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The impact of land use constraints in multi-objective energy-noise wind farm layout optimization

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ABSTRACT

Recently the environmental impact of onshore wind farms is receiving major attention from both governments and wind farm designers. As land is more extensively exploited for wind farms, it is more likely for wind turbines to be in proximity with human dwellings, infrastructure (e.g. roads, transmission lines), and natural habitats (e.g. rivers, lakes, forests). This proximity makes significant portions of land unusable for the designers, introducing a set of land-use constraints. In this study, we conduct a constrained and continuous-variable multi-objective optimization that considers energy and noise as its objective functions, based on Jensen's wake model and the ISO-9613-2 noise standard. A stochastic evolutionary algorithm (NSGA-II) solves the optimization problem, while the land-use constraints are handled with static and dynamic penalty functions. Results of this study illustrate the effect of constraint severity and spatial distribution of unusable land on the trade-off between energy generation and noise production.

1. Introduction

In recent decades, electricity generation from wind energy has shown a sustained growth all over the world. In 2012, 44.8 GW of wind energy capacity was installed in the world, which brought the total installed wind capacity to 282.5 GW [1]. This milestone made wind energy account for 3% of world's electricity demand [2]. In 2013, the wind energy market continued to grow, with the United States of America adding 12 GW of wind power generation capacity (under construction), and with Canada adding 1.6 GW of generation capacity [2]. In the European Union, wind energy represented the largest share of new installed capacity among all energy sources [3] during 2013. These statistics indicate a strong global growth in wind energy generation, increasing the associated market for related products and services [2].

Notwithstanding these trends, wind energy still faces difficulties for wide adoption. Recently, the health and environmental impacts of onshore wind farms have become a matter of concern for governments and wind farm designers. Although it is not proven that the noise production of turbines has negative health impact on human beings, a number of jurisdictions have established regulations that limit noise emissions [4–6]. Besides the potential health issues, extensive land exploitation for wind farms increases their interference with natural habitats and causes negative environmental impact [7]. This interference together with the noise production of wind farms reduce the available land for turbine sitting.

Wind farm design can be a lengthy and iterative process, in which the designer has to maximize the energy generation or revenue, while verifying compliance with environmental and safety regulations or restrictions. Most of the researchers in this area have strived to maximize energy or revenue of wind farms [8,9]. However, their studies fail to elucidate the nature of the energy-noise trade-off especially under severe land use constraints. Furthermore, the current approaches are not able to investigate the impact of the extent of land use constraints on the optimization results. Thus, these approaches fail to generalize case-specific layout optimization.

In this work, we study the energy-noise trade-off for the wind farm layout optimization (WFLO) problem while considering a set

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of land use constraints. In other words, this work aims to maximize the energy generation and minimize the noise production while investigating the sensitivity of this trade-off to land use constraints. To this end, the unconstrained multi-objective energy-noise optimization carried out by Kwong et al. [10,11] is extended to include land use constraints. The optimization is performed using a multi-objective, continuous-variable Genetic Algorithm (GA) [12] based on non-domination sorting (NSGA-II, [13]) and the constraints are handled with penalty functions [14].

2. Literature review

In this section, we discuss previous studies that have proposed models or algorithms for the WFLO problem and, due to our focus on constrained wind farm optimization, we also discuss previous work in constraint handling methods for evolutionary algorithms.

Regarding studies on WFLO problem, two main optimization approaches have been applied successfully, namely (i) heuristics and (ii) mathematical programming methods. First, optimization heuristics have been the most commonly used approach, and both stochastic and deterministic versions have been reported in the literature. Methods such as GA and Particle Swarm Optimization (PSO) [15] are the common stochastic heuristics used for solving WFLO problem [8,9,16,17]. In addition, deterministic heuristics such as Extended Pattern Search (EPS) of Du Pont and Cagan [18] are also used in this context; however, they have not ever been as common as stochastic methods. Most of the studies using heuristic methods considered energy or cost as their objective function, while Şişbot et al. [19] carried out a multi-objective energy-cost GA optimization. Kwong et al. [10,11] considered noise as the second objective function for the first time and solved the unconstrained problem with continuous variable GA. Their study showed that there is a trade-off between energy generation and noise production.

