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Impact Analysis of Demand Response on the Optimal Placement of Solar PV Systems in the Distribution Network

Vivek Saxena[1,2*]
https://orcid.org/0000-0002-5769-1864

Narendra Kumar[1]
https://orcid.org/0000-0002-6841-6550

Uma Nangia[1]
https://orcid.org/0000-0001-6922-2582

[1]Delhi Technological University, New Delhi, India; [2]A.B.E.S. Engineering College, Ghaziabad, India.

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*Correspondence: vvksaxena1234@gmail.com; Tel.: +91-9999510653 (V.S.).

HIGHLIGHTS

- Bilevel approach to enhance penetration of green energy in the power system.
- Demand response coordination with the optimally-integrated distributed generations.

Abstract: In recent years, there has been a growing interest in integrating distributed generation (DG) technologies into the distribution network (DN) to improve system efficiency, reduce carbon emissions, and increase the power system's reliability. However, the optimal placement of DG systems within the DN is a difficult task, since it is dependent on several variables, including load demand, renewable energy sources, and energy storage systems (ESS). In this context, demand response (DR) programs can play a vital role in enhancing the efficiency of DG systems, since they allow consumers to lower their energy usage during peak hours and move their demand to off-peak hours. DR and solar photovoltaic (SPV) systems are two prominent technologies that can play a substantial role in the power DN. In this paper, a bi-level particle swarm optimization (PSO) method is employed to determine the best allocation of DG in the coordination of DR. In the suggested methodology, the first level of optimization determines the optimal size and location of DG, and the second level of optimization determines the optimal power dispatch in the coordination of DR. The proposed method is implemented on the IEEE 33 bus system, and the results demonstrate that the power quality parameters have significantly improved.

Keywords: Bilevel Optimization; Demand Response; Distributed Generation; Particle Swarm Optimization; Solar PV.

INTRODUCTION

Two essential components of a smart grid system are demand response (DR) and distributed generation (DG). The types of DG may be renewable or nonrenewable energy sources. The optimal placement of SPV in the DN is contingent on a number of parameters, including the location of the loads, the available solar resources, and the DN's capacity. The investigation of the effect of DR on the optimal location of SPV systems in the DN is an important topic that has gained considerable attention in recent years.

DR refers to the capacity of consumers to modify their electricity use in response to price fluctuations or other signals. Integration of DR into the DN can aid in the reduction of peak demand, improvement of the grid's dependability, and reduction of the need for expensive infrastructure investments [1]. Many methods exist for analyzing the influence of DR on the optimal placement of SPV plants in the DN.

- Capacity planning: DR can help to reduce the peak demand on the DN, which can in turn reduce the need for additional generation capacity. This can impact the optimal placement of SPV systems in the network, as the capacity requirements may be lower.
- Load profile: DR can also impact the load profile of the network, which can impact the optimal placement of SPV systems. For example, if DR results in a shift in the peak load to a different time of day, the optimal placement of SPV systems may be different.
- Voltage stability: The integration of SPV systems in the DN can impact the voltage stability of the network. DR can help to manage voltage fluctuations by adjusting the consumption in response to changes in voltage. This can impact the optimal placement of SPV systems, as the locations that can provide the most benefit in terms of voltage stability may change [2].
- DN configuration: The optimal placement of SPV systems in the DN also depends on the network configuration. DR can impact the network configuration by reducing the need for additional infrastructure upgrades or by changing the location of the loads. This can impact the optimal placement of SPV systems.

The relationship between energy generation from an SPV system and other parameters is influenced by factors such as solar irradiation, panel efficiency, system orientation, shading, and temperature. These parameters also affect power quality [3,4].

In ref. [5], the authors proposed an integrated technique for incorporating renewable distributed generation (RDG) and DR into the planning of low-carbon sustainable distribution systems. In comparison to standard planning paradigms, the results illustrate the efficacy of the suggested methodology in enhancing the efficiency of RDG operations and reducing the CO_2 footprint of DN. The methodology provides a balance between economic and environmental benefits, and it has been demonstrated that the integration of RDG and DR choices in distribution system planning is beneficial in reducing carbon emissions and minimizing costs. This study utilizes an interior-point-method-embedded discrete genetic algorithm to effectively and accurately solve the model.

In ref. [6], the authors demonstrated that how temperature-controlled loads (TCL) demand flexibility can be used as part of a DR management architecture to improve the reliability and affordability of the power system. Using temperature measurements and consumer preferences, the study measures how flexible TCL demand is and predicts that solar power generation will make DR more reliable. The proposed distributed DR management architecture simplifies optimization and enhances optimality, resulting in reduced power consumption during peak reduction and emergency DR requests and low variability during capacity firming requests. Different DR requests are measured using two indices: DR reliability and consumer comfort. The proposed technique is implemented on Energy Plus-Matlab co-simulation.

In ref. [7], the authors proposed a structure for a solar photovoltaic-based microgrid (PV-MG) and looks into how DR affects the problem of optimizing its dispatch. The objective is to minimize the total cost of running PV-MG and moving energy around in ESS while taking into account different constraints on equality and inequality. The case study shows that the proposed optimization model works well to optimize the dispatch of the PV-MG and that the non-dominated sorting genetic algorithm-II works well to get Pareto solution sets. At the end of the paper, the typical dispatch schemes are looked at to see if the established optimization model is reasonable and works.

The authors of ref. [8] proposed a two-stage robust microgrid coordination strategy to address the difficulties of managing uncertain renewable DG resources and load demands in microgrids. Price-based demand response (PBDR) is scheduled daily, and dispatchable DG such as microturbines is changed hourly to maintain power balance and obtain economic benefits. Coordination of the PBDR and multiple DG units is proposed using a two-stage robust optimization model with guaranteed robustness against uncertainty. The simulation results demonstrate that the proposed strategy can deal with the unpredictability of renewable energy and demand while optimizing microgrids. The optimization is demonstrated with the use of column- and constraint generation algorithm

In ref. [9], the authors proposed and concluded the potential of DR and photo voltaic distributed generation (PVDG) can be measured, which helps plan sustainable DN with the help of end users. Changes to the rules, like the optional time of use tariff in Brazil, are needed to boost both DR and PVDG at the same time. The rational use of electricity, which is based on economic efficiency, is the basis of the method. This method gives a complete framework for the benefits and challenges of incorporating DR and/or PVDG into planning for power utilities. By doing a thorough analysis of the power grid and figuring out how cost-effective DR and/or PVDG are, power companies can figure out the best and most cost-effective ways to meet their customers' energy needs. The open distribution system simulator is used to conduct the simulations.

In ref. [10], the authors presented the method for sizing PV and ESS while taking DR into account gives a complete way to optimize the operation of PV and ESS systems while meeting the electricity needs of consumers. By taking into account the cost for PV and ESS systems, variation of daily load, and power utilities can make informed decisions about the optimal size of PV and ESS systems that will minimize the total cost of the system while meeting consumers' electricity needs. The MILP model was implemented in GAMS v.24.1.3 and solved using CPLEX v.12 as the solver.

In ref. [11], transmission expansion planning (TEP) has traditionally been done based on peak demand, but this may not be the best or most efficient way to do it. DR and DG are being considered as ways to deal with this. These things can have a big effect on how controllable and cost-effective power systems are, both in the short and long term. The proposed framework was realized by differential evaluation program.

In ref. [12], the authors used a direct approach of load flow to optimize the size and location of SPV-based DGs in the primary distribution system. The objectives include reducing power loss, improving voltage profile, and gaining economic benefits. DGs are placed at a single location to enhance system performance, and the estimated optimal size of a DG becomes a constraint for locating the SPV-based DGs.

In ref. [13], the authors suggested the optimal operating method for renewable energy-supported isolated microgrids. It employs carbon capture-based technologies to reduce CO2 impact and incorporates an emission-averse model. A fee is imposed due to CO2 emissions from diesel engines. The study compares a carbon capture unit with a fossil fuel-based unit, considering renewable energy penetration and carbon emission factors. Results show the microgrid's highest profitability at 40% RE penetration, with increased emission factors negatively affecting economics at that level.

