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Distributed Generation for Microgrid Optimization Employing an Autonomous Genetic Algorithm with a Fuzzy Decision-Making Multiobjective Approach

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ABSTRACT
The efficient functioning of Microgrids, which function as useful infrastructure to integrate local loads and Distributed Generations (DGs), has attracted a lot of interest lately. The main focus of this study is on the multi-objective optimization of distributed generators (DGs) in a microgrid using fuzzy decision-making and a self-adaptive genetic algorithm (GA). There are five objective functions taken into consideration: purchase cost, construction cost, transmission loss, offset of voltage, and environmental cost. To increase speed and efficiency, the algorithm takes self-adaptation into account for population size, mutation probability, selection, and standardization of objective functions. Fuzzy decision-making is also used to find the best possible answer. The results of the simulation show how well the algorithm finds optimal solutions, improving the microgrid's real-time control. These results point to possible uses for energy management systems in microgrids.

Keywords: Distributed Generator (DG), Genetic Algorithm (GA)

1.Introduction

As distributed generation (DG) and microgrids (MG) have developed, utilizing DGs efficiently has become crucial for MG. Many benefits result from the integration of DGs, such as decreased line losses, increased power quality, enhanced voltage profiles, and strengthened system security and stability [1]. Deferred investments for facility upgrades, lower operation and maintenance (O&M) costs for some DG technologies, higher overall efficiency resulting in higher productivity, lower healthcare costs because of better environmental conditions, lower fuel costs due to higher efficiency, lower reserve requirements and related costs, and lower operating expenses because of peak shaving are some examples of the economic benefits.

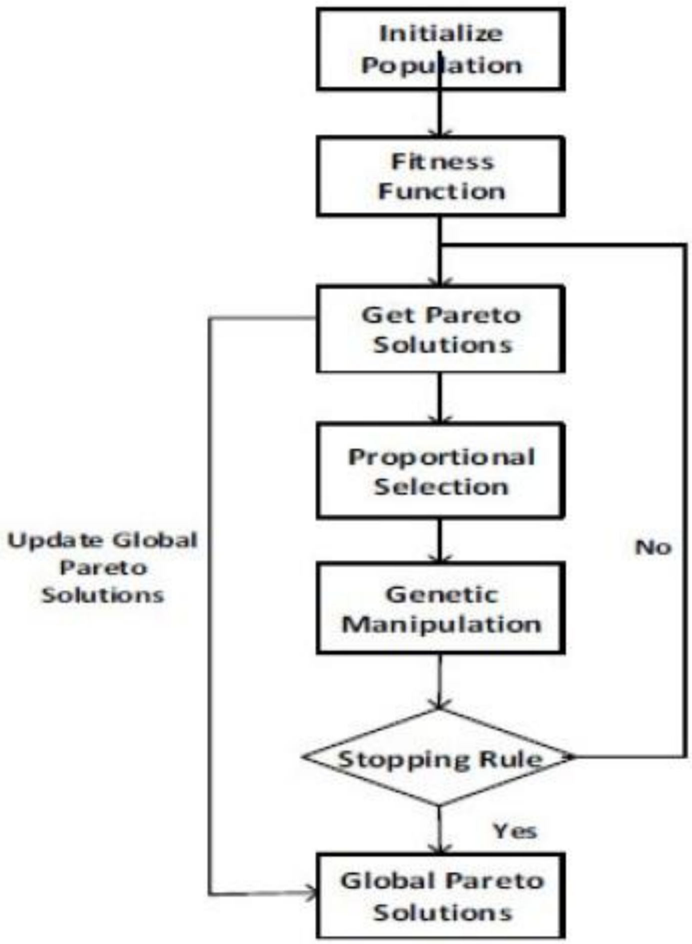
Moreover, benefits to the environment include decreased emissions of pollutants and the encouragement of the production of energy derived from renewable sources [2].

The synchronization of distinct DG units is one of the many difficulties that the development of DG faces. One prospective solution to coordination issues is the introduction of energy management systems (EMS) [4] and multi-agent systems (MAS) [3]. In order to determine the system state and adjust parameters appropriately, these systems make use of sophisticated real-timedatacollecting. DG unit optimization has been the subject of numerous studies from a variety of angles. The importance of sophisticated data analysis and optimal dispatch as changing requirements for MG energy management was highlighted in [4]. [5] used genetic algorithms (GA) to optimize the market earnings of DGs. centered on reducing operational expenses and employed linear programming to optimize a distributed system made up of photovoltaic (PV), batteries, and a wind farm. The outcomes emphasized the importance of generated power and battery life. [7] used GA to reduce the amount of line losses. The aforementioned publications mostly focus on distributed systems single-objective optimization, ignoring frequently occurring trade-offs between different optimization targets. In order to achieve the best dispatch in a system with distributed sources, a thorough method taking into account system capacity, voltage level, line loss, and generating cost is used in [8]. This optimization problem is addressed by a novel self-adaptive method. Its application is restricted to load dispatching for power, and the simulation system has a comparatively small number of generation nodes.

