Optimal Energy Management in Smart Distribution Networks Considering Responsive Loads and Network Reconfiguration for Enhancing Technical and Economic Objectives

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Abstract

Energy management (EM) in distribution systems has gained significant attention in recent years. Coordinating electricity generation and consumption is crucial for energy savings, cost reduction, and achieving technical and economic objectives (EO). Demand-side participation through responsive loads (RLs) in smart distribution networks (SDNs) facilitates optimal EM and operation, contributing to the long-term improvement of distribution network performance. The primary objective of this paper is to present an efficient model for optimal EM planning in a smart distribution network, considering RLs and the impact of network reconfiguration on enhancing technical and economic goals. In this study, a 33-bus IEEE distribution network is analyzed for daily EM , incorporating ten different load levels with varying probabilities for each level. The optimization algorithm employed in this research is the Genetic Algorithm (GA), used to optimize the objective functions. The results demonstrate that demand-side participation through responsive loads, along with optimal network reconfiguration, can effectively reduce daily energy loss costs and improve the voltage profile of the distribution network.

Keywords: Smart distribution network, responsive loads, network reconfiguration, genetic algorithm, loss cost reduction, voltage profile improvement.

1. Intruduction

Demand-side load participation in energy management (EM) serves as a reliable solution for ensuring economic and sustainable electricity supply to consumers. As the final stage in electrical energy delivery, this approach represents an innovative EM strategy that is directly connected to or located near the distribution network. To achieve economic, technical, environmental, and regulatory benefits in power systems, it is essential to optimize the size, location, and type of distributed energy resources. Effective operation of smart distribution networks (SDNs) relies on the efficient utilization of responsive loads (RLs) on the demand side. RLs constitute a key capacity in demand-side management within SDNs[1].

Reconfiguration of power distribution systems is a method for restructuring distribution networks that does not require the installation or deployment of new equipment. Instead, it utilizes existing equipment and switches in a simple and cost-effective manner to reduce power losses. In each distribution network, there are normally open and normally closed switches. By closing some of the normally open switches and simultaneously opening the same number of normally closed switches, the power flow path in the distribution network can be altered to minimize system losses. Since distribution networks always operate in a radial configuration, their reconfiguration must be conducted in a way that preserves this structure. Given the dynamic nature of power flow in distribution systems, it is unrealistic to expect a fixed network structure to fulfill technical and economic objectives (EO) at all times [2-4].

The variable nature of loads in power systems necessitates the adoption of optimization methods to achieve technical and EO . In this regard, the reconfiguration of distribution networks using remotely controlled switches gains significant importance. Achieving this requires accurate load forecasting in scientific studies and precise load modeling, considering its irregular nature, or incorporating it into manual control processes [5-6].

Due to their radial structure, distribution networks experience significant power losses. Therefore, the primary objective of distribution network operation planning is to reduce power loss costs and improve the voltage profile. One of the most effective and widely used methods to achieve this goal is network reconfiguration, which can substantially reduce power losses [7-9].

Accordingly, in this paper, RLs are utilized as a demand-side management strategy to reduce energy consumption costs and enhance the technical objectives of a smart distribution network. Additionally, the impact of network reconfiguration on improving economic objectives is examined within the framework of a one-day operational planning approach.

1.1. Literature Review

In [10], an intelligent EM system is proposed to optimize the performance of a microgrid (MG). This paper also considers the photovoltaic output under various weather conditions and the hourly electricity prices of the main grid. However, this approach does not account for load participation in demand response programs or the impact of network reconfiguration. In [11], the analysis of an EM System (EMS) based on renewable energy strategies for MGs is examined. This study emphasizes the importance of reducing operational costs and optimizing the utilization of renewable energy resources. The EMS is designed to minimize costs by enabling multiple real-time operational setpoints for energy generation units, thereby enhancing efficiency and reducing operational expenses. By employing optimization strategies, the system creates favorable conditions for effective energy resource utilization and flexibly responds to fluctuations in supply and demand. This paper demonstrates that EMS can serve as a critical tool for managing renewable energy resources, benefiting not only energy producers but also consumers. As this system contributes to lowering operational costs, it can potentially lead to a reduction in the final energy price. In [12], both economic and emission objectives are considered in the MG operation planning. The adaptive mesh direct search algorithm is employed to minimize the system cost function. However, this approach does not take into account the participation of RLs in the energy market. In [13], a high-reliability distribution system is utilized for the economic operation of an MG. The proposed method enhances operational reliability and reduces power outages in the MG. Additionally, this study incorporates ring networks in distribution systems to improve performance. In [14], a deterministic EM system is proposed for an MG. This approach integrates advanced photovoltaic (PV) generation, energy storage units, and gas microturbines. The planning process is conducted in two levels: central EM within the MG and local EM on the consumer side. However, this study does not consider the need for storage forecasting and demand response programs within the MG. Additionally, the impact of network reconfiguration in distribution networks has not been analyzed. In [15], a model for optimal MG planning is presented, incorporating multi-period islanding constraints. The objective of this model is to minimize the total operational costs of the MG, which include both the cost of local generation resources and the cost of energy obtained from the main grid. To separately analyze the islanded operation challenges and grid-connected operation issues, the corner relaxation decomposition method is utilized. Moreover, island reduction is primarily employed to coordinate these two challenges. In this study, mixed-integer linear programming (MILP) is applied to model the MG components, including loads, generation units, and energy storage systems. In [16], which examines the environmental and economic challenges of smart MGs, the quantum genetic algorithm (QGA) is utilized as an approach for cost optimization and emission reduction. By leveraging the principles of quantum computing, this algorithm offers enhanced capabilities compared to traditional genetic algorithms, providing improved efficiency in optimization processes. However, a major limitation of this study is the lack of consideration for the unpredictable nature of renewable energy generation in energy planning. This issue can have negative impacts on decision-making and economic outcomes, as energy generation from renewable sources such as solar and wind is typically subject to significant fluctuations.

