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Optimal Planning of Distributed Energy Resources in Distribution Microgrid to Improve Resource Owner Profit and Network Resiliency

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Abstract

The objective of this study is to strategize the allocation of resources within the distribution microgrid. The primary goals are to diminish active power loss and voltage discrepancies, enhance resilience, decrease the expense of procuring energy from the main network, augment the incorporation of distributed renewable energy sources, and optimize the profitability of integrating distributed generation and storage resources into the power supply. In this article, the microgrid design challenge is approached through the focus on a nonlinear optimization model. The Biogeography-based optimization algorithm is employed to tackle this complex problem. Moreover, the planning solution is crafted to address uncertainties, incorporating factors such as wind speed, solar radiation, and consumption load variability within the distribution network. To validate the efficacy of the proposed methodology, the standard 33-bus test system is scrutinized. The outcomes underscore the remarkable efficiency of the proposed solution, showcasing its potential for practical applications in optimizing microgrid performance.

Keywords: Independent Microgrid, Distributed Wind Generation Resources, Distributed Solar Generation Resources, Energy Storage, Biogeography-Based Algorithm.

1. INTRODUCTION

In recent years, electric distribution networks have undergone significant advancements. The rise in distributed generation (DG) resources and energy storage, the widespread adoption of microgrids, and the establishment of electricity markets at the distribution level mark pivotal developments

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in this field. While these advancements offer numerous advantages, they also present challenges.

Challenges include uncertainties related to the output power of renewable DG resources and deviations from technical constraints within the network, such as bus voltage domain and feeder thermal capacity. This research aims to strategically integrate diverse DG resources into electric distribution microgrids. The objective is twofold: to enhance the profitability of DG owners and bolster the network's resilience against interruptions from the upstream network.

Network resilience, in this context, refers to the network's ability to restore power to de-energized loads, especially in the face of natural disasters such as floods and storms. This study addresses these challenges and explores solutions to optimize the integration of DG resources, ensuring both economic viability and network robustness.

Numerous studies have explored various strategies in the planning of recent advancements within the realm of distribution networks. Reference [1] delves into the optimal planning of Distributed Generation (DG) resources, enhancing microgrid reliability through a multi-objective optimization approach that factors in the uncertainty associated with electric vehicles. Reference [2] introduces a stochastic model for energy management in smart microgrids featuring renewable DG resources. In rural areas, Reference [3] outlines the planning of DG resources to establish intelligent buildings isolated from the national network. Reference [4] presents an energy management system geared towards reducing daily operational costs and maximizing microgrid productivity by sourcing most of its loads internally.

Addressing the variability of renewable DG, Reference [5] employs optimal planning techniques within microgrids to mitigate fluctuations and enhance reliability. Reference [6] focuses on dynamic storage planning within microgrids to manage interruptions from wind-based DGs. Reference [7] determines the optimal capacity and installation locations for DGs to enhance customer reliability. Delving into economic aspects, Reference [8] investigates operating independent distribution networks powered by renewable DGs such as solar and biomass resources. Reference [9] aims to alleviate distribution network congestion and voltage issues in the presence of wind DGs.

Additionally, Reference [10] not only explores the advantages of wind DG resources but also conducts economic analyses to determine electricity pricing due to the presence of DGs, valuing their integration into the distribution network. Reference [11] introduces a two-stage model for short-term and long-term planning of DGs—wind, solar, and diesel-based accompanied by storage, with the goal of reducing power supply costs and minimizing losses. Lastly, Reference [12] addresses challenges faced by distribution network operators, including increased DG penetration rates and significant load fluctuations. It emphasizes optimal planning strategies for these resources within microgrids.

While extensive research has been conducted on Distributed Generation (DG) resource planning within microgrids, few studies have comprehensively tackled the planning of diverse DGs within microgrids in the context of the electricity market, considering both economic and technical perspectives. This study aims to establish a model for planning and developing various DGs, encompassing both renewable and non-renewable resources, at the distribution network level, with the ultimate goal of segregating the distribution network into independent microgrids.

The objectives of this research encompass several key areas. Firstly, it aims to augment the installed capacity of DGs within the distribution network, thereby reducing the dependency on the upstream network. Secondly, the study strives to enhance the resilience of distribution networks against interruptions from the upstream network. Additionally, the research aims to boost the income of DGs operating within microgrids by facilitating their participation in electricity markets.

The subsequent sections of this article unfold as follows: the second part delves into the formulation of the optimization problem concerning the design and operation of microgrids. In the fourth section, the proposed method is applied to a 33-bus distribution network, accompanied by insights into the implementation considerations. Finally, the thesis is summarized and concluded in the fifth section, encapsulating the findings and implications of the research.

2. MATHEMATICAL MODEL

In this section, we establish the framework for planning Distributed Generation (DG) resources within the distribution network. The aim of this planning process is to identify the most efficient locations and capacities for these resources within the network.

A. Cost Function

The problem of planning distributed generation in the microgrid involves defining an objective function, represented by equation (1). This equation encapsulates the essence of the distributed generation planning problem within the microgrid context.

$$\min \quad F=\sum_{t=1}^{N_t}\Delta t\times\begin{bmatrix}(PG_t\times Cp_t)+(\sum_{i=1}^{N_b}\left|V_{i,t}-1\right|\times Cv_t)+\\(\sum_{j=1}^{N_{br}}Ploss_{j,t}\times Cl_t)+(\sum_{k=1}^{N_{micro}}ENS_{k,t}\times Cr_t)\\-\sum_{n=1}^{N_{ess}}(Pdch_{n,t}-Pch_{n,t})\times Cb_t\\-(\sum_{m=1}^{N_{dg}}PDG_{m,t}\times Cb_t)-(\sum_{r=1}^{N_{rdg}}PRDG_{r,t}\times Ce_t)\end{bmatrix} \tag{1}$$

In accordance with equation (1), the objective function comprises seven components. The initial term denotes the cost associated with procuring energy from the upstream network. The second segment quantifies the expense linked to voltage deviations across network buses. The third aspect represents the expenditure associated with network energy usage. The fourth component signifies the penalty incurred due to unmet energy demand. Notably, a more resilient distribution network, capable of swiftly restoring loads after upstream interruptions, results in reduced unsupplied energy within the network.

