International Journal of Advanced Engineering, Management and Science (IJAEMS)
Peer-Reviewed Journal
ISSN: 2454-1311 | Vol-10, Issue-3; Mar-Apr, 2024
Journal Home Page: https://ijaems.com/
DOI: https://dx.doi.org/10.22161/ijaems.103.7

Review on Optimization of Microgrid Using Various Optimization Techniques

Jinendra Rahul, Ramesh Kumar Pachar, Jitendra Singh, Suman Sharma, Bharat Modi

Department of Electrical Engineering, Swami Keshvanand Institute of Technology, Management and Gramothan, Jaipur, India

Received: 20 Feb 2024; Received in revised form: 03 Apr 2024; Accepted: 10 Apr 2024; Available online: 18 Apr 2024

Abstract— *The development of a smart grid includes the microgrid. Microgrids are essential to the development of the present and future electricity networks, as they can provide many advantages to the expanding and complex power systems, such as better power quality, increased integration of clean and renewable energy sources, increased efficiency, and increased network stability and reliability., etc. It is basically a small power system which has distributed energy resources (like renewable energy etc.). This paper conducts a literature review on Optimization Algorithms of Microgrid. We provide a summary of the typical system structure, which consists of energy end users, energy distribution systems, energy storage systems, and energy generation systems. Finally, we identify areas for future microgrid research challenges.*

Keywords— ***microgrid; microgrid control; renewable energy; photo voltaic; optimization.***

I. INTRODUCTION

India has produced much more renewable energy in the last few years. The Ministry of New and Renewable Energy (MNRE), the business sector, and the Regional Energy Development Agency all play a part in the expansion of this renewable energy plant. Policies for government assistance are also encouraging the adoption of renewable energy. In order to attain sustainable energy supplies, the Indian Planning Commission has released the Integrated Energy Policy Report (IEPR), which emphasizes the necessity of maximizing domestic supply programs and diversifying energy sources [1].

By 2032, renewable energy may make up 11–13% of India's energy mix, according to the IEPR. The reference [1] presents a number of issues and workable answers pertaining to the widespread use of renewable energy technology in India. India has developed solar, wind, small hydro, and biofuels as grid-interactive energy sources. Based on India's plentiful supply of biofuels in a variety of forms, it is predicted that biofuels would become increasingly important in the ensuing decades. In the area of distributed energy, the nation has erected 33 grid-interactive solar photovoltaic power plants and synchronized them with a negligible amount of bioenergy with the financial assistance of MNRE. These facilities have a max installed capacity of 2.125 MW, which is expected to produce. The nation has a large number of remote places that could use concerted action development. The MicroGrid located on Sagar Island is among the most well-known. MNRE, the Indian government, the West Bengal Renewable Energy Development Agency (WBREDA), and the India and Canada Environment Fund (ICEF) are co-financiers of the project. Currently, 400-kilowatt diesel generators and 250 kilowatts of solar energy are used to provide Sagar Island's electricity needs. On the other hand, a lot of prospective customers are waiting on power. WBREDA has made the decision to construct a 500-kW wind-diesel hybrid power plant in order to meet these criteria. In general, WBREDA has carried out renewable energy program activities in the Sundarban region. Based on the real electricity usage of residential, commercial, and industrial users, a three-tiered pricing structure for electricity has been established. Residential customers pay Rs 5 per kWh, business users pay Rs 5.5 per kWh, and industrial users pay Rs 6 per kWh for electricity. [2; 3]

A bibliometric review of the literature relevant to earlier studies on microgrid optimization strategies is presented in this paper.

II. SYSTEM STRUCTURE OF MICROGRID

Power supply systems in particular have grown more complex in recent times [4–9] [10]. All forms of Energy Information Systems (EIS) have a common physical structure and equipment set, which encompasses integrated power supply, gas supply, heating, hydrogen supply, cooling, and other energy systems together with associated communication and information infrastructure. A schematic representation of a microgrid system is shown in Figure 1. The following is an overview of each microgrid structure:

(1) *Energy generating system:* It is capable of direct energy transmission through pipelines, cables, overhead lines, and other means without the need for energy conversion.

(2) *Energy distribution system:* It is capable of achieving a change in energy grade or energy form transformation. Electric energy is transformed into hydrogen using electric hydrogen generating equipment. Gas is converted into electrical energy using fuel cells. A shift in energy grade can be achieved by using specialized equipment, such as heat pumps, which can absorb heat from a low-temperature heat source and release it to a high-temperature heat source through electric energy. Modern energy power production devices, such as photovoltaic (PV) and wind turbines, transform solar and wind energy, respectively, into electrical energy.

(3) *Energy storage system:* By reducing peaks and filling troughs, energy storage devices can decrease the mismatch between cooling/heating demands and gas turbines. These devices include power storage, heat storage, and cold storage equipment.

