Optimization of Wind Farm Layout

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This paper presents a method for determination of optimum positions of single wind turbines within the wind farms installed on arbitrary configured terrains, in order to achieve their maximum production effectiveness. This method is based on use of the genetic algorithm as optimization technique. The wind turbine aerodynamic calculation is unsteady, based on the blade modeled as a vortex lattice and a free-wake type airflow behind the blade. Optimization method is developed for two different fitness functions. Both functions use the total energy obtained from the farm as one of the key variables. The second also involves the total investments in a single wind turbine, so the optimization process can also include the total number of turbines as an additional variable. The method has been tested on several different terrain configurations, with special attention paid to the overall algorithm performance improvements by selecting certain genetic algorithm parameters.

Keywords: *wind farm layout, genetic algorithm, differential evolution, potential flow, lifting surface, panel method, free-wake model.*

1. INTRODUCTION

Once suitable wind farm site is established, the next step should be wind farm design. It presents significant multidisciplinary engineering challenge and mainly consists in wind turbine selection, wind farm rating, wind farm layout determination and energy production analysis. Wind farm layout (distribution of wind turbines on the wind farm site) is affected by several factors which must be used in account: wind direction and wind energy distribution, wake interactions between wind turbines, land availability and possibility of construction. Up to date, several methods have been applied in order to try to optimize wind farm layouts.

Ozturk and Norman [1] approach the problem with a greedy heuristic method. They try to maximize the profit, instead of the power output, defined by the estimated selling price for a kWh of electricity in a given market. Therefore, in objective function they use the term which presents the expected profit per kWh generated by the wind farm. The optimization method consists in trying different operations recursively (add, remove and move a turbine) in order to maximize the profit defined in objective function. A perturbation is added to try to avoid local minima. The wake model is very simple and does not take into account wake interference in the middle of the wind farm. Nevertheless, the method is very interesting as it performs quite fast and allows the wake model to be independent from the optimization algorithm.

Mosetti et al. [2], Vila Moreno [3] and Grady et al. [4] use genetic algorithms to approach the wind farm optimization problem. In [2] and [4], a square wind farm is subdivided into a 10 × 10 grid. Genetic algorithms are utilized to determine the cells to install turbines so as to minimize the cost per unit energy. In the case of a wind farm, the individuals are the possible layouts of the turbines, the population is the assembly of the different individuals and the constraints are the minimum turbine separation and the wind farm boundaries. In above studies is demonstrated the effectiveness of genetic algorithms for solving the wind farm layout optimization problem. However, due to the binary coding method of the genetic algorithms used in [2-4], turbines could only be installed at the centre of selected cells.

Donovan [5] formulates a model based on the generalized vertex packing problem (GVP), seeking to maximize the power generated in accordance with the constraints based on the number of turbines, turbine proximity and turbine interference. The mathematical background can be found in Hanif and Smith [6]. The wake model used in Donovan [5] is not specified, but this method seems nonviable for sophisticated wake models.

Finally, Elkinton et al. [7] are developing the OWFLO project, standing for Offshore Wind Farm Optimization, a more comprehensive study that combines an energy production model (taking into account wake effects, electrical losses and turbine availability) with offshore wind farm component cost models.

The existing work that has tackled wind farm layout optimization problem is very limited. Therefore, there is potential for improvement upon existing solution methods.

In this paper is presented method for the layout optimization of a wind farm given a certain site and a certain number of turbines. The method is based on Genetic Algorithms as optimization technique, as they have been given a lot of attention as very potentially powerful optimization methods, and have already been applied successfully in many and hard optimization problems. Also, they are already successfully used by several researchers for optimal wind farm design problems. Our research has tried to apply Genetic

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Algorithm method to the wind farm layout design problem with several improvements in calculation of fitness function [8].

The positions of turbines in a wind farm are adjusted freely, instead of being in the center of each cell (as in [2] and [4]), so that the wake effects could be further reduced and more wind energy could be captured. Since the optimization variables in this case are real value, a real-coded genetic algorithm is employed. In order to obtain wake effects more accurate, an improved wake model is used for calculation of each turbine wake shape and wake interactions.

2. GENETIC ALGORITHMS

2.1 General description

Genetic algorithms (GA) are general-purpose search algorithms which use principles inspired by natural genetic populations to evolve solutions to problems. The basic idea is to maintain a population of chromosomes which represent candidate solutions to the concrete problem that evolves over time through a process of competition and controlled variation. Each chromosome in the population has an associated fitness to determine which chromosomes are used to form new ones in the competition process which is called selection. The new ones are created using genetic operators such as crossover and mutation. GAs have had a great measure of success in search and optimization problems. The reason for a great part of their success is their ability to exploit the information accumulated about an initially unknown search space in order to bias subsequent searches into useful subspaces i.e. their adaptation. This is their key feature, particularly in large, complex, and poorly understood search spaces where classical search tools are inappropriate, offering a valid approach to problems requiring efficient and effective search techniques. Although there are many possible variants of the basic GA, the fundamental underlying mechanism can be shown as:

Procedure GA
begin (1)
  $t = 0$;
  initialize $P(t)$;
  evaluate $P(t)$;
  While (**Not** *termination-condition*) **do**
  begin (2)
    $t = t + 1$;
    select $P(t)$ *from* $P(t - 1)$;
    recombine $P(t)$;
    evaluate $P(t)$;
  end (2)
end (1)

where $P(t)$ denotes the population at generation t.

As a part of real-coded GA, one of the recently developed optimization techniques, Differential Evolution (DE) has proven to be an efficient method for optimizing real-valued multi-modal objective functions. Besides its good convergence properties and suitability for parallelization, DE's main assets are its conceptual simplicity and ease of use.

2.2 Differential evolution

Differential Evolution (DE), like other GAs, starts with a large collection design vectors, the initial population. It interprets the function value of a vector as a measure of that individual's fitness as an optimum. Then, guided by the principle of survival of the fittest, the initial population of vectors is transformed, generation by generation, into a solution vector.

The overall structure of the DE algorithm (Fig. 1) resembles that of most other population-based searches. Two arrays are maintained, each of which holds a population of n-dimensional, real-valued vectors. The primary array holds the current population while the secondary array accumulates vectors that are selected for the next generation. Selection occurs by competition between the existing vectors and trial vectors. The trial vectors used by DE are formed through mutation and recombination of the vectors in the primary array.

Mutation is an operation that makes small random alterations to one or more parameters of an existing population vector. Mutation is crucial for maintaining diversity in a population, and is typically performed by perturbation. Traditional GAs uses a fixed type of perturbation, such as adding random numbers to individual parameters.

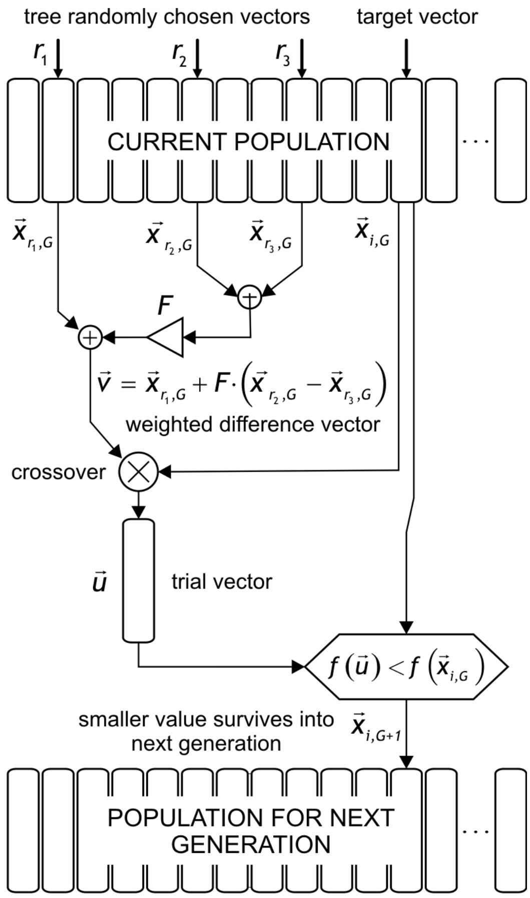

Figure 1. DE scheme

The problem with this approach is that it fails to account for the fact that what might be a small perturbation for one parameter might be gigantic for another. DE avoids this problem by using the population itself as the source of appropriately scaled perturbations. In this way, as convergence approaches, those variables having a narrow and well-defined range around the minimum will have small variation among the population members, resulting in their mutations being relatively small. This automatic adaptation significantly improves behavior of the algorithm as convergence nears.

3. TURBINE BLADE AND WAKE MODEL

3.1 Analytical model

The flow field is assumed to be potential (inviscid and irrotational) and incompressible. In that case velocity potential satisfies the Laplace equation:

$$\Delta\Phi = 0 . \tag{1}$$

Unsteadiness is introduced by unsteady boundary condition:

$$\left(\vec{V} - \vec{V}_T\right)\cdot \vec{n} = 0 \tag{2}$$

of the Kelvin theorem:

$$\frac{D\tilde{\Gamma}}{Dt} = 0 \tag{3}$$

and the unsteady form of the Bernoulli equation:

$$\frac{p - p_\infty}{\frac{\rho_\infty}{2}} = V_\infty^2 - V^2 - 2\frac{\partial\Phi}{\partial t} \tag{4}$$

where: Φ is velocity potential, $\vec{V}$ is absolute fluid velocity, $\vec{V}_T$ is lifting surface velocity, $\vec{n}$ is the normal of the lifting surface at a certain point, and $\tilde{\Gamma}$ is the bound circulation.

In order to define the aerodynamic characteristics of blades, two models should be established: blade model and wake model.

The blade is modeled as a thin lifting surface, which enables a complete 3D modeling around wind turbine blades. Unfortunately, it cannot deal with compressible and viscous flows.

Numerical modeling of the wake must be done very carefully due to its high influence on the lift force generation. The free-wake model, which is applied in this paper, is one of the most advanced, since it can cover all relevant problems connected with the wake influence.

3.2 Unsteady Kutta condition

In case of inviscid problems, it is necessary to satisfy Kutta condition at the trailing edge.

On the basis of unsteady Bernoulli equation, the difference between upper and lower surface pressure coefficients is:

$$\Delta C_P = C_{P_\mathrm{U}} - C_{P_\mathrm{L}} = -\frac{V_\mathrm{U}^2 - V_\mathrm{L}^2}{V_\infty^2} - \frac{2}{V_\infty^2}\frac{\partial}{\partial t}\left(\Phi_\mathrm{U} - \Phi_\mathrm{L}\right) \tag{5}$$

where subscripts U and L denote upper and lower surface values.

In case of the thin lifting surface, with the assumption that spanwise velocity components are small, the potential difference can be written as an integral from leading edge to a certain point M at the surface:

$$\Phi_\mathrm{U} - \Phi_\mathrm{L} = \int_{LE}^{M} \left(V_{\mathrm{U}T} - V_{\mathrm{L}T}\right)\mathrm{d}l \tag{6}$$

where the tangential velocity difference is the local bound vortex distribution:

$$\gamma = \left(V_{\mathrm{U}T} - V_{\mathrm{L}T}\right). \tag{7}$$

Final equation defining the potential difference is:

$$\Phi_\mathrm{U} - \Phi_\mathrm{L} = \int_{LE}^{M} \gamma \mathrm{d}l . \tag{8}$$

If we assume that spanwise velocities are small, the difference of velocity squares can be calculated as:

$$V_\mathrm{U}^2 - V_\mathrm{L}^2 \approx 2V_\infty\gamma . \tag{9}$$

By substituting (9) and (8) in (5), the following equation can be obtained:

$$\Delta C_P = -\frac{2}{V_\infty^2}\left(V_\infty\gamma + \frac{\partial}{\partial t}\int_{LE}^{M}\gamma\mathrm{d}l\right). \tag{10}$$

The Kutta condition can be expressed as the uniqueness of pressure coefficients at the trailing edge, which, mathematically expressed, takes the form:

$$\Delta C_p = \frac{2}{V_\infty^2}\left(V_\infty\gamma_{II} + \frac{\partial}{\partial t}\int_{LE}^{TE}\gamma\mathrm{d}l\right) = 0 . \tag{11}$$

Since it is impossible to be $V_\infty = \infty$, the relation within the parentheses must be equal to zero:

$$V_\infty\gamma_{TE} + \frac{\partial}{\partial t}\int_{LE}^{TE}\gamma\mathrm{d}l = 0 . \tag{12}$$

The integral in the upper equation is, in fact, the contour circulation which covers the lifting surface:

$$\tilde{\Gamma} = \int_{LE}^{TE}\gamma\mathrm{d}l \tag{13}$$

so, the (12) can be written as:

$$V_\infty\gamma_{TE} + \frac{\partial\tilde{\Gamma}}{\partial t} = 0 . \tag{14}$$

The expression for unsteady Kutta condition comes out directly as:

$$\frac{\partial\tilde{\Gamma}}{\partial t} = -V_\infty\gamma_{TE} . \tag{15}$$

If the right hand-side part is substituted with (9) written for the trailing edge, we obtain:

$$\frac{\partial\tilde{\Gamma}}{\partial t} = -\frac{V_{\mathrm{U}TE}^2 - V_{\mathrm{L}TE}^2}{2} = -\left(V_{\mathrm{U}TE} - V_{\mathrm{L}TE}\right)\frac{V_{\mathrm{U}TE} + V_{\mathrm{L}TE}}{2} . \tag{16}$$

From this equation it can be clearly seen that the variation of the lifting surface circulation in time can be compensated by releasing vortices of magnitude $\left(V_{\mathrm{U}TE} - V_{\mathrm{L}TE}\right)$ at the velocity $\left(V_{\mathrm{U}TE} + V_{\mathrm{L}TE}\right)/2$.

3.3 Discretization and numerical solution procedure

The method for the solution of this problem is based on the coupling of the dynamic equations of blade motion with the equations of aerodynamics. It is not possible to obtain an analytical solution of this problem, so discretization and numerical approach must be accepted.

Dicretization in time is done by observing the flow around the blade in a series of positions that it takes at certain times t_k (k = 0,1,2…), which are spaced by finite time intervals Δt at different azimuths.

Discretization of the thin lifting surface is done by using the panel approach. By this method, the lifting surface is divided in a finite number of quadrilateral surfaces – panels. Vorticity distribution is discretized in a finite number of concentrated, closed quadrilateral linear vortices, whose number is equal to the number of panels, in such a way that one side of the linear vortex is placed at the first quarter chord of the panel, and represents the bound vortex of the corresponding panel. The opposite side of the vortex is always placed at the trailing edge, while the other two sides are parallel to the flow. The wake is represented by quadrilateral vortex in the airflow behind the lifting surface. One side of it is connected to the trailing edge, while the opposite one is at the infinity. The other two sides (trailing vortices), which actually represent the wake, are placed parallel to the airflow. The vorticity of the quadrilateral vortex is equal to the sum of the vorticities of all bound vortices of the panels that correspond a certain lifting surface chord, but opposite in direction. Then the trailing edge vorticity is equal to zero.

Model established in such a manner corresponds to the steady flow case (Fig. 2). On the other hand, it can be very easily spread in order to include the unsteady effects.

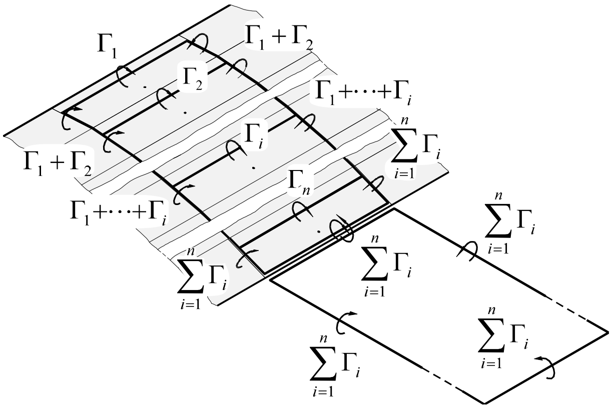

Figure 2. The steady panel scheme

3.4 Vortex releasing model

The variation of the lifting surface position in time induces variation of circulation around the lifting surface as well. According to the Kelvin theorem, this variation in circulation must also induce the variation around the wake. According to the unsteady Kutta condition, this can be achieved by successive releasing of the vortices in the airflow (Fig. 3).

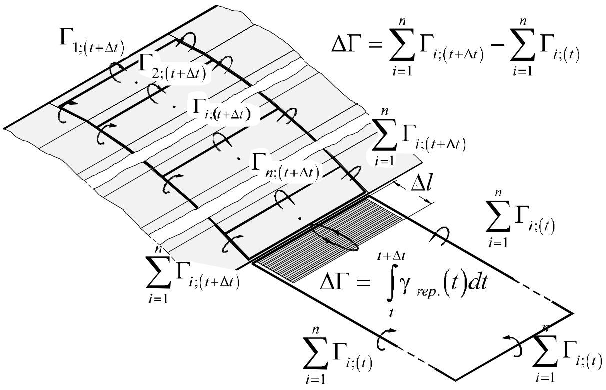

Figure 3. Vortex releasing

Suppose that the lifting surface has been at rest until the moment t, when it started with the relative motion with respect to the undisturbed airflow. The vortex releasing, as a way of circulation balancing, is done continually, and in such a way a vortex surface of intensity $\gamma(t)$ is formed.

At the next moment $t + \Delta t$, the flow model will look like in Figure 4. The circulation of the vortex element joined to the trailing edges equal to the difference in circulations at moments $t + \Delta t$ and t.

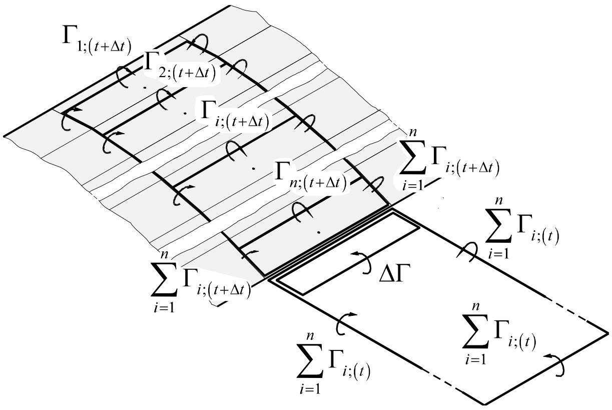

Figure 4. Unsteady panel scheme

We will discretize the vortex “tail” by replacing it with the quadrilateral vortex loop, whose one side is at the trailing edge, and the opposite side is at the finite distance from the trailing edge (shed vortex). By this we can obtain the final model for unsteady case.