2.Design Flow

The optimization of DG sizes and locations has also been studied [9–20]. An approach that can handle discontinuous load models and multiple DG allocations is introduced in [9]. focuses on using genetic algorithms and optimal power flow calculations to determine the best location and size for distributed generation units. [11] compares the newly suggested Rank Evolutionary Particle Swarm Optimization (REPSO) method with Evolutionary Particle Swarm Optimization (EPSO) and Traditional Particle Swarm Optimization (PSO) in order to determine the best sizing of DG. [12] tackles a novel optimization issue that chooses utility-containing DG unit types, locations, and sizes while taking protection coordination and harmonic distortion limitations into account in order to get the maximum distributed generation penetration level. An overview of techniques for determining where distributed generators should be placed in distribution systems tomaximizebenefitsisgivenin[20]. Emerging as a prominent optimization technique, Genetic technique (GA) imitates processes seen in natural development [2, 21]. GA, which has its roots in stochastic search methods and the principles of natural selection, has several benefits, including low mathematical requirements, global search effectiveness because of evolution operators, and adaptability for hybridization with heuristics that are domain-dependent.

This study addresses the optimization problem of DGs' active and reactive output power involving many renewable sources in the context of real-time control within a Multi-Agent System (MAS) or Energy Management System (EMS) for microgrids. Using a self-adaptive evolutionary algorithm, it takes into account five objective functions: voltage offset, line loss, and operating cost (which includes acquisition, construction, and environmental costs). Fuzzy decision-making is also included to choose a suitable solution from the Pareto solutions. The tested case highlights how the suggested method may effectively and efficiently find appropriate solutions based on actual demand, hence improving real-time control in microgrids' MAS or EMS.



.Figure 1. Genetic Algorithm Flow Chart

3. Multi Objective Optimization Model

Within the framework of this investigation, g(x) and h(x) stand in for the restrictions of the problem. Often, achieving optimality for one goal can cause another goal's optimal value to deviate. Attaining ideal values for every target at the same time might be difficult. Pareto solutions, on the other hand, provide a set of solutions in which improving any objective value will inevitably result in a decline in at least one other objective. These solutions are frequently used as the best options in multi-objective optimization problems because they represent a stable state for all variables.

In order to optimize a microgrid with a collection of Distributed Generators (DGs), line loss, voltage offset, purchasing, construction, and environmental costs are all included in the objective function. The cost of purchasing power to power the microgrid from the main grid is represented by the purchase cost, assuming that the microgrid runs on renewable energy while the main grid usesfossilfuels. The power produced by DGs may be computed since load and line parameters are known and network reconfiguration is not taken into account. We then use the Newton-Raphson Power Flow Algorithm to estimate line losses and bus voltages. Considering bus voltage offsets as constraints could result in a large increase in constraints, which would affect the speed of convergence and algorithm performance. By combining many punishment functions and increasing the population, the solution puts the dominance of objective functions at danger. However, the overall performance of the algorithm must be prioritized, considering the range of flexible voltage-regulation techniques available. One of the objective functions in the study is voltage offset, which is complemented with a punishment function. The voltage offset is written as |Ui - 1| if the voltage at bus i is represented as (p.u.) Ui.

