**Optimization of the selection of distributed generation sources using a genetic algorithm**

Abduraxim Taslimov 1, A’zam Turayev2, a, Azimjon Yuldashev3

1 Tashkent state technical university named after Islam Karimov, Tashkent, Uzbekistan

*2 Territorial Division of the State Technical Supervision Authority under the Ministry of Defense of the Republic of Uzbekistan, Karshi, Uzbekistan*

*3**Nukus state technical university, Nukus, Uzbekistan*

a) Corresponding author: azam21044@gmail.com

**Abstract.** This article presents the principles of constructing a mathematical model for selecting the parameters of distributed generation units using a genetic algorithm. The algorithm for solving the optimization problem is described, and the efficiency of the proposed method is evaluated by comparing its performance with a full-enumeration approach on a simplified network example. The results demonstrate that the genetic algorithm significantly reduces computational time while maintaining the accuracy of the obtained solutions.

**INTRODUCTION**

Modern power systems are undergoing rapid development, and the trend toward consumers installing their own energy supply sources is steadily increasing. In the Republic of Uzbekistan, such sources typically include gas-piston and gas-turbine units with capacities ranging from several tens of kilowatts to several tens of megawatts. These units are connected to distribution grids with voltage levels of 0.4–35 kV.

Under these conditions, traditional methods of technical-economic comparison of installation options have become inefficient and labor-intensive. Solving the problems of optimal placement and capacity determination of distributed generation units requires the application of modern modeling and optimization methods based on mathematical and computational algorithms.

Among the most important approaches are those that allow simultaneous consideration of multiple factors, including the structure of the electrical network, operating modes, consumer characteristics, energy loss levels, system reliability, and overall stability.

In this context, the use of intelligent algorithms — such as genetic algorithms, particle swarm optimization, neural networks, and other evolutionary techniques — is of particular interest. These methods are capable of finding optimal solutions in complex systems characterized by multiple criteria, uncertainties, and a large number of variables. This makes them especially effective for designing distributed generation systems in Uzbekistan’s power networks.

To illustrate the approach, a simplified case commonly encountered in the analysis of distribution areas supplied by individual transformer substations is considered. The possible types of generation units suitable for installation are determined first. In the optimization-oriented mathematical model, the number of blocks of each permitted type is taken as a decision variable.

The system of constraints may include requirements related to the permissible export of excess power to the external grid, power balance at each node, thermal balance, environmental limits, available land for equipment placement, and other technical factors.

It is assumed that for all considered units, the primary technical and economic indicators (TEI) are known in advance: nominal capacity, forecasted fuel consumption, and other parameters specific to each type of equipment and each possible placement scenario

**EXPERIMENTAL RESEARCH**

A distribution network supplying several transformer substations (TS) of an industrial or urban facility with forecasted loads at 0.4 kV nodes is illustrated in Figure 1. Based on previous studies, the potential areas suitable for locating distributed generation (DG) units have been identified, taking into account thermal requirements, equipment delivery and installation costs, site limitations, and operational expenses.

РG 4

РG 3

РG 1

R 2 РG 2

R5 P2

P1

R 1

BB

R 4

R 3

P 4 P5 P3

РG 5

**FIGURE 1.** Configuration of the electrical distribution network and potential locations for installing distributed generation (DG) units

To partially meet the demand of the transformer substations, the possibility of purchasing a portion of the required electrical energy from the distribution network at retail tariffs is allowed. The main criterion for optimization is defined as the total cost, which includes capital expenditures for constructing a DG unit complex and operational costs associated with utilizing this equipment.

Various optimization methods have been proposed in mathematical modeling literature. The most common approaches, such as linear and nonlinear programming models, operate effectively only with continuous variables. However, when applied to practical problems of distributed generation, the resulting optimal values of generator capacities often do not coincide with the standard nominal ratings offered by manufacturers. Attempts to round these values to the nearest standard size typically distort the results and reduce accuracy [4].

