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OPTIMAL MICRO-SITING OF WIND TURBINES IN A WIND PARK USING PARTICLE SWARM OPTIMIZATION ALGORITHM

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Abstract

Micro-siting of wind turbines is a key technology for wind farm configuration. In this paper, the particle swarm optimization (PSO) method is utilized to optimize placing of wind turbines in a wind park. The location of each wind turbine could be freely adjusted within a cell in order to maximize the generated energy. It is improved wind farm efficiency and extract more electrical power with respect of the random location of wind turbines in the wind park . The proposed model can be useful in the studies of wind farm designers as a supportive tool for the estimation of the optimal micro-siting of wind turbines in a wind farm.

Keywords-wind farm; Particle Swarm Optimization (PSO); optimization; wind turbine.

INTRODUCTION

Wind energy has been accepted as good and efficient energy source with large industry manufacturing and thousands of Mega Watts is being installed as new capacity each year. A considerable knowledge containing the technology and science of wind turbines and wind farms has been established. Wind farms or as they are occasionally called wind parks, are locally concerned of tied groups of wind turbines which are connected electrically and commercially. Renewable energy sources have attracted the last years, lots of attention due to the technology development, their non-dependence on fossil fuels and their friendliness to the environment. Wind energy and consequently wind farms constitute one of the greatest renewable energy sources with rapid expansion all over world. One of the main problems in the design and construction of a wind farm, in order to maximize its energy production and its efficiency, is the optimal number of wind turbines to be installed. The optimal wind turbines number depends on several different factors such as: the terrain morphology,the wind farm area, the wind turbine size, the wind speed, the wind direction and the cost of the total wind turbines' installation.

Already the wind turbines are mature in technology, but for multi-megawatt production in wind farms, we have to proceed to an optimization of the production to be financially competitive to the conventional forms of energy production. In the present study, the optimization is made by means of maximum energy production. The basic factor that is examined is the optimal positioning of wind turbines in a wind farm, based on the criteria. In this paper, a particle swarm optimization method is used to optimize the problem. The optimization is made through a program code that was developed in java, based on the particle swarm optimization method.

2. Past approaches

Many attempts have been made towards an optimal wind turbines positioning. As Bansal et al. claim in their essay, 10 ha/Mw can be taken as the land requirement of wind farms, including infrastructure [2]. Of course many conditions, like the morphology of the terrain, the speed and the direction of the wind and also the turbine size will specify the spacing between the wind turbines in a wind farm. Patel , taking account of that criteria reached, in 1999, came to the conclusion that the

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optimal placement for the wind turbines in a wind park is in rows of 8–12 rotor diameters apart in the windward direction, and of 1.5–3 rotor diameters apart in the crosswind direction [3]. Three years later, in 2002, Ammara et al. conclude that Patel's conclusion about the sparse wind turbine positioning was inefficient, as it was not exploiting the wind energy potential of the site. Hence, Ammara et al. proposed a scheme that would yield similar production to the sparse scheme, but would have less land requirements. Ammara et al.'s [4] scheme was a dense, staggered sitting scheme. Although this scheme managed successfully to reduce the land requirements, for a certain amount of wind turbines, it was still an intuitive method of placement. A completely different approach was made first from Mosetti et al. [5] and then from Grady et al. [6] using the genetics algorithms as their basic tool in order to find the optimal wind turbines placement in a wind farm. Mosetti et al., in 1994, were the first to approach the optimal placement of wind turbines by means of using genetic algorithms. In Mosetti et al.'s essay, algorithms were developed for wind farm performance evaluation and optimization. The whole optimization is based on finding the optimal results for the variables of investment cost and the total power extracted in the farm, which is under examination. Mosetti et al. used simple wind and cost models in order to focus more on the effectiveness of the algorithm. Because Mosetti et al.'s presented configurations did not yield even the simplest empirical placement schemes. Grady et al. made a study in 2005, based again on genetic algorithms that focused on the effectiveness of the genetic algorithms optimization procedure in identifying optimum configurations. The present study is based on the same models that Mosetti et al. and Grady et al. used and we try to obtain more optimal and effective results by using a different methodology, which is the particle swarm optimization method.

2.MATHEMATICAL MODELS

2.1 WAKE EFFECT IN A WIND FARM

Rasoul Rahmani(2010) A wind turbine is a device for extracting kinetic energy from the wind. By removing some of its kinetic energy the wind must slow down but only that mass of air which passes through the rotor disc is affected. No air flows across the boundary and so the mass flow rate of the air flowing along the stream-tube will be the same for all stream-wise positions along the stream-tube. Because the air within the stream-tube slows down, but does not become compressed, the cross-sectional area of the stream-tube must expand to accommodate the slower moving air. As the air passes through the rotor disc, by design, there is a drop in static pressure such that, on leaving, the air is below the atmospheric pressure level. The air then proceeds downstream with reduced speed and static pressure - this region of the flow is called the wake.