FORMULATION OF PROBLEM

In this paper, the following objectives have been considered for the realization of the proposed framework:

Minimizing transmission losses in a distribution network is a crucial aspect of efficient power system operation. Transmission losses occur due to resistance in the wires, which leads to a voltage drop and energy loss as electricity is transmitted from the source to the end-users. Hence, minimizing power loss is one of the objective functions, defined as follows. [14]:

$$£_1 = \sum_{t=1}^{24} P_{\mathrm{L}\,(\mathrm{t})} \tag{1}$$

$$P_{\mathrm{L}\,(\mathrm{t})} = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{ij\,(\mathrm{t})}\left(P_{i\,(\mathrm{t})}P_{J\,(\mathrm{t})} + Q_{i\,(\mathrm{t})}Q_{J\,(\mathrm{t})}\right) + \beta_{ij\,(t)}\left(Q_{i\,(\mathrm{t})}P_{j\,(\mathrm{t})} - P_{i\,(\mathrm{t})}Q_{j\,(\mathrm{t})}\right)\forall t \tag{2}$$

where $\alpha_{ij\,(\mathrm{t})} = r_{ij}\cos\left(\delta_{i\,(\mathrm{t})} - \delta_{j\,(\mathrm{t})}\right)/V_{i\,(\mathrm{t})}V_{j\,(\mathrm{t})}$ and $\beta_{ij\,(\mathrm{t})} = r_{ij}\sin\left(\delta_{i\,(\mathrm{t})} - \delta_{j\,(\mathrm{t})}\right)/V_{i\,(\mathrm{t})}V_{J\,(\mathrm{t})}$

$P_{\mathrm{L}\,(\mathrm{t})}$	Power transmission losses
$P_{i\,(\mathrm{t})}$	Real power at i^{th} node at any time t
$P_{J\,(\mathrm{t})}$	Real power at j^{th} node at any time t
$Q_{i\,(\mathrm{t})}$	Reactive power at i^{th} node at any time t
$Q_{J\,(\mathrm{t})}$	Reactive power at j^{th} node at any time t
$V_{i\,(\mathrm{t})}$	Voltage at i^{th} node at any time t
$V_{J\,(\mathrm{t})}$	Voltage at j^{th} node at any time t
r_{ij}	resistance of branch between i^{th} and j^{th} node
$\delta_{i\,(\mathrm{t})}$	Angle of voltage at i^{th} node
$\delta_{j\,(\mathrm{t})}$	Angle of voltage at j^{th} node

Reverse power flow occurs when DG units generate more power than the local load demands, causing excess power to flow back into the grid. This can cause stability and safety issues in the DN, as well as increase the risk of voltage fluctuations and equipment damage. Hence, DG integration considers reversing power flow.

$$£_2 = \sum_{t=1}^{24} P_{R\,(t)} \tag{3}$$

$$P_{R\,(t)} = \begin{cases} 0, & \text{if } I_{\mathrm{G}\,(t)} \geq I_{\mathrm{S}} \\ \mathrm{Re}\left(V_{\mathrm{G}\,(t)}\, I^{*}_{\mathrm{G}\,(t)}\right) & \text{if } I_{\mathrm{G}\,(t)} < I_{\mathrm{S.}}\,. \end{cases} \tag{4}$$

$P_{R\,(t)}$	Reverse power at time t
$I_{\mathrm{G}\,(t)}$	Current from grid at time t
$V_{\mathrm{G}\,(t)}$	Voltage of grid at time t
$I_{\mathrm{S.}}$	Designated limit of reverse current

Node voltage deviation refers to the difference between the actual voltage level and the desired or nominal voltage level at a particular node in an electrical power system. Voltage deviation can be caused by various factors, including load variations, reactive power flow, and voltage drop in the transmission and distribution lines. Voltage deviations can cause several issues in the power system, including reduced system efficiency, increased losses, and damage to equipment. Large voltage deviations can lead to equipment failures, voltage collapse, and blackouts. The objective of violation of voltage limits can be stated as follows [15]:

$$£_3 = \left(1 + \sum_{t=1}^{24} V_{D\,(t)}\right) \tag{5}$$

$$V_{D\,(t)} = \begin{cases} \left|V_{\mathrm{Min}} - V_{i\,(t)}\right| & \text{if } V_{i\,(t)} < V_{\mathrm{Min.}} \\ 0 & \text{if } V_{\mathrm{Min.}} \leq V_{i\,(t)} \leq V_{\mathrm{Max.}} \\ \ell & \text{if } V_{i(t)} > V_{\mathrm{Max.}} \end{cases} \tag{6}$$

where ℓ is the large value or unacceptable value.

$V_{D\,(t)}$	Penalty for deviation of voltage
$V_{\mathrm{Max.}}$	Maximum value of permissible voltage at node
V_{Min}	Minimum value of permissible voltage at node

OBJECTIVE FUNCTION

A fitness function with weightage factors of distinct objective functions is required to accomplish objecti ves. Fitness function (Υ_1) for level 1 optimization:

$$min(\Upsilon_1) = \varphi \times M \times £_3 \tag{7}$$

where $M = £_1 + £_2$ and φ is the daily to yearly conversion product. $£_1$ and $£_2$ are relevant to the power and $£_3$ is relevant to voltage.

The DR planning and scheduling approach of DGs is taken into consideration at level 2 of the optimization objectives. The following objective function will be taken into consideration for level 2 of the optimization problem:

$$min(\Upsilon_2) = M \times £_3 \tag{8}$$

In this context, the fitness function for level 2 is denoted by Υ_2.

It is vital to have a dispatch strategy, which is determined upon by the DR aggregator. In the level 2 of optimization, the dispatch strategies of SPV and DR are considered. This helps to minimize the aforementioned fitness function.

Demand response aggregator

A demand response aggregator (DRA) is a third-party entity that works with energy consumers to manage their energy consumption during periods of peak demand. The aggregator coordinates with multiple consumers to reduce their electricity consumption during peak demand periods and sells the reduced energy consumption back to the grid operator or utilities as a form of DR. The DRA acts as an intermediary between the grid operator and the energy consumers. It helps the consumers reduce their energy consumption during peak hours by offering financial incentives, such as reduced electricity rates, to those who agree to participate in demand response programs. The aggregator then aggregates the reduced energy consumption from multiple consumers and sells it back to the grid operator or utilities. The DRA uses various technologies and strategies to manage energy consumption, such as automated demand response systems, smart thermostats, and energy management systems. These technologies allow the aggregator to remotely control and adjust energy consumption in real-time, based on grid conditions and market prices [16].

DRAs play a critical role in helping grid operators manage peak demand, reduce energy costs, and improve system reliability. By incentivizing energy consumers to reduce their energy consumption during peak periods, demand response aggregators help to balance the supply and demand of electricity and reduce the need for additional generation capacity.

The following are some of the DR restrictions that are taken into consideration:

$$P_{i(t)} = \left(P_{Gi(t)} - P_{Di(t)}\right)\forall t, i \tag{9}$$

$$Q_{i(t)} = \left(Q_{Gi(t)} - Q_{Di(t)}\right)\forall t, i \tag{10}$$

$$P_{Di(t)} = \left(P_{in,i(t)} + P_{el,i(t)}\right)\forall t, i \tag{11}$$

$$\sum_{i=1}^{N} \sum_{t=1}^{24} \left(P_{in,i(t)} + P_{el,i(t)}\right) \times \Delta t = E_i^{Total} \tag{12}$$

$$P_{el,i}^{min} \leq P_{el,i(t)} \leq min\left(\left(C - P_{in,i(t)}\right), P_{el,i}^{max}\right)\forall t \tag{13}$$

$$P_{el,i}^{max} = \mu\sum_{t=1}^{24} L_{d,i(t)} \tag{14}$$

Where C and μ is the contract load and DR penetration rate respectively.