The fifth and sixth components encompass the revenue generated by DGs and storage owners from selling power to the network. Lastly, the seventh component captures the reward attributed to the participation of renewable DGs in the distribution network. To optimize this objective function, a set of constraints, including both technical and economic considerations, are taken into account. These constraints form an integral part of the optimization process, ensuring the efficient and balanced planning of DG resources within the distribution network.

B. Constraints

In this section, we outline the set of constraints for the proposed problem model concerning the planning of DGs resources and electrical energy storages.

1. *Active and reactive power balance condition*

Constraints (2) and (3) illustrate the requirements for active and reactive power balance across the entirety of the distribution network. These relations ensure a consistent balance between the active and reactive power generated by DGs and energy storage, maintaining the network's stability and reliability.

$$P_{G,i} - P_{L,i} = \sum_{k=1}^{n} V_i V_k Y_{ik} \times \cos(\theta_{ik} + \delta_k - \delta_i) \qquad \forall i \tag{2}$$

$$Q_{G,i} - Q_{L,i} = \sum_{k=1}^{n} V_i V_k Y_{ik} \times \sin(\theta_{ik} + \delta_k - \delta_i) \qquad \forall i \tag{3}$$

In this regard, $P_{G,i}$ and $Q_{G,i}$ are the active and reactive power produced in bus i, and $P_{L,i}$ and $Q_{L,i}$ are the active and reactive power consumed in bus i. V_i is the voltage of i-th bus and Y_{ik} is the admittance between bus i and k. δ is the bus voltage angle and θ is the admittance phasor angle.

2. *Bus voltage constraint*

Equation (4) expresses the bus voltage constraint.

$$V_{\min} \le V_i \le V_{\max} \tag{4}$$

According to this condition, the voltage of each bus should not exceed a certain limit. V_i is the i-th bus voltage, and V_{min} and V_{max} are the minimum and maximum values of the bus voltage, respectively. The voltage of each bus can change between 0.95 and 1.05 units.

3. *Constraint of feeder capacity Equation*

Equation (5) expresses the power requirement of each feeder.

$$Uc_f \le fc_{f,\max} \tag{5}$$

In this regard, U_{cf} shows the power passing through feeder f in megavolt-amperes and $fc_{f,max}$ shows the rated capacity of the feeder. In this research, the thermal capacity of the feeder is equal to 6.6 megavolts.

4. Restriction of candidate buses for installation of DGs

Equation (6) shows the constraints of candidate buses for installing DGs resources.

$$Pdg_{s,i} = 0 \quad \forall s \in N_s \ \& \ \forall i \notin cnd_{dg} \tag{6}$$

According to this relationship, the output power of DGs at buses that are not candidates for installing DGs is equal to zero. In this regard, it shows the set of candidate buses for the installation of DG resources. $Pdg_{s,i}$ shows the generation power of the wind DG on bus i in mode s. All network buses except the main post are candidates for installing resources in this research.

5. Limitation of candidate buses for storage installation

Equation (7) identifies the eligible buses for the installation of storage resources.

$$\begin{aligned} &dischrg_{s,i} = 0, \ \forall s \in N_s \ \& \ \forall i \notin cnd_{storage} \\ &chrg_{s,i} = 0, \ \forall s \in N_s \ \& \ \forall i \notin cnd_{storage} \end{aligned} \tag{7}$$

According to this relationship, the charging and discharging power of storage at buses that are not candidates for storage installation is equal to zero. In this regard, $cnd_{storage}$ shows the set of candidate buses for storage installation. Also, $dischrg_{s,i}$ and $chrg_{s,i}$ are the discharge and charge power of the storage at bus i in s mode. All the network buses except the main post in this research are candidates for the installation of storage.

6. Determining the number of DGs

Equation (8) indicates the number of DG resources that can be installed in the network.

$$\sum_{i=1}^{N_b} Ndg_i \le dg_{\max} \tag{8}$$

According to this constraint, the number of distributed N_{dg} sources installed in the distribution network buses is limited to dg_{max}. It is assumed that a maximum of four DGs of 0.5 MW can be installed in the network from each type of DGs. It is assumed that all resources are used in unit power factor and their reactive power is zero.

7. Specify the number of storages

Equation (9) shows the limitation of the number of storage resources that can be installed in the network.

$$\sum_{i=1}^{N_b} Nstorage_i \le storage_{\max} \tag{9}$$

According to this constraint, the number of $N_{storage}$ storage installed in the distribution network buses is limited to $storage_{max}$. In this research, it is assumed that a maximum of four storage units with a capacity of 0.5 MW can be installed in the network. Also, it is assumed that the storage units are operated at unit power factor and their reactive power is zero.

8. Specifying the storage charge amount

The following relationship shows the condition of the amount of charge of the storage device.

$$soc_{\boldsymbol{min}} \le soc_s \le soc_{\boldsymbol{max}} \tag{10}$$

According to this equation, the charge rate of the storage tank in each state s is limited to socmin and socmax. In this research, the minimum and maximum value of the storage charge status is considered zero and 100%. In the research scenario, it is assumed that the storage device undergoes charging or discharging every hour, depleting or replenishing at a rate of 5% of the total storage capacity. In other words, this translates to a 20% charge or discharge of the total storage capacity within each 4-hour period. The decision of whether to charge or discharge the storage is a variable that the optimization algorithm optimally determines.

- To solve the optimization problem, the key variables considered in this research are:
- The location and capacity of installing all kinds of DGs, including wind, solar, and diesel resources.
- The location and capacity of installing electrical energy storage.
- Charging and discharging status of energy storage.