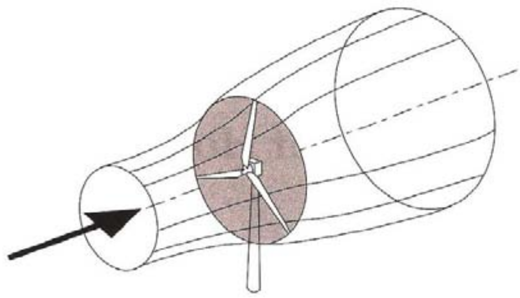

Fig 1 **The energy extracting stream-tube of a wind turbine.**

The flow field is assumed to consist of an expanding wake with a uniform velocity deficit that decreases with distance downstream. The initial free stream velocity is U0 and the turbine diameter is D. the velocity in the wake at a distance X downstream of the rotor is UX with a diameter of DX. the wake decay constant k, determines the rate at which the wake diameter increases in the downstream direction J. F. Manwell (2002).

The wake decay constant, k, is totally related to the parameters of wind turbines. Equation (1) shows the relation between k and the turbine parameters, where Z is the hub height and Z0 is the roughness coefficient for the surface.

$$K = \frac{0.5}{\ln\left(\frac{Z}{Zo}\right)} \quad (1)$$

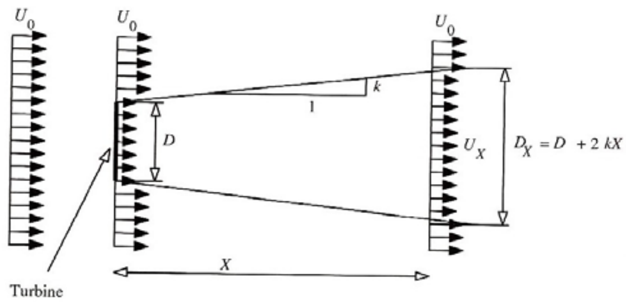

Fig. 2. Schematic view of wake description

In this model the same as many other semi-empirical models, the initial non-dimensional velocity deficit (the axial induction factor), α, is assumed to be a function of the turbine thrust coefficient:

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$$a = \frac{1}{2}\left(1 - \sqrt{1 - C_T}\right) \qquad (2)$$

Where CT is the turbine thrust coefficient where the (2) demonstrates the ideal Betz model J.

The wake model used here is a simple one. Some simple assumptions were made in order to focus on the applicability of the method. Of course, it is the same model that Mosetti et al. and Grady et al. used; so the two methodologies will be compared under the same circumstances. Here, we assume that the momentum is conserved inside the wake, so the wind speed, u, downstream the turbine is

$$u = u_0\left[1 - \frac{2a}{1+\alpha(\frac{x}{r1})}\right] \qquad (3)$$

Where u_0 is the mean wind speed, x is the distance downstream of the turbine, r1 is the downstream rotor radius and a is the entrainment constant, as shown in Fig. 2

2.2 Power output

The power output from a wind turbine is given by the well known expression below:

$$P = \frac{1}{2} C_p \rho A U^3 \qquad (4)$$

Where ρ is the density of air (1.225 kg/m3), CP is the power coefficient, A is the rotor swept area, and U is the wind speed [1]. Equation (4) demonstrates that the output power of the wind turbine is proportional to the cube of the wind speed. Although for each type of wind turbine we have a different coefficient multiplying to U, we consider the situation that wind turbine is being placed in a wind farm with U0=12 m/s just to have a comparison with previous works. In this type the (4) will be rewritten to following shape:

$$P_i = 0.3U_i^3 \qquad (5)$$

$$P_{total} = \sum_{i=1}^{N} 0.3\, U_i^3 \qquad (6)$$

In (5) Pi and Ui are the power output and wind speed of ith turbine, and in (6) Ptotal is the total output power of the wind park considering that N is the total number of wind turbines which has been placed in it.

Chunqiu Wan(2009) stated that the optimal micro-siting problem is quite complicated and involves many independent variables, it cannot be solved by traditional gradient-based optimization methods. A genetic algorithm is employed to solve such a problem.