3.5 Discretization of wake

The established vortex releasing model is appropriate for the wake modeling using the “free wake” approach.

During the time, by continuous releasing of the quadrilateral vortex loops, the vortex lattice formed of linear trailed and shed vortices is created.

The collocation points of the vortex lattice are node points. The wake distortion is achieved by altering the positions of the collocation points in time, by application of a rather simple kinematics relation:

$$\vec{r}_i\left(t+\Delta t\right) = \vec{r}_i\left(t\right) + \vec{V}_i\left(t\right)\Delta t \,. \tag{17}$$

The velocities of the collocation points are obtained as sums of the undisturbed flow velocity and velocities induced by other vortex elements of the flow field.

Induced velocities are calculated using the Biot-Savart law. In order to avoid the problems of velocity singularities, line vortex elements are modeled with core. The existence of the vortex core has remarkable influence in blade-wake interactions, since in this way large velocity irregularities on the blade close to the wake are avoided (Fig. 5).

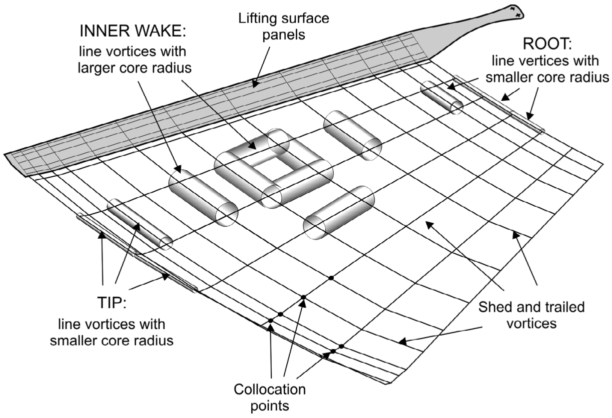

Figure 5. Discretized wake

In this way, a discretized wake model, consistent with the panel model of the lifting surface and vortex releasing is obtained.

3.6 Discretization in time of unsteady Kutta condition

Let us consider the unsteady Kutta condition from the aspect of the assumed discretized model. It is necessary to substitute the partial derivative in (15) with the finite difference form:

$$\frac{\partial\tilde{\Gamma}}{\partial t}=\frac{\tilde{\Gamma}(t+\Delta t)-\tilde{\Gamma}(t)}{\Delta t}=\frac{\Delta\tilde{\Gamma}}{\Delta t}. \quad (18)$$

By substituting this equation in (15), we obtain:

$$V_\infty\gamma_{TE}+\frac{\tilde{\Gamma}(t+\Delta t)-\tilde{\Gamma}(t)}{\Delta t}=0. \quad (19)$$

In case of numerical solutions, it is customary to satisfy Kutta condition in vicinity of the trailing edge. According to that, the intensity of the distributed vorticity at the trailing edge γ_{TE} is treated as equal to the intensity of the distributed vorticity at the trailing edge panel γ_n. The intensity of the distributed vorticity is constant at every panel, so it can be written:

$$\gamma_{TE}=\gamma_n=\frac{\Gamma_n}{l_n} \quad (20)$$

where γ_n is intensity of the distributed vorticity at the trailing edge of panel, and l_i is the panel cord length. Substituting this equation in (19), the difference of circulations around the lifting surface at the moments $t + \Delta t$ and t can be calculated by:

$$\tilde{\Gamma}(t+\Delta t)-\tilde{\Gamma}(t)=-V_\infty\frac{\Gamma_n}{l_n}\Delta t. \quad (21)$$

4. DEFINITION OF EQUATION SET

The boundary condition of impermeability of the lifting surface should be satisfied at any moment of time, t_k ($k = 0,1,2\ldots$) in a finite number of points of lifting surface:

$$\left(\vec{V}_i-\vec{V}_{Ti}\right)\cdot\vec{n}_i=0;\quad i=1,2,\ldots,n. \quad (22)$$

Points at which this condition must be satisfied are called the control points. One of them is placed on each panel, at the three-quarter chord panel positions. By this, at every moment of time, the number of lifting surface impermeability conditions is equal to the number of unknown values of circulations of bound vortices.

The equations of motion of the lifting surface are known, as well as the velocities $\vec{V}_{Ti}$ of all characteristic points, and their normals $\vec{n}_i$ as well.