2. The research problem modeling

In this paper, improving the voltage profile of the smart distribution network is considered as the first objective function, while reducing the power loss cost in the smart distribution network is defined as the second objective function. This study is formulated as a bi-objective optimization problem, aiming to optimize both objective functions simultaneously. Since both objective functions are defined from the perspective of the smart distribution network operator, the assigned weighting coefficients for each function are considered equal (ω_1=ω_2=0.5).

$$OF^{Total} = \{\omega_1 \times (OF1 = VPI) + \omega_2 \times (OF2 = PLI)\} \quad s.t\ \{\omega_1 + \omega_2 = 1 \quad \forall s \tag{1}$$

$$\left(\begin{array}{l} \overbrace{\overbrace{(\sum_{s=1}^{10} \rho_s \times \left(\sum_{i=1}^{33} \left| V_{i,s} - 1 \right| \right)) -}^{Without\ RL\&Rec...} \overbrace{(\sum_{s=1}^{10} \rho_s \times \left(\sum_{i=1}^{33} \left| V_{i,s} - 1 \right| \right))}^{With\ RL\&Rec..}}^{OF1=VPI} \\ s.t \quad \sum_{s=1}^{10} \rho_s = \%100 \end{array} \right) \tag{2}$$

$$\left(\begin{array}{l} \overbrace{\overbrace{(\sum_{s=1}^{10} \left(\rho_s \times P_{Loss}^{s} \times Cost_s \right)) -}^{Without\ RL\&Rec...} \overbrace{(\sum_{s=1}^{10} \left(\rho_s \times P_{Loss}^{s} \times Cost_s \right))}^{With\ RL\&Rec...}}^{OF2=PLI} \\ s.t \quad \sum_{s=1}^{10} \rho_s = \%100 \end{array} \right) \tag{3}$$

In equation (2), the first objective function is formulated to improve the voltage profile over the planning period, considering both the absence and presence of RLs and network reconfiguration. In equation (3), the second objective function, which aims to maximize the profit derived from loss reduction, is modeled for both cases: with and without RL and network reconfiguration over the same time period. In the above equations, ρ_s represents the probability of occurrence for each load level throughout a 24-hour period. Each objective function is simultaneously evaluated using the GA under equation (1), incorporating weighting coefficients to determine the optimal values of the objective functions.

As stated in the first and second objective functions, the number of load levels for a 24-hour scheduling period has been determined, along with the probability of occurrence for each load level. In these equations, $V_{i,s}$ represents the per-unit voltage profile of the smart distribution network at bus iii for load level s, where the objective is to maintain the voltage of all buses at all time intervals and load levels at 1pu.

Additionally, $P_{Loss}{}^{s}$ denotes the cost of power losses in the distribution network at load level s, and finally, $cost_s$ represents the electricity consumption tariff for each load level s. The power loss for each load level is calculated using the following equation.

$$P_{Loss} = \sum_{b=1}^{32} \left(R_b \times I_b^2 \right) \quad \forall s \tag{4}$$

In this modeling, R_b represents the resistance of line b, while I_b denotes the current magnitude in the smart distribution network lines. In this paper, the modeling is conducted on a 33-bus distribution network, where the number of lines in this radial distribution network is 32.

The optimal location and participation percentage of RLs considered in this study for each load level are determined to facilitate the optimal implementation of demand response programs, which will be executed by smart distribution network operators. These parameters are formulated in this modeling based on the following equations. As shown in these equations, the participation level of RLs in reactive power reduction at each load level is calculated considering the power factor of the respective bus.

$$\left[\left(P_s^{RL_i} \right)^2 + \left(Q_s^{RL_i} \right)^2 \right]^{1/2} \leq \%PER_s^{RL_i} \times S_s^{RL_i} \quad \forall S, RL \tag{5}$$

$$PF_s^{RL_i} = \frac{P_s^{RL_i}}{\left(P_s^{RL_i} + Q_s^{RL_i} \right)^{1/2}} = \text{cte} \quad \forall S, RL \tag{6}$$

$$Q_s^{RL_i} = \tan(\cos^{-1}(PF_s^{RL_i}) \times P_s^{RL_i} \quad \forall S, RL \tag{7}$$

where $PER_s{}^{RLi}$ represents the percentage of load reduction by each responsive load for each load level, optimally determined within the range of 0% to 50% of the consumed load at the respective bus.

In this paper, the direct load control method, which is one of the RL programs, is utilized. This approach plays a significant role in demand-side management and can be employed by the distribution network operator at each peak load level. However, to ensure the implementation of RLs and facilitate consumer participation in EM at each load level, it is necessary to establish bilateral agreements between the electricity distribution company and consumers participating in demand management. These agreements serve as an operational guarantee, defining the commitments of both parties and ensuring the effective execution of the process.

Next, the load flow model of the smart distribution network is presented. As is well known, the primary objective of load flow analysis is to determine the voltage at each bus within the network for each time period. Accurately calculating bus voltages plays a crucial role in both short-term and long-term studies of distribution networks, including identifying buses with significant voltage drops beyond standard limits, estimating energy losses, and calculating the costs associated with these losses. By utilizing the input data and information from the distribution network, the network operator can conduct a detailed technical analysis and develop an appropriate plan for EM and optimal network operation for the upcoming day. In the following section, the direct load flow (DLF) method, which is one of the widely used approaches for radial distribution network load flow analysis, is presented along with its corresponding mathematical formulations. In this load flow method, the relationship between branch current (B_s) at each load level and load current (I_s) at the same load level must first be determined using a matrix called the $BIBC_s$ matrix [17].

$$[B_s]=[BIBC_s][I_s] \qquad \forall s \tag{8}$$

where the $BIBC_s$ matrix is a binary matrix for each load level s that represents the relationship between the load current and branch current. This matrix is defined as an upper triangular matrix with values of 0 and 1. Furthermore, the relationship between the B_s and the electric potential difference of all buses in the network relative to the reference bus voltage (ΔV_s) is modeled using the $BCBVs$ matrix for each load level, which can be expressed as follows:

$$[\Delta V_s]=[BCBV_s][B_s] \qquad \forall s \tag{9}$$

For each load level during the scheduled planning period, the BIBCs and BCBVs matrices serve as the fundamental structures for developing smart distribution network guidelines. Since the BIBCs matrix represents the relationship between injected load currents and branch currents at each load level, and the BCBVs matrix defines the relationship between branch currents and bus voltages at each load level, the voltage variations of network buses, which result from branch current variations at the same load level, must be directly computed using the BCBVs matrix. Therefore, the relationship between injected currents and bus voltages for each load level is modeled using the following equation:

$$\begin{aligned}[\Delta V_s]&=[BCBV_s][BIBC_s][I_s]\\&=[DLF_s][I_s] \qquad \forall s\end{aligned} \tag{10}$$

where the DLFs matrix establishes the relationship between the voltage differences of distribution network buses and bus load currents, this matrix must be modeled for each load level. Additionally, the relationship between the bus load currents of the smart distribution network and the power consumption at each bus must be formulated using the equation below [18]. Accordingly, an equation is derived where the only unknown variable is the bus voltages of the smart distribution network for each load level, which is modeled as follows. It should be noted that since the power consumption at different buses varies across different load levels, the voltage drop at each bus will also be different for each load level. As a result, the load flow results for each load level will be unique, and these results will be presented in the results section through corresponding figures and tables.

