USING MULTIOBJECTIVE GENETIC ALGORITHMS FOR OPTIMAL RESOURCE MANAGEMENT IN AN AUTONOMOUS POWER SYSTEM

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Abstract: *This paper presents the results of research of multi-objective genetic algorithms applied to solving the problem of system construction and power management. Research is determined by the need for optimal and efficient distribution of different types of energy (renewable or residual) and attempts to improve overall energy efficiency in the energy system which is independent of centralized networks.*

Keywords: stand-alone power system, genetic algorithm, Multi-Objective Evolutionary Algorithm, Non-dominated Sorting Genetic Algorithm-II, Archive-based Micro Genetic Algorithm -2, ε- Multi-Objective Evolution Algorithm

WYKORZYSTANIE WIELOOBIEKTOWYCH ALGORYTMÓW GENETYCZNYCH DO OPTYMALNEGO ZARZĄDZANIA ZASOBAMI W AUTONOMICZNYM SYSTEMIE ENERGETYCZNYM

Abstract: *Artykuł przedstawia rezulataty badań nad zastosowaniem wieloobiektowych algorytmów genetycznych do rozwiązania problemów tworzenia/projektowania i zarządzania systemem energetycznym.. Przeprowadzenie badań zostało uwarunkowane potrzebą optymalnej i efektywnej dystrybucji różnego rodzaju energii (odnawialna czy pozostałe) oraz próbą poprawy ogólnej efektywności energetycznej w systemie energetycznym, niezależnym od zcentralizowanych sieci.*

Keywords: niezależny system energetyczny, algorytm genetyczny, wieloobiektowy algorytm ewolucyjny, Non-dominated Sorting Genetic Algorithm-II, Archive-based Micro Genetic Algorithm -2, ε- Multi-Objective Evolution Algorithm

Introduction

Recently the topic of multiobjective optimization methods and multicriteria decision making has become increasingly popular, many new methods and algorithms were suggested to solve multicriteria problems in various spheres. Using multiobjective optimization is stimulated by the emergence of high-speed computing and numerical analysis of models for solving engineering problems. Computational methods and algorithms based on evolutionary principles have become a significant development; they are widely used because most engineering problems are characterized by NP-complexity, and it is often desirable to have rapid calculation of approximate solutions. Evolutionary algorithms (EA) are adaptive search techniques based on natural principles. Adaptive nature of EA helps to use them to develop optimization algorithms through appropriate variation operators and approximated functions of life. Genetic algorithm (GA) is one of the evolutionary techniques that can successfully be used as a tool for optimization. An approach based on population in GA makes it resistant to premature convergence, that is a powerful tool for working with non-linear and multi-modal functions [1].

This article focuses on the key issue of different types of multicriteria GA for solving the problem of optimal allocation of energy resources for autonomous power system, the main features of multicriteria GA for solving multiobjective optimization, and the selection and comparison of the most effective of them. The ability of parallel GA search solutions in different parts of the region of solutions makes it possible to find a set of different solutions to the challenges of non convex, discontinuous and multimodal regions of the solutions. Crossover operator in GA can handle the structure of good solutions to suit different purposes in order to create new solutions not dominant in the unexplored regions of Pareto front. Moreover, most multicriteria GAs do not require manual setting of priorities, scope and scale for the purpose. Therefore, an approach based on modified genetic algorithms became a popular heuristic approach to solving multicriteria optimization problems.

1. Methods

To verify the computational efficiency of algorithms in multicriteria problems of optimal resource allocation we have implemented the following algorithms: Non-dominated Sorting GA-II (NSGA-II), Archive-based Micro Genetic Algorithm-2 (AMGA-2) and ε-Multi-Objective Evolutionary Algorithm (ε-MOEA). This choice depends on certain objective characteristics and properties of these algorithms which will be presented below.