These variables form the basis of the optimization algorithm, enabling the comprehensive planning and management of diverse energy resources within the network.

3. SIMULATION AND RESULTS

A. Implementation Considerations

The proposed solution is implemented on the 33-bus IEEE standard distribution network, as illustrated in Figure 1. The total active load for the network is 2300 kW, and the total reactive load is 1800 kW. The network operates at a voltage level of 12.66 kV, with each bus having a voltage variation range between 0.95 and 1.05 per unit (p.u.). Furthermore, the thermal capacity of the network feeders is 6.6 MVA.

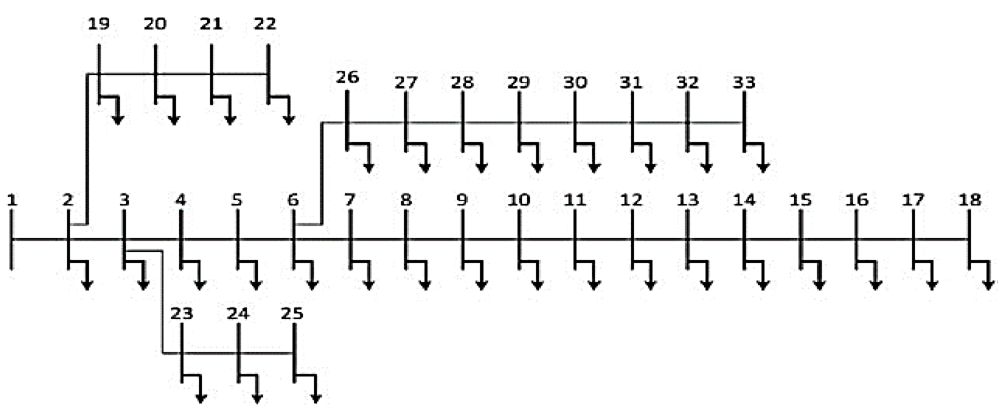

Fig. 1. The 33-bus distribution network.

Table 1. ***Segmentation of the studied network*.**

Microgrid number	Buses belonging to each microgrid sector	Load (MW)
1	19-22	0.36
2	1-18	1.605
3	23-25	0.93
4	26-33	0.92

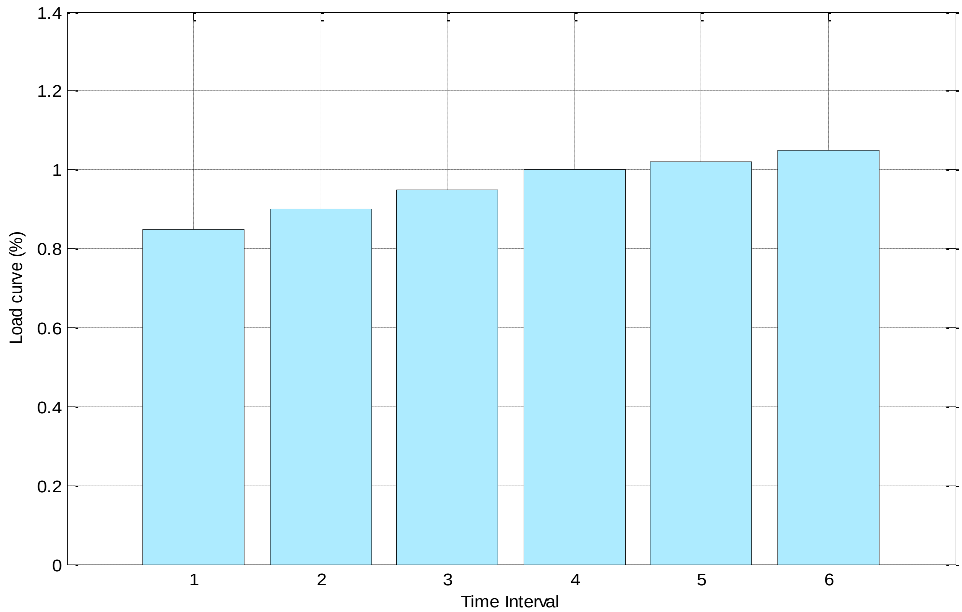

Fig. 2. The load curve of the studied distribution network.

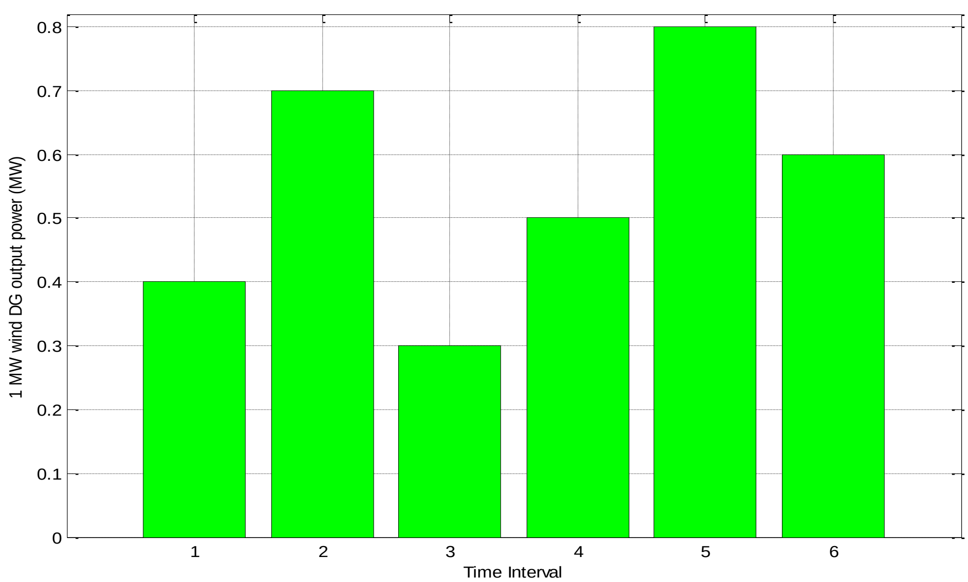

Fig. 3. Generation rate curve of wind DG resources.

