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Voltage Deviation Improvement in Microgrid Operation through Demand Response Using Imperialist Competitive and Genetic Algorithms

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Abstract: In recent decades, with the expansion of distributed energy generation technologies and the increasing need for more flexibility and efficiency in energy distribution systems, microgrids have been considered a promising innovative solution for local energy supply and enhancing resilience against network fluctuations. One of the basic challenges in the operation of microgrids is the optimal management of voltage and frequency in the network, which has been the subject of extensive research in the field of microgrid operational optimization. The energy demand is considered a crucial element for energy management due to its fluctuating nature over the day. The use of demand response strategies for energy management is one of the most important factors in dealing with renewables. These strategies enable better energy management in microgrids, thereby improving system efficiency and stability. Given the complexity of optimization problems related to microgrid management, evolutionary optimization algorithms such as the Imperialist Competitive Algorithm (ICA) and Genetic Algorithm (GA) have gained great attention. These algorithms enable solving high-complexity optimization problems by considering various constraints and multiple objectives. In this paper, both ICA and GA, as well as their hybrid application, are used to significantly enhance the voltage regulation in microgrids. The integration of optimization techniques with demand response strategies improves the overall system efficiency and stability. The results proved that the hybrid method provides valuable insights for optimizing energy management systems.

Keywords: demand response; microgrid; voltage deviation; ICA; GA

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1. Introduction

The increasing penetration of renewables for power systems grids and the distributed energy resources (DERs) for local energy supply increases the importance of microgrids. There are many advantages of microgrids, including improving grid stability, increasing energy efficiency, and providing more flexibility in energy distribution. For example, to understand how and why microgrids enhance grid stability, it should be said that they can work independently or alongside the main grid, and this plays an important role in modern energy systems. They can be disconnected from the main grid when there is a disturbance, ensuring that key places like hospitals still have power. Microgrids are also flexible and can be adjusted to follow the changes in energy demand and help to smoothen out peaks and dips in the network. Renewable energy sources like solar and wind contribute to a cleaner energy supply, and help relieve the demand from the main grid, especially during times of high demand. One of the challenges that can be mentioned due to the operational complexity of microgrids is the optimal management of voltage and frequency, which leads to ensuring the stability of the network and more effective performance of microgrids [1]. Microgrids use a few different methods to keep their power stable like:

1. Droop Control (DC): This adjusts the frequency based on how much power generators are producing power. If the load goes up and the frequency drops, the generators automatically change their output to fix it, and this helps keep everything stable.
2. Battery Energy Storage Systems (BESS): Batteries store extra energy when there is more power than needed and release it when there is more demand. Batteries work with inverters that help to manage the grid's frequency by adding or taking away power as needed.
3. Automatic Generation Control (AGC): Some advanced microgrids use AGC to keep track of the frequency and adjust generator output automatically. This helps to keep everything balanced in real time.
4. Load Shedding: If adjusting generation is not enough to stabilize the frequency, load shedding is used. This means temporarily turning off some loads to reduce demand and help bring the frequency back to normal [2].

On the other hand, the demand for energy consumption is changing throughout the day and night, and it is necessary to implement strategies that can dynamically respond to these changes. One of these strategies that have been developed to manage energy consumption patterns in response to supply conditions is demand response (DR). By using DR strategies, microgrids can achieve better energy management and thus increase system efficiency and stability [1].

Microgrids can operate independently or in conjunction with the main power grid. These benefits make them a crucial component of modern energy infrastructure:

1. Islanding: Microgrids can disconnect from the main grid during disturbances and operate independently. This feature, known as "islanding", ensures that critical services such as hospitals, military facilities, and emergency services continue to have power.
2. Flexibility to Demand Response: Microgrids can respond to changes in energy demand quickly, providing additional power when needed and reducing consumption during low-demand periods.
3. Integration of Renewable Energy: Microgrids incorporate renewable energy sources like solar and wind, along with energy storage systems. This ability reduces greenhouse gas emissions and provides a stable and sustainable energy supply.
4. Load Balancing: Microgrids can reduce the strain on the main grid and balance load demands, especially during peak demand periods, by managing local energy generation and consumption.

Evolutionary algorithms are advanced optimization techniques that are used to ease complex optimization problems related to microgrid management. ICA and GA have shown great potential in facing these challenges, which are able to solve difficult optimization problems with different constraints and multiple objectives. In this paper, ICA and GA are applied individually and then combined to create a hybrid algorithm that has all the features of both algorithms to minimize voltage regulation in microgrids through load response strategies. The reduction of voltage deviations and the improvement of overall microgrid performance are to be evaluated, which can have significant impacts on the design and management of future microgrid systems and provide insights on how to use advanced optimization algorithms to improve microgrid stability and efficiency [3]. Reducing voltage fluctuations improves the microgrids' operation by making the system more stable and lowering the chances of power issues or breakdowns. It can increase energy efficiency by reducing transmission losses. Keeping voltage stable also ensures better power quality, which is an important issue for delicate electronics and machinery. Additionally, stable voltage helps equipment last longer by reducing wear and tear, which can lower maintenance costs. Less voltage variation also means less power losses in the distribution process [4,5].

DR is one of the control and management tools for the power network that can be used to improve the operation of the grid. This tool has been used to reduce the overall cost, reduce the transmission line losses, and improve voltage deviation. For summary as a comparison with existing work:

1. Cost—Benefit Analysis of DR Programs in Power Grids: Paper [6] explored the cost-benefit analysis of DR programs using an open modeling framework, focusing on improving grid reliability and reducing operational costs. This paper provides a detailed analysis of how to improve power grid efficiency and reliability and reduce operating costs using DR programs, but it does not cover the lack of Real-Time optimization, which can greatly enhance the efficiency of DR programs, especially in dynamic grid environments.
2. Developed a residential DR model network: Paper [7] developed a residential DR model and evaluated its impact on the voltage profile and losses in distribution networks. Also, the study uses a DR model to simulate the impact of different load control strategies on the distribution system. The results showed that DR can significantly improve the voltage profile and reduce losses, with increased efficiency and reliability of the distribution network. One limitation of this study is that the work was conducted only for residential areas, and no optimization was performed for commercial and industrial areas. Also, the direct effects of residential DR applications on voltage profiles and system losses, which are critical parameters in distribution network efficiency, have not been analyzed.
3. Increase the efficiency through DR: Paper [8] showed strategies to increase the efficiency of microgrids through DR optimization and power-sharing mechanisms. This study used the bee colony algorithm to reduce both operational costs and power losses. This study used a certain amount of power without using it as a constraint, and this amount can increase or decrease along with the price, which is considered a drawback of the work.
4. Compared optimizations: Paper [9] Compared various optimization algorithms, including PSO-ANN, GA-ANN, ICA-ANN, and ABC-ANN, for estimating heating loads in smart cities, highlighting the efficiency of hybrid approaches but not specifically targeting the voltage deviation in microgrids. While the study addresses heating load estimation, it does not explore voltage deviation problems, which are critical in the operation of microgrids.
5. Heuristic methods: Paper [10] employed heuristic methods for optimal allocation of renewable distributed generations to minimize energy losses and voltage deviation, but it does not specifically integrate DR strategies. This paper focuses on optimizing the allocation of renewable DGs to reduce energy losses, but it does not incorporate DR strategies, which could further enhance system performance and reliability.

