Received: 28 March 2022 | Revised: 9 June 2022 | Accepted: 15 July 2022

DOI: 10.1049/rpg2.12560

IET Renewable Power Generation

The Institution of Engineering and Technology WILEY

ORIGINAL RESEARCH

Heuristic DRP-DG optimization strategy adopted for maximizing total social welfare in the real time Indian utility network

Punnianathan Sharmila[1] | **Senthilkumaran Mahadevan**[2] | **Jeevarathinam Baskaran**[3] | **Chandrasekaran Nayanatara**[1]

[1]Department of EEE, Sri SaiRam Engineering College, Chennai, India

[2]Department of EEE, Sri Sivasubramaniya Nadar College of Engineering, Chennai, India

[3]Department of EEE, PSG Institute of Technology and Applied Research, Coimbatore, India

Correspondence
Punnianathan Sharmila, Sri SaiRam Engineering College, Chennai, India.
Email: sharmila.eee@sairam.edu.in

Abstract

The energy sector is subjected to an increase in power demand year after year. This increase in energy demand will continue due to the need for energy for modern societies. The service providers should face this situation smartly using renewable energy sources to avoid the intermittent nature of these sources and the fluctuations in the demand. Demand response programs (DRP) can play a vital role in increasing the correlation between the loads and the available generation from renewable energy sources (RES). Modern power systems recommend the use of distributed generation (DG) sources to reduce the transmission losses, contingency, and cost of energy and to increase the system reliability, efficiency, and power system loadability. Optimal DR use in the DG can further improve its performance which is the main focus of this paper. Here, a novel DRP-DG strategy is introduced to size and allocate the DG units for minimum congestion in IEEE 33-bus benchmark power system and real Indian power system having 17 buses. The active involvement of the consumers in the DRP facilitates the ultimate objective of maximized total social welfare (TSW) with minimized generation costs. To justify the above multi-objective optimization, two stages of heuristic optimization are introduced in which the rules are fired in the primary stage for determining the optimal size of DG. Implementation of DRP for achieving comprehensive objective function is vindicated in the secondary stage. A real-time Indian utility network is considered and a trade-off output is realized using heuristic fuzzy logic (FL) and genetic algorithm (GA). The results obtained from using the proposed strategy proved its superiority in achieving substantial cost reduction and maximum TSW compared to other soft computing techniques.

1 | INTRODUCTION

The electricity demand continues to rise along with the economic growth. In recent years, there has been a growing interest in integrating DGs in the distribution system due to their numerous technical, environmental, and economic benefits [1]. Meanwhile, the grid infrastructure is not keeping pace with power generation additions. Usage of the right mix of renewable sources can optimize the total generation and enable stable grid operation [2]. Integration of DGs improves the reliability of energy supply, reduces power loss, lowers operation costs, enhances the voltage profile of the distribution network, and increases the existing power system loadability [3]. The emphasis of Indian power sector is towards consumption of more solar and wind power generation units in coordination with DR. Computational technique for the proper management of DGs that helps in peak load management and reduction in network losses is proposed in [4]. However, high DGs penetration could be counterproductive if they are not optimally placed [5]. A hybrid technique is introduced in [6] to simultaneously optimize the DG parameters for maximizing the customer benefit. An efficient analytical method for allocating optimal mix of different DG types is proposed in [7] to minimize power loss in distribution systems. A bi-level programming technique is implemented for coordinated planning of DGs and energy storage during uncertainties of DG outputs [8]. Also, the influence of integrated energy storage with DG has been found to boost the output power performance of renewable DGs significantly [9]. Besides reducing the energy loss and improving the network performance, the challenges due to the high penetration of DGs can be mitigated by implementing DR strategy. Optimal resource planning in the presence of DR ensures the flexibility and reliability of wind energy-integrated power system [10]. Implementation of DR has greatly reduced the DG capacity which is followed by the surplus generation serving the short-term peak loads [11]. A day-ahead load shifting technique is proposed for residential, commercial, and industrial customers to make informed decisions regarding their energy consumption to achieve significant savings [12]. A price variation in DR is introduced based on the type of the consumer's load reduction and a real-time pricing strategy is implemented to maximize the retailer's profit [13]. The incentive-based demand-side management model increases the benefits of retailers by proactively adjusting the incentives to the customers based on their behaviour during both peak and valley periods [14]. Genetic Algorithm was implemented in [15] and scheduling of appliances was done to satisfy the peak demand. A DR strategy presented in [16] divides the load into two different categories based on the supply priorities of loads. Part of these loads is called high priority loads which should be supplied at any operating situation of the power system and the other part is the low priority loads in which it can be shifted from the deficit generation periods to the surplus generation ones. The DR integration makes the grid more flexible with proper coordination among DG devices in the distribution networks [17]. During unpredictability in renewable energy and network contingencies, improved flexibility is achieved through synchronised generation and demand side management [18]. A combined MOPSO and fuzzy decision-making algorithm facilitates better planning of DSM to optimize the economic and environmental indices [19]. Application of Fuzzy Logic (FL), Artificial Neural Network (ANN), and Evolutionary Computation (EC) techniques in minimizing energy consumption and scheduling problems are discussed in [20]. The comparative study made between energy optimization and scheduling shows significant improvement in the demand and supply-side efficiency. A game theory algorithm is developed to implement real-time pricing (RTP) strategy in a residential area to reduce the cost involved in electricity pricing [21]. The participation of customers in energy management strategies greatly helps in reducing the maximum peak demand [22]. Load priority is employed to fix the dynamic load scheduling in a residential smart grid environment [23]. The time of use (TOU) strategy introduced in [24] reduces the peak of the load curve and thus aids in cost saving. In [25], storage system and DRP are combined into a reliability test system for improving the generation cost and reliability. However, technical issues such as power losses, voltage deviations are not explored in [25, 26]. Under static and dynamic conditions, the responsive load scheduling strategies suggested in [27] provide an optimal trade-off solution with the greatest peak load reduction.

