0.12
60	31.07	49.71	20	10	80	10	23.98	**23.92**	0.26
70	31.07	49.71	20	10	80	10	23.34	**23.53**	0.80
80	31.07	49.71	20	10	80	10	22.73	**22.72**	0.04
90	31.07	49.71	20	10	80	10	22.11	**22.03**	0.35
100	31.07	49.71	20	10	80	10	21.61	**21.60**	0.06

The solid line in Fig. 4 represents the relationship between the installation cost per kilowatt installed and the cost of construction labor, while the management labor cost and the technician labor cost are constant. It is seen that the installation cost increases with the cost of construction labor. The installation cost per kilowatt installed increases from 1982 \$/kW to 2040 \$/kW (approximately a 2.93% increase), while the cost of construction labor changes from 10 \$/h to 28 \$/h (approximately a 180% increase). Overall, the relationship between the installation cost per kilowatt installed and the cost of construction labor appears to display an approximately linear behavior, as represented by the dashed line in Fig. 4.

3.4. Estimated annual O&M cost

The RS-WFC annual O&M cost model is illustrated by estimating the O&M cost of a wind farm in the state of New York. The input parameters include three parts: (i) the number of wind turbines, (ii) the cost of technician labor, and (iii) the cost of management labor. Both, the *estimated* and *actual* reference annual O&M costs are shown in Table 11. The largest RAE value is 0.80% when there are 70 wind turbines installed in a wind farm, which is deemed acceptable. The RMSE value is 0.0728 and the PRESS value is 0.4145 (Table 10). The average annual O&M cost (considering all data points) is estimated to be 22.57 \$/kW. The RMSE and the root of PRESS values are approximately 0.32% and 2.85% of the average annual O&M cost, respectively. The low values of the three performance metrics (RAE, RMSE and PRESS) illustrate the ability of the RS-WFC model to estimate the annual O&M cost of a wind farm with reasonable accuracy.

Fig. 5(a) shows the relationship between the annual O&M cost per kilowatt installed and the number of wind turbines. It is observed that, when the number of wind turbines increases from 10 to 100, the annual O&M cost decreases sharply from 26.67 \$/kW to 21.60 \$/kW, approximately a 19.01% reduction. This illustrates how the number of wind turbines exerts great influence on the annual O&M cost of a wind farm. Approximately, the annual O&M cost decreases by one dollar (per kilowatt installed) for every 20 wind turbines added. However, it can also be seen that when the number of wind turbines is small (less than 20), the change in the annual O&M cost is not clearly evident. Fig. 5(b) presents the relationship between the annual O&M cost and the cost of management labor.

In practice, the O&M cost is generally estimated based on the actual annual yield of the wind farm. The capacity factor should be assumed or estimated to determine the annual yield, which is site specific. Typical capacity factors of wind farms are 20–40% (Boccard, 2009). In this paper, a generic O&M cost function is

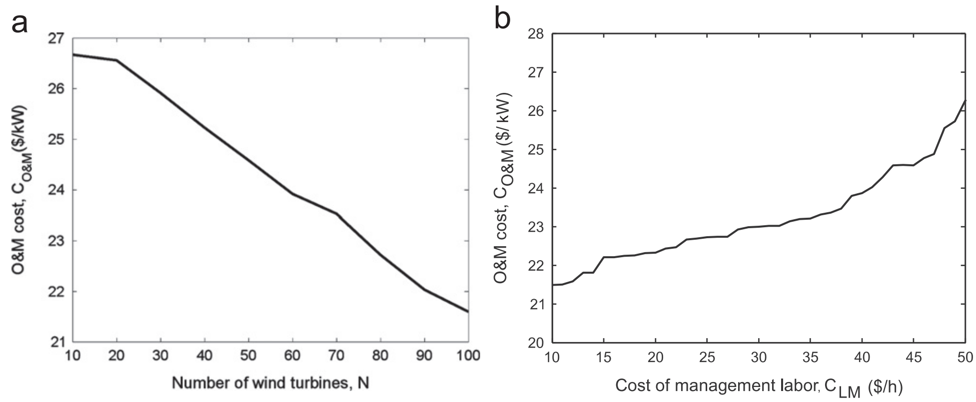


Fig. 5. Relationship between the annual O&M cost and the input factors: (a) Relationship between the annual O&M cost and the number of wind turbines. (b) Relationship between the annual O&M cost and the labor cost.