In this proposed work, A new method has been studied by examining the shortcomings of previous literature work. This work has covered all the situations of DR and has considered all residential, industrial, and commercial demands in the optimization. Two different optimization techniques are used, including ICA and GA and their combination, and by examining all DR strategies, the best model for decreasing the voltage deviation is found.

This work's contributions can be summarized in the following three main points:

1. Hybrid Optimization: A hybrid model of ICA and GA is proposed to leverage the strengths of both algorithms, which helps achieve better convergence and solution accuracy.
2. Dynamic DR Strategies: The proposed approach dynamically adjusts load based on real-time demand and supply conditions to enhance voltage stability.
3. Comprehensive Evaluation: The proposed work is implemented based on a 33-Bus IEEE sample network and demonstrated significant improvements in the voltage profiles compared to individual and traditional optimization methods.

The work structure comprises five sections, covering the concept of DR, the proposed method, simulation results, and concluding remarks, with a focus on the technical and comprehensive exploration of DR in microgrid management.

1.1. Demand Response (DR)

DR programs include methods of Demand Side Management (DSM), which refers to the change in the consumption of customers due to the change in the price of electricity in the market. It should be mentioned that some of these programs were also used in the traditional electricity system in the form of multi-tariff meters. Economists believe that price changes are the right way to encourage consumers to consume optimally. This kind of electricity pricing causes two long-term and short-term changes in the load consumption pattern. In the long run, the high price of electricity causes savings in electricity consumption. If the price difference between the tariffs of peak hours and off-peak hours is large, consumers are encouraged to install energy storage devices so that they can avoid the consumption of electric energy during peak hours when the price of electricity is high. Therefore, in the long term, creating different tariffs for electricity consumption will increase the efficiency of energy expenditures. Also, in the short term, some customers can reduce their electricity usage or transfer it to off-peak hours. For example, an industrial consumer, if it is not profitable to produce the product during the peak hours of electricity consumption, considering the price of electricity during these hours, will give up the production of goods during these hours [11].

Also, the DR program can change the form of electricity consumption in such a way that the peak load of the system is reduced, and the usage of electricity is transferred to off-peak hours. The response to the demand can be in the form of replacing the electricity supplied by the power system with domestic production. Implementing DR programs is very important because electricity is not preferred to be widely stored at the level of the high-power systems generation, so the amount of production capacity available must always be equal to or greater than the total load of system consumers. In addition, the cost of installing new power plant units is very high and time-consuming. By implementing a DR, the consumption of consumers who tend to reduce their consumption during peak hours will be reduced, thereby avoiding the additional cost of creating generation capacity for a short period of time each year [12]. This program involves strategies aimed at aligning energy demand with available supply. These strategies include real-time pricing, shifting energy usage, and incentive-based initiatives that motivate consumers to lower or shift their energy consumption during peak periods.

DR can also increase the system's reliability. These strategic programs can often reduce consumption and solve problems with system or local capacity limitations. In emergency situations or when system reserve levels are low, the power company must ration power to consumers to prevent cascading outages and maintain system integrity. However, the provision of load-shedding services by consumers reduces the losses caused by involuntary load-shedding. This could occur because the voluntary participation of consumers in establishing the balance of production and consumption in emergency situations is more economical and appropriate than cutting off consumption. The real price of electricity can be used to reduce the load and solve the problem of the limited capacity of the system [13].

The DR program can be classified as follows:

Price-based DR such as Real-Time Pricing (RTP), Critical Peak Pricing (CPP), and Time of Use (TOU) tariffs offer customers different rates that reflect the value and cost of electricity over different time periods. With this information, customers tend to use less electricity when electricity prices are high.

Incentive-based DR that pays participating customers to reduce their loads during times of demand is supported by the program, which is either caused by grid reliability problems or high electricity prices.

As shown in Figure 1, time-varying retail tariffs include TOU, RTP, and CPP rates, which can be characterized as "price-based" DR. In these tariff options, the price of electricity fluctuates according to changes in the basic costs of electricity production. Customers receiving these rates can reduce their electricity bills if they respond by timing their electricity use to take advantage of lower-priced periods and/or avoid using when prices are higher. Customer response is typically driven by an internal economic decision-making

process, and any load shifting is entirely voluntary. Incentive-based DR programs represent contractual arrangements designed by policymakers, grid operators, and utilities to reduce demand from customers during critical times. These programs incentivize participating customers to reduce load during peak periods. Incentives may take the form of explicit bill credits or payments for pre-contractual or metered load reductions. Customer registration and response is voluntary, although some demand response programs impose penalties on customers who register but do not respond when events are announced or when they meet their contractual obligations. To encourage curtailment during peak demand, many companies have already implemented TOU rates or have plans to introduce such rates [11,12]. The main purpose of applying such a program is to reduce the load curve during peak periods. However, some companies implemented these programs in peak periods as mandatory. Schedules can be successfully implemented if peak customer demand is experienced during the day. On the other hand, voluntarily maintaining the schedule for customers during the peak period (economic decision) does not create any obligation for customers to reduce the load during peak periods. In this case, the utility load factor cannot be meaningful for such applications when most customers do not have peak periods. A review of daily load curves for commercial and industrial customers is the first step towards the implementation of the appropriate DR program [14].

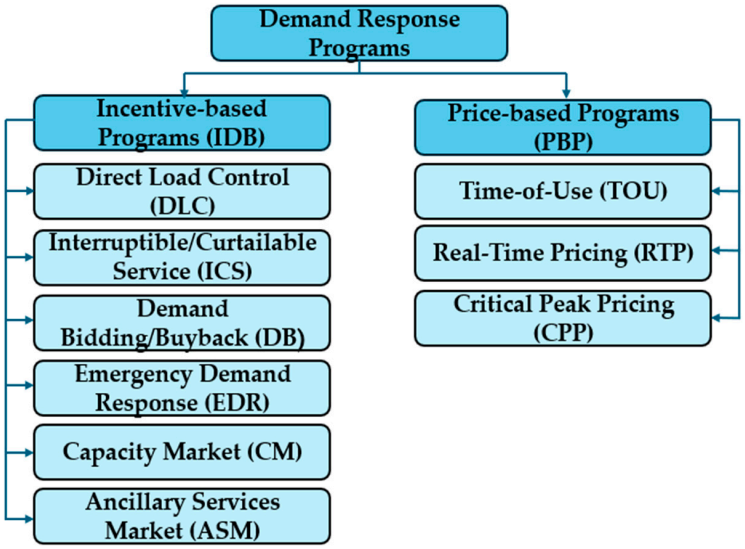


Figure 1. Demand response programs [11].