TABLE 1 Categorization used for DRP–DG optimization

	DG	DRP	Concurrent optimization	Comprehensive case analysis	Feasible optimized solution
[1, 2, 4]	Y	N	N	N	N
[12, 13]	N	Y	N	N	N
[5, 15]	Y	N	Y	N	N
[18, 20, 22]	N	Y	N	Y	N
[7, 8, 9]	Y	Y	N	N	Y
Proposed	Y	Y	Y	Y	Y

YES (Y)/ NO (N).

From the literature review, it is observed that integration of DRP with DG may provide techno- economic benefits to the distribution network. However proper coordination is an important issue to achieve the tradeoff benefit. It is evident that simultaneous optimization is needed for removing the stiffness of the grid; thereby the utility for the customer can be benefited by proper tuning of DG parameters which is explored in this research as shown in Table 1.

The main objective of this research is to integrate DRP–DG to provide an energy management solution. Also, peak load reduction is ensured by adapting different consumption habits thereby both utility and user are benefitted under all possible comprehensive cases. To enhance the performance multi objective investigation is formulated by taking Bus Voltage (BV) and Congestion Index (CI) as rule-based parameters. Prioritization of multi-objective optimization is implemented with concurrent optimization of DG parameters. The same is integrated for different load patterns with diverse customers which is not possible by conventional computational technique. Therefore, heuristic computation is performed: To begin with, base case optimization of DG units is simulated by FL. Secondly, multiple case study with DRP is simulated using FL-GA in IEEE 33 bus and in the real Indian utility system. Moreover, the proposed results are compared with individual optimization algorithms. The standard deviation with min-max significance is tabulated for the proposed technique.

The major contributions of this paper are as follows:

1. Rule based selection of DG parameters with DRP is performed for maximizing the TSW with minimum congestion thereby enhancing the performance of the distribution network.
2. Multiple cases are framed and tested on standard 33-bus and in a real Indian 17-bus distribution system.
3. Base case and comprehensive case study evaluation is performed and concurrent optimization of DG parameters is simulated.
4. Heuristic FL-GA is developed for the proposed multiple cases to solve the operation problem of distribution network.

The rest of this paper is designed to show the modelling of the DG with DRP in Section 2. The problem formulation and optimal placement and sizing of the DG with DRP are shown in Section 3. The hybridization of fuzzy logic and genetic algorithm (FL-GA) for optimization of DG parameters are introduced in Section 4. The simulation results of the proposed strategy are shown in Section 5. The conclusions are introduced in Section 6.

2 | MODELLING OF THE DG WITH DRP

A coordinated control strategy for optimal tuning of DGs with DRP to achieve techno-economic benefits is proposed in this section. The model of the proposed strategy is shown in the following subsections:

2.1 | DG modelling

The demand response program is integrated with the distribution system in the presence of multi-DG and DRP. The modelling of different DG types is shown in the following points:

Type 1-DG: DG capable of delivering only real power that is supplied at unity power factors such as photovoltaic, micro-turbines, fuel cells, and bio-gas. The power output of the solar PV depends on the hourly irradiance and ambient temperature at that point as shown in Equation (1).

$$P_{pv(t)} = P_{stc}\,\frac{G_t}{G_{stc}}\,\left[1 + (K_i\,(T_t) - T_{stc})\right] \tag{1}$$

Type 2-DG: DG is capable of supplying real power but consumes reactive power such as wind turbines. The power extracted from the wind turbine is shown in Equation (2) [24].

$$P_{wt} = \begin{cases} 0 & 0 \le v_a \le v_{cin} \\ P_r * \dfrac{(v_a - v_{ci})}{(v_r - v_{ci})} & v_{ci} \le v_a \le v_r \\ P_r & v_r \le v_a \le v_{coff} \\ 0 & v_{coff} \le v_a \end{cases} \tag{2}$$