In this study, it is assumed that the analyzed distribution network can be divided into four independent microgrids. Table 1 provides detailed data for each microgrid, specifying the load and bus numbers associated with each microgrid. Notably, the 3.7 MW load of the distribution network is distributed across these four microgrids. This segmentation allows for a comprehensive analysis and optimization of each microgrid's resources and operations.

In this study, wind, solar, and diesel-based Distributed Generators (DGs), as well as storage resources, are presumed to be installable within each microgrid, with a maximum capacity of 0.5 MW. The optimization process is conducted based on a daily time frame divided into 6 intervals, each lasting 4 hours. The intervals are structured from midnight to 4 am as the initial period, followed by subsequent 4-hour intervals. Network load patterns and solar/wind DG generation rates, detailed in Figures 2 to 4, are taken into account.

Additionally, it is assumed that during the third and fifth intervals, the distribution network will be disconnected from the national grid. In these periods, if DG resources are not integrated into the network, the entire network load remains unmet, underscoring the critical need for efficient resource planning and deployment within the microgrid system.

To compute the objective function, various cost coefficients are taken into account, as outlined in Table 2 and depicted in Figures 5 to 7. These coefficients encompass energy losses, bus voltage deviations, procurement costs from the upstream network, transactions involving DGs and storage resources, expenses due to unsupplied energy, and rewards for the involvement of renewable DGs.

It is important to note that the cost of energy losses per Megawatt-hour (MWh) is determined based on the electricity price for domestic customers in Iran, ranging from 100 to 800 Toman per kilowatt-hour (kWh). To ensure consistency, the cost factor for total network bus deviations from 1 per unit (p.u.) is normalized with the total cost of losses. This normalization is crucial to align the components of the objective function within a comparable range. Specifically, the cost factor for bus voltage deviations is determined using the objective function sentence normalization technique, considering the absence of a standardized method for quantifying the impact of voltage deviations. Consequently, this coefficient is derived from mathematical logic rather than practical interpretation.

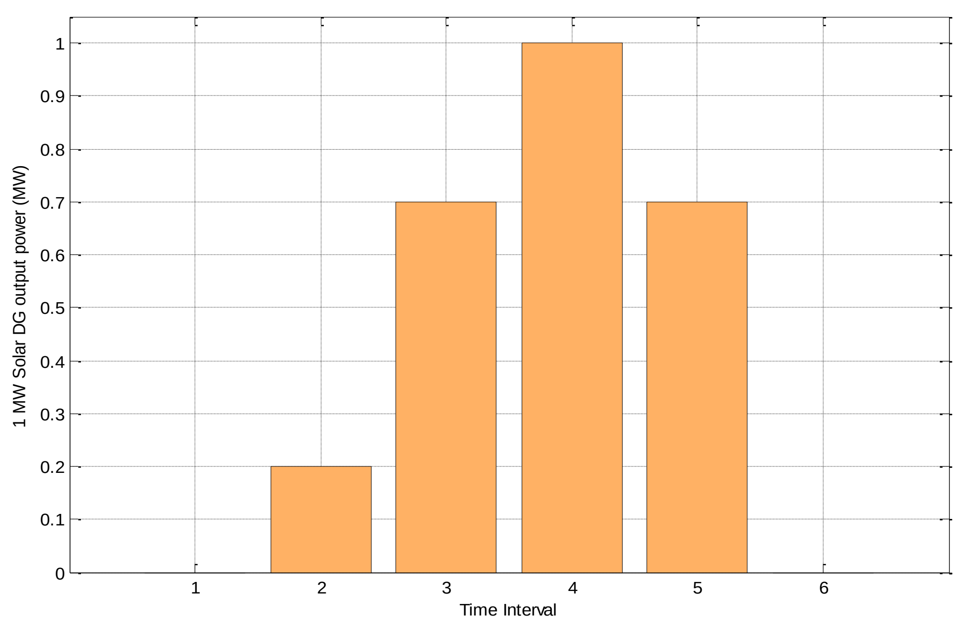

Fig. 4. Generation rate curve of solar DG resources.

Table 2. ***Hypothetical coefficients in the evaluation of the objective function.***

Value	Parameters
500.000	Energy cost (Toman/MWh)
50.000	Bus voltage deviation cost (Toman/p.u.h)
1.000.000.000	Energy not supplied cost (Toman/MWh)

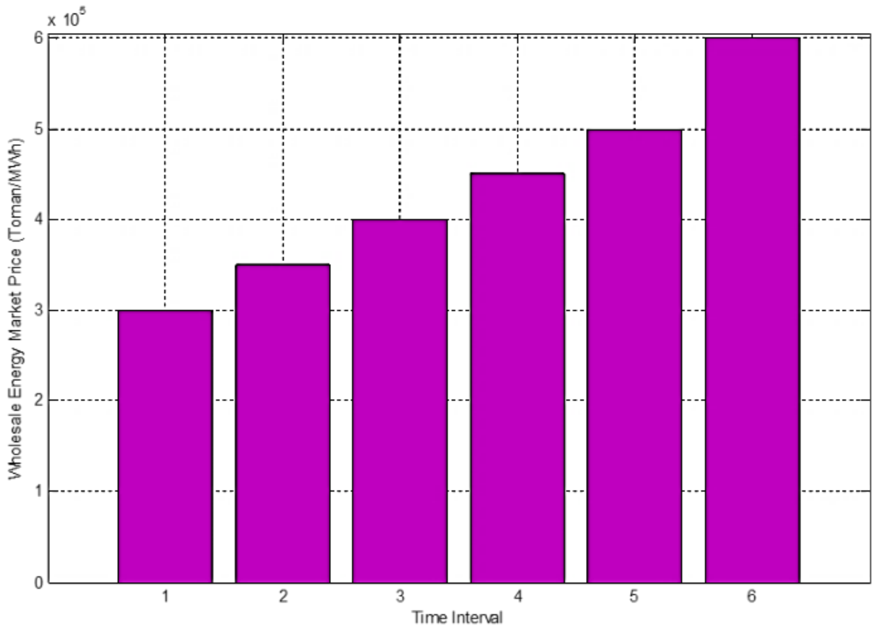

Fig. 5. The price of buying energy from the upstream network.