1.2. Voltage Deviation

When the voltage of a power grid changes slowly (less than 1% per second), the difference between practical and normal voltage is known as "Voltage Deviation". There are some factors that affect the voltage level, like transmission path, supply distance, power flow dispersion, voltage management, and reactive power compensation. Voltage deviation is a main factor in power quality [15]. The voltage deviation formula, as per various power quality standards, typically measures the deviation of the actual voltage from the nominal voltage and is given by:

$$Voltage\ Deviation(\%) = \left(\frac{Vmeasured - Vnominal}{Vnominal}\right) \times 100 \quad (1)$$

$Vmeasured$ is the actual voltage measured at a specific point and can be the voltage observed at a specific location or at a piece of equipment. $Vnominal$ is the standard or ideal voltage level that is designed for the system and often represents the voltage level that equipment and infrastructure are rated to.

2. Energy Management Model

2.1. Proposed Technique

The proposed method has been presented to model the proposed structure by considering the DR. The goal of this method is to make sure that the voltage in a microgrid stays stable. Voltage stability is crucial for keeping the power system running smoothly and safely, especially when dealing with sensitive equipment. By focusing on reducing how much the voltage deviates from ideal levels, the work aims to enhance the overall reliability and performance of the system. Voltage is controlled through a combination of managing power outputs from generators and distributed energy sources, along with using demand response programs. Generators and distributed sources have specific limits for voltage and reactive power to ensure they do not disrupt the system. Demand response programs help by adjusting power usage based on current needs. This approach helps to maintain a steady voltage and keeps everything balanced.

The constraints differ because traditional generators and distributed generation sources have different roles and capabilities. Traditional generators are larger and can handle both voltage and reactive power more precisely, so their constraints reflect that. On the other hand, distributed generators, like solar panels or wind turbines, are smaller and less consistent, so their constraints focus more on the amount of power they produce.

Also, operational constraints are different for different voltage levels, and the amount of power flowing through each line is different. Voltage constraints ensure the system operates within safe voltage ranges to avoid issues. Line loading constraints keep power flow to be within safe limits to prevent overheating and any potential damage. These constraints are essential for maintaining the system's safety and reliability. Load constraints involve setting limits on how much power can be used, especially after implementing demand response programs. This work manages how much power can be increased or decreased based on the system's needs. This flexibility helps to control the voltage and balance the system requirements, ensure stable operation, and avoid major disruptions. In this regard, the plan is presented along with related explanations. DR in power distribution systems, like all optimization problems, seeks to select the best member from a set of attainable members for which the objective is minimized. Therefore, this issue can be shown as follows in Equation (2):

$$\begin{gathered} minf(x,y)\ s.t. \qquad h(x,y) = 0 \\ g(x,y) \geq 0 \\ \underline{x} \leq x \leq \overline{x} \\ y_i \in D_{yi},\ i = 1,\ 2, \ldots, n_y \end{gathered} \tag{2}$$

The decision variables are represented by $x = (x_1,\ x_2,\ \ldots,\ x_{nx})$, $y = (y_1,\ y_2,\ \ldots,\ y_{nx})$, where D_{yi} is the set of discrete values for variable y_i. The functions are h, g, and $g(x,y) = g(x,y) = (g_1(x,y), g_2(x,y), \ldots, g_p(x,y))^t$ are nonlinear. Vectors $\overline{x} \in R^{nx}$ an $\underline{x} \in R^{nx}$ are the upper and lower bounds of variable x, respectively.

2.2. Objective Function

The objective function in the load response optimization problem can be a combination of different variables. These often include minimizing the amount of active power loss (ohmic) of the power system, reducing the total network voltage deviations or the cost of program implementation, or a combination of them (multi-purpose objective function), and it is usually considered as the goal for the optimization problem. The main objective of the work is to minimize voltage deviation.

2.3. Minimizing the Bus Voltage Deviation

Improving the system voltage profile is one of the most important security goals in the normal working conditions of the power systems grid. This issue is very important

for voltage-sensitive loads. If the voltage of the busbars is considered a constraint, often, the resulting voltages approach the upper limit of the allowable range (maximum value). This will cause the power system to not have the reserve needed to provide reactive power when incidents occur. One of the effective methods to prevent this situation is to choose the absolute deviation of the voltage of all buses from their desired value as an objective function. Minimizing the amount of voltage deviation of all buses will improve the voltage profile. In this case, the power system will operate with higher security, and the quality of service will increase.

Therefore, to solve this problem, the bus voltage deviation from the acceptable value is considered as an objective function as follows in Equation (3):

$$Minimize\ TVD = \sum_{i \in N_L} \left| V_i - V_i^{ref} \right| \tag{3}$$

where V_i is the voltage of bus i, V_i^{ref} is the desired voltage at bus i, TVD is the total voltage deviation of the power system, and N_L is the number of load buses in the system.

2.4. Generator Constraints

The voltage and reactive power output limits for generators are given by Equations (4) and (5):

$$\boldsymbol{V_{G_i}^{min}} \leq \boldsymbol{V_{G_i}} \leq \boldsymbol{V_{G_i}^{max}}, \quad i = 1, \ldots, N_G \tag{4}$$

$$\boldsymbol{Q_{G_i}^{min}} \leq \boldsymbol{Q_{G_i}} \leq \boldsymbol{Q_{G_i}^{max}}, \quad i = 1, \ldots, N_G \tag{5}$$

where N_G is the number of generators.

2.4.1. Distributed Generation Constraints

Distributed generation sources are constrained as follows in Equation (6):

$$\boldsymbol{P_{DG_i}^{min}} \leq \boldsymbol{P_{DG_i}} \leq \boldsymbol{P_{DG_i}^{max}}, \quad i = 1, \ldots, N_{DG} \tag{6}$$

where N_{DG} is the number of distributed generators.

2.4.2. Operational Constraints

Operational constraints, including voltage and line loading constraints, are shown in Equations (7) and (9):

Voltage constraints

$$\boldsymbol{V_{L_i}^{min}} \leq \boldsymbol{V_{L_i}} \leq \boldsymbol{V_{L_i}^{max}}, \quad i = 1, \ldots, N_{Line} \tag{7}$$

$$\boldsymbol{S_{L_i}} \leq \boldsymbol{S_{L_i}^{max}}, \quad i = 1, \ldots, N_{Line} \tag{8}$$

where: N_L represents the number of load buses, V_{Li} denotes the voltage of load bus i, $V_{L_i}^{min}$ is the minimum voltage of load bus i, and $V_{L_i}^{max}$ is the maximum voltage of load bus i. S_{L_i} indicates the apparent power flow through line i, while $S_{L_i}^{max}$ is the maximum apparent power flow through line i. Additionally, N_{Line} refers to the number of network lines.

Load Constraints

For active power

$$P_{Dd} = P_{Dd1} + \Delta \boldsymbol{P_{Dd}^{up}} - \Delta \boldsymbol{P_{Dd}^{down}} \tag{9}$$

$$\boldsymbol{P_{Dd}^{min}} \leq\ P_{Dd}\ \leq\ \boldsymbol{P_{Dd}^{max}} \tag{10}$$

$$\Delta \boldsymbol{P_{Dd}^{up}},\ \Delta \boldsymbol{P_{Dd}^{down}} \geq 0 \tag{11}$$

Here, P_{Dd} represents the load power after implementing the DR program, P_{Dd1} is the load power before implementing the DR program, ΔP_{Dd}^{up} and ΔP_{Dd}^{down} are the amounts of

load power increase and reduction, respectively. P_{Dd}^{max} and P_{Dd}^{min} are the maximum and minimum load power, respectively.

