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# Optimization of wind farm layout with modified genetic algorithm based on boolean code

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ABSTRACT

A modified genetic algorithm (GA) is developed based on the Boolean code to optimize the layout of turbines in the wind farm. With the proposed method, a 2 km × 2 km wind farm with flat terrain under three wind scenarios is planned to yield the lowest unit cost per power output. Comparing with the optimized results from previous studies, lower cost can be obtained from the proposed method. The proposed method also shows high convergence stability and efficiency regarding different dense grid configurations. The algorithm is therefore particularly suitable for siting of wind turbines in a highly dense grid. Besides, the proposed algorithm has been prepared with good adaptability and it can be adapted easily for solving optimization problems in different engineering studies.

## 1. Introduction

Wind energy, due to its renewability and sustainability, is an ideal alternative to fossil fuels. There is a rush in the exploitation of wind energy in recent years, and it has become a major source of power other than fossil fuel. To harvest the wind energy, wind farms in various scales and forms have been developed worldwide. However, the cluster of wind turbines causes low power generation of downstream turbines comparing with upstream that share higher wind speed, and this is known as the wake effect. Existing studies showed that wake effect resulted in a 10%–20% loss of the total power generation in normal wind farms (Barthelmie et al., 2009). To diminish this loss, the number and the position of the turbine should be carefully studied avoiding the wake effect. More turbines, generally, would generate higher total power with lower marginal cost of construction. However, due to the wake effect, the profit (total power output/total cost) of wind farm could also be reduced if the siting of the wind turbines is not suitable. Therefore, wind farm optimization is a balance of the power output and the cost to yield the highest profit.

Combinations of turbines and their position determine wind farm layout arrangement strategies. An area divided into $N \times N$ cells would have $2^{N \times N}$ layouts for each cells either has a turbine or not. Facing the huge solution domain, wind farm layout optimizations are usually solved mathematically by optimization algorithms. Mosetti et al. (1994) first introduced the genetic algorithm (GA) to the problem. A 2 km × 2 km wind farm with flat terrain was optimized under three wind scenarios. The wind farm was divided into $10 \times 10$ cells with each one representing a potential position for a wind turbine. If the turbine was placed in this position, the value of that cell is 1, otherwise the value was 0. Each configuration of wind farm could then be represented as a 100 bit 0–1 string, and the total number of possible configurations was $2^{100}$. With the selection, crossover and mutation of the codes, GA optimized the solution to give the best strategy with a minimum objective value—the cost per unit power generation.

Following Mosetti's study, Grady et al. (2005) used a larger population and more generations in the GA to give better solution with a lower objective value. Mittal (2010) studied the same case with a fine grid scheme. Results showed that the density of the grid was significant in the optimization procedure where a high dense grid increased the accuracy of optimization. Wang et al. (2009) developed a grid unrestricted GA using the real code. This code showed a higher accuracy comparing with the GA using binary code. However, the number of turbines had to be known *a priori*. Gao et al. (2016) validated the multi-population GA with the optimization of a wind farm same as Grady et al. (2005) and Mittal (2010), and it gave better results. Mora et al. (2007) and Gonzalez et al. (2010) adopted different objective functions in GA to account for different economic situations. The effects of many economic factors are investigated such as initial capital investment, the discount rate, yearly income, etc. Applying a multi-objective GA, Chen et al. (2015) increased

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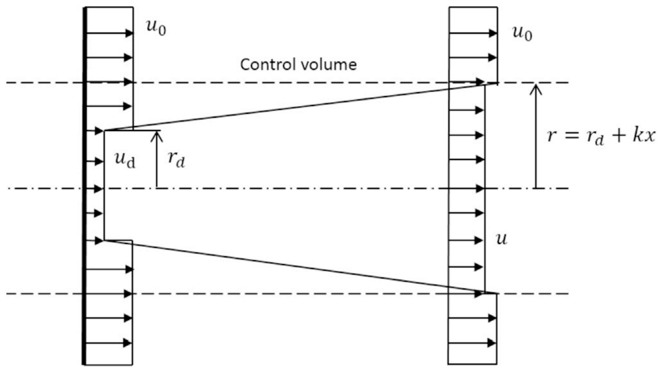