Another challenge arises from the need to account for logical dependencies. Many parameters of DG units installed in real distribution networks change discretely with the generator size, rather than continuously. In some cases, the selected value must be chosen from a predefined set of permissible options, requiring the use of logical operators. Incorporating such elements into the mathematical model makes gradient-based optimization methods infeasible.

Specialized solution techniques, such as branch-and-bound, have been developed to address discrete optimization problems. Nevertheless, their practical implementation becomes computationally complex due to the combinatorial nature of the problem.

One of the simplest alternatives is the use of zero-order methods, which do not rely on derivatives and operate by enumerating all possible variants. Although universal, this approach suffers from the “curse of dimensionality”: the computational burden increases exponentially as the number of variables grows.

To overcome the challenges described above, optimization problems can be solved using algorithms inspired by natural mechanisms—specifically evolutionary computation techniques. In this study, a genetic algorithm (GA) is applied to solve the DG placement and capacity optimization problem [5]. This approach significantly reduces the computation time required to find an optimal solution compared to traditional methods.

The genetic algorithm effectively avoids falling into local minima and remains stable with respect to increases in problem dimensionality, since the computational cost does not grow exponentially with the number of variables. Moreover, the use of GA operates directly on the objective function without requiring analytical derivatives or continuity of the decision variables, which makes it suitable for solving problems with logical constraints and discrete parameters.

The general principle of the genetic algorithm is based on natural selection and evolutionary development. By modeling these biological mechanisms, the algorithm explores the solution space and identifies the best (optimal) candidates among numerous possible alternatives (Figure 2).

**If no**

**If no**

**Mutation**

**F3(n31, n32,…,n3i, p31, p32,…,p3i ,)**

**F3'(n31, n32,…,n3i, p31, p32,…,p3i ,)**

**Output of the result**

**F(n̅,p̅)→min**

**Crossover of individuals**

**F1(n11, n12,…,n1i, p11, p12,…,p1i ,)**

**→ F13(n31, n32,…,n3i, p11, p12,…,p1i ,)**

**→ F31(n11, n12,…,n1i, p31, p32,…,n3i ,)**

**F3(n31, n32,…,n3i, p31, p32,…,p3i ,)**

**Ranking and selection of individuals based on fitness**

**Replacement of eliminated individuals**

**Formation of the initial population**

**F1(n11, n12,…,n1i, p11, p12,…,p1i,)**

**FN(nN1, nN2,…,nNi, pN1, pN2,…,pNi ,)**

**Constra- int  
checking**

**Checking  
the termi  
nation** **condi--  
tions of the**   
**computa-  
tio**n

**If yes**

**If yes**

**FIGURE 2.** Block diagram of the operation of the genetic algorithm

In the developed model, each chromosome represents a set of parameters being optimized — the number and nominal power values of distributed generation units located at each permissible site at a specific time interval. These values are randomly selected from a predefined allowable range. A single chromosome forms an individual defined by the objective function F(n1,n2,…,ni; p1,p2,…,pi), where and represent, respectively, the number and nominal capacity of DG units at node . These parameters constitute the vectors and .

During evolutionary modeling, several chromosomes (individuals) coexist simultaneously, forming a population of size . The individuals undergo a selection process, where the fittest chromosomes survive and reproduce. The reproduction process is implemented through crossover, in which parts of the parent chromosomes are combined to produce new offspring chromosomes that inherit characteristics from both parents. Each chromosome is also subject to mutation, a probabilistic alteration of one or more parameters.

Each newly generated individual is evaluated according to its fitness value, determined by the objective function. Only individuals with the best performance, those with minimal total cost, are selected for the next generation. This ensures progressive improvement of the population and convergence toward optimal values.

The algorithm iteratively repeats the processes of selection, crossover, mutation, and replacement until a termination condition is met. The stopping criterion may include a maximum number of generations, achieve a specified level of convergence, or match the solution obtained by full enumeration.

As a result, the genetic algorithm simultaneously processes multiple possible solutions and avoids being trapped in local minimum, making it a powerful tool for optimizing the placement and sizing of distributed generation units. The final solution corresponds to the globally optimal or near-optimal configuration.