The reactive power equations are structured similarly to the real power constraints:

$$Q_{Dd} = Q_{Dd1} + \Delta \boldsymbol{Q_{Dd}^{up}} - \Delta \boldsymbol{Q_{Dd}^{down}} \quad (12)$$

$$\boldsymbol{Q_{Dd}^{min}} \leq Q_{Dd} \leq \boldsymbol{Q_{Dd}^{max}} \quad (13)$$

$$\Delta \boldsymbol{Q_{Dd}^{up}}, \Delta \boldsymbol{Q_{Dd}^{down}} \geq 0 \quad (14)$$

3. Optimization Methods

Optimization means defining a function and finding its inputs within the defined range so that the function is optimized to the desired value (minimum or maximum). There are three optimization methods:

- Deterministic methods
- Stochastic methods
- Hybrid methods

Deterministic methods are based on mathematical rules, sensitive to initial points, and require derivatives of objective functions but do not guarantee reaching the optimal point. Stochastic methods rely on statistical rules that can find the optimal point but converge slowly. Hybrid methods determine initial points from deterministic methods and use stochastic methods after combining more than one method to generate a hybrid method [12].

Optimizing a nonlinear discrete function with many local optima and large dimensions is very difficult. Various optimization methods have been used for such functions. Gradient optimization methods have been used to solve many optimization problems. Recently, interior point methods, which have faster convergence and better ability to handle inequality constraints, have been used for optimization problems. Additionally, quadratic programming and nonlinear programming methods are also considered for solving these problems. However, all these methods struggle from nonlinearity and constraints with many local optima. Different techniques have been suggested to overcome these limitations, but they are still in development, especially for solving large-scale problems [12].

Even though algorithms like ICA and GA are effective, figuring out the best settings—like population size, mutation rates, and elitism—can be tough. Their performance can swing quite a bit based on these factors, often involving a lot of trial and error to get things just right. In microgrid situations, using a more straightforward, deterministic approach could lead to more consistent results by cutting out the randomness. However, this paper sticks with metaheuristic methods since they're better suited for handling complex problems with multiple goals.

3.1. Genetic Algorithm

In the last decade, many random search methods have been invented to solve optimization problems. GA is one of the most effective optimization methods. It was proposed by Holland in 1975 based on the structure of genes and chromosomes [14]. This algorithm, inspired by the nature of living organisms and their hereditary role in gradual evolution, calculates the optimal value of mathematical systems. The GA starts its work with an initial population that is randomly created. This initial population consists of different designs. A string called a chromosome is used to specify a specific design; these strings represent the features of the desired design. On the other hand, the length of each chromosome depends on the number of optimization variables. Each of these strands consists of a number of genes.

The gene parameter is used to specify the value of each design variable, which is displayed as a string of binary numbers. GA examines these chromosomes during the process of solving problems and assigns values to these chromosomes or plans according to their importance or fitness. This action is performed by the fitness function, so the higher

fitness of each design means that the desired design is better. There are several ways to define the fitness function, the most common of which are as follows in Equation (15):

$$F_i = (f_{max} + f_{min}) - f_i \quad (15)$$

where f_{max} and f_{min} represent the maximum and minimum values calculated for the objective function in the desired iteration, respectively, and F_i and f_i are the calculated value and the fitness assigned to its plan, respectively. The fitness function (Equation (15)) helps to determine which solutions are the most optimal by comparing their performance (measured by the deviation of the objective function).

In the continuation of the GA, better designs are selected by the selection operator to create the next generation, and weak designs are discarded. In this algorithm, several methods are provided for the selection operator, which can be mentioned as two methods of selecting the rotating wheel and selecting the competition. After a group is chosen to produce a new generation, it is the turn of the linkage operator to combine individuals two by two, producing two new individuals each time, and this continues until a new population is formed. Although there are many ways to do the transplant, the most common one is the single-point transplant.

The next operator involved in the generation process is mutation. The function of this operator is that bits of a string are selected randomly and with a small probability, and the value in them is copied. This means that if the desired bit value is zero, it changes to one, and vice versa. In fact, this action creates variety and searches for more design space. Finally, a new generation of designs will be created, and this new generation must have a better fit than the previous generation. This process continues until the criteria for stopping the algorithm are met, such as reaching an acceptable level of answers, passing a certain predetermined time, passing a certain number of repetitions (generations), or passing a certain number of repetitions in case there is no specific improvement [16,17]. Figure 2 shows the flow chart of a GA [9].

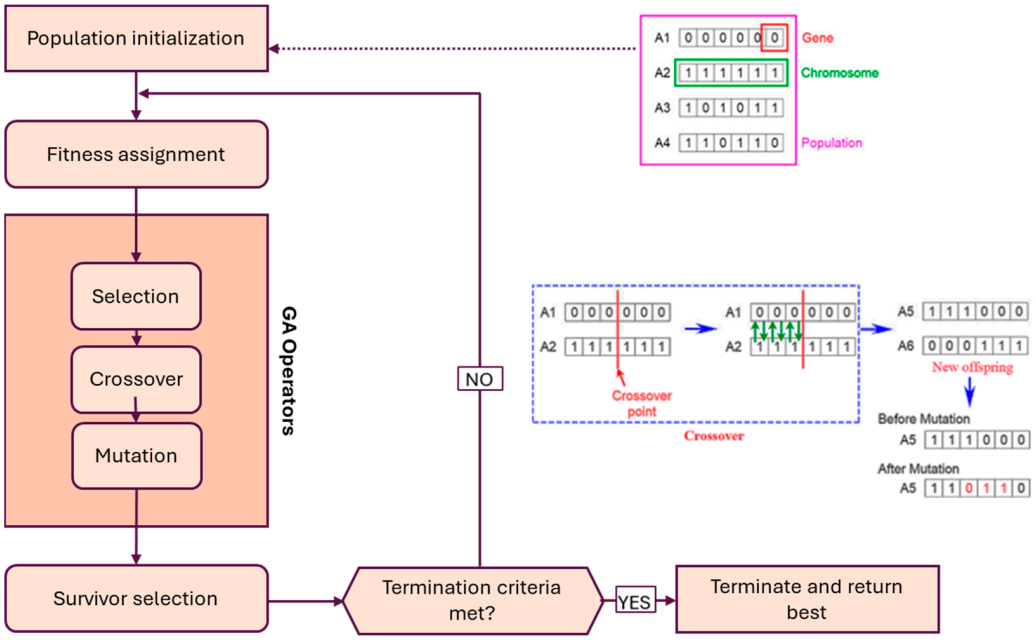


Figure 2. Flowchart of a genetic algorithm [9].