$$\begin{aligned}I_{i,s}^{k}&=I_{i,s}^{r}(V_{i,s}^{k})+jI_{i,s}^{i}(V_{i,s}^{k})\\&=\left(\frac{P_{i,s}+jQ_{i,s}}{V_{i,s}^{k}}\right)^{*} \qquad \forall s\end{aligned} \tag{11}$$

$$\left[\Delta V_s^{k+1}\right]=[DLF_s]\left[I_s^{\,k}\right] \qquad \forall s \tag{12}$$

Based on the above equations and their integration, the only unknown variable in the equation is the voltage of each bus in the distribution network. This value is determined using the iterative method, where with increasing iterations, voltage variations at the buses become negligible. In this condition, the voltage of each bus converges to an optimal value and is accurately determined.

One of the most critical factors in EM modeling for distribution networks is considering the balance between the input power to the distribution network and the power consumed within the network [19-20]. Failure to account for this balance in modeling and mathematical equations can lead to technical issues, including distribution network instability and voltage collapse at multiple buses. In this study, network reconfiguration and consumer participation through RLs result in variations in power flow across the distribution network branches. The active power input to the distribution network consists of active power supplied from the upstream network and the amount of active power contributed by responsive loads. Accordingly, the power consumption within the smart distribution network includes the power consumed by loads connected to the network buses. Additionally, the reactive power balance must be considered, which includes reactive power supplied from the upstream network and the amount of reactive power contributed by responsive loads. It is essential to note that the balance of active and reactive power must hold for each load level throughout the scheduled planning period, considering the network load and the participation of responsive loads. The following equations model the active and reactive power balance in the presence of responsive loads.

$$P_s^{U-Grid} = P_s^{Demand} - \sum_{i=1}^{N_{RL}} P_s^{RL_i} \quad \forall s \tag{13}$$

$$Q_s^{U-Grid} = Q_s^{Demand} - \sum_{i=1}^{N_{RL}} Q_s^{RL_i} \quad \forall s \tag{14}$$

where $P_s^{U\text{-}Grid}$ and $Q_s^{U\text{-}Grid}$ represent the active and reactive power input to the smart distribution network from the upstream network at each load level. Additionally, P_s^{Demand} and Q_s^{Demand} denote the active and reactive power consumption of loads connected to the distribution network buses for each load level.

As you know, high voltage drops in the distribution network impose various technical challenges on network performance. Therefore, improving the voltage profile has been considered as the first objective function in this study. Next, the voltage constraints for each bus at each load level are presented. It should be noted that in the IEEE proposed structure for the 33-bus radial distribution network, the reference bus has no load, and its voltage is set to $1pu$ in the modeling process.

$$V_{min} \le \left|V_{i,s}\right| \le V_{max} \quad \forall i,s \tag{15}$$

$$\left|V_{1,s}\right| = 1\ p.u \qquad \forall s \tag{16}$$

where V_{min} and V_{max} represent the minimum and maximum standard voltage for each bus, respectively, within the range of 0.95pu to 1.05pu.

The existing infrastructure of each distribution network imposes limitations on energy penetration into these networks. The total injected power (including active and reactive power) from the upstream network to the smart distribution network is subject to input capacity constraints for each load level, as represented in the following equation:

$$\sqrt{\left(P_s^{U-Grid}\right)^2 + \left(Q_s^{U-Grid}\right)^2} \le S_{max}^{U-Grid} \quad \forall s \tag{17}$$

3. Simulation results

3.1. Assumptions of the Problem Under Study

Based on the presented concepts, the significance of RLs in EM for SDNs was emphasized. Furthermore, the role of network reconfiguration in enhancing both short-term and long-term objectives of distribution networks was thoroughly examined. The primary goal of this paper is to investigate the impact of RLs and network reconfiguration on improving both technical and economic objective functions for a 33-bus smart distribution network using a GA.

Another objective of this article is to present an optimized mathematical model for the placement and optimal sizing of RLs at each load level throughout a 24-hour period. In this study, a daily load model with ten load levels (ranging from 10% to 100%) and varying probabilities is proposed. The fig. 1 illustrates the load levels, the probability of occurrence for each level, and the corresponding electricity tariff. As observed, each load level has a specific probability of occurrence and a corresponding electricity tariff. According to this figure, electricity prices are higher during peak load periods compared to low-load periods.

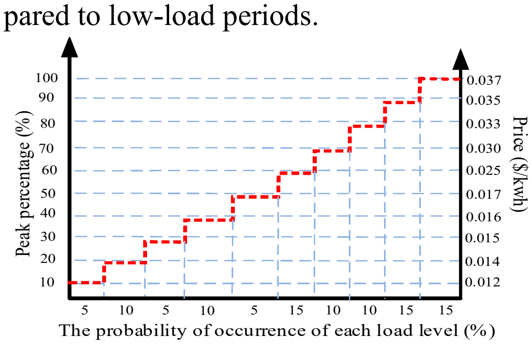

Fig. 1. Load Levels and Electricity Tariff Prices

To observe the simulation results, a standard IEEE 33-bus radial distribution network, as shown in the fig. 2, has been used. This distribution network has a radial structure, and the reconfiguration process must be carried out in a way that preserves this structure. In this network, Bus 1 has been selected as the reference bus, and no load is consumed at this bus. Additionally, according to the IEEE standard, the voltage level of this distribution network is considered 12.66 kV, which in per unit terms is less than 1. As shown in the figure, in the initial state, lines 33, 34, 35, 36, and 37 are open and not included in the circuit.