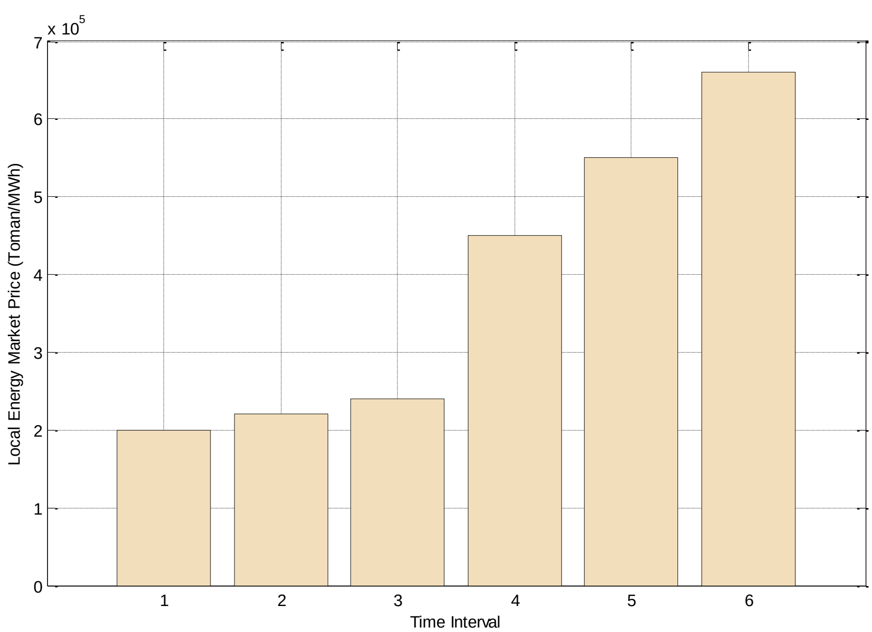

Fig. 6. Energy purchase/sale price from/to DG and storage resources.

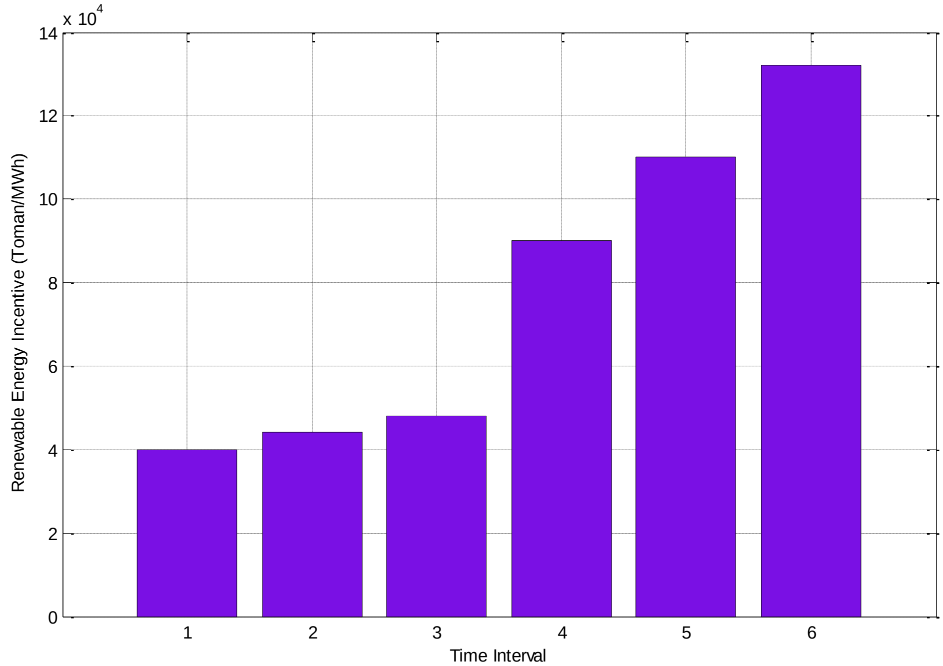

Fig. 7. Reward for the participation of renewable DGs in supplying load.

Moreover, the cost coefficient for unsupplied energy is established as a penalty coefficient. The objective is to minimize de-energized energy, ensuring successful utilization of the distribution network's islanding capabilities. However, this coefficient is driven by the problem's mathematical framework and lacks direct real-world interpretability, as it cannot precisely model the actual damage incurred by customers during power interruptions.

B. Simulation Results Analysis

In this section, we delve into the practical implementation of the optimization process, taking into account the considerations detailed in the preceding section. To optimize the objective function, we employed the biogeography-based optimization algorithm, utilizing parameters specified in Table 3. This algorithm is chosen for its rapid convergence, compatibility with integer variables, and minimal parameter complexity.

Figure 8 illustrates the progression of the objective function. The horizontal axis represents the number of iterations, while the vertical axis signifies the objective function value in Toman. Notably, the objective function value has turned negative, indicating that the profits generated by DG owners outweigh the costs associated with operating the distribution network.

Tables 4 to 7 showcase the optimized outcomes resulting from the implementation of the optimization process. These tables include details on the optimal placement and capacity for DGs and storage resources, as well as the optimal utilization of storage and diesel-based DG resources. It is essential to highlight that Table 7 provides insight into scenarios where renewable DGs or storage resources are unable to meet the load demands of each microgrid. In such cases, the responsibility of supplying the load falls upon the diesel-based DGs. The specific quantities of diesel-based DGs required for each period and microgrid are documented in this table.