3.2. Imperialist Competitive Algorithm

This method is based on the modeling of the socio-political process of colonialism. In this method, the first population (initial countries) is created based on a random distribution. In this method, each country is a design. Then, the value of the cost function is calculated for each design, and at the end, the countries are sorted by cost in ascending order (countries

with the lowest cost are in the first order). In the next step, it is the turn of creating empires. Each empire consists of a colonizing country and a few colonies. Each colonizing country has a certain amount of power that is obtained based on Equation (16):

$$P_n = \left| \frac{C_n}{\sum_{i=1}^{Nimp} C_i} \right| \tag{16}$$

In the above formula, C_n is the normalized cost of the colonizing country, C_i is the cost of the colonizer, and $max\{c_i\}$ is the cost of the first colony.

The normalized cost of each colonizing country is calculated based on based Equation (17).

$$C_n = max\{c_i\} - c_n \tag{17}$$

After the colonizer countries are selected, the number of colonies of each colonizer needs to be obtained, and to do this Equation (18) is used.

$$N.\mathrm{C_n} = \text{round } \{P_n . (N_{col})\} \tag{18}$$

Here, P_n is the normalized power of the nth colonizer, *Ncol* is the total number of colonies, and the relation shows how colonies are distributed among empires based on their power. The stronger the empire, the more colonies it controls. After determining the number of colonies, the colonies are distributed among the empires with a random distribution. In the method of colonial competition, each colonizing country tries to bring its colonies closer to its position, which is called attraction policy. In order to prevent premature convergence, revolutions are used in the colonies in such a way that a random number for each colony is considered first, it is then compared with the revolution rate. If the random number is lower than the revolution rate, the colony can undergo sudden changes. One of these changes can be the change of one of the design variables in this country. Two empires may find themselves in a situation where their colonists are located close to each other. In this case, the two empires will merge.

- Determining the distance vector between two colonists is performed using Equation (19).

$$\text{Distance Vector} = (\boldsymbol{X_i})\text{imp1} - (\boldsymbol{X_i})\text{imp2} \tag{19}$$

This equation calculates the difference between the *i*-th variable of two colonists (imp1 and imp2). It represents the vector difference along the *i*-th dimension.

- Determining the distance between two colonists is performed using Equation (20).

$$\text{Distance} = \sqrt{\sum_{\mathbf{1}}^{\mathbf{nVar}} \{\mathbf{DistanceVector}\}^{\mathbf{2}}} \tag{20}$$

The distance vector is the difference between the coordinates of the two points in each dimension. For example, if two points A and B with coordinates are given (x_1, y_1, z_1) and (x_2, y_2, z_2), the distance vector components would be ($x_2 - x_1$), ($y_2 - y_1$), and ($z_2 - z_1$).

- Determining the threshold distance is performed using Equation (21).

$$\text{Threshold Distance} = \text{Uniting Threshold } \times \sqrt{\sum_{\mathbf{1}}^{\mathbf{nVar}} (\boldsymbol{X_{u_i}} - \boldsymbol{X_{l_i}})^{\mathbf{2}}} \tag{21}$$

In the threshold distance equation, X_{u_i}, X_{l_i}, respectively, are the maximum and minimum values of the *i*th design variable. If the distance between two colonizers is less than the integration threshold (Threshold Distance), the empire whose colonizer costs more will join another empire as a colony.

After finishing these steps, each empire (with its main country and colonies) is ranked from the least to the most expensive. If a colony turns out to be cheaper than its main country, it moves up in the ranking. The weakest empire and its least efficient colony will

be transferred to another empire. Finally, each empire's total cost is calculated by adding the cost of the main country and a weighted average of the costs of its colonies.

Empire Cost is calculated using Equation (22):

$$\text{EmpireCost} = \text{ImpCost} + \zeta \times \text{mean}(\text{ColoniesCost}) \quad (22)$$

The normalized Cost of Each Empire is calculated using Equation (23):

$$(\mathbf{NormEmpCost})_{\mathbf{i}} = \max(\text{EmpireCost}) - (\mathbf{EmpCost})_{\mathbf{i}} \quad (23)$$

In these equations: EmpireCost represents the total cost associated with an empire, ImpCost denotes the cost of the imperialist, ζ is a constant factor, mean (ColoniesCost) is the average cost of the colonies, max(EmpireCost) indicates the maximum cost among all empires, $(\text{EmpCost})_i$ is the cost of the *i*-th empire.

Also, the probability of taking over each empire is determined by Equation (24):

$$P_n = \left| \frac{(\mathbf{NormEmpCost})\mathbf{i}}{\sum_1^{\mathbf{NoImp}} (\mathbf{NormEmpCost})\mathbf{i}} \right| \quad (24)$$

When an empire has no colonies, its colonizing country must become a colony of one of the empires. The process of assigning that colonizer to other empires is similar to the previous step. At the end of each iteration, the convergence condition is checked, and if this condition is met, the algorithm stops. Otherwise, it must be continued to be repeated [18,19]. Figure 3 shows the flowchart of ICA.

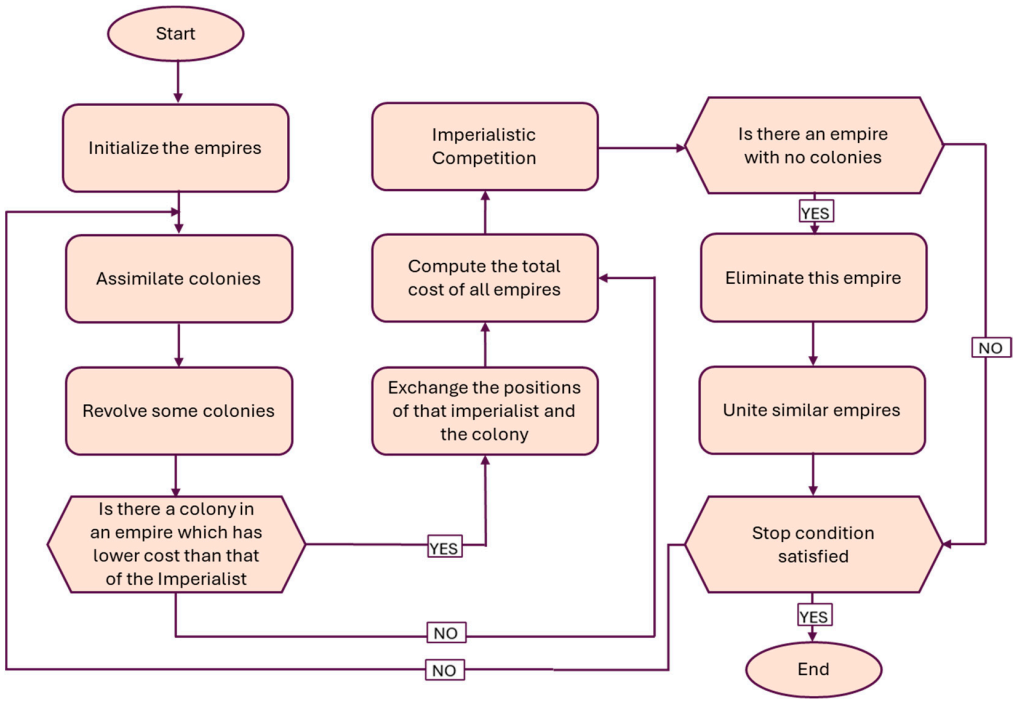


Figure 3. Flowchart of the Imperialist Competitive Algorithm [20].