Type 3-DG: DG capable of supplying only reactive power such as the synchronous condenser. The reactive power injection is measured using the following equation:

$$Q_{dgm} = Q_{dm} + \frac{1}{A_{mm}}\left[B_{mm}P_{dm} - \sum_{n=1, n\neq m}^{N} (A_{mn}Q_n + B_{mn}P_n)\right] \tag{3}$$

$$A_{mn} = \frac{r_{mn}}{V_m V_n}\,\cos\,(\delta_m - \delta_n) \tag{4}$$

$$B_{mn} = \frac{r_{mn}}{V_m V_n}\,\sin\,(\delta_m - \delta_n) \tag{5}$$

$$r_{mn} + j\,x_{mn} = Z_{mn} \tag{6}$$

2.2 | DRP modelling

Demand response program is one of the strategies used for modifying the demand curve of customers to be more correlated with the available generation from RES [28]. This strategy can substantially reduce the size of the energy storage systems and other components of the power system which can be translated into a substantial reduction in the cost of energy. Moreover, DRP can substantially improve the reliability of the power system where it allows the customers to contribute the responsibility of maintaining the stability of the power system by reducing their loads during the critical situation or deficit of the generation. The optimal determination of the tariff with the use of the DRP will substantially improve the performance of the power system as will be shown in the results of this study.

The network under study and the data on DRP capability is gathered and the levelling in load profile is established by formulating the following mathematical problem.

Minimize:

$$\sum_t \left(P^t_{loadactive} - P^{mean}_{loadactive}\right)^2 \tag{7}$$

Subject to:

$$P^t_{load\ active} = P^t_{load,\,NR} + P^t_{load,R} + P^t_{load} \tag{8}$$

$$P^t_{load} = \sum_{load} P^t_{T,load} \tag{9}$$

$$P^{t-t'}_{d,\,total} \le P_{level} * P^t_{T,load} \tag{10}$$

After performing DRP, power flow analysis is carried out and the outcomes for all comprehensive cases are simulated.

2.2.1 | Total generation cost index

The generation of electricity in the power system under study is obtained from two different sources, the DG and from the utility grid. The following equation is used to show the total of energy during one day:

$$CI_{Gen} = C_{dg} + C_{grid} \tag{11}$$

$$C_{dg} = \sum_{t=1}^{24}\left[\sum_{j=1}^{n_{DG}}\left(P_{j(t)} * C_{j(t)}\right)\right] \tag{12}$$

$$C_{grid} = \sum_{t=1}^{24}\left[P_{grid(t)} * Mp_{(t)}\right] \tag{13}$$

Hence, the fitness function for cost minimization with DRP is summarized in Equation (14).

$$Minimize F_1 = \left\{ \sum_{m=1}^{ND} \sum_{m=1}^{NG} \sum_{m=1}^{NDG} \in \left(CI_{Gen,m} \right) \right\} \quad (14)$$

3 | OPTIMAL PLACEMENT AND SIZING OF DG WITH DRP

The penetration of DG with DRP ensures the quality of power supply to the consumer, without overloading the line and also at acceptable voltage levels. The optimal values of the DG device maximize the TSW and minimize the power loss in the network as much as possible thereby increasing the loadability. Hence, the objective function is to maximize the TSW with minimum power loss and generation cost in the power system.

3.1 | Formulation of the objective function

TSW is the difference between the monetary assessment of electricity to the customer and the income of selling electricity. These two parameters are indicated in monetary terms. Here, the cost and income are expressed in terms of the dollar. Since the supplier receives what the consumer pays, electricity cost and sales revenue are similar and those two parameters get canceled which results in Equation (14). The objective function TSW is a quadratic function with the demand and the generation as shown in Equation (15).

$$\begin{aligned} Max\ TSW = & \sum_{m=1}^{ND} \left(x_{dm} P_{dm}^2 + y_{dm} P_{dm} + z_{dm} \right) \\ & - \sum_{m=1}^{NG} \left(x_{gm} P_{gm}^2 + y_{gm} P_{gm} + z_{gm} \right) \\ & - \sum_{m=1}^{NDG} \left(x_{dgm} P_{dgm}^2 + y_{dgm} P_{dgm} + z_{dgm} \right) + Cost_{(i,t)} \end{aligned} \quad (15)$$

Thus, the objective function can be used on all the buses that have DG with the loading capability of λ, as shown in the Equation (16)

$$Maximize\ F2 = \sum_{m=1}^{N} Max_{TSW}^{\lambda} \quad (16)$$

The system considers the demand of ith customer and therefore, Equation (15) maximizes the difference between total income and total cost. Quadratic and cubic cost functions are considered normally to model the actual response of the entire generator and load bus system. The total real power loss for a kth transmission line connected between mth and nth bus is considered as shown in Equation (17):

$$P_L = \sum_{m=1}^{N} \sum_{n=1}^{N} [A_{mn} (P_{dm} P_{dn} + Q_{dm} Q_{dn}) + B_{mn} (Q_{dm} P_{dn} - P_{dm} Q_{dn})] \quad (17)$$

The minimization of the total real power loss of the system can be stated as shown in Equation (18).

$$Minimize\ F3 = \sum_{k=1}^{Nl} PLR_k \quad (18)$$

The goal of the optimization is to find the best location of DG devices in accordance with a defined criterion.