Table 3. ***Biogeography-based algorithm settings.***

Value	Parameters
100	Iteration
20000	Population size
A random number between 0 and 1	Migration rate
1-Migration rate	Immigration rate
0.1	Mutation ratre

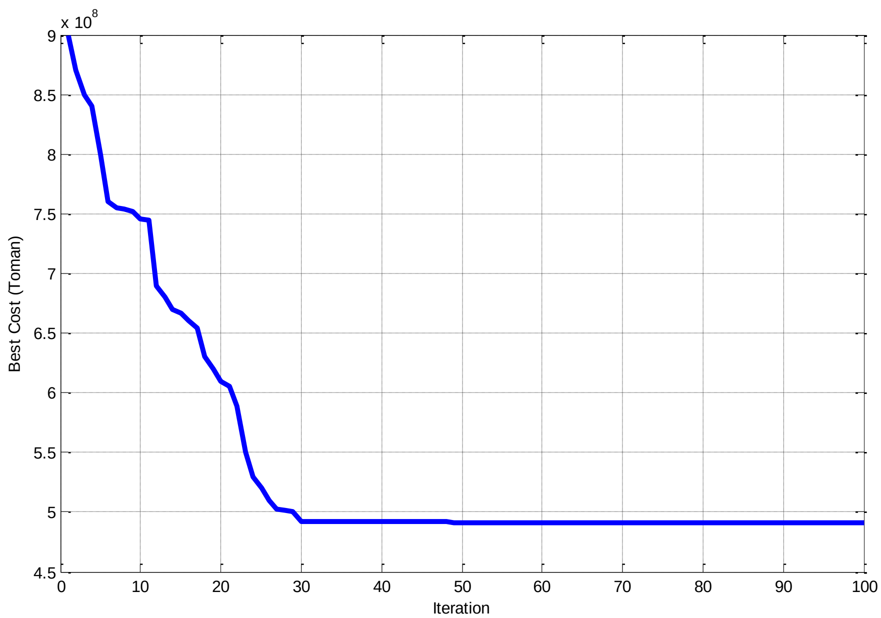

Fig. 8. The process of improving the objective function.

Table 4. ***optimal location for installing resources in each microgrid.***

	Microgrid number			
	1	2	3	4
Wind-based DG bus	21	17	25	31
Solar-based DG bus	20	8	25	32
Storage bus	21	2	23	32
Diesel DG bus	19	13	24	29

Table 5. ***Optimum installation capacity of resources in each microgrid.***

	Microgrid number			
	1	1	1	1
Wind-based DG capacity (MW)	0.27	0.49	0.5	0.5
Solar-based DG capacity (MW)	0.26	0.5	0.49	0.5
Storage capacity (MW)	0.024	0.12	0.17	0.16

Table 6. ***Optimum storage charging/discharging status in each microgrid.***

Time Intervals	1	2	3	4	5	6
Microgrid 1	1[a]	-1	1	-1	1	-1
Microgrid 2	1	-1	-1	1	-1	1
Microgrid 3	1	-1	1	-1	1	-1
Microgrid 4	1	-1	1	-1	-1	1

* 1: charge, -1: discharge

Table 7. ***Optimal amount of diesel unit generation in each microgrid.***

Time Intervals	1	2	3	4	5	6
Microgrid 1	0.15	0.29	0.24	0.09	0.29	0.24
Microgrid 2	0.49	0.5	0.5	0.44	0.37	0.5
Microgrid 3	0.48	0.47	0.33	0.33	0.22	0.5
Microgrid 4	0.49	0.49	0.48	0.49	0.37	0.48

By applying the optimal response to the studied distribution network, Figures 9 to 14 respectively show the bus voltage curve, the power passing through the feeders, the amount of unsupplied energy of the network per hour, the amount of electrical energy loss per hour, the amount of voltage deviations, and the cost of providing energy to the network in normal and optimal modes.

The impact of the optimal response on the distribution network's performance is evident. Figure 9 demonstrates a significant enhancement in the voltage levels across network buses during all 6 time intervals compared to the regular state. Additionally, Figure 10 compares the power flowing through the feeder in the sixth time period, characterized by the highest network load factor, between the optimal and normal modes. These comparisons highlight the marked improvements in network stability and load management achieved through the implementation of the optimized solution.