(4) *End users of energy:* People who utilize energy for refrigeration, power, heating, and other applications; this group includes industrial, residential, commercial, and other users.

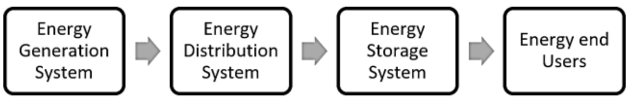

Fig.1. Structure of a MG.

III. IMPORTANT EQUATIONS AND CONSTRAINTS

Systems for generating power include diesel generators, batteries, photovoltaic power, and wind power. The incentive demand response direct control approach transfers the load and provides compensation throughout the dispatch time.

PV Power Generation: The following connection describes how a PV power generation system's output power is influenced by the external temperature T_{amb} and illumination R [11],

$$P_{PV} = P_{PV,STC} \times \frac{R}{R_{STC}} \times (1 - \lambda(T_a - T_r)) \qquad (1)$$

$$T_a = T_{amb} + \frac{R}{R_{STC}} \times (T_{NOC} - 20) \qquad (2)$$

In equations (1) and (2), R_{STC} is the illumination value under standard test conditions; $P_{PV,STC}$ is the maximum power under standard test conditions; λ is a coefficient; T_r is the reference temperature of the PV unit; T_a is the actual temperature of the PV unit and T_{NOC} is normal operating conditions temperature of the PV unit, respectively.

Wind Power Generation: The following equation can be used to convert wind energy into fan power output for wind turbines [12–14].

$$P_W = \frac{1}{2}\rho \pi R^2 V^3 C_P \qquad (3)$$

Where, V is the wind speed from the blade tip; R is the radius of the fan blade; ρ is the air density and C_p is the wind energy conversion efficiency. C_p is determined by the blade pitch angle θ and the blade tip speed ratio λ. C_p is defined as,

$$C_P = f(\theta, \lambda) \qquad (4)$$

The blade tip speed ratio λ is defined in equation (4) as,

$$\lambda = \frac{W_W R}{V} \qquad (5)$$

Where, W_w represents the fan's mechanical angular velocity in rad/s.

Diesel Generator: A diesel generator's fuel consumption rate (F) is a direct function of its generated output power.

$$F = F_0.Y_{gen} + F_1.P_{gen} \qquad (6)$$

Where, F_0 is the intercept coefficient; Y_{gen} is the rated power of diesel generator; F_1 is the slope and P_{gen} is the actual output power. The diesel generator's working power constraints are as follows:

$$L_{\min} \le \frac{P_{gen}}{Y_{gen}} \le 1 \qquad (7)$$

Where L_{min} is the diesel engine's minimum load rate.

Also, the carbon emission $CO_2(P_d)$ generated by a diesel generator has the following formula [15],

$$CO_2(D_d) = a + b.P_d + c.P_d^2 \qquad (8)$$

Where a, b, and c are the diesel's carbon emission coefficients; the values of these coefficients (evaluated from practice) are 28.1444, 1.728, and 0.0017, respectively. [11].

Battery: The function of electric energy for each charge and discharge is,

$$E_b = C_b.U_b.D.\mu_b \times 10^{-3} \tag{9}$$

In equation, D is the maximum permitted discharge depth; μ_b is the discharge efficiency; C_b is capacity of a single lead-acid battery and U_b is a rated voltage of supply.

The battery's output power is generally determined by its stable working voltage and controlled working current, which is around 0.1 CA.

$$P_b = C_b.U_b \times 10^{-4} \tag{10}$$

The primary limitations that affect a microgrid's ability to operate at the lowest possible cost are those related to transmission capacity between a microgrid and a larger grid, generation capacity, power balance, placement of the microgrid energy storage system, etc. [16–19]

Power Balance Constraints:

$$\sum_{i=1}^{N} P_{gen,j} + P_{buy}(t) - P_{sell}(t) = P_{load} \tag{11}$$

Where P_{load} is the necessary power of the load and $P_{gen,j}$ is the producing power of the generating units (PV, fan, and energy storage) in any given period of time.

Generation Capacity Constraints:

$$P_{DGi}^{\min} \le P_{DGi} \le P_{DGi}^{\max}, (i = 1, 2, ...N) \tag{12}$$

Where $P_{DGi}^{\max}$ and $P_{DGi}^{\min}$ are the maximum and minimum generating power of the ith generating unit, respectively.

Transmission Capacity Constraints between (Large Grid and Microgrid):

$$P_{Line}^{\min} \le P_{Line} \le P_{Line}^{\max} \tag{13}$$

Where $P_{Line}^{\min}$ is the minimum and $P_{Line}^{\max}$ is maximum power transmission capacities, respectively.

Location Constraints of Microgrid Energy Storage System: When determining and optimizing the placement and capacity of an energy storage system, consideration should be given to the system's allowed range of voltage variation and power balance.