3.1.1 | Equality constraints

Equality constraints are based on the power flow equation.

$$\left. \begin{aligned} P_n &= P_{gn} + P_{dgn} + P_L - P_{dn} \\ Q_n &= Q_{gn} + Q_{dgn} + Q_L - Q_{dn} \end{aligned} \right\} \quad (19)$$

3.1.2 | Inequality constraints

Generation limits
Real power generation limits of each generator connected to the bus n:

$$P_{gn}^{min} \le P_{gn} \le P_{gn}^{max}$$

Line flow limits between buses m and n are shown in the following:

$$S_{mn} \le S_{mn}^{max}$$

$$S_{nm} \le S_{nm}^{max}$$

Bus voltage limits are shown in the following:

$$V_n^{min} \le V_n \le V_n^{max}$$

For the base case, OPF, which does not contain DG units connected to it, the net power from the DG units is set to zero as shown in the following equation:

$$P_{dgn} = 0$$

TABLE 2 Fuzzy rules

Congestionindex (CI) \ Bus voltage (BV)	Low	Medium low (ML)	Medium (MD)	Medium high (MH)	High
Low	ML	ML	LOW	LOW	LOW
Medium low (ML)	MD	ML	ML	LOW	LOW
Medium (MD)	MD	MD	ML	LOW	LOW
Medium high (MH)	MH	MH	MD	ML	LOW
High	HIGH	MH	MD	ML	ML

Similarly, the generated power from the load buses is set to zero as shown in the following equation:

$$P_{gn} = 0$$

The purpose of this research is to optimally schedule the DRP to achieve the minimized generation cost and peak load reduction with maximized TSW. Therefore, the objective function is given as:

$$\mathbf{F}\,(\mathbf{Max}) = \{W_{1*}\,(\mathbf{1/F1}) + W_2 * \mathbf{F2} + W_3 * (\mathbf{1/F3})\}$$

where W_1, W_2, and W_3 are the weight value of functions F1, F2, and F3, respectively. The values of these weight values are subjected to the constraint:

$$\sum_{s=1}^{3} \mathrm{W}_s = 1,$$

where W_s ranges between [0,1].

4 | HYBRIDISATION OF FL-GA FOR OPTIMISATION OF DG PARAMETERS

This hybrid algorithm aims to get the best trade-off solution, which is not possible by an individual method. The setback in solving this type of problem by conventional technique is that they mainly depend on the derivatives of the objective function. A dual step approach is performed in which FL is applied to identify the control strategy and the optimized outputs are passed on to the GA. In both steps, DRP is embedded to solve the dynamic objective function and to reach the global optimum. Also, the optimum solution is guaranteed and the solution does not diverge under all possible conditions.

For optimal control problems, fuzzy logic techniques are primarily applied since a quick control strategy is needed and a qualitative definition of action plans is available. The two primary activities performed are shown in the following points:

1. Finding optimal membership functions for control and action variable.
2. Finding an optimal set of rules between control and action variable.

The rules are established in Table 2, by considering the BV and the CI as variables. These variables are used to ascertain the group of fuzzy rules and it is used to determine the buses where DG devices installation has a greater or minor benefit improvement effect. The fuzzy variable membership relationship function is shown in Figures 1 and 2. The fuzzy variables have five choices: Low, Medium-Low (ML), Medium (MD), Medium-High (MH), and High. The maximum membership function value of these choices is always one. The fuzzy membership functions are developed from known inputs such as *BV*, *CI*, and the output membership functions are determined. According to the membership function, the fuzzy rules are established.

The two extreme situations are shown in the following points and shown clearly in the rules table:

- DG essential at low BV and High CI.
- DG less essential at High BV and low CI.

The fuzzy variables indicate the lack of DG devices in the power system network and determine the allocation sensibility degree of each bus, as shown in Figure 2.

GA is a population-based search approach that works on the principle of natural evolution to solve the given problem. The foundation behind GA is the continued existence and imitation of the fittest and it develops new and better results without any initial guess.

Each type of load has different consumption patterns and different lengths of operation time. Therefore, the design scheme should be able to tackle all these involutions which is less possible by other intelligent techniques. Therefore, the equation below is used to find maximum number of possible time steps N. This algorithm uses 24 number of hourly time intervals

Length of chromosomes $= N$

Considering above all constraints, the maximum value of feasible time steps N is given by the following equation:

$$N = \left\{ (24 - m_d) * m_d + \sum_{n=1}^{m_d - 1} n \right\} * K_{dt} \tag{20}$$

The role of mutation in GA is to restore lost or unexpected genetic material into a population to prevent the premature convergence of GA to sub-optimal solutions. It ensures that the probability of reaching any point in the search space never