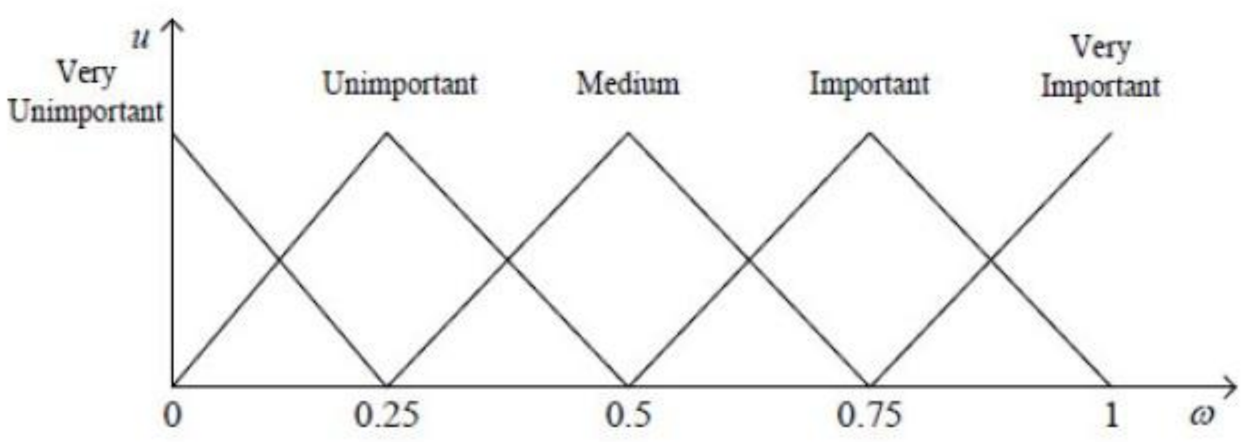


Figure 2. Triangle function

When the expression inside the square bracket is rounded to the left, the outcome is that the exceeding component is ten times greater than the original, which penalizes the objective value with a larger number. A practical solution is to use a 5% voltage offset to increase the penalty's efficacy.

The purchase cost results from obtaining power from the main grid, as was previously explained. When the microgrid functions as an islanded system, a large-capacity battery can be thought of as the primary grid. The Newton-Raphson Power Flow Method can be used to compute the balance bus power, or Pin, which represents the power that needs to be obtained from the main grid.