Table 12
Total annual cost estimated by the RS-WFC model for New York state.

Case number	D (m)	P_0(MW)	N	C_t ($/kW) Reference	RS-WFC	RAE (%)
1	49.00	0.60	50	131.32	**131.60**	0.21
2	55.00	0.85	60	129.94	**129.93**	0.01
3	59.20	1.00	40	130.66	**130.53**	0.10
4	65.00	1.25	50	129.22	**129.55**	0.26
5	80.50	1.50	60	126.98	**126.67**	0.24
6	82.00	1.65	50	127.45	**127.32**	0.10
7	84.25	2.00	40	127.61	**127.90**	0.23
8	88.00	2.10	60	126.39	**126.40**	0.01
9	100.00	2.50	30	127.93	**127.16**	0.60

proposed on the basis of kW installed, without assuming any particular site/resource conditions.

In addition, the power generation model provided in the paper can be readily modified to estimate the annual yield of the wind farm, provided wind data is available for the site concerned. This estimation would allow the representation of the O&M cost in $/kWh.

3.5. Estimated total annual cost

The variation of the total annual cost with the number and the turbine rotor diameter is discussed in this subsection. The estimated result is illustrated through comparison with the commercial wind farm data in the state of New York region, which is shown in Table 12. It is seen that the largest RAE is 0.60% for case 9 (when the rotor diameter and the number of wind turbines are 100 and 30, respectively), and the estimated total annual costs are nearly equal to the reference values for the other eight cases. The RMSE value is 0.3328 and the PRESS value is 0.4124 (Table 10). The average total annual cost of all the points is estimated to be 128.46 $/kW. The RMSE and the root of PRESS values are approximately 0.26% and 0.50% of the average total annual cost, respectively. The low values of the three performance metrics (RAE, RMSE and PRESS) indicate that the RS-WFC model can adequately estimate the total annual cost of a wind farm.

Fig. 6(a) shows the relationship between the total annual cost per kilowatt installed and the wind turbine rotor diameter. It is observed: (i) that the total annual cost per kilowatt installed decreases when the rotor diameter increases; and (ii) that the change in the total annual cost per kilowatt installed is significantly decreased when the rotor diameter increases beyond 85 m. Fig. 6(a) and Table 7 indicate that the use of small wind turbine might not generally be cost effective.

Fig. 6(b) shows the relationship between the total annual cost and the number of wind turbines. It is seen that there is no additional appreciable decrease in the total annual cost per kilowatt installed, when the number of turbines increases beyond a certain threshold number. In addition, this threshold number decreases when the turbine rotor diameter increases.

4. Power generation model

Sorensen and Nielsen (2006) showed that the total power extracted by a wind farm is significantly less than the simple product of the power extracted by a stand-alone turbine and the number of wind turbines in the farm. This difference is attributed to the mutual shading effect of wind turbines (Katic et al., 1986). To account for the wake effect, a power generation model is required. The power generated by a wind farm (P_{farm}) comprised N wind turbines is evaluated as a sum of the power generated by each individual turbine, which is given by

$$P_{farm} = \sum_{j=1}^{N} P_j \tag{12}$$

4.1. The unrestricted wind farm layout optimization (UWFLO) power generation model

The UWFLO power generation model used in this paper was recently developed by Chowdhury et al. (2012, 2010a,b). A rectangular wind farm of given dimensions, consisting of N turbines, is considered in the model. Fig. 7 shows the input and output structure of the UWFLO power generation model. C_p and a represent the power coefficient and the induction factor of a wind turbine, respectively.

4.2. Wake model

The wake model used in this paper is adopted from Frandsen et al. (2006). This model employs the control volume concept that relates the thrust and the power coefficients to the velocity deficit. The growth of the wake behind any Turbine-j is given by

$$D_{wake,j} = (1+2\alpha\bar{s})D_j \tag{13}$$

$$\bar{s} = \frac{s}{D_j} \tag{14}$$

where $D_{wake,j}$ is the diameter of the expanding wake at a distance s behind Turbine-j. The parameter α is the wake spreading

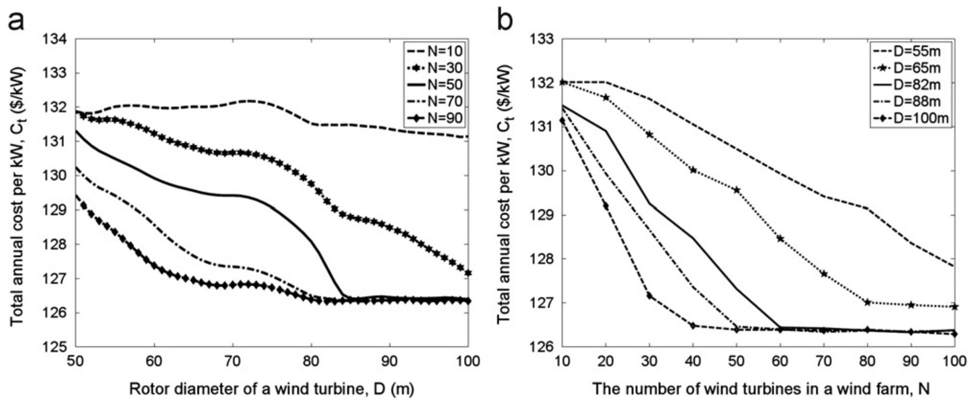


Fig. 6. Relationship between the total annual cost and the input factors: (a) The total annual cost per kilowatt installed based on the turbine rotor diameter. (b) The total annual cost per kilowatt installed based on the number of wind turbines.

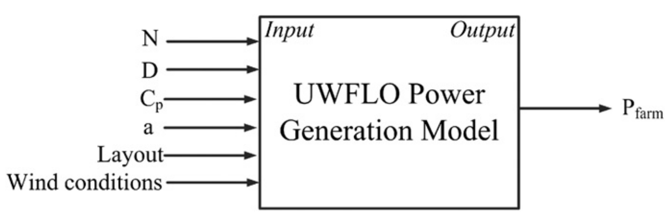


Fig. 7. Input and output structure of the UWFLO power generation model.

constant, which is evaluated by (Frandsen, 1992)

$$\alpha = \frac{0.5}{\ln\left(\frac{z_H}{z_0}\right)} \tag{15}$$

where z_H and z_0 are the average hub height of the turbines and the average surface roughness of the wind farm region, respectively. The wind velocity in the wake is given by

$$U = \left[1 - \frac{2a}{(1+2\alpha s)^2}\right] U_j \tag{16}$$

where a is the induction factor, which is a measure of wind velocity reduction, as defined by

$$a = 0.5\left(1 - \frac{U_{back}}{U_{front}}\right) \tag{17}$$

where U_{front} and U_{back} are the velocities of the wind in front of and behind the turbine, respectively. According to the ideal flow assumption, the induction factor and the power coefficient are related by

$$C_p = 4a(a-1)^2 \tag{18}$$

5. Optimizing cost of energy

5.1. Cost of energy (COE)

COE is measured by Levelized Production Cost (LPC), which is given by (Zhang et al., 2010a)

$$COE = \frac{C_t \times P_0 \times N \times 1000}{AEP_{net}} \tag{19}$$

where AEP_{net} is the net annual energy production (kWh). AEP_{net} is evaluated as

$$AEP_{net} = 365 \times 24 \times P_{farm} \tag{20}$$

5.2. Wind farm optimization problem formulation

The objective of optimization is to minimize the COE for a wind farm. The optimization problem is formulated as follows:

$$\min_{V}: \quad f = \frac{C_t \times P_0 \times N \times 1000}{AEP_{net}(V)} \tag{21}$$