$P_{Gi(t)}$	Real power generation at i^{th} node for the time period t
$P_{Di(t)}$	Real power demand for the time period t
$Q_{Gi(t)}$	Reactive power generation at i^{th} node for the time period t
$Q_{Di(t)}$	Reactive power demand for the time period t
$P_{in,i(t)}$	Nonreceptive load at time t
$P_{el,i(t)}$	Receptive load at time t
E_i^{Total}	Energy demand per day
$L_{d,i(t)}$	Load per hour for the time period t
$P_{\mathrm{DG},i}$	Real power injection by DG
P_{DG}^{max}	Maximum value of real power generation by DG

Participants in mandatory DR programs are liable to face financial penalties if they fail to adjust their electricity consumption as instructed by the aggregator. The scheduling of demand should aim to strike a balance between the total electricity consumption and the available resources throughout the day. Rather than simply reducing overall consumption, the objective of DR is to reshape the demand profile. The total demand at any given time, denoted as t, is the sum of all types of loads, including both receptive and non-receptive loads, as shown in equation 11. The receptive load shifts the demand as per the instructions of the DRA.

Equation 12 illustrates the scheduling constraints that must be followed to meet the responsive demand while ensuring it does not significantly impact the overall daily demand. The lower and upper limits of the responsive demand are represented by equation 13.

The peak value of the responsive demand is influenced by the level of DR penetration, and further details regarding this relationship can be found in equation 14.

Constraint for SPV output

The constraint for SPV generation limit is given as:

$$0 \leq P_{\mathrm{DG},i} \leq P_{DG}^{max}\forall i \tag{15}$$

Constraint for feeder

The constraint for the thermal limits is given as:

$$\boldsymbol{I_{ij(t)} \leq I_{ij}^{max}}\ \forall \boldsymbol{t, i, j} \tag{16}$$

$I_{ij(t)}$	Current flowing between i[th] and j[th] Node at t
I_{ij}^{max}	Maximum permissible value of current

Constraints for power balance

The constraints for real power and reactive power are given as:

$$P_{i(t)} = V_{i(t)} \sum_{j=1}^{N} V_{j(t)} Y_{ij} \cos\left(\theta_{ij} + \delta_{j(t)} - \delta_{i(t)}\right) \forall t, i \tag{17}$$

$$Q_{i(t)} = -V_{i(t)} \sum_{j=1}^{N} V_{j(t)} Y_{ij} \sin\left(\theta_{ij} + \delta_{j(t)} - \delta_{i(t)}\right) \forall t, i \tag{18}$$

Y_{ij}	Admittance matrix between i[th] and j[th] Node
θ_{ij}	Angle of impedance between ith and j[th] Node
N	Number of buses

Modeling of demand

The demand modeling of the system is given in the following equations:

$$P_{D,i(t)} = \Omega_{i(t)} P_{D,i}^{0} \forall t, i \tag{19}$$

$$Q_{D,i(t)} = \Omega_{i(t)} Q_{D,i}^{0} \forall t, i \tag{20}$$

where $\Omega_{i(t)}$ is the assigned load factor for the time period t.

Modeling of PV output

Solar power generation is dependent on several other elements as well. These factors include the type of panel and its area, the angle at which the panel is tilted, and the amount of solar radiation that is received. To facilitate this analysis, it is assumed that all other factors will remain identical during the specified time. The transformation of the current in relation to the rated voltage may be found as follows:

$$I_{sm(t)} = \begin{cases} I_{sm} \text{ if } S_{r(t)} \geq S_r^r \\ I_{sm} \times S_{r(t)}/S_r^r \text{ if } S_{r(t)} < S_r^r \end{cases} \tag{21}$$

I_{sm}	Current of solar PV
$S_{r(t)}$	Solar radiation at t
S_r^r	Rated value of solar radiation for PV

OPTIMIZATION TECHNIQUE

Particle Swarm Optimization (PSO) is a way for computers to find the best answer to a problem by imitating the way animals act. Each particle in the swarm is a possible answer to the optimization problem, and its position and speed change are based on what it has learned and what the whole swarm has learned. The objective function tells the swarm where each particle should go. During each iteration, the PSO method uses a particle's current position, its best position from before, and the best position found by any other particle in the swarm to change its speed and location [17]. This process keeps going until there is a reason to stop. At Level 1, optimal decision-making occurs to determine the key planning variables, including the location and size of PV systems. Meanwhile, at Level 2, the focus shifts to optimizing the hourly dispatch of DR programs. This optimization aims to maximize the operational advantages for the distribution system operator (DSO). Any evolutionary method can be used to solve the difficult problem of multilevel optimization. Based on a review of the relevant published material, it has been found that PSO is the most common way to solve the DG planning optimization problem [18,19]. The simulation parameters for the optimization technique are given in the table 1. The flowchart of bilevel optimization approach is illustrated in Figure 1.

Table 1. Simulation parameters of multilevel optimization technique.

Parameters	Level-1	Level-2
Swarm size	20	50
Inertia weight	1	1
Inertia Weight Damping Ratio	0.99	0.99
Personal Learning Coefficient	1.5	1.5
Global Learning Coefficient	2	2
Maximum Number of Iterations	50	50

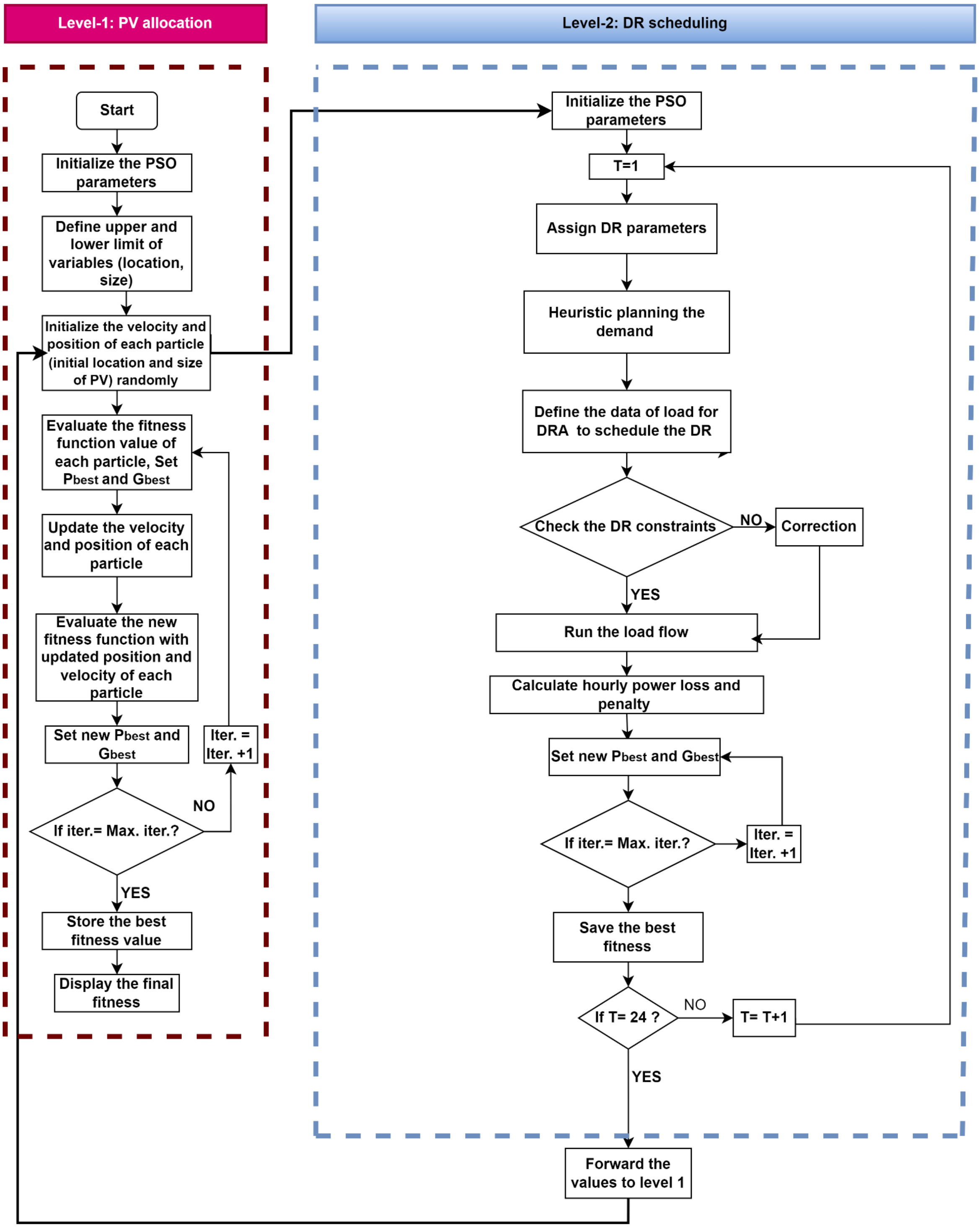

Figure 1. Framework of proposed bilevel optimization approach.