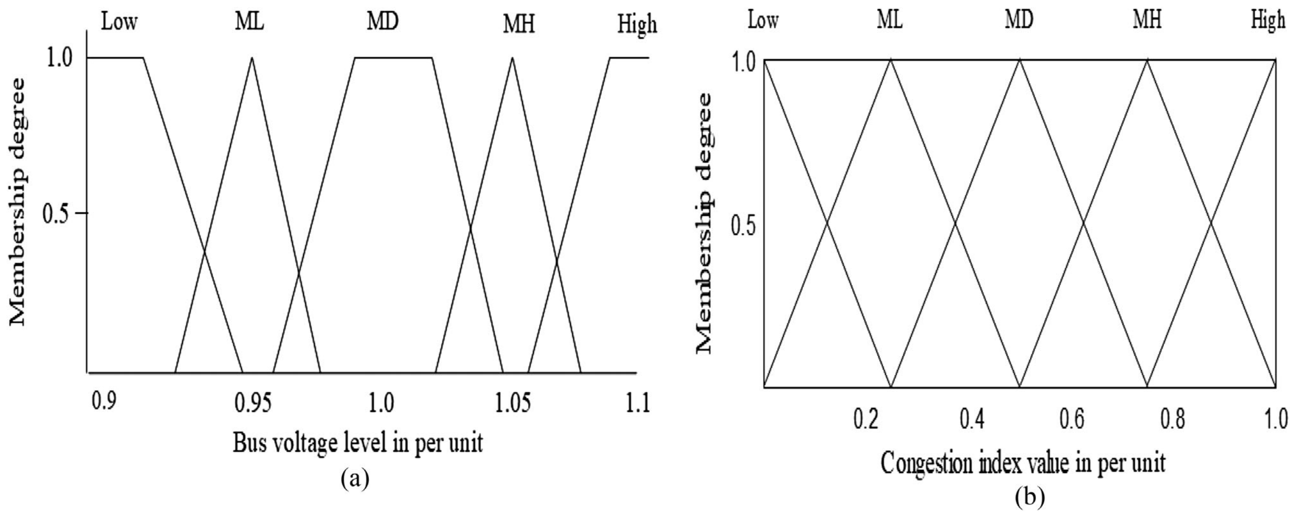

FIGURE 1 Input relationship function for (a) bus voltage (b) congestion index

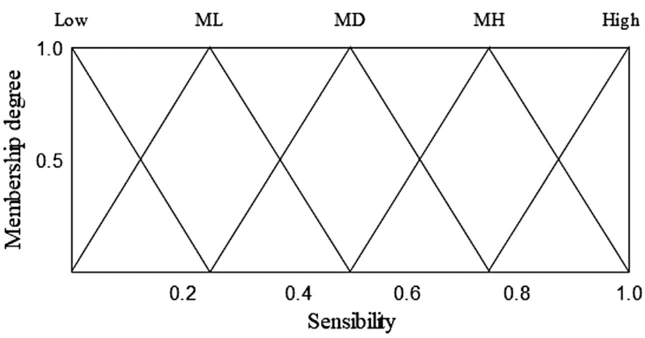

FIGURE 2 Relationship function of bus allocation sensibility

becomes zero and polynomial mutation is adopted in this research.

The mutated solution of $X_i^{(1,t+1)}$ at generation (t+1) after mutation is given as:

$$Y_i^{(1,t+1)} = X_i^{(1,t+1)} + \left(X_i^U - X_i^L\right)\delta_i \tag{21}$$

where δ_i is the scaling factor and it is expressed by:

$$\delta_i = \begin{cases} 2r_i^{\left(\frac{1}{\gamma_{m+1}}\right)} - 1 r_i \leq 0.5 \\ 1 - \left(2\left(1 - r_i\right)\right)^{\frac{1}{\gamma_{m+1}}} r_i \geq 0.5 \end{cases} \tag{22}$$

The abscissa can be treated as variables in GA and an optimization problem can be posed to find these variables for maximizing a control strategy. The fuzzy logic is applied for DG devices location problem by the following steps and shown in detail in Figure 3:

1. Assign the values of input variables CI, BV from the load flow data.
2. Partition the universe of discourse of each variable into several sets, assigning each linguistic label such as low, medium-low, medium, medium-high, and high.
3. Determine a membership function for each fuzzy set.
4. Assign the fuzzy relationships between BV, CI, and output thus forming the rule base.
5. Choose the appropriate scaling factor such as CI [0 1], BV [0.9 1.1] and output [0 1].
6. Fuzzify the CI and BV to the output function.
7. Use fuzzy approximate reasoning (Fuzzy rules) to infer the output from each rule.
8. Aggregate the fuzzy outputs given by each rule and apply defuzzification to form a crisp output.

5 | SIMULATION RESULTS

Using VC++ software package, the computational power flow studies are simulated. The reliability of the proposed distribution system is tested in the Indian utility 17 bus as shown in Figure 4.

All the parameters taken into consideration, that is, the type, location and rating of the DGs are chosen in a random way. The optimized selection values help to achieve the maximum benefit to the customers with minimized losses.

The following computational parameters are included in the manuscript:

Population size = 150
Number of generations = 200
Mutation constant = 0.01
Crossover constant = 0.7 (Two-point crossover)

To execute the efficiency of the hybrid approach, a comprehensive trade-off solution is performed to arrive at a suitable optimized output which is not possible using the individual heuristic technique. The optimal DG size, type, and rating for