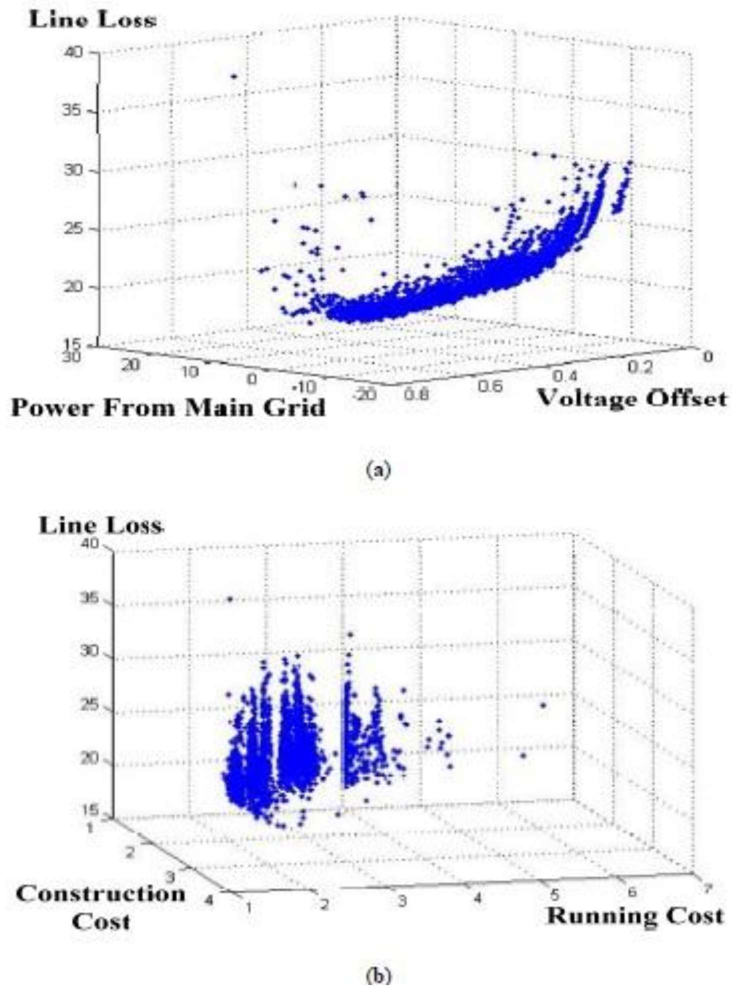


Figure 3. 3D Pareto Solution

5. Self Adaptive Genetic Algorithm

Among the most effective intelligent algorithms is the Genetic Algorithm (GA), which includes important elements including chromosome coding, first population generation, fitness function assessment, gene editing, next generation selection, and algorithm termination. Genetic operations are carried out prior to the selection phase in order to increase the generational variability for inheritance. There are an infinite number of Pareto solutions since the goal functions are continuous. In practice, the scale of each generation varies dynamically during the algorithmtosupportawiderrangeofParetosolutions.The chromosome is made up of the kind of distributed sources and the produced active and reactive power, stored in a real matrix, assuming the initial population size is NP. Buses 1, 2, and 3 in a 7-bus system are coded as DG buses, and theirchromosomesreflectthisdesignation. Crossover and mutation are two aspects of gene modification. Both resulting chromosomes are handed on to the following generation once two randomly chosen cutting sites are selected. The cutting point must appear between non-zero elements in order to cut effectively. The disruption of both active and reactive power is a component of mutation. The worldwide search capability is represented by a mutation probability of 10% and a crossover probability of 95%. Throughout the iteration process, this probability can be changed to speed up convergence and accomplish a certain level of self-adaptation. The subsequent generation, which includes new NP chromosomes, is lawful and exemptfromregulation. There are two steps to the selection strategy: finding Pareto solutions and using proportional selection to create more chromosomes. NSGA-II [26] is the source of inspiration for the Pareto solution extraction procedure. A global Pareto solution saver is initiated with NPi chromosomes in generation I. One option is saved first, and then the other solutions are contrasted. An external solution is either included to the saver or ignored depending on whether it is non-inferior, superior, or replaces the internal solution. As ηk drops with increasing iteration time k, accelerating the convergence rate, the small parameter improves the inheritance probability of the poorest chromosome, gradually diversifying genes in the following generation.

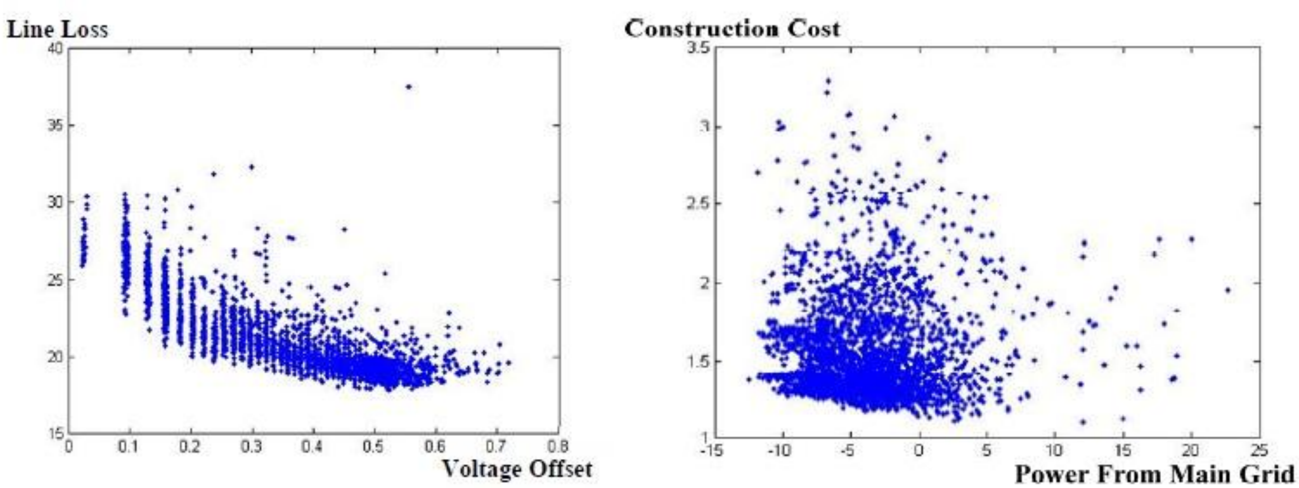


Figure 4: 2D Pareto Solution

6. Fuzzy Design

All bus voltages are within the allowed range and the average voltage offset is 1.016 when all DGs' active and reactive outputs are set up as shown in Table 4. The biggest variation, 1.0499, is over half of the permitted offset range for voltage. At 0.7975, the line loss is 1.42% of the total active power. The five-objective optimization's value is marginally higher than this one since the line loss descriptions are different. But since two-objective optimization usually produces better outcomes than the five-objective problem, the voltage offset is much smaller.

There are roughly five to ten distinct solutions in the fuzzy decision of the two-objective optimization, making it difficult to choose the best one. There are two possible strategies for solving this. First, by offering

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7. Conclusion

The main focus of this study is on Distributed Generators (DGs) and their optimal operating strategy inside a microgrid. A self-adaptive Genetic Algorithm (GA) and fuzzy decision-making are used to solve the optimization issue, which has five objective functions. The optimization process becomes much faster and more efficient when self-adaptive mechanisms are included in our suggested GA method. The computational findings show that this algorithm finds appropriate solutions for the power of distributed generators (DGs) quickly and efficiently, leading to significant reductions in line loss, voltage offset, and related expenses. These kinds of developments are very helpful for real-time control systems such as Multi-Agent Systems (MAS) andEnergyManagementSystems(EMS). Future research is expected to take network reconfiguration into account for real-time control and optimization. Furthermore, a wider variety of DG kinds, such as large-capacity

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