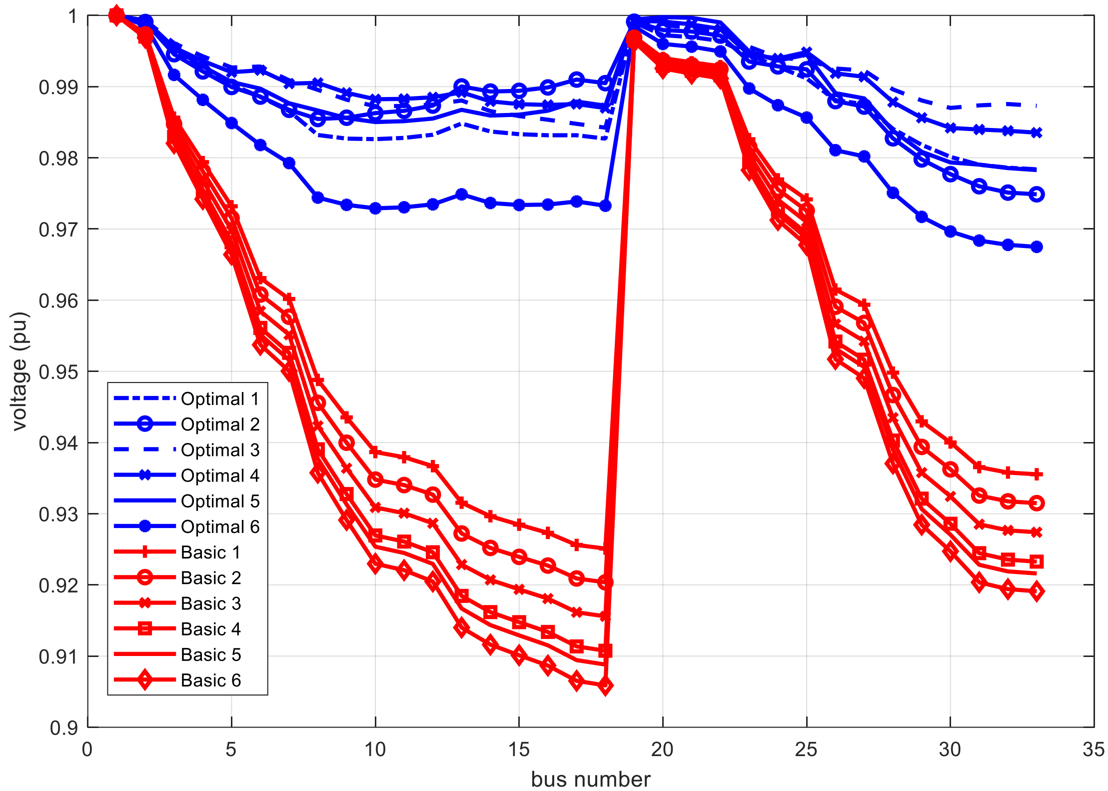

Fig. 9. Comparison of bus voltage curve in optimal and normal modes.

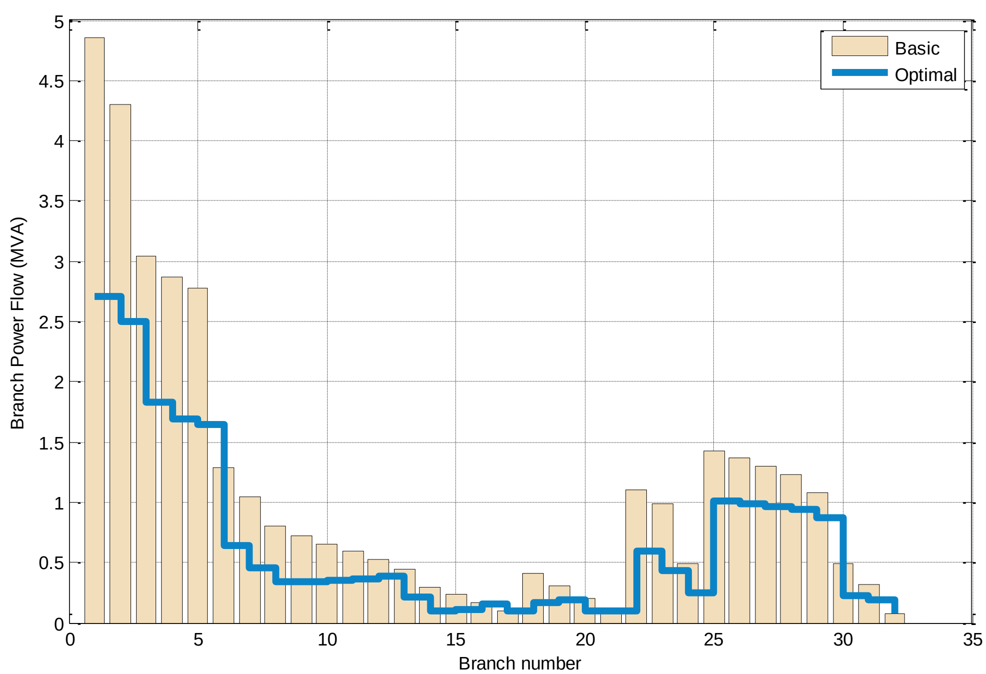

Fig. 10. Comparison of the power curve passing through the feeders in optimal and normal modes.

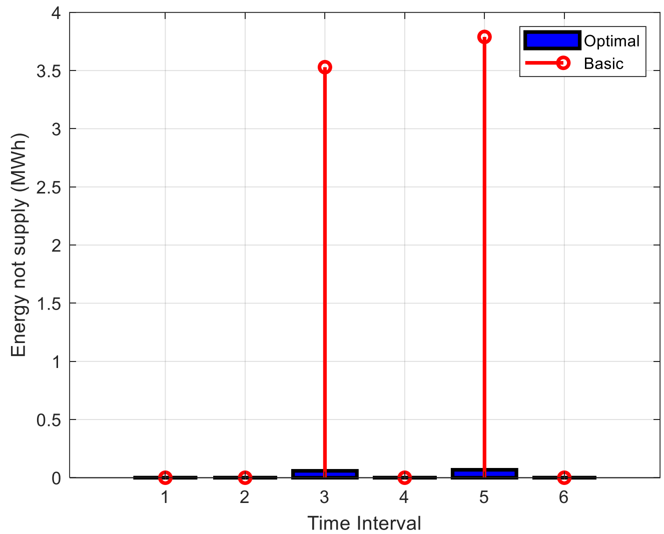

Fig. 11. Comparing the amount of unsupplied energy in each hour of the third- and fifth-time intervals.

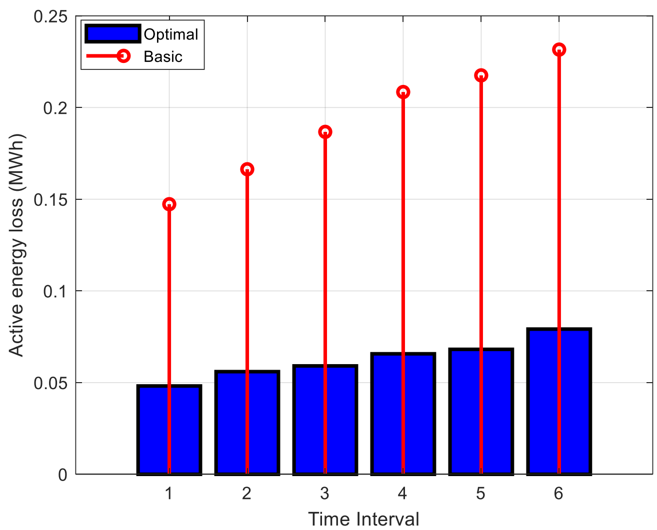

Fig. 12. Comparing the amount of energy loss in each time interval in optimal and normal modes.