At each flow field point, velocity can be divided to the free stream velocity and perturbation velocity:

$$\vec{V}_i=\vec{V}_\infty+\vec{w}_i. \quad (23)$$

The perturbation velocity is induced by lifting surface and wake vortex elements. It is calculated by Biot-Savart law. At every moment, the wake shape and circulations of its vortex lines are known, and so the wake induced velocity at every flow field point is known as well. On the other hand, the circulations of the bound vortices are unknowns (their positions are defined by the lifting surface shape). The boundary condition for the i-th control point can be written as:

$$\sum_{i=1}^{n}a_{i,j}\Gamma_{ji}(t)=b_i \quad (24)$$

where $a_{i,j}$ are the coefficients depending of the blade geometry, and b_i are the coefficients containing the influence of the wake and free-stream flows.

This way, by writing equations for all control points, the equation set of the unknown bound circulations is obtained.

Besides this equation set, the Kutta condition must be satisfied. By adding the Kutta conditions to the equation set, an overdetermined equation set is obtained. It can be reduced to the determined system by the method of least-squares. After that, it can be solved by some of the usual approaches, by which the unknown values of circulations Γ_i at the time t are obtained.

5. DETERMINATION OF THE AERODYNAMIC FORCE

After unknown circulations Γ_i are obtained, velocity at every point of the flow field is known, and we can use them for the determination of aerodynamic forces that act on the blade. The calculation aerodynamic force is necessary for the defining of the blade position at the next moment of time. The total aerodynamic force is calculated as the sum of forces acting on all panels.

$$\vec{F}=\sum_{i=1}^{n}\vec{F}_i. \quad (25)$$

Aerodynamic force acting on a single panel can be defined by introducing the Kutta condition in a vector form:

$$\vec{F}_i = \rho \vec{V}_\infty \times \Gamma_{i(\text{ef.})} \overrightarrow{BC} \qquad (26)$$

where $\overrightarrow{BC}$ is bound circulation vector, and effective circulation is calculated from the leading edge to the quarter-chord position of the *i*-th panel in discretized form:

$$\Gamma_{i(\text{ef.})} = \Gamma_i + \frac{1}{V_\infty}\frac{\partial}{\partial t}\left(\sum_{k=1}^{i-1}\Gamma_k + \frac{\Gamma_i}{4}\right). \qquad (27)$$

6. OPTIMIZATION PROCESS

The first steps in the process of genetic optimization are determination of the fitness function and definition of the variables and constant parameters of the optimization process, i.e. the definition of the chromosome of the individual.

6.1 Definition of the fitness function

Optimization process has been performed for the two different fitness functions. For a wind farm it is very important to determine the total energy that can be obtained from it. Because of that, in both cases the fitness function has the elements of the maximizing of the total obtained energy.

In the first case, the fitness function is the ratio of the total energy that is obtained from the wind farm, denoted as P_{total}, versus the energy sum of the isolated wind turbine, denoted as $P_{\max}$, for the same wind conditions at the flat terrain.

$$\text{fitness function 1} = \frac{P_{\text{total}}}{P_{\max}}. \qquad (28)$$

In the second case, the fitness function takes into account an economical factor, being the investment costs. In order to reduce the time required for the genetic algorithm calculations, a simplified model of the investment cost determination has been applied, in the sense that this factor is influenced only by the number of wind turbines. By this model it is assumed that nondimensional value costs/year is equal to one for one wind turbine, and that the maximum cost reduction is 1/3 for each added wind turbine. According to that, the costs/year for the whole wind farm can be expressed in the form:

$$\text{costs} = \mathrm{N}\left(\frac{2}{3} + \frac{1}{3}e^{-0.0174\mathrm{N}^2}\right). \qquad (29)$$

Fitness function which also incorporates the costs and total power obtained from the wind farm can be written in the form:

$$\text{fitness function 2} = \frac{\text{costs}}{P_{\text{total}}}. \qquad (30)$$

Defining such an fitness function and by its minimizing during the optimization process, a disposition of the turbines within the wind farm can be obtained, which gives the best ratio of the obtained power and the investments. This fitness function can also be spread in the sense that the number of the wind turbines can be included as the optimization factor, which will be the subject of the next phase of these investigations.

6.2 Selection of the parameters and definition of the chromosome

The next step is the definition of the individuals, i.e. definition of the individual's chromosome. To simplify the optimization process, we will assume that the terrain configuration where the farm will be positioned is known, that the farm will consist of the same turbines, meaning the same type, rotor diameter and the tower height. We will also assume that for the given terrain configuration the wind data are known, and also that the wind velocity and direction are constant. Such simplifications imply that the only variables of the fitness function are the *x* and *y* coordinates of the points where the wind turbines are positioned (the *z* coordinate can be obtained from the terrain configuration, Fig. 6).