3.3. Hybrid Method

The proposed hybrid used in this work is based on using both GA and ICA in one model to keep both features. The initial population for the GA is either randomly generated or based on some heuristic. The same initial population serves as the starting point for the ICA. Then, both GA and ICA will require fitness evaluations. For GA, fitness is used to select parents and generate offspring. For ICA, fitness helps in assigning colonies to

imperialists. The third step is to use a hybrid of ICA and GA to keep both features in one model.

3.3.1. Genetic Algorithm Operations

1. The best individuals are selected based on fitness, ensuring that high-quality solutions have a better chance of being chosen.
2. New candidate solutions are produced by combining features from two or more parents, potentially creating more optimal solutions.
3. Random variations are introduced to ensure diversity and prevent premature convergence.

3.3.2. Imperialist Competitive Algorithm Framework

1. Represent high-quality solutions from the current population.
2. Initially, the population of imperialists was based on proximity or fitness.
3. Imperialists influenced their colonies, and colonies moved towards their imperialists. Imperialists also competed to acquire more colonies.

3.3.3. Hybrid Integration

The hybrid is used here to use the advantages of both individual techniques. GA is used for local search. Genetic operators are used to refine solutions and enhance their quality on a local scale. ICA is used for global search. ICA ensures global exploration by adjusting colony positions and maintaining varied search spaces. The hybrid model alternates between GA and ICA processes to further refine solutions. It continues until a stopping criterion is reached like reaching a maximum number of iterations or achieving the desired accuracy of solutions is met. Figure 4 shows the optimization process sequence.

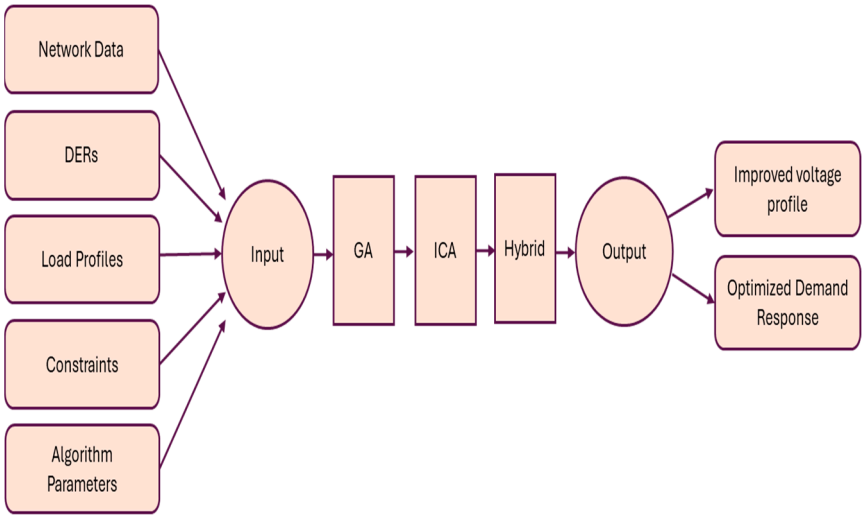


Figure 4. Optimization process sequence.

The proposed diagram for Figure 4 is divided into three main sections:

1. Input Section, which includes network data, distributed energy resources, load profiles, constraints, and algorithms parameters as follows:
   a. Network Data: It has the following inputs:
      - The structure of the IEEE 33-bus network used for simulations.
      - Voltage limits at each bus.
      - Line parameters (resistance, reactance, susceptance).
      - Active and reactive power loads for each bus.
   b. Distributed Energy Resources (DERs):
      - Voltage and reactive power limits for generators.

- Power generation limits for distributed generation sources (e.g., solar panels, wind turbines).

c. Load Profiles:

- Power demand at each bus (residential, commercial, industrial loads).
- Demand before and after the implementation of the Demand Response (DR) program.

d. Constraints:

- Voltage constraints for load buses.
- Line loading constraints to avoid overheating or overloading of power lines.
- Reactive power limits for generators and DERs.

e. Algorithm Parameters (for ICA, GA, and the hybrid model):

- Initial population for the optimization.
- Parameters like mutation rates, selection criteria, and convergence thresholds for the GA.
- Power and colony distribution rules for the ICA.

2. Optimization Algorithms: Refers to two main algorithms (GA and ICA), which ultimately leads to a hybrid algorithm. This section illustrates how the input data is processed.
3. Output section: This section shows the results obtained after processing the data by the algorithm, which includes two main items (improved voltage profile and optimized demand response).

A comparison of different optimization techniques is listed in Table 1.

Table 1. Comparison of Optimization Techniques.

Technique	Key Features	Advantages	Drawbacks
Deterministic Methods	Mathematical rules require derivatives	Fast convergence	Sensitive to initial points, may not reach global optimum
Stochastic Methods	Statistical rules, random searches	Can find global optimum, handles nonlinearity	Slow convergence
Hybrid Methods	Combination of deterministic and stochastic	Balances speed and accuracy	Complexity in implementation
Genetic Algorithm (GA)	Inspired by natural selection, uses a fitness function	Handles complex problems, flexible	May converge slowly, computationally intensive
Imperialist Competitive Algorithm (ICA)	Inspired by imperialistic competition	Efficient for large-scale problems	Can get trapped in local optima
Hybrid GA-ICA	Combines GA and ICA techniques	Improves convergence and accuracy	Increased computational complexity

4. Simulation Results

The network under study includes 33 main buses as seen in Figure 5. Bus number 1 is connected to the main network, and the required power of the loads is obtained through this bus from the main network. The permissible range of voltage change of the generators is assumed to be between 0.95 and 1.05 per unit. Also, the active and reactive loads of the whole network are 3.715 MW and 1.8 MVAR, respectively. The operating voltage of this network is 12.66 kV. The 33-bus network includes resistance, reactance, line susceptance,

and the amount of permissible power passing through the lines. The base load values are the values presented in [21]. Further information is provided in Appendix A.

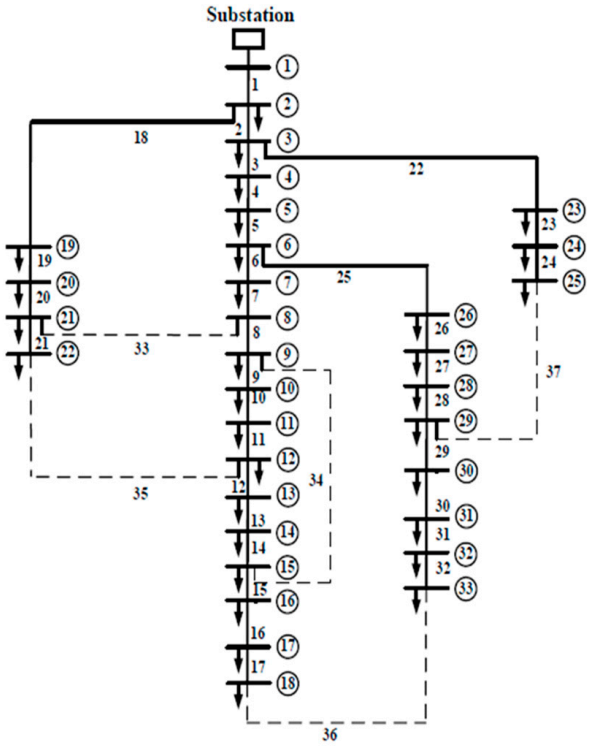


Figure 5. IEEE 33-Bus network.

