USING GENETIC ALGORITHMS TO SOLVE OPTIMIZATION PROBLEMS IN POWER ENGINEERING

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ABSTRACT:

Against the backdrop of continuous productivity growth in the electric power industry, the implementation of advanced technologies and the improvement of various technological process control systems have become critical issues. One of the most promising developmental directions is the application of optimization algorithms based on the principles of natural selection

A Genetic Algorithm (GA) is an optimization and modeling algorithm based on Charles Darwin's principle of natural selection [1]. Genetic algorithms pre-analyze a set of input parameters for an optimization problem and operate on a collection of individuals (a population), which are represented as strings containing encoded solutions. During the process of selecting the most suitable solutions based on the problem's constraints, the 'fittest individual'-the carrier of the optimal solution-'survives.' It is this approach that distinguishes GAs from most other optimization algorithms, which typically operate on a single solution and improve it methodically.

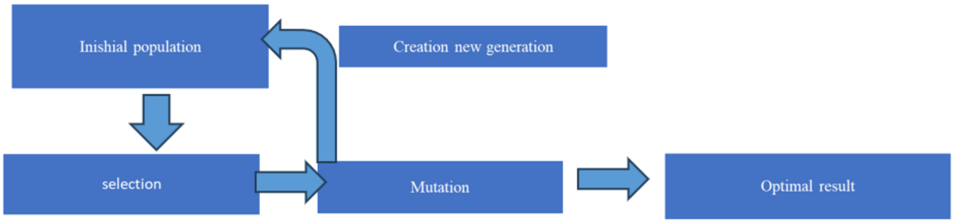

Fig. 1. Block diagram of the genetic algorithm

The first step of the algorithm involves creating an initial population of individuals by generating random parameters. The next step is the selection of individuals that best satisfy the specified solution parameters. Subsequently, the selected individuals undergo 'crossover' (recombination). Some of the copied individuals receive random changes to their parameters (code alteration), a process known as 'mutation.' If the resulting individuals do not provide a suitable solution, a new generation is created. This cycle continues until an optimal solution to the problem is found based on a specific criterion.

The GA described above is known as the 'canonical' genetic algorithm and was developed by American researcher John Holland in 1975. It is important to note that, currently, genetic algorithms represent an entire class of algorithms aimed at solving a wide variety of problems [2]. Examples of various GAs include the following algorithms:

1. Canonical GA;
2. Genitor;
3. Punctuated Equilibrium method;
4. Hybrid algorithm;
5. GA with non-fixed population size;
6. CHC algorithm (Cross-population selection);
7. Parallel GAs.

Genitor employs a different selection strategy. Two individuals are randomly selected from the initial population to undergo crossover. Their 'offspring' then replaces the least fit individual in the current population, with the exception of its own 'parents.' The algorithm can run indefinitely and is terminated only when the solution resulting from repeated eliminations meets the requirements of the given task.

The punctuated equilibrium method is based on a paleontological theory that describes the evolution of all living things on the planet as a result of changes in the Earth's crust. In part, this method is similar to the canonical GA, with the exception that after selection, all the most suitable solutions are mixed, thereby increasing the average fitness of all individuals in the population [3].

The distinctive feature of a hybrid algorithm lies in the combination of the canonical GA with other solution search methods. In each generation, all resulting offspring are optimized using a selected method before being recorded into a new population. Subsequently, standard GA operations are performed: selection of parental pairs, crossover, and mutation. Since all individuals are already located near local optima, the probability of achieving the global maximum for a specific problem increases significantly.

In a GA with a non-fixed size, the concept of 'age' is introduced, which allows for the elimination of the selection stage. Age depends on the fitness of each individual and its proximity to the local optimum of the objective function. Parents and offspring coexist simultaneously in two different populations. 'Deceased' individuals are removed from the main population, and new offspring are added to it. Consequently, the formula for the objective function of the new generation is as follows:

$$Popsize(t+1) = Popsize(t) + AuxPop(t) - D(t) \quad (1)$$

where D(t) represents the deceased individuals, AuxPop(t) is the auxiliary population, and Popsize(t) denotes the main population [4].

The application of the CHC algorithm leads to an optimal solution quite rapidly due to the absence of a mutation stage. A relatively small initial population is created, in which an offspring inherits exactly half of the genes from both the father and the mother. Selection is performed exclusively between offspring and parents. Furthermore, the duplication of individuals is prohibited, which allows the algorithm to avoid redundancy and ensure convergence toward a solution.