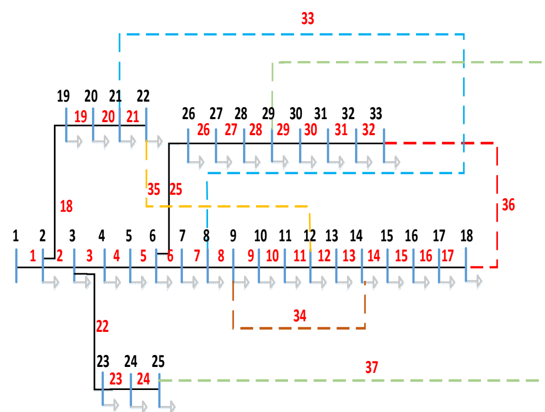

Fig. 2. 33-Bus Radial Distribution Network

In the initial state, without reconfiguration, lines 33 to 37 are not included in the circuit to maintain the radial structure of the distribution network. If reconfiguration is performed and the network requires structural changes, some lines will be disconnected, while others will be added to the circuit. In every scenario, the reconfiguration must be optimized to ensure that the radial structure of the network is preserved.

The objective of this article is to optimize the placement and determine the optimal participation percentage of responsive loads, as well as to optimize the reconfiguration of the smart distribution network. To achieve this, in the genetic algorithm, the genes in each chromosome correspond to the number of problem variables, including the locations of responsive loads, the participation percentage of responsive loads, and the number of opened and closed lines for each load level.

In this study, eight buses have been identified as those capable of participating in demand-side management as responsive loads. These buses have signed agreements with the electricity distribution company, and in case of network demand, with prior notice and the availability of bidirectional communication infrastructure between the distribution network and consumers, they can reduce their consumption by up to 50% for each load level.

Accordingly, fig. 3 illustrates a sample proposed chromosome designed to achieve the objective functions. As shown in this figure, in each iteration of the genetic algorithm, during the generation of each population, chromosomes consist of three main components:

- Locations of responsive loads.
- Participation percentage of responsive loads.
- Numbers of opened lines in the reconfiguration process.

This figure represents an example of a chromosome structure for each load level. According to fig. 3, each chromosome is formed, and the processes of crossover, mutation, recombination, and other necessary operations within the genetic algorithm are performed. Ultimately, after several iterations, the results converge to optimal values, and the unknown variables of the problem are determined by the algorithm within an optimized chromosome that aligns with the defined objectives.

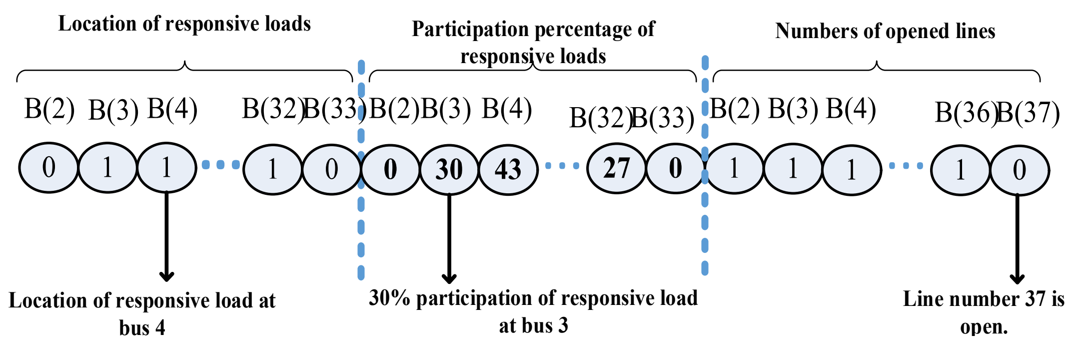

Fig. 3. Proposed Chromosome Structure

3.2. Results

To analyze the results of this study, four different scenarios have been considered:

- Scenario 1 (baseline condition): In this scenario, the distribution network operates in its initial state, without any smart infrastructure. Under these conditions, RLs cannot participate in EM , and network reconfiguration is not possible.
- 2- Scenario 2 (smart grid and responsive load participation): In this case, with the smartening of the distribution network and the establishment of bidirectional communication infrastructure between consumers

and the distribution network operator, eight buses are identified as responsive loads, capable of reducing up to 50% of their consumption to support EM in the distribution network.

- Scenario 3 (impact of reconfiguration in a smart distribution network): This scenario examines the effect of network reconfiguration alone, without considering the participation of responsive loads. The information from each bus is transmitted to the distribution network operator through existing information technology infrastructure, allowing the operator to reconfigure the distribution network according to the defined objectives.
- Scenario 4 (combined reconfiguration and responsive load participation): In this scenario, both responsive load participation and network reconfiguration are considered simultaneously within the smart distribution network. This allows for a comparative analysis of all scenarios, assessing the impact of each factor in optimizing the study's objectives.

In the following sections, the results of each scenario are presented and analyzed using related figures.

3.2.1. Scenario 1

The simulation results of the studied network for a daily scheduling in the baseline condition, without responsive load participation and without network reconfiguration, are presented in table 1. According to the results in this table: The daily power loss cost of the network is approximately 76$. The voltage profile deviation of the buses from the per-unit value of 1 is around 10. The daily power loss in the distribution network is calculated to be approximately 785 kW. The minimum voltage level of the network drops to 0.9038pu, which is outside the standard acceptable range for distribution networks.

The objectives of this study are to improve the voltage profile and reduce the cost of power losses in the distribution network. Since scenario 1 is considered the baseline condition for the studied distribution network, the values of the first and second objective functions are not included in this scenario. Instead, this table presents only the power loss, power loss cost, and voltage profile deviation.

In table 2, the line numbers of the open distribution network in the base case, i.e., scenario 1, are presented. These open lines indicate the radial nature of the distribution network and demonstrate the radial operation of the distribution network. In subsequent scenarios, the impact of RLs and reconfiguration on the network structure, as well as changes in the open lines of the distribution network, will be examined and compared with the base case.

Table 1. Scenario 1 study results

Objective function	Value
$OF1 = VPI$	-
$\overbrace{(\sum_{s=1}^{10}\rho_s \times \left(\sum_{i=1}^{33}\lvert V_{i,s}-1\rvert\right))}^{Without\ RL\&Rec...}$	9.68
$OF2 = PLI$	-
$\overbrace{(\sum_{s=1}^{10}\left(\rho_s \times P_{Loss}^{s} \times Cost_s\right))}^{Without\ RL\&Rec...}$	75.91$
OF^{Total}	-
Ploss	785.59 kW
Minimum network voltage	0.9038

Table 2. The number of open lines in scenario 1

Load level	Number of opened lines
All load levels	33-34-35-36-37

In Fig. 4, the voltage profile for each load level of the studied distribution network is shown. According to this figure, at higher load levels, the voltage drop in the network is high and exceeds the standard limit (5%). Additionally, at the terminal buses, the voltage drop is more significant. Based on this figure, the greatest voltage drop occurs at load level 10, which is the highest load level. At bus number 18, which is the farthest from the reference bus, the bus voltage is approximately 0.9038 pu.