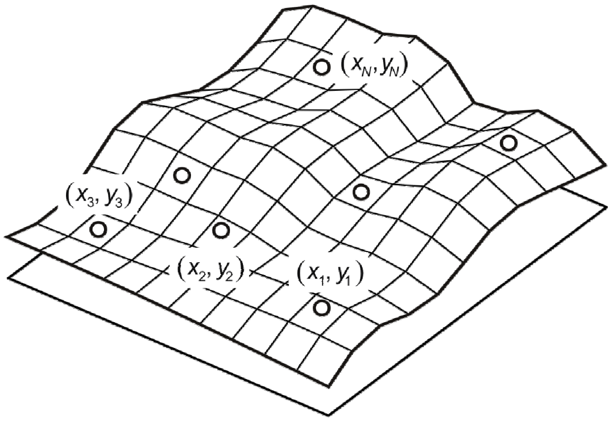

Figure 6. Layout of wind turbines on the site and variables which define a chromosome of an individual in the process of genetic optimization

For N wind turbines of which the wind farm consists, the chromosome is simply formed as by joining the coordinates into an array, according to the following pattern:

x_1	y_1	x_2	y_2	…	…	x_N	y_N

It can be seen that one individual actually represents a layout. Population consists of a certain number of individuals, i.e. possible dispositions of wind turbines on the site.

In the optimization process the following parameters of the wind farm have been selected:

- wind turbine rotor diameter $D = 40$ m
- tower height $H = 60$ m
- the field size 400 × 400 m
- wind speed $V = 10$ m/s.

6.3 Optimization process for the fitness function 1

The optimization process was initially done for the fitness function 1, with the following parameters of the differential evolution:

- number of wind turbines on the farm N = 8
- size of the population D = 20
- parameters of the differential evolution process F = λ = 0.81
- probability of the crossover CR = 0.75.

The number of wind turbines on the farm comes out from the need to perform the calculations within the reasonable time limits, while the software is still in the process of development. The population of 20 individuals, i.e. possible wind turbine layouts within the farm is quite sufficient in the process of differential evolution for such configuration of the terrain, although it would be worth making attempts even with the higher numbers, in order to verify the software capabilities in most general cases of application. The other parameters have been determined empirically, according to similar optimization problems and according to several test runs of this particular software.

The flow of the optimization process is shown in Figure 7. From this diagram it can be seen that the method converges reasonably fast toward the optimum solution.

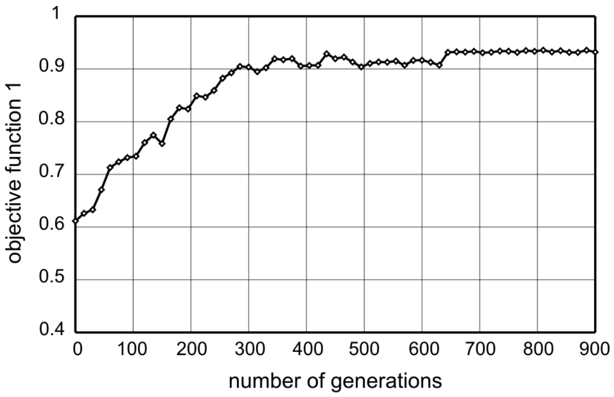

Figure 7. Flow of the optimization process for fitness function 1

Figure 8 shows the optimum distribution of eight wind turbines on the given terrain configuration, as obtained in the 865-th generation of the optimization process.

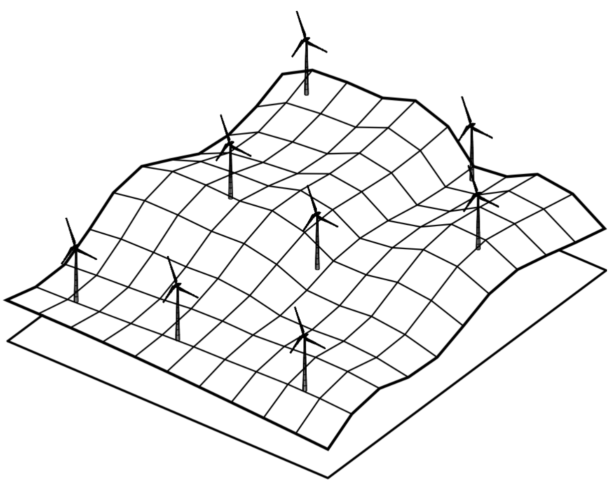

Figure 8. Optimum distribution of the wind turbines for the fitness function 1

6.4 Optimization process for the fitness function 2

The optimization process was the done for the fitness function 2, with the following parameters of the differential evolution:

- number of wind turbines on the farm N = 8
- size of the population D = 20
- parameters of the differential evolution process F = λ = 0.84
- probability of the crossover CR = 0.78.