The efficiency of the algorithm is further enhanced by preventing premature convergence to local minima, as the genetic algorithm maintains diversity in the population through random recombination and mutation mechanisms. This significantly reduces the probability of becoming trapped in suboptimal regions of the solution space.

To determine the optimal locations and capacities of distributed generation units, the software environment “Easy NP 2.0” was utilized [9].

The optimization process begins with constructing a mathematical model of the distributed generation integration problem that can be adapted to the algorithm. The general principles of forming this model are described in [6].

The economic indicators of gas-piston units can typically be approximated using linear or quadratic dependencies. Figure 3 presents the relationship between the nominal capacity of Deutz cogeneration units and their cost, which can be represented by the following linear expression:

*Ғ (Р*г)=142,919+0,314 *Р*г , (1)

where is the nominal capacity of the unit, kW.

The coefficients of this linear dependence were determined using the least squares (LS) method. According to the results in [6], installation costs, transportation expenses, design and construction work, fuel consumption, and 0.4 kV cable installation costs can all be approximated effectively using linear functions. However, for certain parameters, quadratic functions yield more accurate results.

The forecasted electrical and thermal loads of the network are determined based on daily consumption graphs and seasonal fluctuations. Electricity tariffs from the external grid may vary throughout the day, directly affecting the economic performance of the distributed generation plant. Therefore, the operation of the plant is analyzed in separate time intervals , within which the network parameters and equipment operating mode are considered constant and equal to their average values for the interval. Although this increases the computational requirements, it significantly enhances accuracy in evaluating operational characteristics.

For each interval, the composition of active equipment is determined, and operational costs are calculated. Capital investments are evaluated based on the maximum number of units operating simultaneously during all intervals, including the required reserve capacity:

*ni* = mах(*ni*1*, ni*2*,…,ni*M*)*. (2)

For each specific case, the optimization model can be extended to account for the particular characteristics of the energy system under study. Additional considerations may include the possibility of selling surplus electricity to external consumers, the cost of fuel supply, land-use constraints, required investments for expanding electrical infrastructure, and modernization of distribution components.

**RESEARCH RESULTS**

The **“Easy NP 2.0”** software package implements these models and allows calculating the total cost of distributed generation integration based on the relevant economic and technical indicators using genetic algorithm procedures.

The capital investment for installing distributed generation units is calculated as follows:

where and are the number of operating and reserve blocks installed at node ; is the nominal rated power of the generator at node , kW; and are the coefficients of the linear approximation.

Capital investments associated with equipment installation and construction works—including “turnkey” engineering solutions—are determined using:

where and are linear approximation coefficients representing construction and installation costs that depend on generator capacity.



**FIGURE 3.** Dependence of Deutz cogeneration unit cost on nominal power

Transportation costs for delivering generator units to the installation site are calculated as:

where and are the coefficients of the linear approximation describing the transportation cost as a function of generator capacity .

These expressions can be extended further to account for other cost components that arise during the installation of distributed generation units.

The interaction between the distributed generation plant and the external power grid may require additional expenses. When the plant operates in parallel with the grid, the station may not export excess energy to the network but may rely on the external grid to compensate for power deficits. In such cases, the total cost of interconnection with the external grid is derived using:

Here, and denote the coefficients representing the additional costs associated with the modernization of protection and automation systems required for grid interconnection; represents the tariff for power reservation according to the terms of the contractual agreement with the distribution company, in UZS/kW; is the number of reserve units installed; is the coefficient associated with the total cost of connecting consumer loads to the distribution network, in UZS/kW; is the coincident peak factor; is the maximum load at node , kW; is the highest nominal generator capacity permitted within the grid; is the nominal rated power of the generator at node .

The values of , , and depend on specific project conditions and may take various values, including zero. To properly incorporate these logical constraints into the model, the following expression is used:

These logical expressions allow the exclusion of economically impractical installation scenarios from the model based on the optimization results, thereby ensuring that the final configuration of distributed generation units remains feasible and efficient.