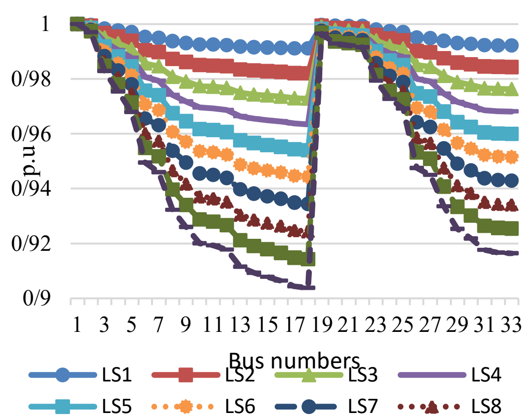

Fig. 4. The voltage profile of the distribution network in scenario 1

The distribution network losses for each load level are shown in fig. 5. This figure demonstrates that as the power consumption in the distribution network increases, the losses also increase proportionally. Therefore, implementing loss reduction strategies during peak consumption hours is more important than reducing losses during other hours of the day.

In fig. 6, the load consumption curve of the distribution network for each load level is shown. According to this figure, the distribution network is considered at 10 load levels for a 24-hour period with different probabilities, and the active and reactive power consumption of the network for the entire day is displayed. It should be noted that the values shown in this figure represent the total power consumption of all buses in the distribution network.

In fig. 7, the minimum voltage of the network for each load level is presented. This figure shows the extent of voltage drop in the network at each load level, and its results will be compared with those of other scenarios. According to this figure, as power consumption in a distribution network increases, the voltage drop also increases and can exceed the standard voltage drop. Based on this figure, for load levels above 60%, the voltage drop exceeds the standard limit.

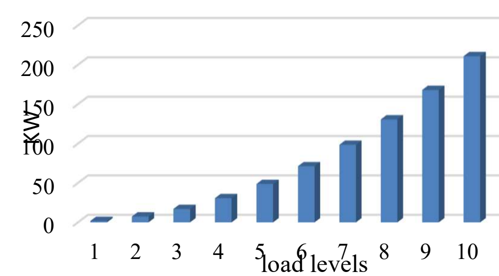

Fig. 5. distribution network losses in scenario 1

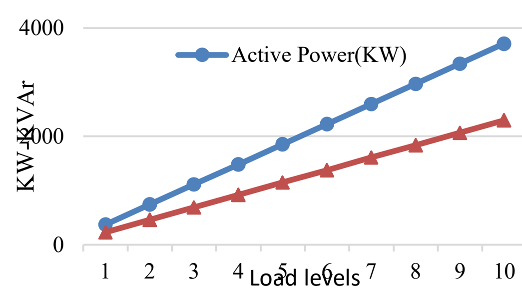

Fig. 6. The load consumption curve of the distribution network in scenario 1

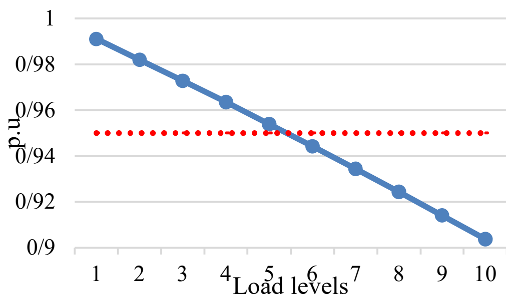

Fig.7. The minimum voltage of the distribution network at each load level for scenario 1

3.2.2. Scenario 2

The results of the studied network for daily planning with the presence of RLs and without reconfiguration are shown in table 3. According to the results in this table, the daily loss cost of the studied network is approximately 25$, representing an improvement of 34%. Additionally, the deviation of the bus voltage profile from the pre-unit value has improved by 13.84%, with a reduction of 1.34 units.

The daily losses for the distribution network are approximately 550kW, showing an improvement of about 30%. This table indicates that the voltage drop in the distribution network reaches close to 0.92pu, which is a 2.31% improvement compared to Scenario 1. However, it is still outside the standard limit and unacceptable for distribution networks. The results obtained for this scenario, in comparison with scenario 1, show a significant improvement due to the presence of RLs in distribution networks. The results related to RLs are explained in the next table.

Table 4 shows the optimal location and percentage of responsive load participation for the high load levels of the distribution network. In this study, responsive loads, based on their optimal location, can participate in EM with an optimal participation percentage (0%-50%) for load levels above 60%. Therefore, the optimal participation percentage and the optimal location of RLs for scenario 2 are shown in the table 4.

In table 5, the number of open lines in the distribution network for scenario 2 is shown. These open lines indicate the radial structure of the distribution network and demonstrate the radial operation of the network. The results of this scenario are similar to those of scenario 1, as no reconfiguration is considered in either scenario 1 or scenario 2.

Table 3. Results of scenario 2 study

Objective function	Value	Percentage of improvement
$OF_1=VPI$	1.34	13.84%
$OF2=PLI$	25.81$	34%
Ploss	550.45kW	29.93%
Minimum network voltage	0.9247	2.31%

In fig. 8, the voltage profile for each load level of the distribution network in scenario 2 is presented. According to this figure, at higher load levels, the voltage drop in the network is significant and exceeds the standard limit (5%). Additionally, the voltage drop is more pronounced at the terminal buses. The highest voltage drop occurs at the tenth load level, i.e., the highest load condition, at bus number 18, which is the farthest from the reference bus, where the voltage is approximately 0.92 pu. The presence of RLs has led to a noticeable improvement in the voltage profile compared to scenario 1. However, the voltage drop still exceeds the allowed limit.