The systematic approaches to wind turbine placement were first proposed by Mosetti et al(1995) and then improved by Grady et al.(2005). In genetic algorithms were applied to wind farm performance evaluation and optimization. The power and efficiency calculations of the optimally placed wind turbines were compared favourably with randomly placed wind farms. However, the results of **Mosetti et al(1995)** were not as good as expected because the numbers of individuals and maximum evolving generations were set low.

3.Optimization:

Grigorios Marmidis (2007) The optimization is made by the mean of maximum energy products and minimum cost installation criteria. It is obtained much greater power outcomes, not always by using more turbines, and for better values of fitness. **Chunqiu Wan(2009)** Power curve is optimized to estimate turbine power generation. Here obtain an research on genetic algorithm micro-siting by incorporating more appropriate models of wind speed distribution and turbine power curves. Andrew Kusiak(2009) The optimization model considered wind farm radius and turbines distance constraints by using evolutionary strategy algorithm. This model maximizes the energy production by placing wind turbines in such a way that the wake loss is minimized.

4**. Particle swarm optimization (pso)**

Besides Genetic Algorithm (GA), Dynamic Programming (DP) and other methods of Artificial intelligence, PSO is another evolutionary computation technique developed by Eberhart and Kennedy, in 1995, which was inspired by the social behaviour of fish schooling and bird flocking. PSO has its roots in artificial life and social psychology, as well as in engineering and computer science. It utilizes a ‘‘population’’ of particles that fly through the problem hyperspace with given velocities. At each iteration, the velocities of the individual particles are stochastically adjusted according to the historical best position for the particle itself and the neighbourhood best position [8].

Advantages over other similar optimization techniques such as GA, namely the following:

1. PSO is easier to implement and there are fewer parameters to adjust.

2. In PSO, every particle remembers its own previous best value as well as the neighbourhood best; therefore, it has a more effective memory capability than the GA.

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3. PSO is more efficient in maintaining the diversity of the swarm (more similar to the ideal social interaction in a community), since all the particles use the information related to the most successful particle in themselves, whereas in GA, the worse solutions are discarded and only the good ones are saved; therefore GA the population revolves around a subset of the individuals [8].

There are some parameters for PSO and different ideas and improvements for modeling [8]. Recently, Chen and Li used stochastic approximation theory to analyse the dynamics of the PSO [9]. The authors proposed a decreasing coefficient that is reduced to zero as the number of iterations increases, and a stochastic velocity with fixed expectation to enhance the exploratory mode of the swarm. While the former facilitates the particles to spread around the problem hyperspace at the beginning of the search, the stochastic velocity term provides additional exploration ability, thus helping the particles to escape from local minima [8]. Fig. 3 shows the movement of a particle in swarm based upon the model has been proposed by [8].

Equation (7) shows the relation between the parameters of PSO in this modelling,

Each particle adjusts its velocity and position with the following equations:

$$v' = v + c1.r1.(pBest - x) + c2.r2.(gBest - x) \qquad (7)$$
$$x'=x+v'$$

- v is the current velocity , v' the new velocity
- x the current position, x' the new position
- r1 and r2 are even distributed random numbers in the interval [0, 1]
- c1 and c2 are acceleration coefficients.

Where c1 is the factor that influences the cognitive behaviour, i.e., how much the particle will follow its own best solution, and c2 is the factor for social behaviour, i.e., how much the particle will follow the swarm's best solution.

ALGORITHM OF PARTICLES SWARMING

Initialization: Randomly initialize a population of a particle.
Population Loop: for each particle do.

Goodness Evaluation and update: evaluate the goodness of the particle. If its goodness is greater than its best goodness .So far, then this particle becomes best particle so far.

Neighbourhood Evaluation; if the goodness of this particle is best along all its neighbours, then this particle becomes the best particle of the Neighbourhood.

Determine Vi: apply equation.

Particle Update: apply the updating rule

Cycle: repeat step2 until a given convergence criterion is met

In current study a square field has been considered for planting the wind turbines. Each wind turbines needs an especial room to be put, that space has been taken equal to times of the rotor diameter which means 5 times 200m as the properties of wind turbine.