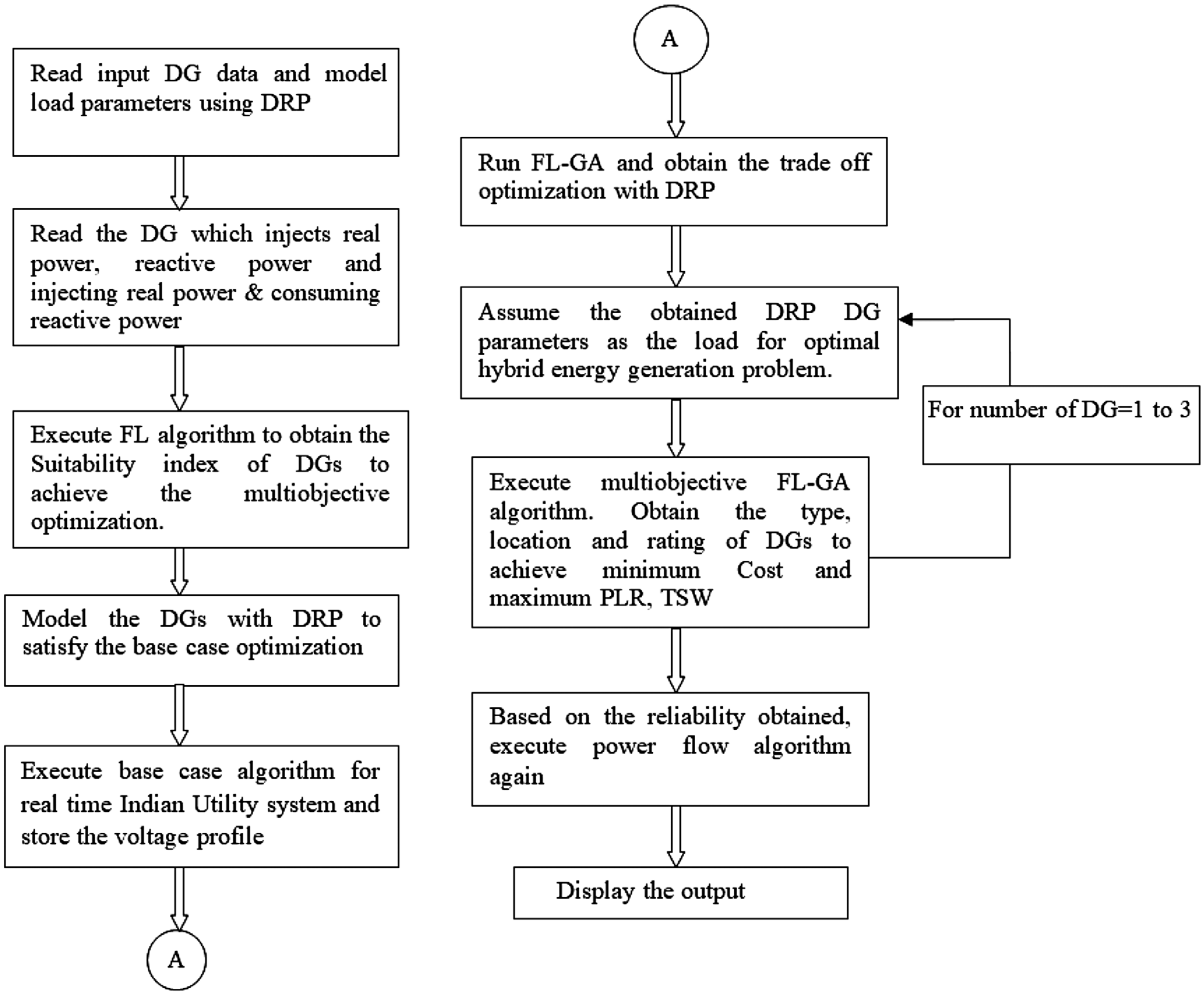

FIGURE 3 Working methodology of hybrid combination

each case is determined by considering DRP in the simulation. To extend the study, the loadability limit was also executed to its corresponding maximum limit and the convergence ability was also checked. The convergence characteristics which converge linearly show the efficiency of the proposed algorithm. The variation of the customers' benefits along with the iteration number is shown in Figure 5. The fitness value along with the iterations is shown in Figure 6. It is clear from Figures 5 and 6 that the optimization algorithm captured the optimal solution within ten iterations which shows the fast convergence performance of the proposed optimization algorithm.

The base case optimization of DG placement is shown in Table 3. The buses that are eligible for DG allocation as well as the number of distinct feasible combinations are investigated. The optimal DG site combination is found, and it is clear that DG penetration at the specified buses keeps the system voltage within acceptable ranges. The real powers at all buses with and without the DG are shown in Figure 7. It is clear from this figure that the terminal voltage at most of the busbars is increased which shows the superiority of using the DG with DRP in improving the voltage at the busbars of the power system. Moreover, the powers at all buses of the Indian power system are shown in Figure 8. It is clear from this figure that, the power limits at all busbars are increased which proves the increase of the loadability of the power system when using a DG with optimal DRP.