Table 4. The number of open lines in scenario 1

Responsive load	Optimal location	Percentage of participation in peak load (%)				
		60	70	80	90	100
RL 1	24	32	33	37	36	50
RL 2	25	42	35	48	47	50
RL 3	14	41	42	41	47	50
RL 4	7	40	34	40	42	50
RL 5	8	47	45	44	43	50
RL 6	18	34	40	39	48	50
RL 7	32	40	31	38	48	50
RL 8	31	40	35	34	48	50

Table 5. The number of open lines in scenario 2

Load level	Number of opened lines
All load levels	33-34-35-36-37

The network losses for each load level are shown in fig. 9 for scenarios 1 and 2. This figure illustrates that as the power consumption in the distribution network increases, the losses also rise proportionally. Furthermore, the presence of RLs has had a positive impact on reducing losses at higher load levels (above 60%).

In fig. 10, the load curve of the distribution network for each load level in scenario 2 is presented. According to this figure, the distribution network is considered at 10 load levels over a 24-hour period with different probabilities, showing the active and reactive power consumption of the network for the entire day. The results from this figure indicate that the presence of RLs has improved the distribution network's consumption during peak hours.

In fig 11, the minimum voltage of the network for each load level in scenarios 1 and 2 is presented. This figure shows the extent of the voltage drop in the network at each load level. According to the figure, as power consumption in the distribution network increases, the voltage drop also increases, and in some cases, it may exceed the standard value. The presence of RLs has resulted in a relative improvement in the voltage drop, such that at 60% of peak load, the maximum voltage drop falls within the standard range. However, at other higher load levels, the voltage drop still remains outside the standard range. Fig. 12 also shows the optimal locations of the responsive loads, calculated using a genetic algorithm, within the distribution network.

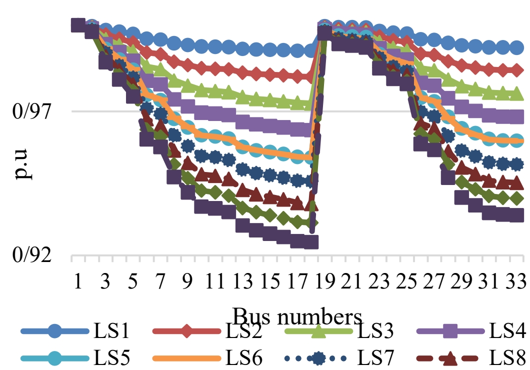

Fig. 8. Voltage profile of the distribution network in scenario 2

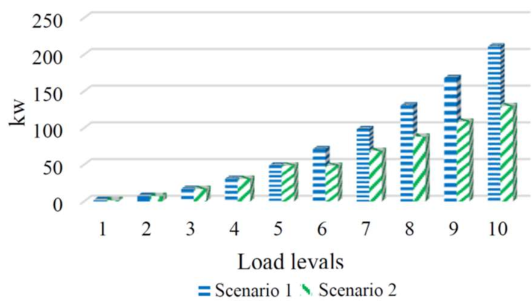

Fig. 9. Distribution network losses in scenario 2

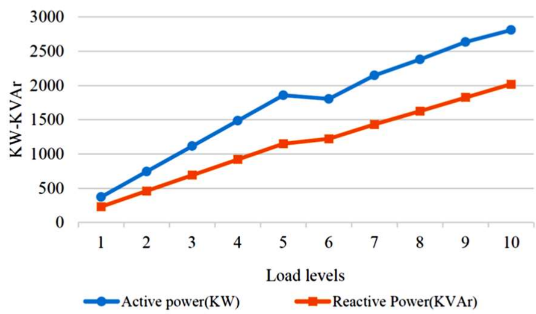

Fig. 10. Load consumption curve of the distribution network in scenario 2

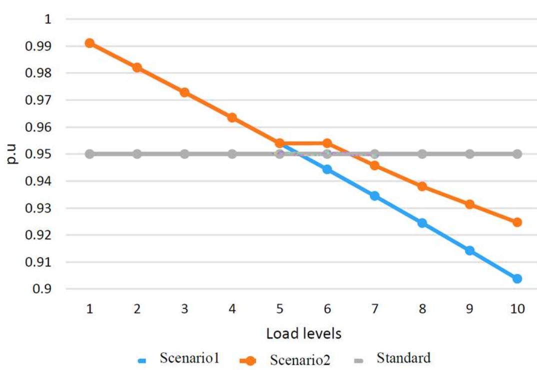

Fig. 11. Minimum voltage of the distribution network in Scenario 2

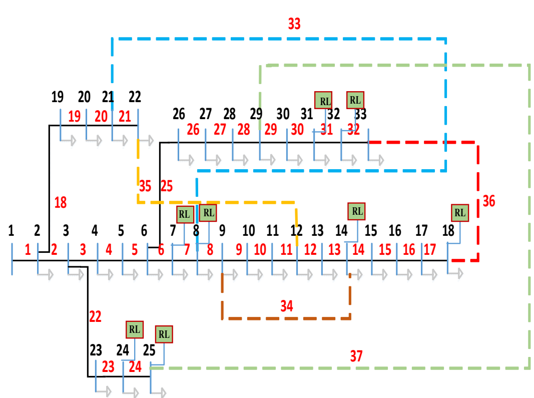

Fig. 12. Optimal locations of RLs in Scenario 2

3.2.3. Scenario 3

The results of the studied network for a daily scheduling scenario, without the presence of RLs and with the reconfiguration of the distribution network, are presented in table 6. According to these results, the daily network loss cost is approximately 43$, indicating a 57% improvement. Additionally, the voltage profile deviation of the network buses from the per-unit value has decreased by 6.26 units, reflecting a 64.66% improvement. The total daily losses of the distribution network are estimated to be around 338 kW, demonstrating a 57% reduction. Based on table 6, the voltage drop in the distribution network reaches approximately 0.95 pu, which represents a 5.17% improvement compared to Scenario 1. This indicates that in this scenario, the minimum network voltage remains within the standard range. The obtained results show that, compared to scenarios 1 and 2, this scenario provides better improvements in distribution network performance through reconfiguration.

Table 7 presents the numbers of open lines in the distribution network for scenario 3. These open lines indicate the radial nature of the distribution network and demonstrate its radial operation. It is important to note that, since the load percentage is the same for all buses in the network, the results obtained from reconfiguration should remain consistent across different load levels. Table 7 confirms this finding.