NSGA-II In recent years a variety of multicriteria evolutionary algorithms were suggested. Ability to find multiple Pareto optimal solutions in a single pass is the main reason of interest. The algorithm has $O(mN^3)$ complexity and a selection operator that creates a crossing-over pool using a combination of parents and descendants populations to select N superior descendants according to adaptability and distribution. Owing to insignificant requirements to computational resources with the use of elitism and distributed fitness approach implementation, the NSGA-II (Non-dominated Sorting Genetic Algorithm-II) algorithm is widely used.

Non-dominated Sorting GA was proposed in research [6] and was the first among similar evolutional algorithms. Main disadvantages of the algorithm are:

- High computational complexity of non-dominated sorting. The problem of the $O(mN^3)$ complexity was essential when population size increased and that conduced to the increase of execution time and computational resources (in every generation the individuals of population are sorted).
- The non-elitism approach. Research shows that using elitism can make GA run faster and lead to effective decisions saving.
- The need to implement diveristy parameter with highest fitness value.

The traditional mechanisms of support diversity in the population strongly depended on the diversity concept and got a wide variety of equivalent solutions. The main problem in fitness diversity is possibility to specify the parameter. In spite of attempts to dynamically compute limits and size of the fitness assignment parameter the population variety saving is desired. We analyzed the algorithm NSGA-II and found the following advantages:

- Reducing the complexity of the algorithm to O (mN3) using optimal data structures.
- Use an external archive of elite solutions.
- The implementation of the fitness assignment without the use of additional parameters.
- Support diversity in the population.

AMGA-2 algorithm is an evolutionary optimization algorithm which uses genetic variation operators for the generation of new solutions. In the scheme of generation which was introduced in the proposed algorithm a certain iteration (generation) in the selection process (selection) involved only those solutions that have been made before the current iteration. However, the algorithm generates a small number of new solutions during the iteration, so it can be classified as an almost stable genetic algorithm. The algorithm works with small size populations and supports an external archive of received fairly good solutions. During every iteration a small number of solutions are generated by the operators of genetic variation. Then the newly created solutions are used to update the archive. This algorithm is called a micro-genetic algorithm with the archive based on the fact that it works with very small populations and uses an external archive to maintain its individuals' search history.

The main recommendation is using a large size archive to get a wide set of solutions for which any other solution is non-dominant. The archive size determines the computational complexity of the proposed algorithm. Even if we consider optimization problems that require significant computing time, the algorithm is very small in comparison with time to be spent on routine analysis. The parent population is created from the archive, and the selection of a parent population is based on a binary tournament used to create a population of descendants. Research provides the following benefits of AMGA-2:

- Attracting the most effective practices.
- Preservation of elite solutions.
- Saving diversity, minimization of computation based on working with small populations.
- Ability to work with almost any type of coding.
- A small sensitivity to the modified algorithm.

ε-MOEA algorithm is a variant of widespread MOEA algorithm which was based on the concept of ε-dominance [2]. Solution search area is divided into equal parts (or hypercubes), and diversity is maintained by ensuring that each part or hypercube contains only one solution. In the proposed multiobjective evolutionary algorithm two populations develop simultaneously: the current population *P(t)* and archival population *E(t)* (where *t* is iteration counter). This multicriteria GA starts with an initial population *P(0)*. Archival population *E(0)* included the *P(0)* solutions over which other solutions on the basis of ε-dominance aren't dominant. Then two solutions, one of the *P(0)* and one with *E(0)* are selected for the crossover. To select the solution *P(t)* we need to choose two random individuals of the population and perform the dominance test. If one solution dominates over the other, then it will be selected, and the next procedures of the algorithm will be performed with the selected solution. Otherwise, if no solutions dominate over others then a solution will be chosen randomly. Let *p* be a chosen solution and *e* be an archival solution that was selected by a specific relationship strategy. The crossover of the descendants creates *C(t)* set; and to involve *c* to the solution archive *E(t)*the algorithm has to perform the dominance test again. The test includes objectives analysis and association *c* with *B(f)* array, where:

$$B_j(f) = \begin{cases} \left\lfloor (f_j - f_j^{\min}) / \varepsilon_j \right\rfloor, (\min(f_j)) \\ \left\lceil (f_j - f_j^{\min}) / \varepsilon_j \right\rceil, (\max(f_j)) \end{cases} \qquad (1)$$