RESULT

On the IEEE 33 bus system, the multilevel optimization method that has been suggested will be used [20]. The test system is shown in figure 2. In this study, the effects of DR technologies are shown and analyzed so that a solution to the problem of finding the optimum way to transmit power in different situations and with different constraints can be found. The objective of this research is to improve the efficiency of power distribution. Using MATLAB software and a computer with an i3 core processor and 12 gigabytes of random-access memory, the optimization objectives are resolved with the help of proposed optimization techniques.

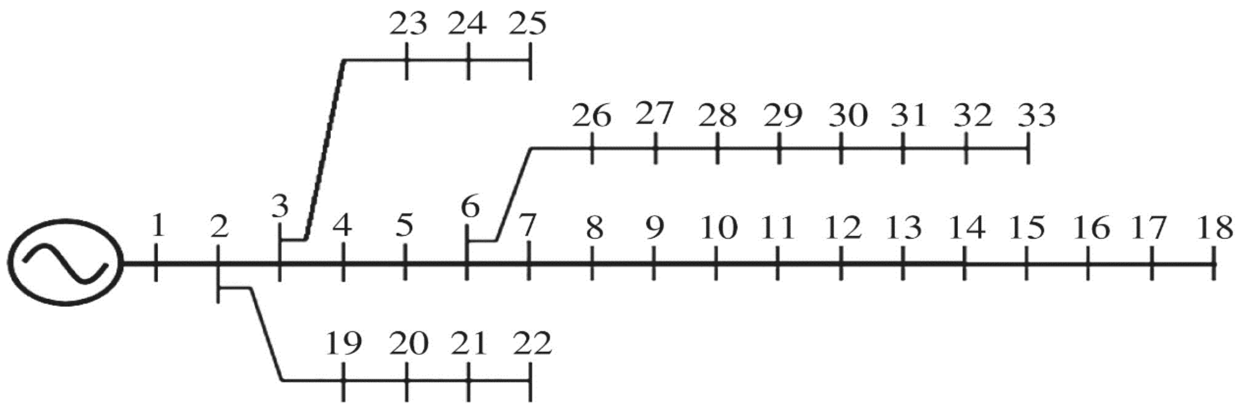

Figure 2. IEEE 33 bus system

Case 1

This scenario considers the base case to demonstrate effectiveness of a recommended technique for incorporating SPV into a 33-bus radial distribution system. The objective functions of the research are based on the consumption pattern of a typical day [21], and the annual energy loss is calculated using the average daily energy loss. The results show the difference between the highest and lowest possible demand, the minimum mean voltage, and the annual energy losses for the base scenario. The lowest demand period is around 5:00 a.m., while the highest demand period is around 8:00 p.m. According to tables 2 and 3, the difference between the highest and lowest possible demand, the minimum mean voltage, and the annual energy losses for this base scenario are respectively 5397.73 kW, 0.978178 p.u., and 1426 MWh.

Case 2

In this case, the authors optimized the placement of DG in a DN using SPV installations. The results showed that incorporating DGs into an optimized method improved power quality parameters such as annual energy loss and minimum mean voltage. The annual energy loss decreased by approximately 21.8%, and the minimum mean voltage increased from 0.978178 to 0.99634 p.u. The optimal size for SPV installations and their locations were outlined in table 3, and the effect of DGs on the pattern of demand, voltage, and active power losses were illustrated in figures 3, 4, and 5, respectively.

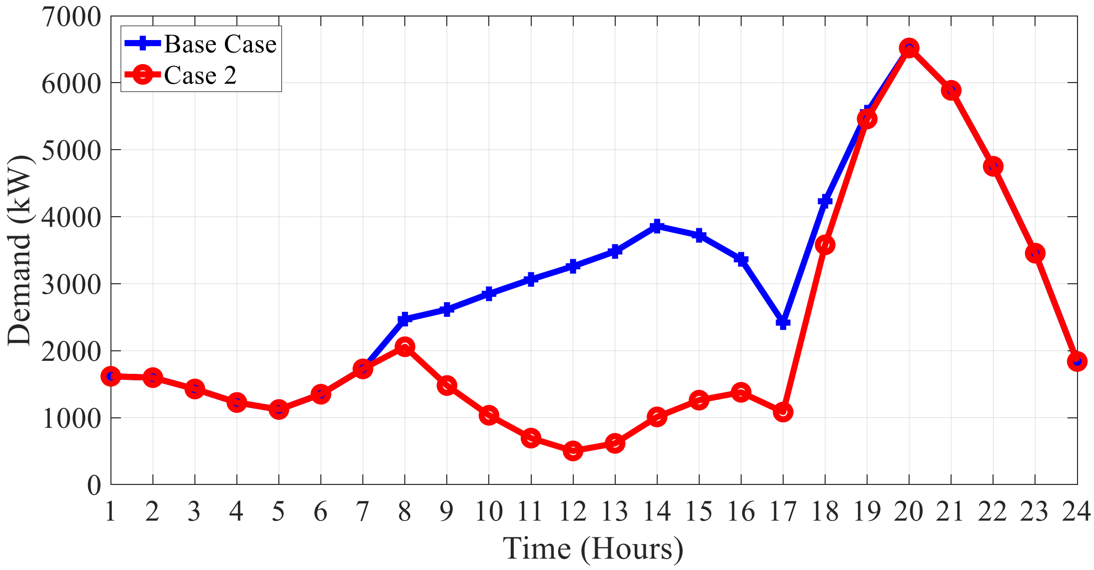

Figure 3. Impact of DGs on demand pattern

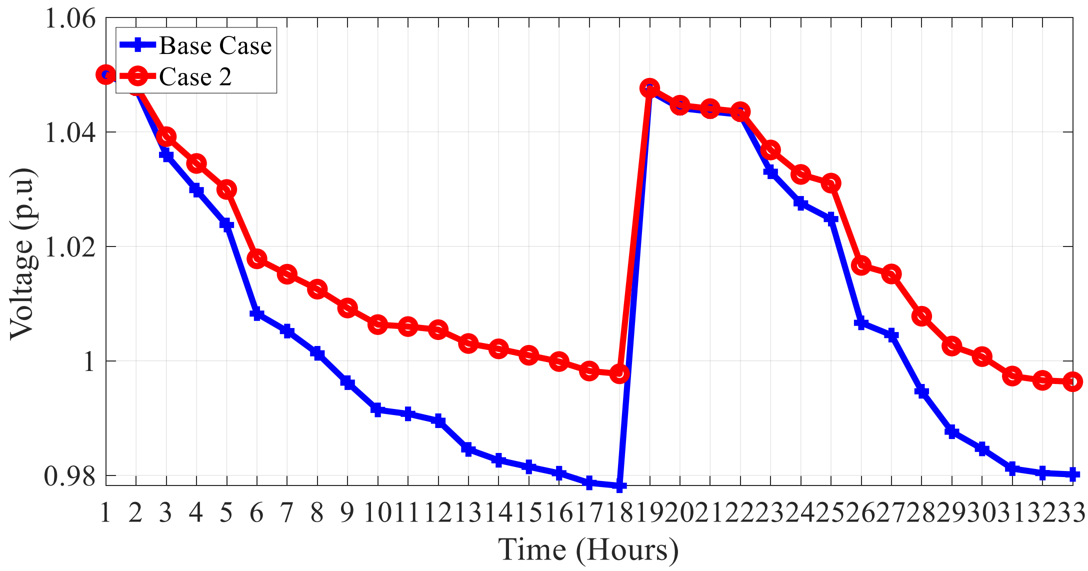

Figure 4. Impact of DGs on voltage pattern

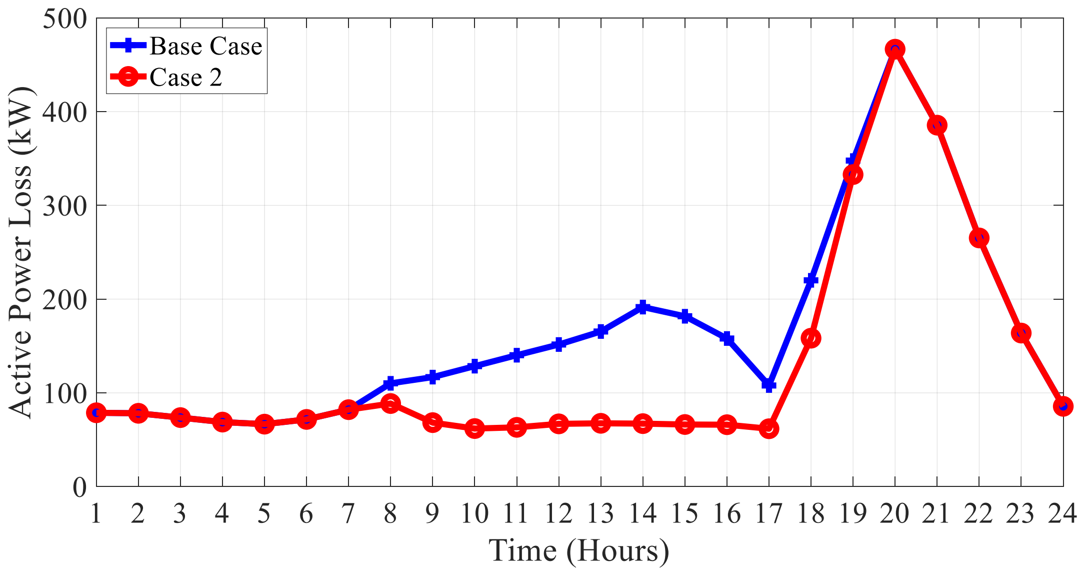

Figure 5. Impact of DGs on active power losses

Case 3

This study evaluates the significance of DR approach in the absence of DG coordination. Two levels of demand elasticity are assumed and benchmarked. DR rate refers to market demand elasticity. In this case, DR rate of 10% and 20% are considered without DG placement. Results show that DR reduces peak demand by 14.72% for a 10% DR rate and 18.32% for a 20% DR rate, and yearly energy loss by 5.96% to 8.2%. DR also reduces active power losses and increases peak-to-valley disparity. Even without DG, DR can be effective. Figures 6 to figure 11 demonstrate the effects of 10% and 20% DR rates on demand, voltage, and active power losses. There is negligible impact of DR rate on the voltage profile of the test system as shown in figure 7 and figure 10.