In addition to capital investments, annual operational costs must also be considered in the optimization model.

For 6–10 kV distribution networks, annual energy losses can be estimated using:

where is the electricity price during time interval , UZS/kWh; is the annual electrical energy loss for interval , kWh.

The energy loss for interval is calculated as:

=

where is the number of days in a year; is the active power loss in the 10 kV network during interval , kW; is the duration of interval , hours.

The power loss for node within a daily load cycle is determined as:

where is the reactive power coefficient of the network; is the nominal network voltage, kV; is the ratio of the average load during interval to the maximum daily load at node ; is the active resistance of the line supplying node , Ohm; is the number of generator units operating at node in interval ; is the number of nodes supplied by the given feeder.

Thus, the principal operational characteristics of the distribution network with embedded distributed generation sources can be computed using the above expressions. Combining capital expenditures and operational costs makes it possible to formulate the total objective function , which depends on the size and configuration of the generation units.

The genetic algorithm then iteratively searches for combinations of and vectors that satisfy all constraints and minimize the objective function.

Considering all cost categories, the optimization problem imposes the following constraints:

The continuous allowable current limit of the 0.4 kV cable lines imposes the following constraint:

, (12)

where — number of parallel cables supplying node ; — length of the cable line; — cross-sectional area of the 0.4 kV cable at node , mm².

**Power rating constraint of 10/0.4 kV transformers**

The total installed generation at each node must satisfy:

(13)

where represents the permissible number of blocks connected to the 10/0.4 kV transformer.

Constraint for limiting power exported to the external grid:

where — power loss during time interval in the 0.4 kV network, kW; — coefficient of average to maximum daily load ratio at node .

These constraints ensure technical feasibility and system reliability. If any constraint is violated by a newly generated individual, that individual is eliminated from the population and replaced by another randomly generated candidate. This iterative process continues until all constraints are satisfied.

To demonstrate the performance of the proposed model, a simplified network (Figure 1) was analyzed. The optimal results obtained using the genetic algorithm were compared with full enumeration (brute-force) calculations. As the list of allowed generator capacities was expanded, the number of possible combinations increased, but the genetic algorithm continued to provide stable results while requiring significantly less computation time.

The following table (table 1) summarizes the computation times for the test network:

**TABLE 1.** Computation Time for the Simplified Network

|  |  |  |
| --- | --- | --- |
| Number of possible variants (million) | Full enumeration (s) | Genetic algorithm (s) |
| 0,0225 | 8 | 5 |
| 0,135 | 44 | 6,5 |
| 3,375 | 960 | 10 |
| 506,25 | 1,4х105 | 20 |

The effectiveness of the genetic algorithm is strongly dependent on the correct selection of its parameters. In this study, the population size was fixed at 30 individuals. Each parent pair generated 10 offspring, and the mutation probability was set at 5%. The implemented software also allows modifying other evolutionary parameters to further refine selection, crossover, and mutation operations, thereby enhancing performance.

The algorithm was terminated once the solution obtained matched the results of the full enumeration procedure. In practical applications, however, termination criteria usually include computational time limits or achieving a specified level of convergence.

Thus, the genetic algorithm demonstrates significant computational advantages while maintaining accuracy, making it a reliable tool for solving distributed generation placement and sizing problems.

**CONCLUSIONS**

The results of this study show that replacing standard stator windings with hybrid windings in doubly fed induction generators (DFIGs) significantly improves machine performance. The hybrid configuration enhances energy efficiency, increases the power factor, and improves electromagnetic behavior under variable operating conditions.

Key advantages of the hybrid winding include:

1. Higher efficiency due to reduced copper losses (7–13%) and improved magnetic field distribution.

2. Increased minimum, maximum, and starting torque.

3. Lower harmonic distortion, resulting in reduced torque pulsation and rotor losses.

4. Stable and efficient operation across a wide range of loads.

Overall, hybrid stator windings offer a technically effective solution for modern DFIG-based wind turbine systems and can contribute to improved reliability and performance in wind power applications.

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