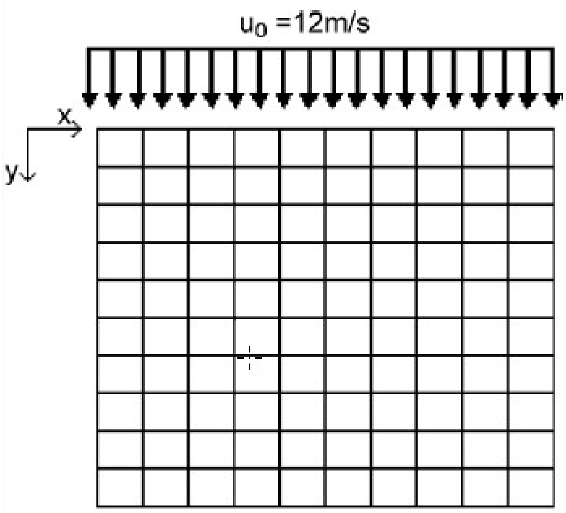

Fig.3. A square field for an optimization

Fig.3 shows the field and the possible places for planting the wind turbines. The wake effect of each turbine does not effect on the adjacent cell so just the wake effect on the behind turbines will be considered. The number of wind turbines has been put as the number of particles in a swarm.

Results

The optimization that was made in our procedure, for a wind farm on a square-shaped terrain will be considered under a single significant condition. The case that is under examination is the basic one: single wind direction with constant wind speed (U ¼ 12 m/s) and intensity. All calculations will start from random configurations that the program will decide, as PSO is a method that uses random numbers. In this version of the program, a better initialization will not save us any time as all

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cases have to be examined for the optimal result. Of course, if we introduce parameters in our program, then a better initialization will reduce the program running time even to half or less.

In this project, we have used a square grid, which was used to place the possible wind turbine. Every cell, in the centre of which we can place a wind turbine, has a width that is equal to five rotor diameters, 5D, or 200 m. Fig.3.

The rule of the thumb spacing requirements in all directions is satisfied by the 5D square grid size. Furthermore, because of the width we have chosen for each cell, the wake of a column of turbines would not affect turbines in the other columns. We use a specific type of wind turbine with the characteristics shown in Table 1.
The power curve for this type of wind turbine is shown in Fig. 4

Table 1

Wind turbine characteristics

Rated power	550KW
Hub height (z) (m)	40
Rotor radius (rr) (m)	40
Thrust coefficient (CT)	0.35

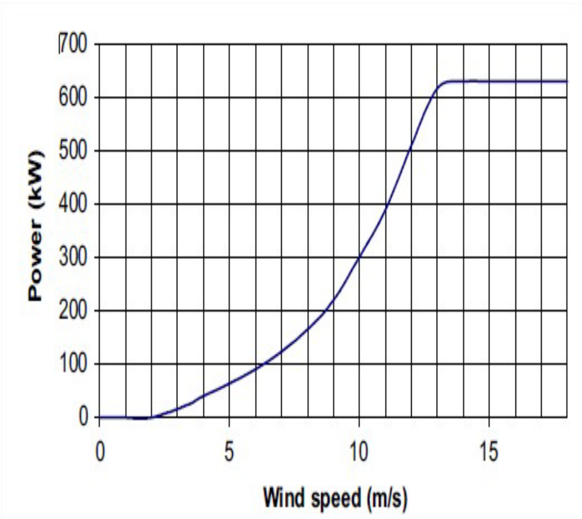

Fig.4.Wind turbine characteristics

The CT thrust coefficient will be considered constant throughout the processes. The power curve presented in Mosetti et al.'s study for the turbine under consideration yields the following expression for power:

$$P_{total} = \sum_{i=1}^{N} 0.3\, U_i^3 \qquad (7)$$

			X	
				X
				X
		X		
			X	

Fig.5 Layout design-I

The total power of the above layout is P=2016 KW

		X		
		X		
		X		X
	X			

Fig.6 layout design-II

The total power of the above layout is P=2003 KW

		X		X
	X			X
			X	

Fig.7 layout design-III

The total power of the above layout is P=2076 KW

	X			
			X	
			X	
X			X	

Fig.8 layout design-IV

The total power of the above layout is P=2030 KW

The layout design-III is gives an optimized result from various combinations.

The layout design-III is achieved a fitness value of 9.31 and it has reached more optimal result when compare to various combinations. Conclusively, we managed to obtain a more optimal placement of the wind turbines as we

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produce much greater amounts of total power output. This program has much more potentiality for even better results.

Conclusion

The results of the present study prove that the particle swarm optimization method can give us a novel approach to the tools that we already have in the field of optimization. The results of the present study demonstrate that PSO based method can be utilized in optimization of wind park, beside its various applications in power engineering. Whereas the wind energy is getting much attraction nowadays, the optimization of wind farms must be done with applying progressive methods. We managed to obtain much greater power outcomes, not always by using more turbines, and far better values of fitness. Still we have to examine more models and other cases to be sure. Certainly, more optimal results can be an outcome of one more complex programming code that will be the subject of a future study.

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