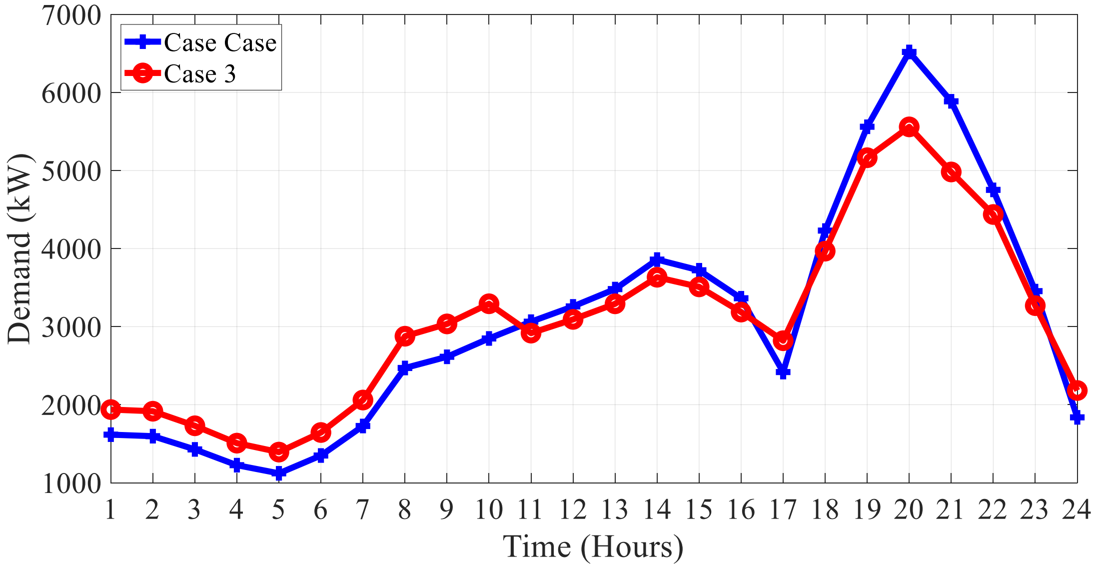

Figure 6. Impact of 10% DR rate on demand pattern

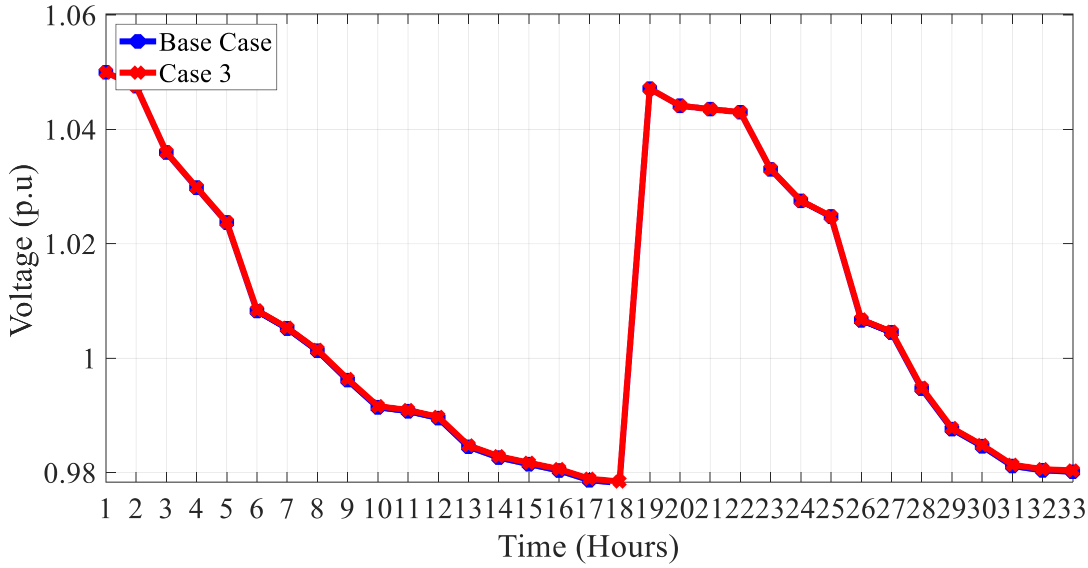

Figure 7. Impact of 10% DR rate on voltage pattern

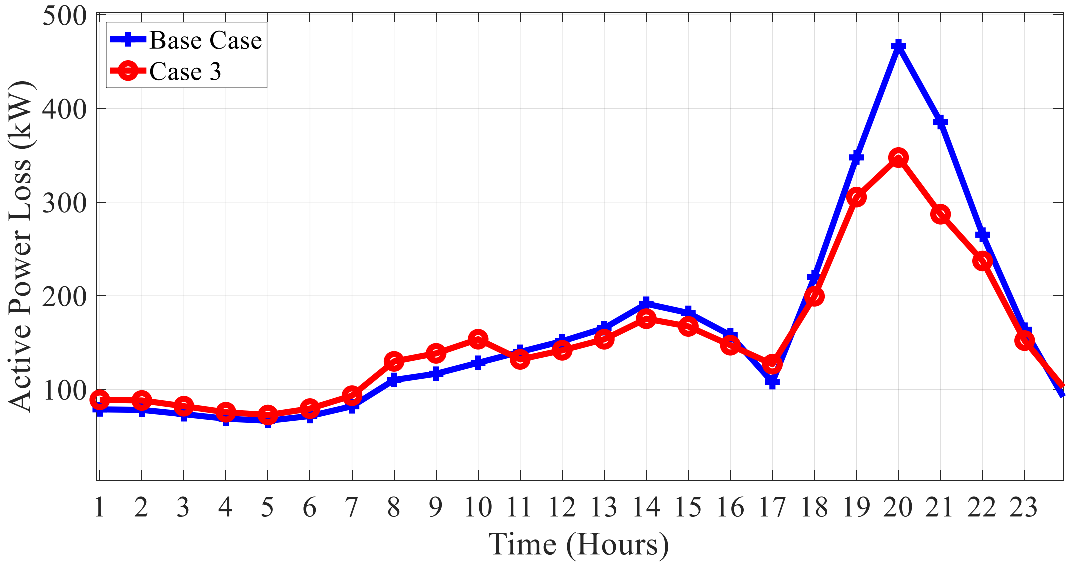

Figure 8. Impact of 10% DR rate on active power losses

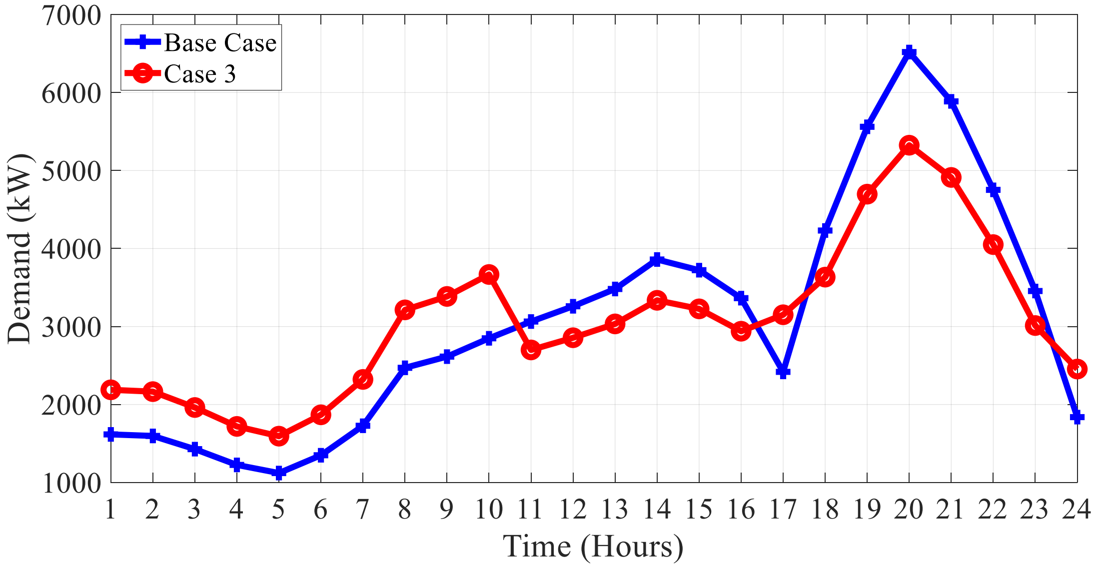

Figure 9. Impact of 20% DR rate on demand pattern

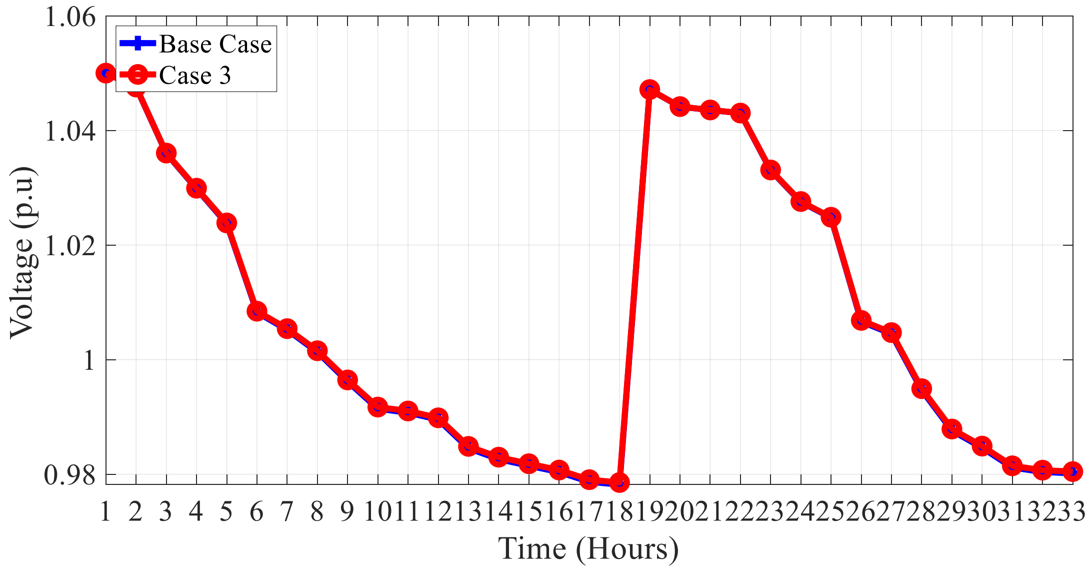

Figure 10. Impact of 20% DR rate on voltage pattern

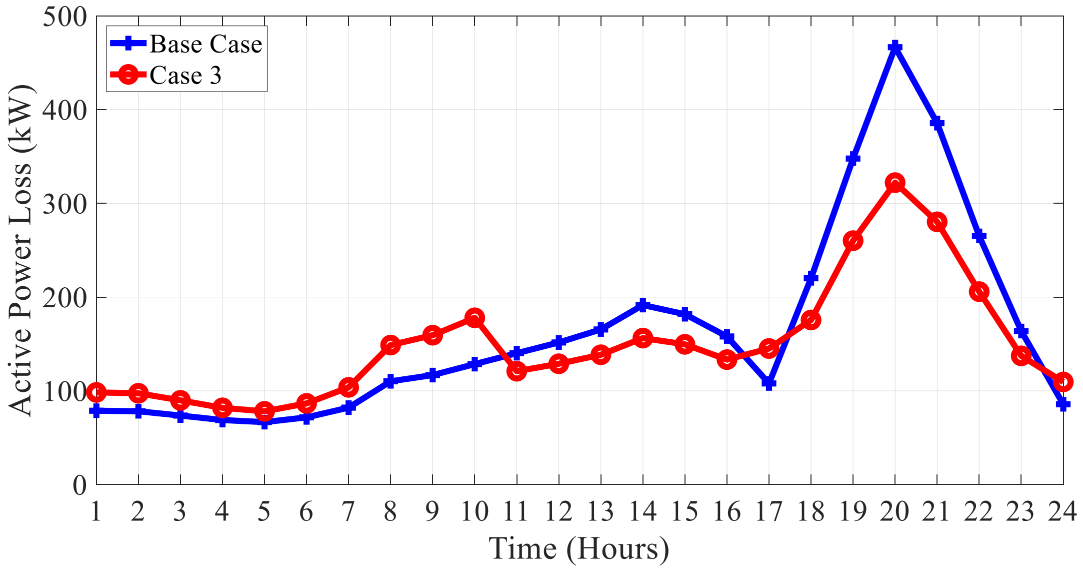

Figure 11. Impact of 20% DR rate on active power losses

Case 4

In this case, after incorporating DGs into DR coordination and planning under system constraints, the analysis is done. This scenario integrates DGs with DR scheduling while considering system constraints. High DR rates and smaller DGs increase system performance. Annual energy loss has decreased significantly. The lowest mean voltage has increased from cases 1 and 2 by 29.03% to 33.31%, depending on the degree of DR rates. The load profile is flatter because DGs reduce the gap from maximum to minimum demand. Figures 12 to figure 14 show that DGs with a 10% DR rate affect demand, voltage, and active power losses. Figures 15 to figure 17 show how DGs with a 20% DR rate affect demand, voltage, and active power losses.