In the electric power industry, genetic algorithms are capable of solving narrow yet critically important optimization problems, such as improving power quality indicators and reducing production costs [5]. The primary subjects of research include indicators such as voltage deviation, harmonic component coefficients, and voltage asymmetry in negative and zero sequences. The problem can be represented as a set of multiple functions (operating costs, capital investments, and losses due to poor power quality), as illustrated in Fig. 2. The optimal solution to the problem, which can be identified using a canonical or other type of GA, is located at the intersection point of these three function graphs.

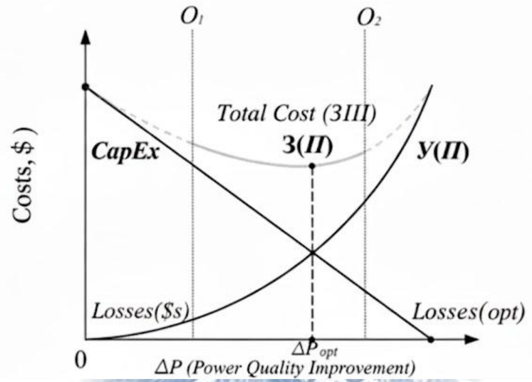

Fig. 2. The nature of cost component changes in power quality management.

TC – total costs; **delta P$_{opt}$** – optimal level of power quality indicator deviations; **O** – technical constraints; **O1** – technical capabilities for power quality improvement; **O2** – technically permissible level of electromagnetic interference.

"Furthermore, genetic modeling is utilized for planning various power supply options based on distributed generation. Such calculations were conducted in Tashkent, resulting in several electrification schemes and operating modes suited to the specified energy and economic conditions [6]. Parallel GAs are employed for the optimal placement of measuring instruments and sensors in automated systems. This significantly enhances the reliability of state estimation, identifies unreliable sensors, and refines the analysis of steady-state modes and the operational reliability of complex electric power systems (EPS) [7].

Mathematical Formulation of the Optimization Problem

In power engineering applications, genetic algorithms are commonly employed to solve multi-objective optimization problems. In this study, the optimization task is formulated as the minimization of an aggregated objective function that simultaneously accounts for operating costs, power losses, and penalties associated with poor power quality indicators:

$$\min\ F = w_1 \cdot C_{\text{op}} + w_2 \cdot C_{\text{loss}} + w_3 \cdot C_{\text{pq}} \quad (2)$$

where C_{op}represents the operating and maintenance costs of the power supply system, C_{loss}denotes the cost associated with active and reactive power losses, and C_{pq}reflects the economic impact caused by deviations in power quality parameters, such as voltage distortion, asymmetry, and harmonic components. The weighting coefficients w_1, w_2, and

$w_3$define the relative importance of each criterion and satisfy the condition $w_1 + w_2 + w_3 = 1$.

The optimal solution is obtained at the point where a compromise between these competing objectives is achieved, corresponding to the minimum value of the total cost function [9-10].

In electric drive systems, GAs are utilized for the dynamic identification of the electromagnetic and mechanical parameters of electrical machines [8]. In control tasks, genetic algorithms are also used in conjunction with other artificial intelligence tools—for example, to 'clean' training and testing datasets provided to neural networks from unwanted values and noise. Thus, genetic algorithms represent a universal and accurate solution for optimization problems, as they operate directly with the objective function rather than its increments. The genetic algorithm code is designed to find specific solutions and does not require a lengthy training phase or extensive computational power.

In conclusion, genetic algorithms (GAs) have proven to be an indispensable tool for addressing the multifaceted optimization challenges inherent in modern power systems. By moving beyond the limitations of canonical versions and incorporating advanced methodologies—such as punctuated equilibrium, hybrid structures, and parallel computing—these algorithms achieve a superior balance between global exploration and local refinement.

The practical application of GAs in cases such as the electrification of Tashkent and the dynamic identification of electric drive parameters demonstrates their versatility and robustness. Unlike traditional gradient-based methods, GAs offer a direct approach to objective function optimization, making them resilient to noise and complex constraints. Furthermore, their integration with other artificial intelligence frameworks, such as neural networks, opens new frontiers for enhancing power quality and operational reliability. As the energy sector shifts toward distributed generation and smart grids, the adaptability and computational efficiency of genetic algorithms will remain critical in ensuring sustainable, cost-effective, and high-quality power supply.

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