**Fig. 1.** Linear wake model.

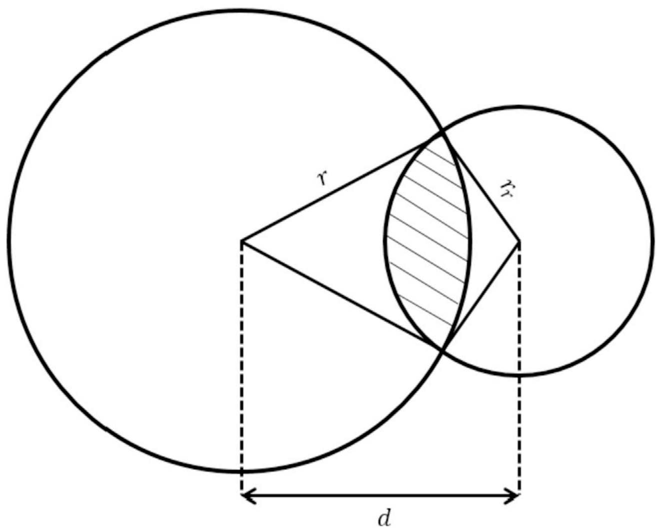
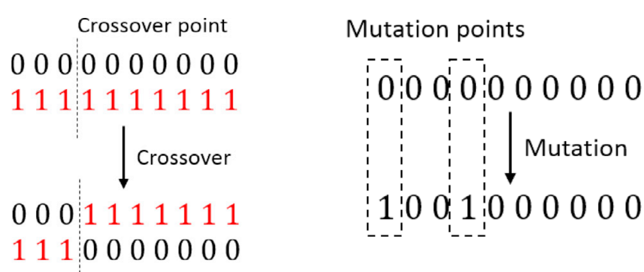



**Fig. 2.** Overlap area.




(a) Crossover (b) Mutation

**Fig. 3.** Operators of GA.

the wind farm efficiency and decreased cost per unit power production at the same time.

More complicated studies with more constraints had been conducted since. Wang et al. (2015a,b) studied the scenario that the land was owned by different owners. Chen et al. (2013) conducted the optimization with turbines of different hub heights. Results showed that an optimal combination of turbines with different hub heights would yield a better solution. González et al. (2015) adjusted the pitch angle and the tip speed ratio of the wind turbine for the maximum overall power production. The results showed that a deliberate reduction of the upstream turbine power coefficient may increase the total power generation. Gao et al. (2014) also conducted a case study in Hong Kong considering the terrain roughness.

Different heuristic algorithms or optimization methods were also adopted and investigated. Marmidis et al. (2008) showed the Monte Carlo simulation yielded better optimizing results comparing with Mosetti et al. (1994) and Grady et al. (2005). However the optimized layout resulted in a random way and could hardly be applied to engineering purpose. Ant colony algorithm showed good performance in finding the global optimal solution of the problem (Eroglu and Seçkiner, 2012). Song et al. (2015) adopted greedy algorithm with virtual particle wake model to the problem, which showed high efficiency in complex terrain situation. Comparing to GA and Monte Carlo simulation, similar results were given by artificial neural network, which suggest the potential availability of the method (Ekonomou et al., 2012). For the existing wind farm, the layout and efficiency could be optimized by sequential convex programming algorithm (Park and Law, 2015). Finally, Particle Swarm Optimization (PSO), in contrast with GA, showed a higher efficiency in computation but lower accuracy and higher possibility to be trapped in local optimum (Amaral and Rui, 2017).

Though various optimizing algorithm have been applied to the wind farm layout optimization problem. The GA with binary code is, in general, most commonly used. As mentioned above, when optimizing the wind farm using GA, the first step is translating layouts as 0–1 codes. Through the iteration of initialization, crossover, mutation and selection of these codes, the solution is optimized constantly. In previous studies, ordinary GA with binary code were applied (Mosetti et al., 1994; Grady et al., 2005; Wang et al., 2015a,b; Gao et al., 2016). However, different from traditional problems that could decode the 0–1 string to decimal value, the 0–1 codes for wind farm layouts should be treated as Boolean codes, which stand for quantity and order. In this study, the Boolean features of the codes are considered and specific modifications are made on GA for the problem like wind farm optimization. The effectiveness and efficiency of the modified method are validated in the optimization of a 2 km × 2 km wind farm with flat terrain under three wind scenarios. The optimized results are compared with those from previous studies. Finally, the effect of the grid density is studied with three different grid schemes.

## 2. Wake modelling and objective function

Based on the linear wake model proposed by Jensen (1983), a revised wake model is adopted to predict the velocity variation of the turbine wake in this study. The wake region is modeled as a conical area as shown in Fig. 1 with uniform velocity distribution.

For the wake region, momentum conservation of the control volume gives:

$$\rho\pi r_d^2 u_d + \rho\pi\left(r^2 - r_d^2\right)u_0 = \rho\pi r^2 u \tag{1}$$

Where where $u_0$is the ambient stream velocity, $u$ and $r$ are wake velocity and radius, $u_d$ and $r_d$are downstream wake velocity and radius.

According to turbine momentum theory, $u_d$ and $r_d$equals to:

$$u_d = u_0(1 - 2a) \tag{2}$$

$$r_d = r_r\sqrt{\frac{1-a}{1-2a}} \tag{3}$$

where $a = \frac{1-\sqrt{1-C_T}}{2}$is the axial induction factor related to the wind turbine thrust coefficient $C_T$, $r_r$ is the rotor radius.

Combine equation (1) and (2), momentum conservation of control volume would gives:

$$\rho\pi r^2 u_0 - 2a\rho\pi r_d^2 u_0 = \rho\pi r^2 u \tag{4}$$

Then the wake velocity $u$ could be derived as: