UDC 004.8(045)
DOI: 10.18372/1990-5548.58.13514

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INTELECTUAL APPROACH TO THE DESIGN OF WIND ENERGY PLANT ROTOR PARAMETERS

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***Abstract*—*It is considered a wind power plant rotor design problem for a rotor with vertical axis of rotation. It is proposed an approarch of efficiency improvement by combined rotor design, consisting of some basic rotors (Darrieus rotors) and some booster rotors (Savonius rotors), with further combined rotor structural parametric synthesis problem solution. This task represents the conditional multicriteria optimization problem, for solution of which it is proposed to use the modificated SPEA2 genetic algorithm. It's proposed procedure of the fitness function construction. The given purpose is supplied with help of computer-aided design system.*

Index Terms—Vertical-axis rotor; genetic algorithm; wind turbine optimization.

I. INTRODUCTION

At present, in the world operated fleet of wind power plants, horizontal-axial make up more than 90%.

The lag in the development of vertical-axis wind turbines (VAWT), despite their advantages is caused by several reasons. A wind generator with a vertical axis of rotation was invented later by horizontal-axial propeller. In addition, the main disadvantage of vertical wind generators was mistakenly considered that for them it is impossible to obtain a ratio of the maximum linear velocity of the working bodies (blades) to wind speed greater than 1 (for horizontal-axis propeller wind turbines this ratio is more than 5:1), which necessitated the use of multiplier systems or more massive low-speed generators [1].

However, there are number of advantages:

– absence of aerodynamic noise;
– starting at low wind speeds;
– independence from wind direction.

There are exist such types of vertical-axial wind turbines: the Darrieus turbine, the Savonius rotor and the H-rotor (Fig. 1).

The main advantage of vertical-axial wind turbines over horizontal-axial is their independence to the direction of the wind. Vertical-axial wind turbine with correctly calculated aerodynamics and geometrical relationships, is capable of self-starting at any direction of the wind, whereas, high power propeller type wind turbines at some angles of inward wind flow relative to the working plane of the wind wheel, an additional source of energy is needed to remove the wind turbine's gondola to the wind or change the angle of attack of the blades.

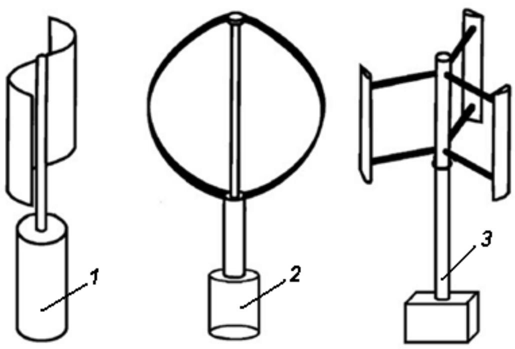

Fig. 1. Types of vertical axial wind turbines:
1 is the Savonius rotor; *2* is the Darrieus turbine;
3 is the Darrieus H-rotor

Coefficient of wind utilization of vertical wind turbines of industrial type (Darrieus H-rotor is considered), varies in the range 0.28–0.40. This value is slightly less than horizontal-axial wind turbines have, but the design of these wind generators is simpler.

This paper is dedicated to reasearch the approach of VAWT efficiency improvement by combined rotor design, consisting of some basic rotors (Darrieus rotors) and some booster rotors (Savonius rotors), with further combined rotor structural parametric synthesis problem solution. This task represents the conditional multicriteria optimization problem, for solution of which it is proposed to use the modificated SPEA2 genetic algorithm. The given purpose can be achieved only with help of Computer-Aided Design System (CADS).

II. CADS STRUCTURE

At the present stage of development various methods of the final and element analysis at design of structural elements are widely applied. However the method-ological basis, i.e. system approach to a problem of development and optimization of VAWT in general (interference of aerodynamic and electric characteristics) is absent.

Methodological approach to development of a design is based on consecutive stage-by-stage (iterative) optimization of components of a design for the purpose of improvement of the WT parameters on the basis of studying of mathematical three-dimensional and functional models of the corresponding components and WT in general, with calculation of the external and internal revolting influences and their influences on work of WT. Theoretical calculations are checked by the pilot studies conducted on the basis of the known and again developed methods, programs and techniques. In general the set of methods and techniques represents the arch or the sequence of the approaches making methodology, i.e. the evidence-based system of development.

The structure of a CADS is a complex which solves a problem of design of a rotor, it is shown in Fig. 2.

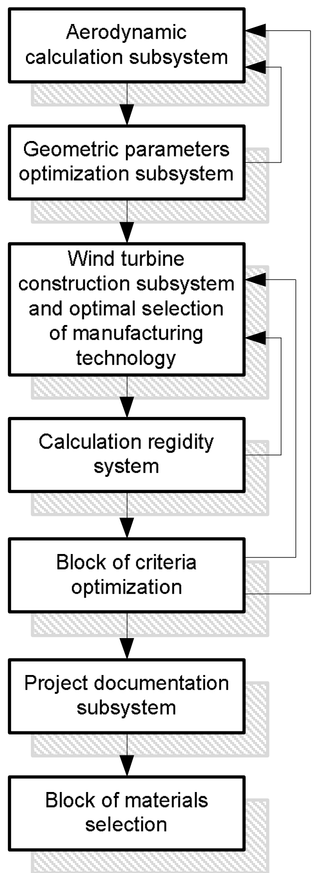

Fig. 2. Block diagram of a CAD

The program will carry out calculations on the basis of the following information:

– rotor geometry (blade width, diameter of the bearing screw, etc.);

– mass assessment (the mass of a rotor on the basis of statistical data);

– environmental conditions (wind speed, temperature, height, etc.);

– parameters of the movement (maximum speed of rotation);

– force of separate materials for every element.

III. PROBLEM STATEMENT

In general, the multicriteria optimization problem includes a set of *N* parameters (variables), a set of objective functions *K* and a set of restrictions *M*.

Thus, under solving a multicriteria problem, it is necessary to find the optimum for *K* criteria, and the problem itself is formally written in the following way:

$$y = f(x) = (f_1(x),\ f_2(x),\ \ldots,\ f_k(x)) \rightarrow \text{opt},$$

where $x = (x_1, x_2, \ldots, x_N)^T \in X$ is the vector of solutions satisfying m restrictions, $g(x) = (g_1(x), g_2(x), \ldots, g_m(x)) \geq 0$; $y = (y_1, y_2, \ldots, y_k)$ is the vector of objective functions.

In this case, X denotes the space of solutions, and Y is the space of the criteria. The restrictions $g(x) \geq 0$ determine the set of admissible solutions of the problem.

The admissible set D is defined as the set of vector-solutions x that satisfy the restriction $g(x)$:

$$D = \{x \in X \mid g(x) \geq 0\}.$$

Multicriteria problems are a special class of problems, where the usual heuristics often lead to contradictions, because they do not even have any universal concept of "optimum" as in the tasks of one-criterion optimization, making it difficult to compare one method of multi-criteria optimization with another. And all because solving this kind of problem is not the only optimal solution, but the set of compromise solutions, better known as *Pareto-optimal* (*effective*) *solutions*. Each of these solutions is optimal in the sense that it can't achieve the improvement by one of the objective functions vector components without diminishing the value of at least one of the remaining components. Therefore, the primary goal of multicriteria optimization tasks solving, in contrast to one-criterion optimization, is finding of different Pareto-optimal solutions that reflect the compromise solution of conflict situations characterized by a set of criteria.

One of the most promising methods for the multicriteria optimization problem solution is genetic algorithms.

A. Analysis of existing multicriteria optimization algorithms

There are evolutionary algorithms of multicriteria optimization:

1) objectivet functions are considered separately;
2) a generalized criterion is constructed;
3) it is used the concept of dominance by Pareto

To properly approximate the Pareto-optimal set for one run, it is necessary to perform a polymodal search to find a representative set of solutions. Therefore, ensuring the diversity of the population is one of the most important aspects of multicriteria optimization by genetic algorithms.

Unfortunately, a simple genetic algorithm leads to one solution, that is not provides such opportunities, therefore, approaches have been developed and developed to this day, which allow to increase the distribution of points in the search space (population diversity).

Along with the support of diversity, the notion of elitism plays an important role, the main idea of which is to always include the best individuals in the next population, so as not to lose good features as a result of genetic operators actions.

In the multicriterial genetic algorithms, a general evolutionary algorithm is taken as the basis. However, under developing specific methods for solving multicriteria problems, the main attention is paid to modifying the stages of fitness and selection assignment with maintaining diversity of the population.

The most common modifications of genetic algorithms that implement various schemes of fitness and selection assignment include the following:

1) VEGA – Vector Evaluated Genetic Algorithm [5];
2) FFGA – Fonseca and Fleming's Multiobjective Genetic Algorithm [6];
3) NPGA – Niched Pareto Genetic Algorithm [4];
4) SPEA – Strength Pareto Evolutionary Algorithm [7];
5) NCGA – Neighborhood Cultivation Genetic Algorithm [8];
6) SPEA2 – удосконалена версія алгоритму SPEA [9].

Based on the comparative analysis of given algorithms accuracy [8], the best results show the algorithms NCGA and SPEA 2, so they were chosen as "starting points" to create their own version of the evolutionary algorithm.

B. Transition from the conditional problem to an unconditional multicriteria problem

In the classical genetic algorithm, there is no scheme for taking into account the constraints of the optimization problem. It is possible to eliminate this drawback in several ways: adding to the standard GA mechanisms of accounting restrictions in the form of penalty functions (static, dynamic, adaptive, death penalties) or specialized genetic operators ("treatment", "treatment 2", "treatment + death penalties", "treatment + death penalties 2", behavioral memory) [3].

In this paper, for the transition to the unconditional optimization problem, it is proposed to use the "treatment" approach. In order to make possible the solution of a conditional problem by methods of multi-criteria optimization, each restriction is considered as a separate objective function and, therefore, initially the conditional problem (with one or several criteria – objective functions) in the end is reduced to an unconditional multi-criteria problem. That is, the original task is presented in the form of a set of criteria: available objective functions plus additional criteria – the degree of execution of restrictions. Thus, the problem of conditional multicriteria optimization takes the following form:

– original task: objective functions – $F(X) \to \text{opt}$, restriction – $G(X) < B$;

– transformed task: objective functions:
$F(X) \to \text{opt}$, $| G(X) - B | \to \min$.

It is necessary to take into account that the main difference between the solution obtained of an unconditional multicriteria problem and the problem with constraints is the need for the final points not only to belong to the Pareto set, but also to be in the admissible domain. Therefore, an additional procedure is introduced, which allows you to "tighten" points in the admissible domain.

IV. GENETIC ALGORITHM (SPEA 2)

Genetic algorithm (GA) is a search-based optimization technique based on the principles of Genetics and Natural Selection [2]. It is frequently used to find optimal or near-optimal solutions to difficult problems which otherwise would take a lifetime to solve. It is frequently used to solve optimization problems, in research, and in machine learning.

Nature has always been a great source of inspiration to all mankind. Genetic algorithms (GAs) are search based algorithms based on the concepts of natural selection and genetics. Genetic algorithms are a subset of a much larger branch of computation known as Evolutionary Computation.

In genetic algorithms, there is a population of possible solutions to the given problem. These solutions then undergo recombination and mutation (like in natural genetics), producing new children, and the process is repeated over various generations. Each individual (or candidate solution) is assigned a fitness value (based on its objective function value) and the fitter individuals are given a higher chance to mate and yield more "fitter" individuals. This is in line with the Darwinian theory of "Survival of the Fittest".

In this way it is kept "evolving" better individuals or solutions over generations, till it is reached a stopping criterion.

Genetic algorithms are sufficiently randomized in nature, but they perform much better than random local search (in which it is supplied various random solutions, keeping track of the best so far), as they exploit historical information as well [1].

Population is a subset of solutions in the current generation. It can also be defined as a set of chromosomes.

The diversity of the population should be maintained otherwise it might lead to premature convergence.

It is proposed an approach of multiobjective optimization, the strength Pareto evolutionary algorithm (SPEA) (Fig. 3). Strength Pareto evolutionary algorithm uses a mixture of established and new techniques in order to find multiple Pareto-optimal solutions in parallel.

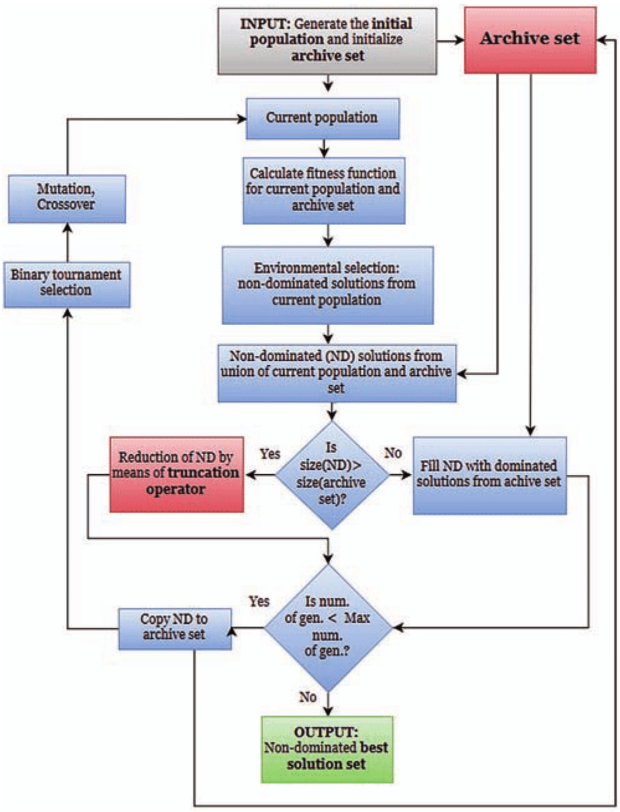

Fig. 3. Block scheme of SPEA2 algorithm

On one hand, similarly to other multiobjective GAs, it:

– stores the nondominated solutions found so far externally;

– uses the concept of Pareto dominance in order to assign scalar fitness values to individuals, and performs clustering to reduce the number of nondominated solutions stored without destroying the characteristics of the trade-off front

On the other hand, SPEA is unique in four respects.

1) It combines the above three techniques in a single algorithm.

2) The fitness of an individual is determined only from the solutions stored in the external nondominated set; whether members of the population dominate each other is irrelevant.

3) All solutions in the external nondominated set participate in selection.

4) A new niche method is provided in order to preserve diversity in the population.

The flow of the algorithm of SPEA optimization is as follows.

Step 1: Generate an initial population P and create the empty external nondominated set P^*.

Step 2: Copy nondominated members of P.

Step 3: Remove solutions within P^* which are covered by any other member of P.

Step 4: If the number of externally stored nondominated solutions exceeds a given maximum N, prune P by means of clustering.

Step 5: Calculate the fitness of each individual in P as well as in P^*.

Step 6: Select individuals from $P + P^*$ (multiset union), until the mating pool is filled. In this study, binary tournament selection with replacement is used.

Step 7: Apply problem-specific crossover and mutation operators as usual.

Step 8: If the maximum number of generations is reached, then stop, else go to Step 2.

V. FITNESS FUNCTION

In genetic algorithms, each solution is generally represented as a string of binary numbers, known as a chromosome. It is necessary to test these solutions and come up with the best set of solutions to solve a given problem. Each solution, therefore, needs to be awarded a score, to indicate how close it came to meeting the overall specification of the desired solution. This score is generated by applying the fitness function to the test, or results obtained from the tested solution.

It is distinguished between evolutionary algorithms of multicriteria optimization, 1) where the objective functions are considered separately, 2) approaches based on classical methods for constructing a generalized criterion and 3) methods that directly use the concept of dominance on Pareto.

In this paper it is proposed method that directly use the concept of dominance on Pareto.

Let's consider the following situation where it had 3 parameters for multicriteria optimization of vertical axial wind turbine:

$$F(x) = \left[F_1(x_1), F_2(x_2), F_3(x_3)\right]. \quad (1)$$

It's necessary to find the most optimal solution from population of chromosomes from existing ones. To find the most optimal, it's necessary to find fitness for each parameter. To find $F(x)$, it necessary to plot two graphs with fitness comparison for $F_1(x_1)$ / $F_2(x_2)$ and find average distance from each fitness crossections to the starting coordinate points (starting point represents the result which it is looked for). Let's create the first one plot(Fig. 3).

After fitness function found for each parameter. It's necessary to define overall fitness for each chromosome in the population. It can be performed using root mean square approach of all solution distances to coordinates start.

$$F(x) = \sqrt{\frac{F_1(x_1)^2 + F_2(x_2)^2 + \ldots + F_n(x_n)^2}{n}}. \quad (2)$$

After that it's necessary to plot for the f1 and f3 (Fig. 4).

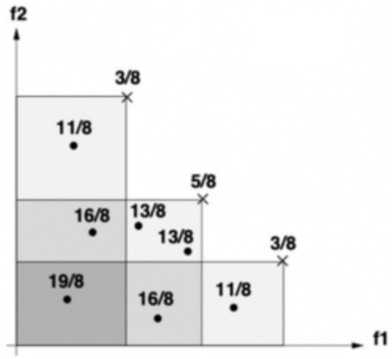

Fig. 3. The fitness plot between f1 and f2 parameters

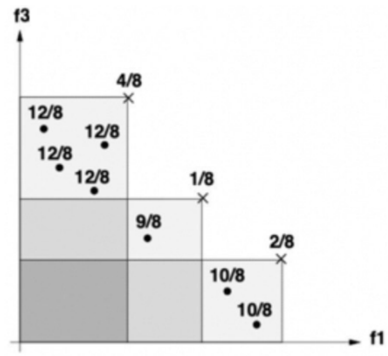

Fig. 4. The fitness plot between f1 and f3 parameters

After the overall fitness obtained it's possible to use obtained solution for the following population generation or to use as the final result.

VI. CONCLUSION

It can conclude that using SPEA2 genetic algorithm it is possible to obtain near optimal multicriteria solution for vertical axial wind Turbines design comparably fast with other traditional methods in order to get efficient shape at lowest possible cost.

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Received October 03, 2018

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В. М. Синєглазов, Ш. А. Хок. Інтелектуальний підхід до проектування параметрів роторів вітроенергетичної установки

У даній роботі розглянуто підхід для багатокритеріальної оптимізації вітроенергетичних установок. Об'єктом дослідження є вітрові енергетичні установки з вертикальною віссю обертання. Алгоритмом оптимізації обрано «Strength Pareto Evolutionary Algorithm» генетичний алгоритм, а для вибору найкращих хромосом метод домінування Парето. Проведення даної роботи дозволяє створити програмні пакети для оптимізації вітроенергетичних установок з вертикальною віссю обертання які дають високий результат в короткі строки.
Ключові слова: вертикально-осьовий ротор; генетичний алгоритм; оптимізація вітроустановки.

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В. М. Синєглазов, Ш. А. Хок. Интеллектуальный подход к проектированию параметров ротора ветроэнергетической установки

В данной работе рассмотрен подход к многокритериальной оптимизации ветроэнергетических установок. Объектом исследования являются ветровые энергетические установки с вертикальной осью вращения. Алгоритмом оптимизации выбран «Strength Pareto Evolutionary Algorithm» генетический алгоритм, а для выбора лучших хромосом метод доминирования Парето. Проведение данной работы позволяет создать программные пакеты для оптимизации ветроэнергетических установок с вертикальной осью вращения которые дают высокий результат в короткие сроки.
Ключевые слова: вертикально-осевой ротор; генетический алгоритм; оптимизация ветроустановок.

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