It is noteworthy that the utilized capacity of feeders within the distribution network has considerably reduced during this period, attributed to the direct supply of load at consumption points. Figure 11 illustrates the hourly unsupplied energy levels in the examined distribution network under normal conditions (without additional resources) during periods 3 and 5 when the network is disconnected from the national grid. In these periods, unsupplied energy is notably high in the standard network setup. However, with the optimal placement and capacity of resources, this value sees a significant reduction in the optimized distribution network. Essentially, the strategic deployment of resources in optimal locations has led to a substantial improvement in network performance.

The network can now fulfill its local load demands by utilizing resources within the distribution network, resulting in minimal blackouts for only a small portion of the network loads. Figures 12 and 13 depict the reduction in energy losses and network bus voltage deviations. Additionally, Figure 14 compares the hourly energy procurement costs from the upstream network under normal and optimal conditions. Notably, the cost of energy supply from the upstream network has significantly decreased across all time intervals. In the optimal state during intervals 3 and 5, there is no injection of power from the upstream network into the distribution network. Table 8 provides a comprehensive comparison of the total objective function values between the normal and optimal states across all 6-time intervals. These comparisons underscore the substantial improvements achieved through the optimized network configuration.

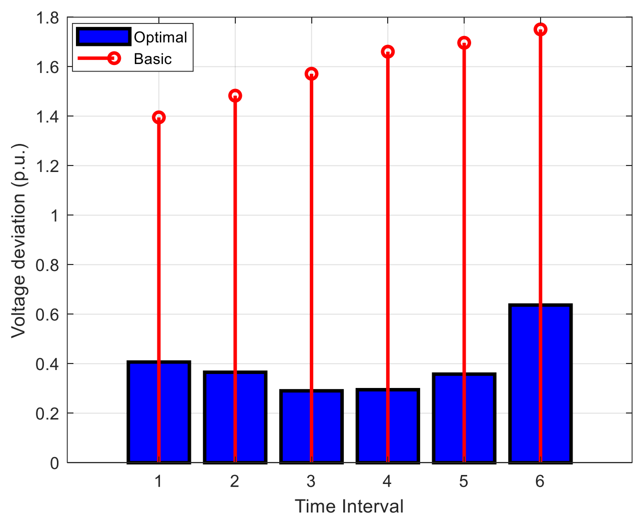

Fig. 13. Comparison of voltage deviations of network buses in optimal and normal modes.

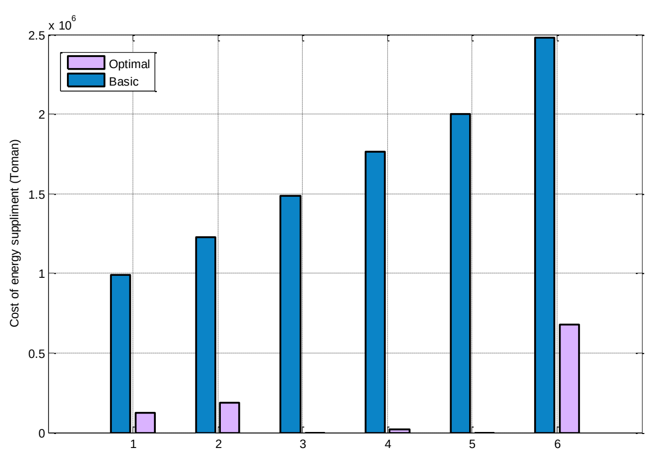

Fig. 14. Comparing the cost of buying energy from the upstream network in optimal and normal modes.

Table 8. ***Comparing the value of the objective function in different time intervals in normal and optimal modes.***

Time intervals	1	2	3
Cost function	2682727	3.79E+09	1952817
Cost function	-460602	66440068	-1322706
Time intervals	4	5	6
Cost function	3.53E+09	1385763	1134915
Cost function	58531220	-166513	-203908

As can be seen, the objective function sentences in the third- and fifth-time intervals are much higher than the objective function value in other time intervals, because in these two-time intervals, the value of the unsupplied energy cost, which is a very large number, is accumulated with other objective function sentences. It can be seen that the value of the objective function in time intervals 1 and 5 in the optimal network has become negative compared to the initial network. In other words, in the optimal network, the profitability of the DGs and storage owners overcomes the distribution network operation costs.

Clearly, the objective function values in the third- and fifth-time intervals significantly surpass those in other intervals. This discrepancy arises from the considerable cost associated with unsupplied energy during these periods, contributing to a substantial increase in the overall objective function values. Notably, in the optimal network configuration, the objective function values for intervals 1 and 5 have turned negative when compared to the initial network setup. In simpler terms, the profitability generated by DGs and storage owners in the optimal network exceeds the operational costs of the distribution network, indicating a financially advantageous and optimized system.

4. CONCLUSION

This study aimed to optimize resources within the distribution microgrid to minimize energy losses, reduce voltage fluctuations, enhance network resilience, cut costs associated with purchasing energy from the upstream network, promote the integration of renewable-based Distributed Generation (DG) resources, and increase the profitability of DGs and storage resources in supplying the load. Employing a nonlinear optimization model, the microgrid design problem was effectively formulated. To address uncertainties, the optimization process incorporated variations in network load, wind speed, and solar radiation. The biogeography-based optimization algorithm was instrumental in solving this complex optimization challenge.

The research findings, validated using the 33-bus test network, demonstrated the remarkable efficiency of the proposed solution. By strategically planning resources amidst uncertainties, the microgrid exhibited enhanced performance, reduced losses, and increased profitability. This comprehensive approach not only contributes to the robustness of microgrid systems but also provides valuable insights for future advancements in distributed energy systems.

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