$$V = \{x_1, x_2, \ldots, x_N, y_1, y_2, \ldots, y_N\} \tag{22}$$

$$\text{s.t.} \tag{23}$$

$$g_1(V) \le 0 \tag{24}$$

$$g_2(V) \le 0 \tag{25}$$

$$0 \le x_i \le x_{farm} \tag{26}$$

$$0 \le y_i \le y_{farm} \tag{27}$$

where x_i and y_i are the coordinates of the wind turbines in the farm. The inequality constraint g_1 is the minimum clearance required between any two adjacent turbines, which is given as

$$g_1(V) = \sum_{i=1}^{N} \sum_{\substack{j=1 \\ j \ne i}}^{N} \max((D_i + D_j + \Delta_{\min} - d_{ij}), 0) \tag{28}$$

$$d_{ij} = \sqrt{\Delta x_{ij}^2 + \Delta y_{ij}^2} \tag{29}$$

where $\Delta_{\min}$ is the minimum clearance required between the outer edge of the rotors of two adjacent turbines. The inequality constraint g_2 ensures that the locations of wind turbines are within a fixed size rectangular wind farm, which is expressed as

$$g_2(V) = \frac{1}{2N}\left\{\frac{1}{x_{farm}} \sum_{i=1}^{N} \max(-x_i, x_i - x_{farm}, 0) + \frac{1}{y_{farm}} \sum_{i=1}^{N} \max(-y_i, y_i - y_{farm}, 0)\right\} \tag{30}$$

where x_{farm} and y_{farm} represent the dimensions of the rectangular wind farm in the x and y directions, respectively. The number of design variables in this optimization problem is equal to $2N$.

5.3. Constrained particle swarm optimization (PSO) algorithm

PSO was originally developed by Kennedy and Eberhart (1995), and was first intended for simulating social behavior (Kennedy, 1997). Later, several improved variations of the algorithm appeared in the literature and have been used in popular commercial optimization packages. The PSO algorithm used in this paper has been derived from the unconstrained version presented by Colaco et al. (2006). A general single objective constrained maximization problem is expressed as

$$\begin{aligned} &\text{Max} \quad f(X_{var}) \\ &\text{s.t.} \quad g_j(X_{var}) \le 0, \quad j=1,2,\ldots,p \\ &\quad h_k(X_{var})=0, \quad k=1,2,\ldots,q \end{aligned} \tag{31}$$

where p and q are the number of inequality and equality constraints, respectively; and X_{var} is the vector of design variables. The basic steps of the algorithm are summarized as

$$x_i^{t+1}=x_i^t+v_i^{t+1}$$

$$v_i^{t+1}=\alpha v_i^t+\beta_l r_1(p_i-x_i^t)+\beta_g r_2(p_g-x_i^t) \tag{32}$$

where,

- x_i^t is ith member of the population (swarm) at the t-th iteration,
- r_1 and r_2 are random numbers between 0 and 1,
- p_i is the best candidate solution found for the ith member,
- p_g is the best candidate solution for the entire population, and
- α, β_l and β_g are user defined constants in the range [0, 1].

The constrained non-domination principle (Deb et al., 2002) is implemented in this algorithm to compare candidate solutions.

6. Case study

A wind farm consisting of a 5×5 array of ENERCON E-82 wind turbines is selected in this study. The parameters of the wind farm and the wind conditions are given in Tables 13 and 14, respectively. The power coefficient (C_p) curve and the induction factor (a) curve are illustrated in Figs. 8(a) and (b), respectively. In Fig. 8(a), the square dot represents the actual power coefficient data provided by the wind turbine manufacturer (Enercon, 2010);

Table 13
Wind farm parameters.

Parameter	Value
Number of wind turbines, N	25
Type of wind turbines	ENERCON E-82
Rated power of each wind turbine, P_0	2 MW
Turbine rotor diameter, D	82 m
Hub height, H	85 m
Cut-in wind speed	2 m/s
Cut-out wind speed	28 m/s
Rated wind speed	13 m/s
Length of the wind farm, x_{farm}	28D
Breadth of the wind farm, y_{farm}	12D
Average surface roughness, z_0	0.7 m

Table 14
Wind conditions.