A significant portion of the literature on the WFLO problem has focused on improving the optimization models by including more realistic features of the wind farms. For instance, Kusiak and Song [20] considered minimum turbine proximity constraints, and enforced a closed wind farm boundary, these constraints were converted to a second objective function and handled in a multi-objective fashion. They showed that this multi-objective optimization maximizes energy and satisfies all the constraints by minimizing constraint violation. Réthoré et al. [21] suggested a two stage optimization model that used GA in the first stage and gradient-based sequential linear programming in the second stage. The second stage relied on an improved model that considered a comprehensive cost function and a more detailed wind resource distribution including more wind directions and speed bins. Saavedra-Moreno et al. [22] improved their model by considering the spatial distribution of wind speed instead of using a single speed/direction wind distribution for the whole farm terrain. Furthermore, Serrano-González et al. [23,24] modified their optimization by taking infrastructure costs and wind data uncertainty into account. Besides all these improvements in wind farm modelling, the most important contribution of the most recent studies with heuristic methods is the switch to continuous-variable formulations [20,10,11,25–27]. This is an important step in reducing the probability of converging to sub-optimal solutions caused by the coarseness of the discretization approaches typically used in the literature.

Formulations of the WFLO problem amenable for solution with mathematical programming methods, such as mixed-integer programming (MIP), have also been proposed. Donovan [28,29] introduced MIP for solving the WFLO problem. Fagerfjäll [30] used traditional branch-and-bound together with a heuristic to improve the performance of the optimization algorithm. Although MIP solvers are widely available in operation research software packages, they all have limitations solving non-linear, non-convex problems such as WFLO. Both Donovan and Fagerfjäll tried to address this problem by simplifying their wake model at the expense of losing accuracy. To address this issue, Archer et al. [31] improved the simplified wake model by introducing a wind interference coefficient, while Turner et al. [32] suggested more accurate linear and quadratic wake models that can be solved by MIP solvers. However, the accuracy problem was resolved by Zhang et al. [33], who proposed the first constraint programming (CP) and MIP models that incorporated the non-linearity of the problem. Similar to the WFLO work using heuristics, proponents of MIP models have also neglected the land use constraints associated with practical instances of the WFLO problem. However, the main limitation of MIP models is their dependence on coarsely discretized domains. For example, even in recent MIP studies [32,33], the wind farm domain is typically discretized into 100–400 potential turbine locations, with memory requirements and solution times increasing dramatically for finer discretizations.

Finally, from the common constraints encountered by wind farm designers, those related with land usage regulations have not received enough attention from researchers. However, there are a few exceptions that considered land-related parameters for their optimization. Chowdhury et al. [25–27] included the impact of land configuration and turbine selection in their study and used PSO for optimization. They minimized cost of energy and represented it as a function of land orientation and aspect ratio. Chen et al. [34] incorporated the participation rates of land owners in their cost function, which was minimized by GA. They showed that land owners remittances account for approximately 10 % of the wind farm's operating cost. In spite of these studies, the environmental/regulatory land use constraints such as setbacks from rivers, lakes, roads and human dwellings, have been neglected in previous work and are a matter of concern in our study.

Hence, we close our review of the literature by discussing previous developments in constraint handling for evolutionary optimization algorithms, which is our method of choice in the present work. Constraint handling approaches for multi-objective optimization with evolutionary algorithms have been based on (i) constrained-domination, (ii) non-domination ranking, or (iii) penalty functions. Firstly, on the constrained-domination side, Fonseca et al. [35] modified the binary tournament operation for parent selection in order to handle the constraints, introducing the concept of constraint domination, i.e. an extended Pareto dominance criterion that also considers constraint violations. Deb et al. [13] also used the same approach as Fonseca's with a slight difference in their constrained domination definition. Secondly, Ray et al. [36] introduced an alternative approach for constraint handling, in which they defined three different non-domination rankings based on the objective functions, constraints, and combined objectives and constraints. The solutions with higher ranks are chosen for next generation with the priority given to the solutions with high ranks regarding the third ranking. Finally, penalty functions have remained the most widely used constraint handling approach in the context of evolutionary algorithms. The penalty function approach recasts the problem as an unconstrained one by adding (if minimization, subtracting otherwise) a function of constraint violation to the objective functions. As a result, penalty functions are generally applicable to constrained optimization problems, regardless of the optimization method used to solve the unconstrained problem. Here, we shall use the penalty function approach, in order to take advantage of its simple implementation and general applicability; the latter can be beneficial for future studies that may use alternative optimization methods.