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Optimizing the number and locations of turbines in a wind farm addressing energy-noise trade-off: A hybrid approach

Prateek Mittal [a], Kishalay Mitra [a,*], Kedar Kulkarni [b]

[a] Department of Chemical Engineering, Indian Institute of Technology Hyderabad, Kandi, Telangana 502285, India
[b] IBM Research, Manyata Embassy Business Park, Nagawara, Bangalore 560045, India

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ABSTRACT

Micro-siting is an optimal way of placing turbines inside a wind farm while considering various design objectives and constraints. Using a well-established Jensen wake model and ISO-9613-2 noise calculation, this study performs a wind farm layout optimization based on a multi-objective trade-off between minimization of the noise propagation and maximization of the energy generation. A novel hybrid methodology is developed which is a combination of probabilistic real-binary coded multi-objective evolutionary algorithm and a newly proposed deterministic gradient based non-dominated normalized normal constraint method. Based on the Inverted Generational Distance metric, the performance of the proposed method is found to be better than the conventional normalized normal constraint method or the concerned evolutionary method alone. Moreover, in contrast to the previous studies, the generated non-dominated front is capable of providing a trade-off between various alternative energy-noise solutions, along with an additional information about the corresponding turbine numbers and their optimal location coordinates. As a result, the decision maker can choose from different competing wind turbine layouts based on existing noise and other standard regulations.

1. Introduction

Wind energy, one of the alternative renewable energy sources, has significant potential to contribute to the energy crisis arising from depleting conventional resources. Due to several advantages of wind operation, e.g. abundant availability, low cost and green operation, the large-scale utilization of wind power has received a noteworthy attention from the industry, federal policies and academic research [1]. According to the Global Wind Energy Council, the global cumulative installed wind capacity is expected to double as much as the current capacity, by the end of 2018 [2] and can provide 25–30% of global electricity supply. Though increasing demand and rising wind energy utilization are extremely encouraging, the challenges of development of a wind farm are manifold. The actual difficulties lie in handling different kinds of practical constraints, such as wind farm topology, inter–turbine distance, overall capacity factor, health of turbine, control of noise generated by turbines, environmental impacts, and visual impacts [3], which in turn create challenges in placing an optimum number of wind turbines in optimal locations inside a wind farm with a target of harnessing maximum energy [4].

Extensive research has been done in micro-siting with a focus on maximization of energy yield with minimum investment. Broadly, two types of approaches, representing the coordinate search space with/without grid, are employed to formulate the optimization problem. In grid-based approaches, the wind farm area is partitioned using uniform grids and the optimum locations are found out of these grid locations only. Though the efficacy of this approach lies in the choice of 'fineness' of the grids, the combinatorial complexity of the problem increases exponentially with increase in grid fineness. Mosetti et al. [5] have determined the optimum layout of turbines using Genetic Algorithm (GA) while minimizing the weighted sum of wind energy and turbines cost. Several other GA based formulations (single and multi-objective) with different objectives are also available in literature performing the wind farm layout design [6]. A modified form of Binary Particle Swarm Optimization method (BPSO) [7] is used to obtain the optimum layout starting with conventional layout of turbines while maximizing the operating income and optimizing the wind farm parameters such as turbine sizing, and hub height. Alternative to this combinatorial integer programming (IP) formulation, researchers used other techniques to increase the freedom of movement of turbines beyond the grid points. Kusiak and Song [8] used evolutionary strategy to determine the optimum layout of turbines while placing them freely inside a circular wind farm

* Corresponding author.
E-mail address: kishalay@iith.ac.in (K. Mitra).

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Nomenclature

Acronyms

AEP	annual energy production
GA	genetic algorithm
IGD	inverted generational distance
IP	integer programming
ITD	inter-turbine distance
MINLP	mixed-integer non-linear programming
MSHA	mine safety and health administration
nD-NNC	non-dominated normalized normal constraint
NLP	non-linear programming
NNC	normalized normal constraint
NSGA II	non-dominated sorting genetic algorithm II
OCF	overall capacity factor
OSHA	occupational safety & health administration
PO	Pareto optimal
RBNSGA II	real binary coded non-dominated sorting genetic algorithm II
SPL	sound pressure level
WFLO	wind farm layout optimization