Parameter	Value
Average wind speed	8.35 m/s
Wind direction	0° with positive *x-axis*
Air density	1.2 kg/m^3

Table 15
User-defined constants in PSO.

Constant	Value
α	0.5
β_g	1.4
β_l	1.4
Population size	250
Allowed number of function calls	50,000

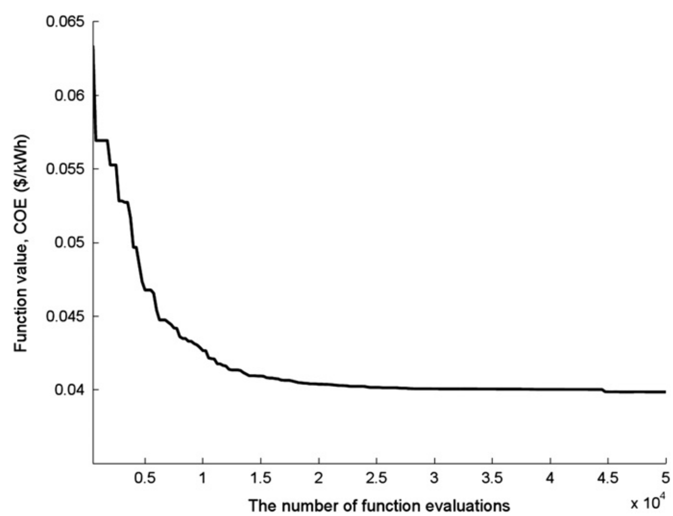


Fig. 9. Convergence history of the optimization.

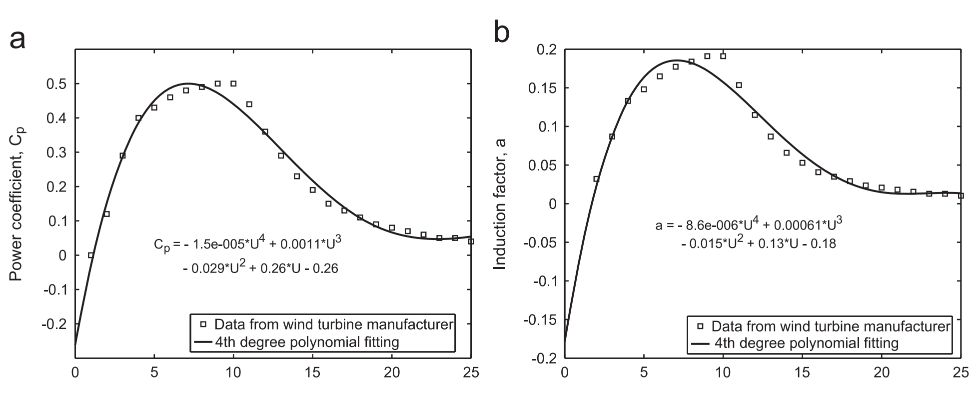


Fig. 8. Estimated power coefficient and induction factor curves: (a) Estimated power coefficient curve, C_p. (b) Estimated induction factor curve, a.

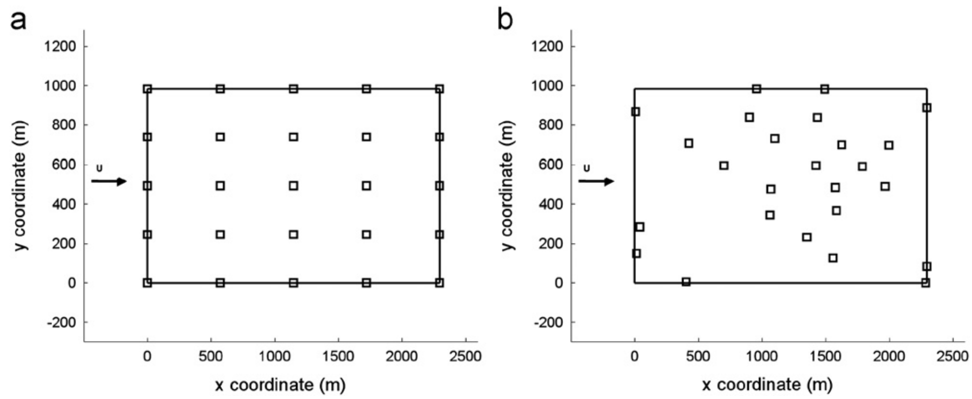


Fig. 10. Comparison of wind farm layout: (a) Original wind farm layout. (b) Optimized wind farm layout.