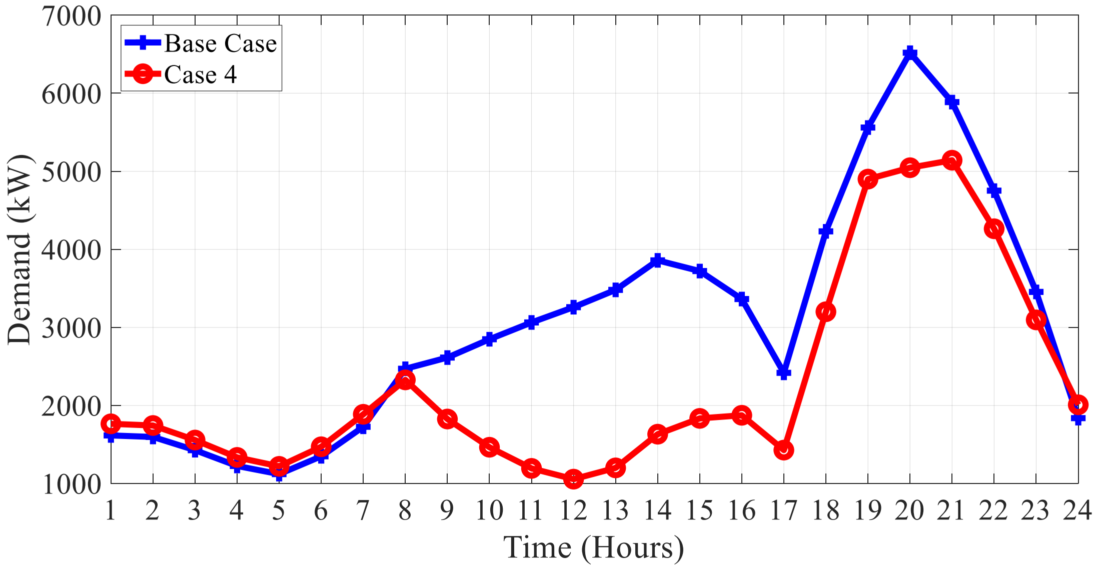

Figure 12. Impact of DG and 10% DR rate on demand pattern

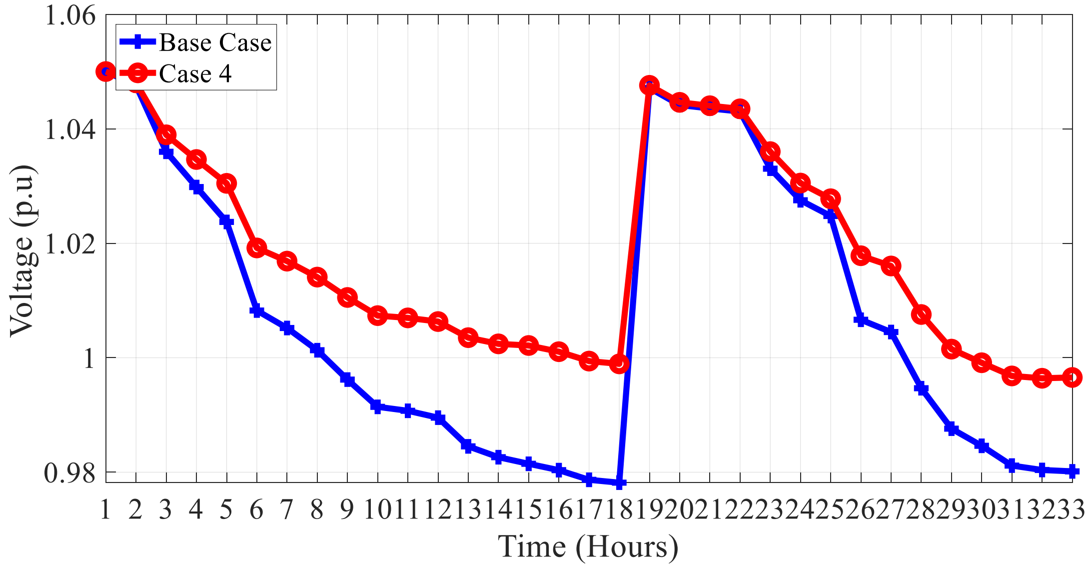

Figure 13. Impact of DG and 10% DR rate on voltage pattern

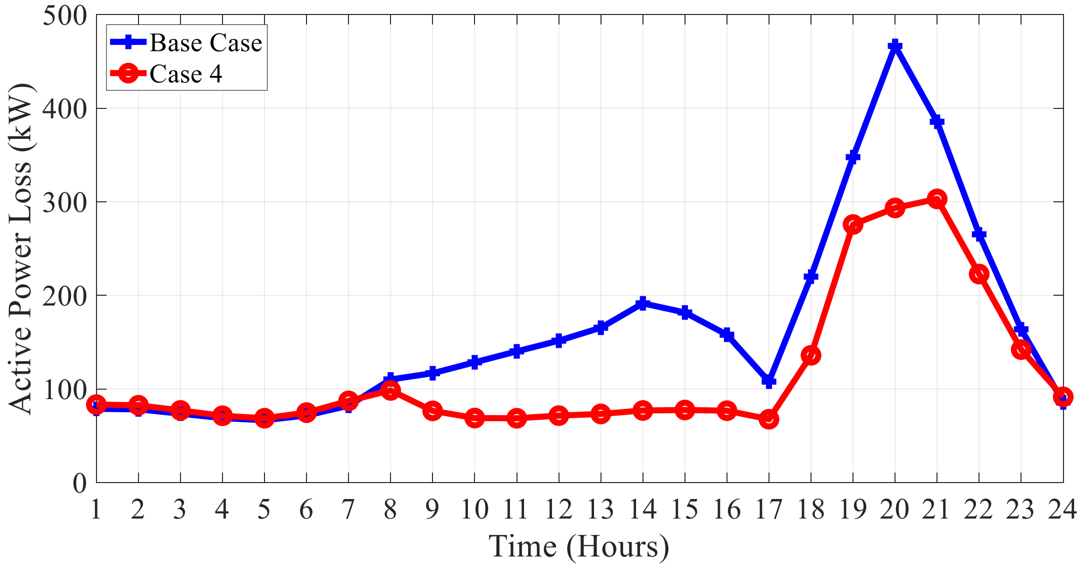

Figure 14. Impact of DG and 10% DR rate on active power losses

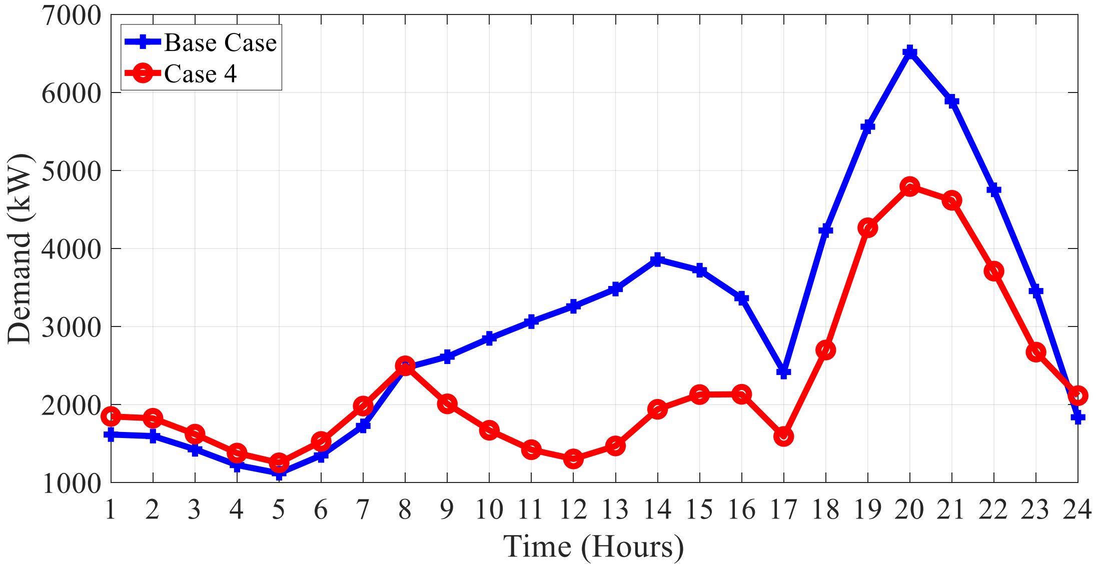

Figure 15. Impact of DG and 20% DR rate on demand pattern

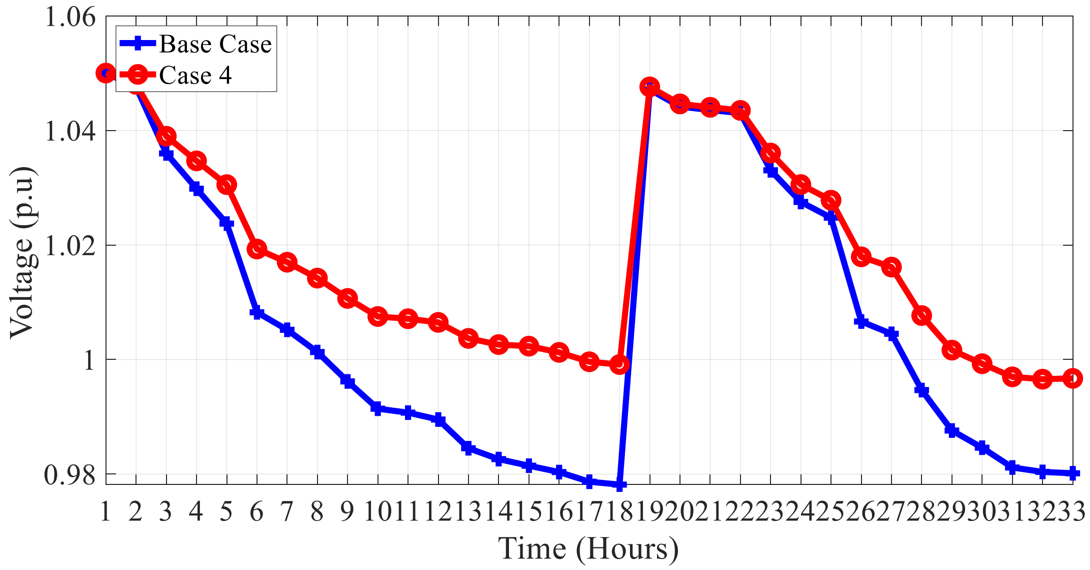

Figure 16. Impact of DG and 20% DR rate on voltage pattern

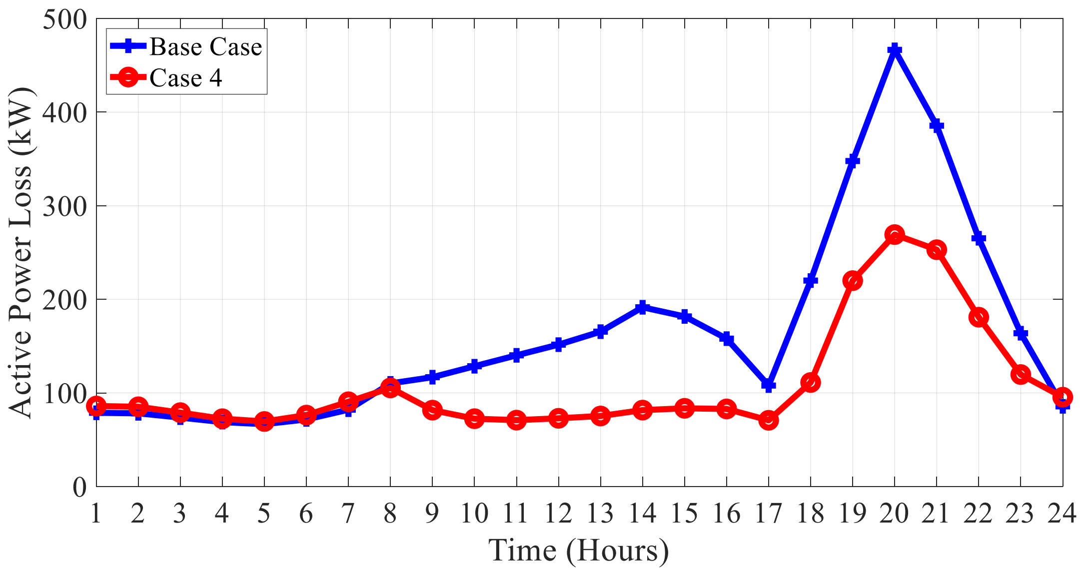

Figure 17. Impact of DG and 20% DR rate on active power losses

Table 2. Effect of the coordination of DR with optimally integrated SPV on demand.

Case No.	Category	Maximum Demand (kW)	Maximum Demand Mitigation %	Difference between Maximum to Minimum Demand (kW)	% Of Maximum Loss Mitigation at 8:00 PM
1	Base Case	6519	0	5397.73	0
2	DG	6519	0	6016.39	0
3	DR@10%	5548	16.1	4166.14	36.09
	DR@20%	5321	18.42	3730.6	42.77
4	DG+DR@10%	5370	17.33	4322.87	33.69
	DG+DR@20%	4790	26.78	3540.31	45.69

Table 3. Outcomes of the coordination of DR with optimally integrated SPV.

Case No.	Category	Optimal Allocation of DG (Bus No., kW)	Annual Losses (MWh)	Reduced losses / Year (%)	DG Penetration (%)
1	Base Case		1426		
2	DG	17(1344)-32(1690)-25(1092)	1098	23	68.76
3	DR@10%		1302	8.69	
	DR@20%		1290	9.53	
4	DG+DR@ 10%	7(1086)-15(1902)-32(914)	996	30.15	65.03
	DG+DR@ 20%	18(408)-29(1816)-11(1602)	934	34.5	63.76

CONCLUSION

While DGs have proven effective in reducing annual energy losses, it is important to consider their potential negative impact on load profile flattening. As the penetration of DGs increases, voltage levels can rise, leading to reverse power flow back into the grid. These challenges highlight the limitations of high DG penetration within the DN. Incorporating DR helps to balance the load profile, minimize the