TABLE 3 Impact of DG on voltage

Range of voltage (p.u)	Available buses (Absence of DG)	Available buses (Presence of DG)
0.47–0.64	5	NIL
0.64–0.72	4	NIL
0.73–0.84	5	NIL
0.85–0.94	1	5
0.94–1.05	1	9
1.05–1.1	NIL	2

Further, the proposed algorithm clusters the load into peak, medium and low load and assigns a priority to the

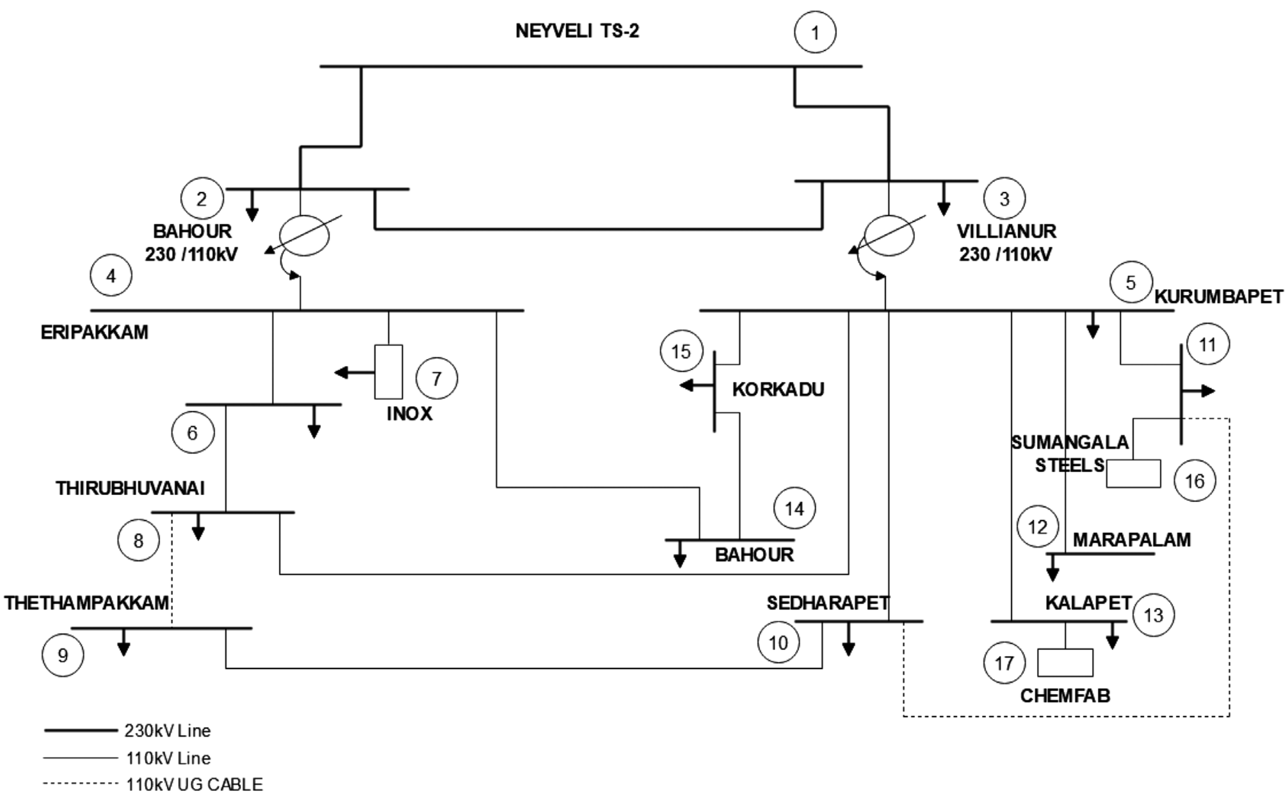

FIGURE 4 The 17-bus Indian power system

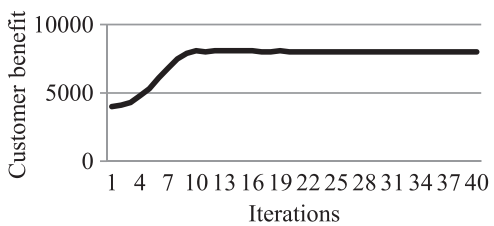

FIGURE 5 Customer benefit along with iterations

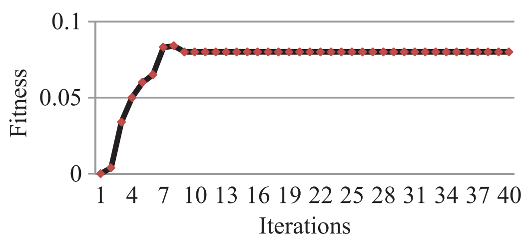

FIGURE 6 Fitness along with iterations

responsive and non-responsive loads. In addition, the research also provides the targeted, forecasted and optimized load distribution pattern to the residential, commercial and industrial consumers. This proves the scalability of the presented approach $Y_i^{(1,t+1)} = X_i^{(1,t+1)} + (X_i^U - X_i^L)\delta_i$. The scalability of the proposed approach as indicated in Figure 9 and Figure 10 is justified by checking the laodability limit. Therefore, a compromise tradeoff between DRP-DG penetration and the achievement of desired objective are developed by taking the loadability limit as the scalable parameter.