Symbols

α	coefficient of sound absorption for each octave-band
$d(vsol, Q)$	closest Euclidian distance between '*vsol*' and all solutions of a selected non-dominated front
$\delta 1(x_i, y_j)$	normalized Euclidian distance (w.r.t. defined ITD) between two turbines '*i*' and '*j*'
$\delta 2(xyT)$	normalized OCF (w.r.t. defined OCF^{lim}) for the obtained turbine layout.
Δu_{ij}	reduced wind speed on turbine '*j*' due to the wake generated by upwind turbine '*i*'
A_j	area of a downwind turbine '*j*'
C_T	coefficient of thrust
D_C	directivity correction for sources that are not omni-directional
d_{ir}	Euclidian distance between turbine '*i*' and the receptor '*r*'
K_W	wake decay constant for Jensen model
L_P	sound pressure level
L_W	octave-band sound power emitted by the source
T_{space}	minimum allowable distance between two turbines
N_T	total number of turbines
N_{upwind}	number of upwind turbines to downwind turbine '*j*'
OCF^{lim}	selected limit of allowable capacity factor
$Pwr(\theta_i, u_j, l_k)$	power of turbine 'k' at location l_k, at wind-speed u_j in direction θ_i
R_{ij}	wake radius formed by an upwind turbine '*i*' on the downwind turbine '*j*'
u_j	effective wind speed at turbine 'j'
u_o	free stream wind speed
$p(\theta_i, l_k)$ & $p(u_o, l_k)$	probabilities of occurrence of wind at turbine location l_k
$\overline{AEP}$ & $\overline{Noise}$	normalized values of AEP and noise, respectively
A_{ij} & d_{ij}	overlapped area and distance between an upwind turbine '*i*' and the downwind turbine '*j*', respectively
N_b & N_r	number of binary and real form of variables, respectively
$\sigma 1$ & $\sigma 2$	modified operators for AEP and noise values, respectively
x_i & y_i	x-axis and y-axis location coordinates for a turbine '*i*', respectively
$\Delta ij(x_i, y_j))$	evaluation parameter for *sigma*1
A & k	scale and shape parameters in Weibull distribution, respectively
$AEP(xyT)$	total energy of *xyT* turbine layout
A_f	octave-band attenuation
Cp & Mp	crossover and mutation probability for RBNSGA II, respectively
D & R_r	rotor diameter and rotor radius of a turbine, respectively
Mod Objective	modified unconstrained objective function
Ngen & *Npop*	number of generations and populations in RBNSGA II, respectively
$noise1(xyT)$	modified value of noise for the turbines layout 'xyT', calculated by using modified operators $\sigma 1$ and $\sigma 2$
Pr	rated power
$Pwr(xyT)$	calculated power for the turbines layout xyT
$Pwr1(xyT)$	modified value of $Pwr(xyT)$ calculated by using modified operators $\sigma 1$ and $\sigma 2$
$SPL(xyT)$	noise of *xyT* turbine layout
Vsol	selected solution from composite Pareto front
xyT	xy-axis location coordinates of N_T number of turbines

and attaining minimized wake loss and maximized energy, simultaneously. Eroğlu and Seçkiner extended this work using the Ant Colony Optimization (ACO) [9] and the results provided more power with more number of turbines inside a wind farm. In another work, the Particle Filtering Method (PFM) [10] has also been used to attain the above task and its efficacy has been demonstrated. Utilizing both grid based and continuous coordinate based approaches, two echelon wind farm layout planning model [11] was developed. Here, Random Key Genetic Algorithm (RKGA) and Particle Swarm Optimization (PSO) algorithms are applied separately to each of the approaches to perform wind farm micro-siting. In contrast, several other mathematical optimization schemes have also been deployed to determine the optimal locations of turbines inside a wind farm with an aim of maximizing the power. Park and Law [12] have used sequential convex programming to optimize the existing wind turbine network in a wind farm. However, Random search method [13] provides a promising results in wind farm layout optimization. Chen et al. [14] performed micro-siting for regular and irregular shapes of a wind farm using novel optimization method. Micro-siting on a complex terrain is carried out with bionic and greedy methods, where the latter provides a better solution in less time [15]. Wind turbine layout and their sizing parameters are also optimized using iterative approach [16]. Using both grid-based and coordinate based wind farm designs, a novel layout plus control method is developed to reduce the power loss [17]. Moreover, several other formulations by controlling the different aspects of wind power generators were developed to obtain the maximum power output while placing the wind turbines inside a wind farm. The turbine characteristics such as blade pitch angle and tip speed ratio are optimized to increase the overall production of wind farm [18]. However, the optimized tip plate configuration of a wind turbine is determined to improve the wind turbine performance [19]. The hub heights of turbines were utilized to increase the power output of a wind farm [20]. Moreover, Optimization strategies are developed to optimize the hub heights in order to gain the maximum net profit [21].