gap between peak and off-peak load demands, and alleviate strain on the system. Put simply, a higher DR rate can improve demand normalization efficiency, especially in cases where the penetration level of SPV systems is lower. As per the implemented framework, the mitigation of maximum demand, reduced energy losses per year, and DG penetration are 26.78%, 34.5%, and 67.76%, respectively. These are the maximum level achieved from case 1 to case-4.

In conclusion, the impact assessment of DR on the optimal placement of SPV systems in the DN has shown significant potential for improving the efficiency and effectiveness of renewable energy integration. The use of DR strategies can help reduce peak demand and enhance the flexibility of the distribution network, allowing for increased penetration of SPV systems while minimizing grid congestion and overloading.

Through simulation studies and empirical analyses, it has been demonstrated that the integration of demand response mechanisms can lead to enhance the power quality parameters and increased penetration level of renewable energy sources. The findings of the impact assessment provide useful insights for policymakers, utilities, and other stakeholders involved in the planning and management of DN.

While further research is needed to fully explore the potential of DR on SPV placement, it is clear that the incorporation of DR into energy systems planning and design will be an essential component of meeting future energy needs sustainably. Ultimately, the impact assessment of DR on the optimal placement of SPV systems highlights the importance of adopting a holistic approach to energy systems planning that considers the interaction between different components of the energy system and the potential for innovative solutions to address complex challenges.

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