In the network under consideration, it is assumed that 5 buses of the network are industrial loads, 10 buses are commercial loads, and the others are residential loads. The results obtained with the aim of minimizing voltage deviation considering the power flowing in the lines are examined using both the GA and ICA individually as hybrids.

A voltage near 1 per unit signifies enhanced system stability. It indicates that the system is functioning properly with fewer voltage fluctuations. Although equipment can generally handle voltage within this range, significant deviations (e.g., close to 0.9 or 1.1 p.u.) can still harm system performance by (a) Increasing power losses, (b) Shortening the lifespan of equipment due to added stress, (c) Reducing the efficiency of sensitive electrical devices and (d) Causing overheating, especially in inductive loads, which may draw more current when the voltage drops. So, the range is generally safe, but operating near the extreme ends of this range (especially over prolonged periods) can lead to inefficiencies, additional losses, and damage to equipment.

Furthermore, lower losses translate to higher efficiency and cost savings. Many electrical devices are designed to operate at voltages of around 1 per unit. Lower voltages can lead to reduced efficiency and potential damage to equipment. Additionally, lower voltage can increase the current in the system, potentially causing overheating and even fire. Maintaining a voltage close to 1 per unit helps to mitigate these risks [10,22]. Here, the ultimate goal of minimizing voltage deviation is divided into four scenarios:

1. Initial state: The state of the network without performing any management (implementation of the load response program) is investigated, as seen in Figure 6. This initial state is considered as the zero scenario. As observed, in this case, the voltage profile is between 0.95 to 1 per unit. Now, for example, the voltage magnitude of bus number 18 at H20 (8:00 p.m.) is 0.95294 per unit, which should be improved after optimization algorithms.

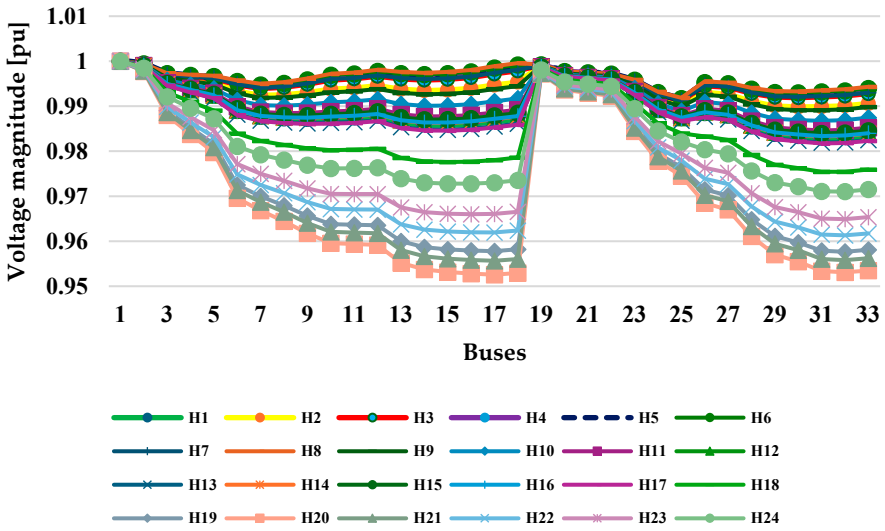


Figure 6. The voltage profile of the network is at different hours of the day in the initial state.

2. First scenario: The first scenario is examined, considering optimization using the ICA. As expected, the voltage profile became closer to 1 per unit, and as an example of that improvement, the voltage at bus number 18 at H20 reached 0.96866 p.u, as seen in Figure 7.

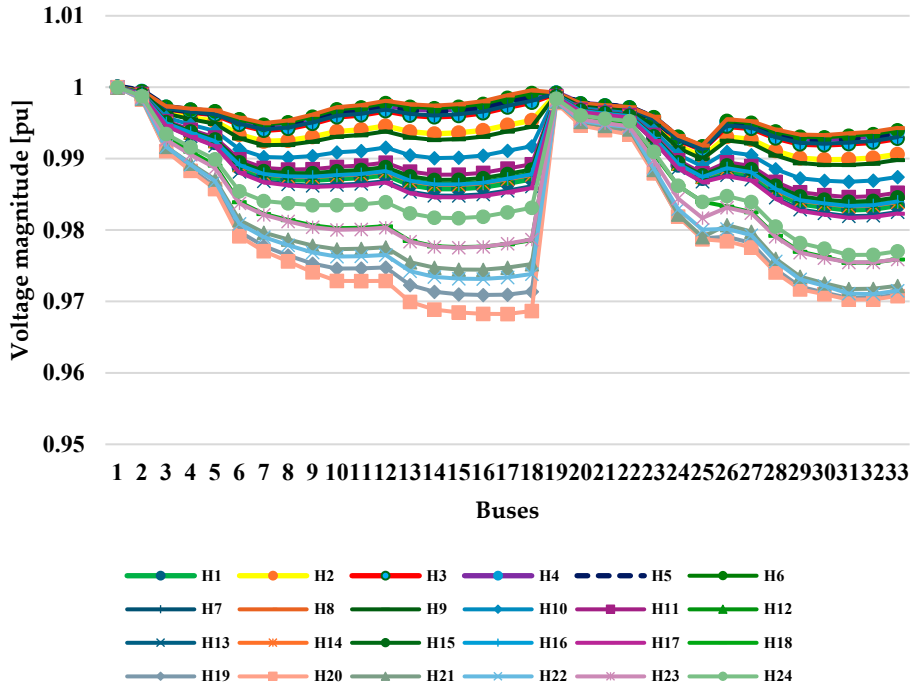


Figure 7. The voltage profile of the network is at different hours of the day in the first scenario.

3. Second scenario: At this stage, GA is used to improve the voltage profile, as seen in Figure 8. In this case, as an example of improvement, the voltage at H20 and bus 18 is improved to 0.97310 p.u. This means that so far, the GA has performed better than the ICA.