and the curved line represents the corresponding quartic curve fit (of the data). In Fig. 8(b), the square dot represents the actual induction factor data derived from Eq. (18), using the values C_p; and the curved line also represents the corresponding quartic curve fit (of the data). It is assumed that the wind farm is developed in the state of New York.

Optimization is performed using the PSO algorithm, which is initiated with a population of random wind farm layouts. The user-defined constants involved in PSO are summarized in Table 15.

The total annual cost per kilowatt installed (C_t), evaluated using the RS-WFC model, is 130 \$/kW. The outcomes of a representative run are illustrated in this paper. The convergence history is shown in Fig. 9. The optimized wind farm layout is shown in Fig. 10(b). It is seen that the optimization converges after approximately 20,000 function evaluations. The COE of the optimized farm is 12.88% lower than that of the original array layout. During optimization, the energy produced by the farm increases from 1.36×10^8 kWh to 1.56×10^8 kWh, which is approximately 14.71%. The resulting annual cost savings for the wind farm is approximately eight million dollars, which is an appreciable value for such a medium scale wind farm. The capacity factor of the wind farm is approximately 35.62%, which is impressive for an onshore wind farm of 25×2 MW wind turbines. However, in a real life wind farm, such a high capacity factor is unlikely. In this paper, a constant unidirectional incoming wind speed of 8.35 m/s has been used, which corresponds to a class 5 site. In a commercial scenario, average wind speeds are generally lower. More importantly, winds approach from different directions. Hence, the scope of farm efficiency improvement through layout planning is significantly less than where there is a unidirectional wind.

7. Conclusion

This paper developed a framework for the engineering planning of wind farms by simultaneously employing a newly developed cost and power generation models. A *Response Surface-Based Wind Farm Cost* (RS-WFC) model was developed and successfully validated, based on available commercial data. The RS-WFC model can estimate (i) the installation cost, (ii) the annual O&M cost, and (iii) the total annual cost of a wind farm. In addition, the RS-WFC model uses mathematical expressions to estimate the cost of a wind farm, which can be used to investigate the sensitivity of various key cost factors. The resulting cost model can be a useful tool for overall wind farm planning. The power generation model was combined with the RS-WFC model to evaluate the COE of a wind farm. This robust cost model addresses key interests of investors, project planning engineers, and policy makers in wind energy.

Several important observations can be made regarding the variation of the farm cost with the key parameters considered: (i) the annual O&M cost roughly decreases one dollar (per kilowatt installed) for every 20 turbines added; (ii) the total annual cost per kilowatt installed decreases when the rotor diameter increases; (iii) the change in the total annual cost per kilowatt installed is significantly decreased when the rotor diameter increases beyond 85 m; (iv) there is no further decrease in the total annual cost per kilowatt installed, when the number of turbines increases beyond a certain threshold number; and (v) this threshold number decreases when the turbine rotor diameter increases. Such information is helpful to farm designers and investors for decision-making regarding the number of turbines and the turbine rotor diameter. Nevertheless, it is helpful to note that these observations are subject to the assumptions made in the cost model, e.g., the use of constant interest rate, and the exclusion of cost factors such as grid connection and infrastructure costs. Further investigation would provide a more comprehensive and amplified view of pertinent economic factors.

The preliminary results indicate that the COE could decrease significantly through layout optimization, to obtain significant annual cost savings. A comprehensive farm planning framework, consisting of RS-WFC, power generation, and optimization, could be uniquely helpful for advancing wind power generation technology.

Future development of the RS-WFC model should consider (i) the distribution of wind speed and direction, (ii) the cost of grid connection, and (iii) other key economic factors. In addition, the cost model can be used to optimize the O&M strategy.

Acknowledgments

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