IV. OPTIMIZATION ALGORITHMS

In the field of research, microgrid optimization is one of the most significant and difficult objectives. Numerous research have been carried out to ascertain the ideal microgrid structure in order to lower energy consumption and enhance economy and dependability. Numerous research in the literature demonstrates that several methods can be used to tackle the optimization of a microgrid. Genetic Algorithms (GAs) are the most commonly utilized algorithm type [20–32]. For instance, Li et al. used a GA to determine the lowest microgrid cost with the goal of choosing the ideal size for microgrid components [23]. Bin et al. [20] created an optimal configuration model of a hybrid AC/DC microgrid taking into account the microgrid life-cycle cost. The model was solved using the elitist Non-Dominated Sorting Genetic Algorithm (NSGA-II). Furthermore, Simulated Annealing (SA) was employed by numerous researchers [24–31] to overcome the issue. Battery scheduling for a home microgrid was the optimization problem that Aiswariya et al. solved using a SA optimization tool [24].

Another popular algorithm is the PSO algorithm [22–37]. To solve a unique operation optimization model for a stand-alone microgrid, Zhang et al. created an effective search algorithm by merging the PSO and SA algorithms [32]. Furthermore, fuzzy decision optimization must be used for many decisions because of the fuzzy environment [38–41; 49]. To evaluate a Battery Energy Storage System (BESS), for instance, Zhao et al. suggested an integrated fuzzy-MCDM (multi-criteria decision making) model [49]. In light of the microgrid's resilience, researchers have employed resilient techniques to enhance the microgrids' versatility and adaptability [42–44].

A decision-driven, stochastic, adaptive, robust microgrid operation optimization model was, for example, presented by Ebrahimi [42]. Furthermore, there exist alternative approaches to address the issue, including gray cumulative prospect theory [108–48], moth flame optimization, ant colony optimization technique, and Grey Wolf Optimization (GWO). Sharmistha et al., for instance, employed GWO, a recently created optimization technique, to maximize the usage of renewable energy sources and reduce a microgrid's energy cost [45]. To find the lowest operation cost, Wang et al. constructed an operation optimization model and optimized it using the moth flame optimization algorithm [46]. Zhao et al. suggested a novel MCDM model integrating the best worst approach to choose the best planning program; this model is relevant and feasible during the assessment and selection process [47].

Generally speaking, there are a few special techniques to deal with optimization problems: robust methods, fuzzy algorithms, SA, PSO, GA and enhanced algorithms, and other algorithms (GWO, moth flame optimization, etc.).

Table 1 provides an overview of their characteristics and related research.

GA is a type of non-deterministic quasi-natural algorithm that offers a powerful method for optimizing intricate systems. Based on earlier studies, a GA has been employed by numerous academics to address the microgrid optimization problem.

Zhao et al. established a dynamic economic dispatch model of a microgrid and used an NSGA-II variation to address the model [22], taking into account the interests of numerous stakeholders. In the end, the model in their study can aid in enhancing the power marketing economy and intelligent service by taking into account the total economic optimization of multi-objective and multi-interest groups within the microgrid.

Table 1. The most popular algorithms' features and associated research.

Algorithms	Features
GA and Improved GA [19-23]	1. Performs quick and random search. 2. The speed is slow, and the programming procedure is complicated. 3. Motivated by the evaluation function and an easy-to-use search process. 4. Is simple to integrate with different algorithms and can be expanded
SA [24-28]	1. The computation method is easy and has several things in common. 2. Suitable for handling complex nonlinear optimization problems 3. Long running time, parameter sensitivity and slow convergence
PSO (including Improved PSO) [32-35]	1. Quick search, Inaccurate and difficult convergence 2. There are fewer parameters to change, and the process is memorized. 3. Is unable to address combinatorial and discrete optimization issues efficiently
Fuzzy algorithms [38-40]	1. Able to produce a more acceptable, scientific assessment that is comparable to the real quantitative evaluation. 2. The computation is intricate, and the subjective determination of the index weight vector
Robust method [42-44]	1. The model's uncertainty is upfront taken into account. 2. The constructed optimization model is able to adjust to the impact of slight parameter changes within a specified set of uncertainties.

V. CONCLUSION

In order to present a typical system structure that consists of an energy generation system, an energy storage system, an energy distribution system, and energy end consumers. We first described the system structure based on the review articles that have already been published. After that, we looked at the optimization techniques used for microgrids and discovered that the most popular ones are simulated annealing and genetic algorithms.

Future microgrid optimization will be far more challenging due to the growing complexity of microgrid systems and their operating environments. In this situation, solving the issue might need the application of artificial intelligence (AI) and machine learning (ML) techniques. As a result, we can say that even though microgrid operation optimization has advanced at a fairly rapid rate in recent years, much work remains.

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