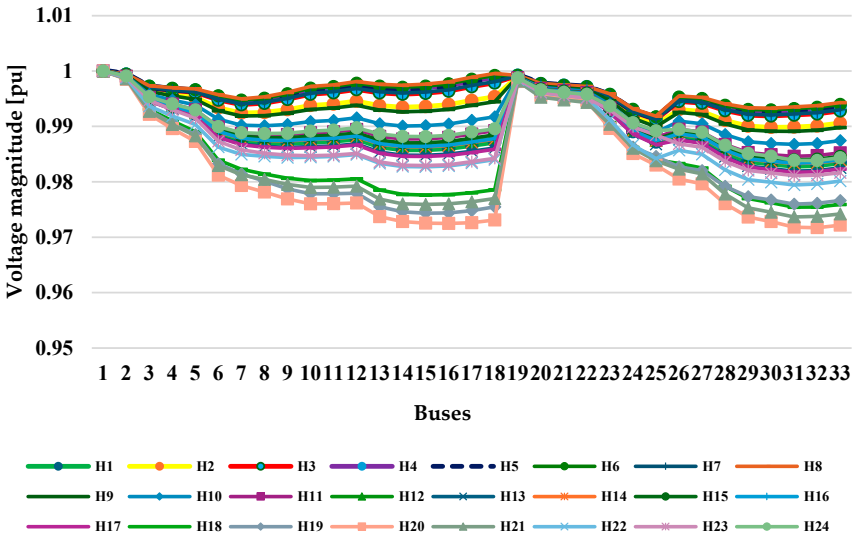


Figure 8. The voltage profile of the network is at different hours of the day in the second scenario.

4. Third scenario: In this stage, the same operations as the previous stage are performed using a combination of the GA and ICA. In Figure 9, it is observed that the voltage at H20 and bus 18 is improved more compared to the previous three scenarios and became 0.97697.

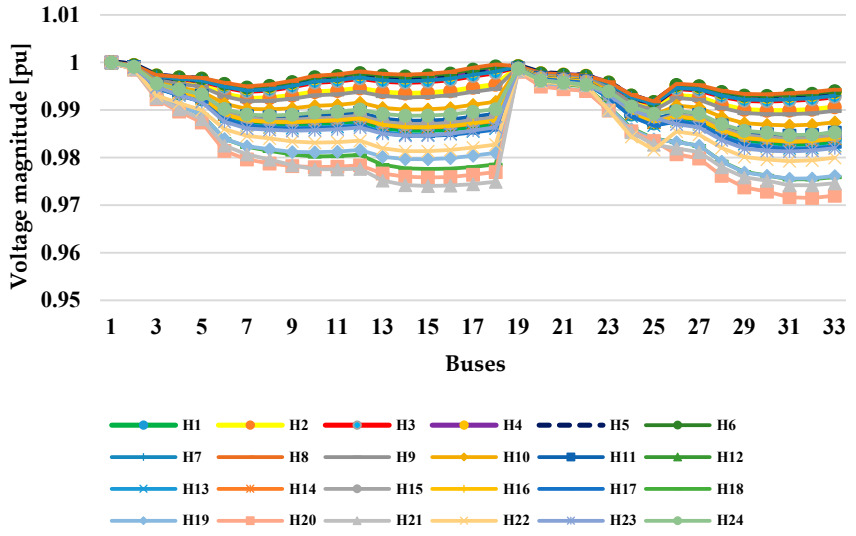


Figure 9. The voltage profile of the network is at different hours of the day in the third scenario.

A comparison between different techniques for buses 27, 28, and 31 at different hours between 21 and 24 is also listed in Table 2 for some hours of the day.

Table 2. Comparison between different techniques for buses 27, 28, and 31 at specific times of the day.

(a) Voltage in per-unit at bus 27 for different hours				
Technique	H21	H22	H23	H24
Base case	0.96888	0.97270	0.97521	0.97945
ICA	0.97978	0.97927	0.98237	0.98392
GA	0.98142	0.98497	0.98625	0.98894
Hybrid	0.98116	0.98482	0.98635	0.98929

Table 2. *Cont*.

(b) Voltage in per-unit at bus 28 for different hours				
Technique	H21	H22	H23	H24
Base case	0.96330	0.96775	0.97068	0.97564
ICA	0.97599	0.97560	0.97906	0.98044
GA	0.97778	0.98216	0.98367	0.98660
Hybrid	0.97798	0.98224	0.98368	0.98704
(c) Voltage in per-unit at bus 31 for different hours				
Technique	H21	H22	H23	H24
Base case	0.95605	0.96148	0.96505	0.97108
ICA	0.97174	0.97110	0.97548	0.97651
GA	0.97367	0.97923	0.98113	0.98388
Hybrid	0.97419	0.97925	0.98130	0.98471

5. Conclusions

This paper presents a comprehensive evaluation of voltage deviation improvement in microgrid operations through the integration of DR strategies optimized by ICA and GA and a hybrid of them. These algorithms prove their effectiveness in scenarios with dynamic demand patterns and varying operational constraints. The proposed method is implemented by using a 33-Bus IEEE sample network to reach the aim. The network is initially considered without any optimization technique, then performed with the optimization techniques using the ICA and GA individually and a hybrid of them. For example, the voltage per-unit at bus 31 at a time of 21:00 is 0.95605 for the base case, and after using ICA, the voltage is improved to 0.97174, and it is improved more after using GA to be 0.9737, and the hybrid techniques improved it more to be 0.97419. The results proved the effectiveness of using the hybrid technique over the individual techniques. The GA provides better results compared to ICA, and the hybrid model further improved the voltage profile as it has more features that will help to improve the performance of the optimization problem.

It is recommended that future research use another intelligent algorithm to determine the manner of voltage deviation. Additionally, In the future, it would be beneficial to explore deterministic methods for optimizing microgrids, as these could offer more stable outcomes in cases where metaheuristic algorithms produce inconsistent results due to their inherent randomness. This study is primarily focused on hybrid metaheuristic techniques because they are well-suited to addressing the complexity of optimization problems in microgrids. Furthermore, further work could investigate the effects of demand response on various types of loads or improve simulation models by considering factors like seasonal changes and consumer habits, which could lead to more reliable conclusions.

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Conflicts of Interest: The authors declares no conflict of interest.

Appendix A

Table A1. Data of existing distribution branches of the 33-bus test system.

From	To	R (Ω)	X (Ω)	Current Capacity (Amp)
1	2	0.0922	0.0477	500
2	3	0.493	0.2511	500
3	4	0.366	0.1864	500
4	5	0.3811	0.1941	500
5	6	0.819	0.707	500
6	7	0.1872	0.6188	500
7	8	1.7114	1.2351	500
8	9	1.03	0.74	500
9	10	1.04	0.74	500
10	11	0.1966	0.065	500
11	12	0.3744	0.1238	500
12	13	1.468	1.155	500
13	14	0.5416	0.7129	500
14	15	0.591	0.526	500
15	16	0.7463	0.545	500
16	17	1.289	1.721	500
17	18	0.732	0.574	500
18	19	0.164	0.1565	500
19	20	1.5042	1.3554	500
20	21	0.4095	0.4784	500
21	22	0.7089	0.9373	500
22	23	0.4512	0.3083	500
23	24	0.898	0.7091	500
24	25	0.896	0.7011	500
25	26	0.203	0.1034	500
26	27	0.2842	0.1447	500
27	28	1.059	0.9337	500
28	29	0.8042	0.7006	500
29	31	0.5075	0.2585	500
30	31	0.9744	0.963	500
31	32	0.3105	0.3619	500
32	33	0.341	0.5302	500

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