With respect to the first process, parameters which control the process of the differential evolution have been slightly altered, as a consequence of several test runs.

The flow of the optimization process is shown in Figure 9. From this diagram it can be seen that the method converges reasonably fast toward the optimum solution, and shows higher stability and convergence rate than the first process.

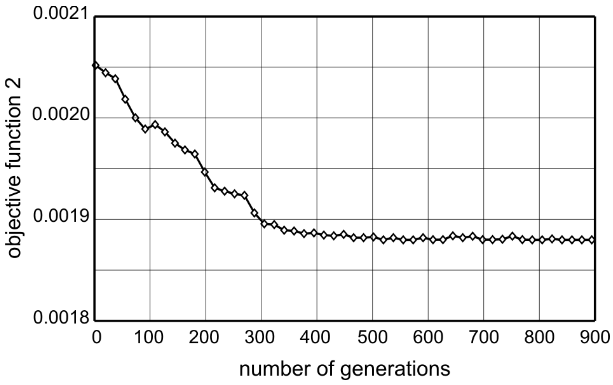

Figure 9. Flow of the optimization process for fitness function 2

Finally, Figure 10 shows the optimum distribution of eight wind turbines on the given terrain configuration, as obtained in the 890-th generation of the optimization process.

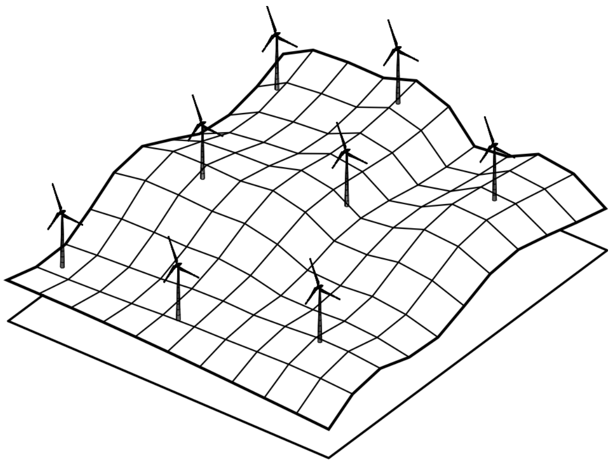

Figure 10. Optimum distribution of the wind turbines for the fitness function 2

7. CONCLUSION

Results presented in this paper show that genetic algorithms can be successfully applied in the preliminary definition of the optimum disposition of the wind turbines on the farm. In wind farm layout optimization, the positions of the turbines should be adjusted freely so that the wind wake effects could be further reduced. However, previous studies provided binary coded genetic algorithm to place turbines in the center of cells in a pre-defined grid. Method presented in this paper optimizes the continuous positions by using real-coded genetic algorithm.

Further advances could be achieved by improving the aerodynamic model, in the sense of including the viscous fluid flow effects. That could be done in two ways: by applying a more complex general fluid flow model or by introducing approximate viscous effects calculations into the existing model. More complex general model coupled with GA, applied on present computers, would be very time consuming. Thus, the second option with the present hardware capabilities would be much more reasonable. Here presented optimization process could be improved by introducing larger populations, while accelerating the optimization process could be achieved by using parallel genetic algorithms.

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ОПТИМИЗАЦИЈА РАСПОРЕДА ВЕТРОГЕНЕРАТОРА УНУТАР ФАРМЕ

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У раду је представљен метод одређивања оптималних положаја ветрогенератора у оквиру фарме, постављене на терену произвољне орографије. Оптимални положаји појединачних ветрогенератора су одређени тако да се постигне њихова максимална ефикасност. Метод је заснован на генетском алгоритму као оптимизационој техници. Аеродинамички прорачун ветрогенератора је изведен на нестационарном потенцијалном струјном пољу. Лопатице ветрогенератора су моделиране као вртложне површине, а вртложни траг је моделиран употребом „freewake“ методе. Оптимизациони модел је развијен за две функције циља. Обе функције користе укупну енергију добијену из фарме као једну од кључних променљивих. Друга функција циља укључује и укупно улагање у сваку појединачну турбину, тако да оптимизациони процес укључује и укупан број ветрогенератора као променљиву. Метод је тестиран на неколико произвољних конфигурација терена, при чему је посебна пажња посвећена избору параметара генетског алгоритма, како би се постигле повољне перформансе оптимизационог процеса.