In fig. 13, the voltage profile for each load level of the studied distribution network in scenario 3 is presented. According to this figure, at higher load levels, the voltage drop in the network is significant. However, with the implementation of network reconfiguration, the voltage at all load levels and for all buses remains within the standard range. The highest voltage drop occurs at the tenth load level, corresponding to peak load conditions, at bus number 31, with a voltage of approximately 0.95pu. The application of reconfiguration and modifications in the network structure has led to a significant improvement in the voltage profile compared to scenarios 1 and 2.

In fig. 14, the distribution network losses for each load level in scenarios 1, 2, and 3 are presented. This figure shows that as power consumption in the distribution network increases, the losses also increase proportionally. Additionally, the presence of RLs has had a positive impact on reducing losses at higher load levels (above 60%). However, in scenario 3, considering network reconfiguration, the reduction in distribution network losses has been more effective compared to scenario 2.

Table 6. Results of scenario 3 study

Objective function	Value	Percentage of improvement
OF₁=VPI	6.26	64.66%
OF2=PLI	4.3.35$	57.1%
Ploss	338.82kW	56.87%
Minimum network voltage	0.9506	5.17%

Table 7. The number of open lines in Scenario 3

Load level	Number of opened lines
All load levels	9-7-14-31-37

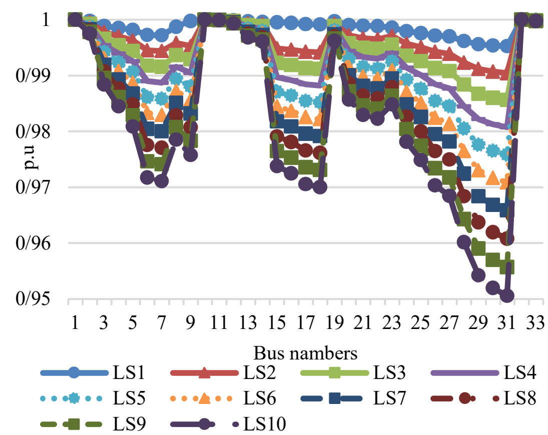

Fig. 13. Voltage profile of the distribution network in scenario 3

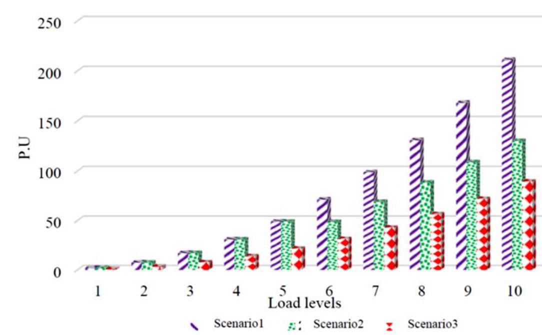

Fig. 14. Distribution network losses in scenario 3

In fig. 15, the minimum voltage of the distribution network for each load level in scenarios 1, 2, and 3 is presented. This figure illustrates the extent of voltage drop in the network at each load level. According to the figure, as power consumption in the distribution network increases, the voltage drop also rises and may exceed the standard limit. The presence of RLs has had a positive effect on reducing voltage drop. However, in scenario 3, with the implementation of network reconfiguration, the minimum network voltage has significantly improved and remains within the standard range.

In fig. 16, the minimum voltage of the network for each load level in scenarios 1, 2, and 3 is presented. This figure illustrates the extent of voltage drop in the network at each load level. According to the figure, as power consumption in the distribution network increases, the voltage drop also rises and may exceed the standard limit. The presence of RLs in scenario 2 has led to a partial improvement in voltage drop, such that at 60% of peak load, the maximum voltage drop falls within the standard range. However, at other high load levels, the voltage drop still remains outside the standard range.

The results of this figure indicate that in scenario 3, with the implementation of network reconfiguration, the voltage at all load levels remains within the standard range. Additionally, compared to scenario 2, a more significant improvement has been achieved.

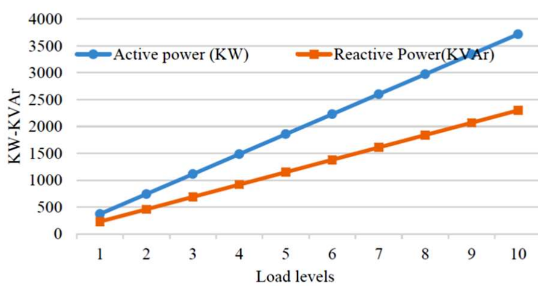

Fig. 15. Load consumption curve of the distribution network in scenario 3

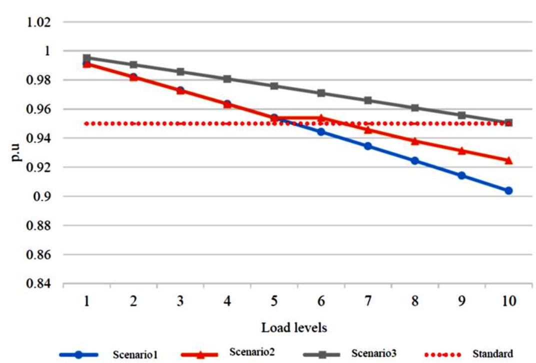

Fig. 16. Minimum voltage of the distribution network in scenario 3

3.2.4. Scenario 4

The results of the studied network for a daily scheduling scenario, considering the presence of RLs and network reconfiguration, are presented in table 8. According to these results, the daily network loss cost is approximately 54$, indicating a 71% improvement. Additionally, the voltage profile deviation of the network buses from the per-unit value has decreased by 6.80 units, reflecting a 70.24% improvement. The total daily losses of the distribution network are estimated to be around 240 kW, demonstrating a 69% reduction. According to the results in this table, the voltage drop in the distribution network has been reduced to approximately 0.96 pu, which represents a 5.8% improvement compared to scenario 1. This indicates that, in this scenario, the minimum network voltage remains within the standard range. The obtained results show that this scenario demonstrates better performance compared to scenarios 1, 2, and 3, as a result of network reconfiguration and the presence of RLs in the distribution network. Table 9 presents the numbers of open lines in the distribution network for scenario 4. These open lines indicate the radial nature of the distribution network and illustrate its radial operation.

Table 8. Results of scenario 3 study.

Objective function	Value	Percentage of improvement
$OF_1=VPI$	6.80	70.24%
$OF2=PLI$	54.09$	71.25%
Ploss	240.63kW	69.36%
Minimum network voltage	0.9563	5.80%

Table 9. The number of open lines in scenario 4.