On the understanding that $f_j^{\min}$ is the minimum possible value of j-th objective function and ε_j is allowed limit of j-th objective function below which values are irrelevant to the user. Detailed examination of the algorithm reveals its following properties and advantages:

- Support of well-distributed solutions.
- Automatic limit of the resulting archive.
- Stability of the algorithm.
- Stimulation of finding solutions which do not dominate over others.
- Diversity support and the use of elitism.

2. Results

A stand-alone power system (Fig. 1) with different sources of power supply is able to effectively use their own resources to maintain the functionality of life support systems.

However, it is impossible to achieve the expected performance without the corresponding equipment and proper maintenance. In this case from the one point of view it's difficult to determine the optimal combination of necessary equipment and machinery for use in the power system; from the other point the management process requires optimal allocation of resources in the system [5].

The basis of DSS are multicriteria genetic algorithms which are based on Pareto ranking and use the concept of Pareto dominance during the fitness functions calculation or appropriation of specified probability of selecting an optimal decision. The population is ordered according to the rule of dominance, and then the value based on the adaptability of the rank in the population is assigned to each solution in contrast to the value based on the objective function. GA provides an opportunity to achieve a uniform distribution of solutions on Pareto front with simultaneous support of diversity in the population, which is interesting in terms of variability of the set of possible solutions.

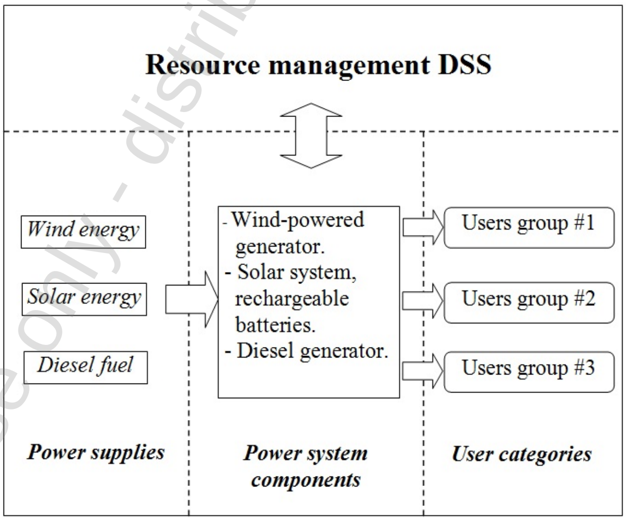

Fig. 1. Resource distribution scheme in a stand-alone power system

The criteria are reduction of equipment purchase costs, operational costs, consumption of various types of energy (solar, wind, diesel fuel for electricity generation) to meet consumer needs. Each criterion was treated as objective function with defined necessary restrictions.

For the simulation of an autonomous power system the following algorithms were chosen: NSGA-II, AMGA-2 and ε-MOEA [3,4]. This choice was appropriate because of certain objective characteristics and properties of these algorithms. Each of these algorithms has some advantages and disadvantages. Algorithm NSGA-II has the following advantages: reducing the complexity of the algorithm to O (mN^3) using optimal data structures, use of an external archive of elite solutions, implementation of the fitness separation without the use of additional parameters, support for diversity in the population. Algorithm AMGA-2 differs as follows: attraction of the most effective practices, conservation of elite solutions, preserving diversity of populations, reduction of calculations, working with small populations, working with almost any type of coding, algorithm sensitivity to small parameters changes. Algorithm ε-MOEA has next features: support of well distributed solutions, automatic limitation of the resulting archive, stability of the algorithm, stimulation of the search for solutions which do not dominate over others, support for diversity, the use of elitism. The simulation results of the stand-alone power systems work during seasons showed that autonomous resource management through multicriteria genetic algorithms is effective.

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