Load level	Number of opened lines
10%	9-7-14-31-37
20%	9-7-14-31-37
30%	9-7-14-31-37
40%	9-7-14-31-37
50%	9-7-14-31-37
60%	9-7-14-31-28
70%	9-7-14-31-28
80%	9-7-14-31-28
90%	9-7-14-31-28
100%	9-7-14-30-28

In fig. 17, the voltage profile for each load level of the distribution network in Scenario 4 is presented. This figure shows that at higher load levels, the voltage drop in the network is significant. However, with the implementation of network reconfiguration and the presence of responsive loads, the voltage at all load levels and for all buses remains within the standard range. According to this figure, the highest voltage drop occurs at the tenth load level, corresponding to peak load conditions, at bus number 27, with a voltage of approximately 0.96 pu. The application of network reconfiguration and the presence of RLs have led to a significant improvement in the voltage profile compared to Scenarios 1, 2, and 3.

In fig. 18, the distribution network losses for each load level in scenarios 1, 2, 3, and 4 are presented. This figure shows that as power consumption in the distribution network increases, the losses also rise proportionally. Additionally, the presence of RLs has had a positive impact on reducing losses at higher load levels (above 60%). In scenario 3, considering network reconfiguration, the reduction in distribution network losses has shown better performance compared to Scenario 2. Furthermore, comparing scenario 4 with the other scenarios indicates that in this scenario, the improvement in network loss reduction is significantly better across all load levels.

In fig. 19, the load consumption curve of the distribution network for each load level in scenario 4 is presented. According to this figure, the distribution network has been modeled at 10 load levels over a 24-hour period, considering different probabilities, and the active and reactive power consumption of the network throughout the day has been shown. The results of this figure indicate that the implementation of network reconfiguration and participation of RLs has improved the distribution network's consumption during peak hours, leading to a more significant reduction in overall network consumption.

In fig. 20, the minimum voltage of the network for each load level in scenarios 1, 2, 3, and 4 is presented. This figure illustrates how the voltage drop in the network varies at each load level. According to this figure, as power consumption in the distribution network increases, the voltage drop also rises and, in some cases, may exceed the standard limit.

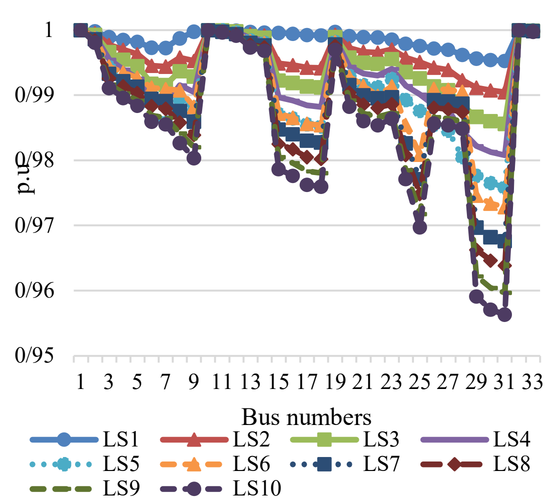

Fig. 17. Voltage profile of the distribution network in scenario 4

The results indicate that with network reconfiguration and participation of responsive loads, the voltage at all load levels remains within the standard range. Additionally, compared to scenarios 2 and 3, a significant improvement in network performance has been achieved.

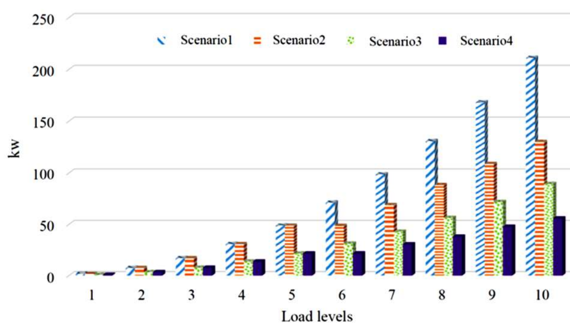

Fig. 18. Distribution network losses in scenario 4

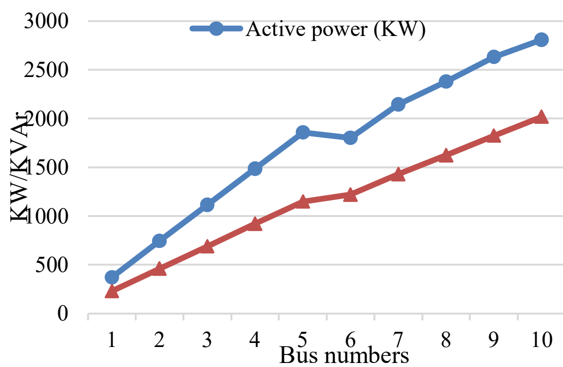

Fig. 19. Load consumption curve of the distribution network in scenario 4

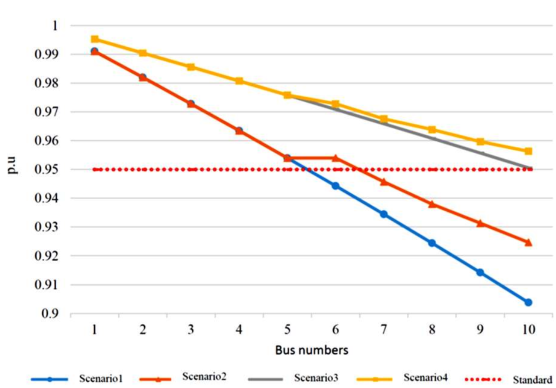

Fig. 20. Minimum voltage of the distribution network in scenario 4

4. Conclusion

This paper examines the results of modeling in four different scenarios, aiming to analyze the impact of RLs and network reconfiguration in smart distribution networks. Initially, the problem assumptions are presented, followed by a comparison of the simulation results under different conditions with the base case, which excludes RLs and network reconfiguration. The findings indicate that the integration of RLs along with network reconfiguration can significantly reduce daily loss costs and improve the voltage profile. Additionally, the paper highlights the use of optimization algorithms, such as the genetic algorithm, for EM in smart distribution networks. These algorithms have successfully identified the optimal combination of loads and network conditions, leading to improved network performance. The results further demonstrate that optimal placement of RLs has a significant impact on reducing network losses. Overall, this study emphasizes the importance of RLs and network reconfiguration in enhancing the performance of power distribution systems and can serve as a guide for the optimal design and management of SDNs in the future.

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