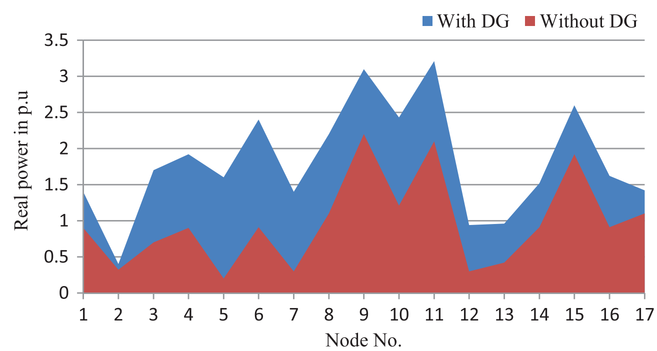

FIGURE 7 Normal loading conditions with and without DG

TABLE 4 Power loss under various loading conditions

Load type	Location of bus	Optimal DG Size (p.u.)	PLR with DG(%)	PLR without DG (%)
Peak load	12	1.43	12.34	23.34
Medium load	5	0.67	5.63	12.64
Low load	15	0.34	4.23	16.86

Table 4 shows the power loss under different loading conditions and different allocations of the DG. With load variations,

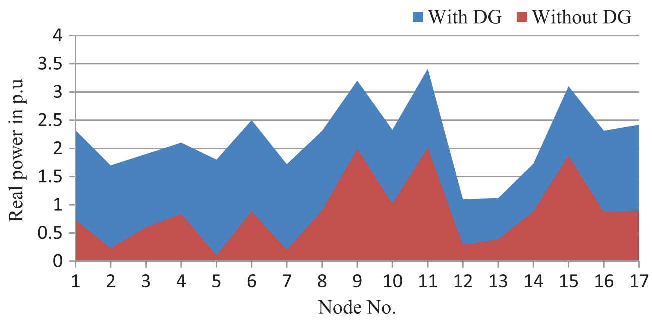

FIGURE 8 Double the loading conditions

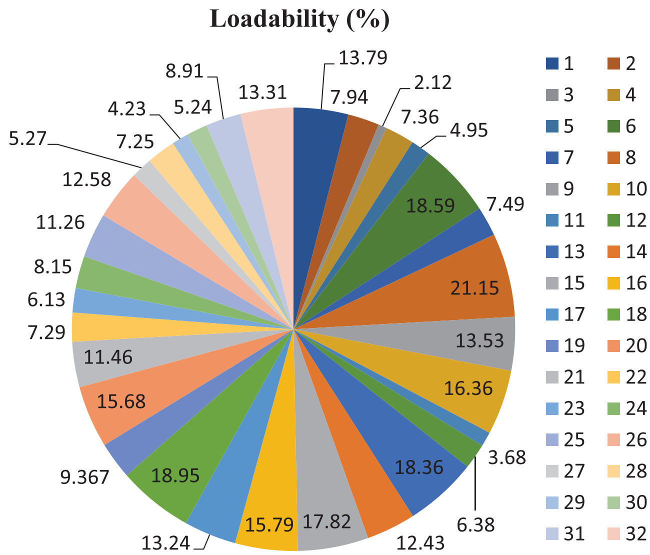

FIGURE 9 Standard test system—Scalability

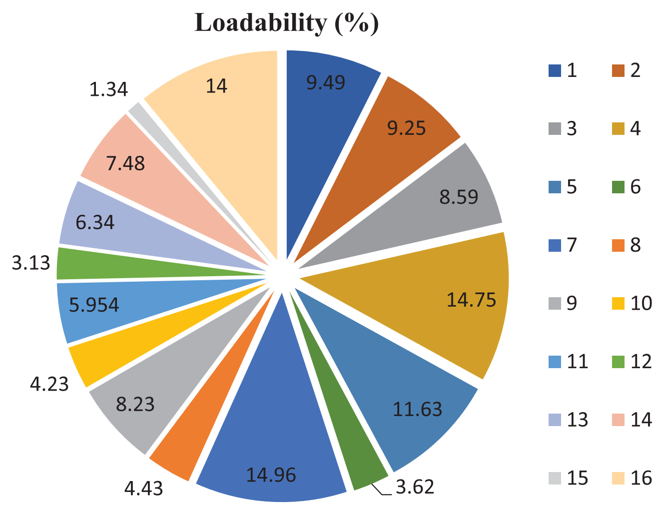

FIGURE 10 Real time Indian utility system—Scalability

it is possible to come up with a different ideal solution for the optimal siting and sizing of DG units. Table 4 demonstrates the impact of these changes and the findings show a trade-off in terms of power losses in the transmission lines (PLR) irrespective of the load variation in the distribution network. Also, Figure 11 shows the substantial reduction in system power loss by the best possible DG placement at the buses with different load levels. The PLR is reduced substantially with the use of the DG with an optimal DRP which proves the superiority of the proposed methodology introduced.

The size, type, and the rated values for various DGs are chosen and the optimized value is used for the maximization in social welfare and in the minimization of losses are tabulated in Table 5.

The increase in the PLR and TSW caused by the placement of DGs is illustrated in Table 5a. To prove the effectiveness of the optimization program, the results are investigated for individual optimization of DG parameters using the proposed GA and MGA techniques. It is worthwhile to note that significant locations are identified but, in some cases, it reaches local optima.

The proposed hybrid optimization approach is comprehensively compared taking into account the constraints set forth to obtain maximum TSW by incorporating DRP strategy along with optimal DG planning. Table 5b illustrates the benefits accrued from their installation. It is observed that the highest PLR of 82.89% and TSW of 31.32% are obtained with the

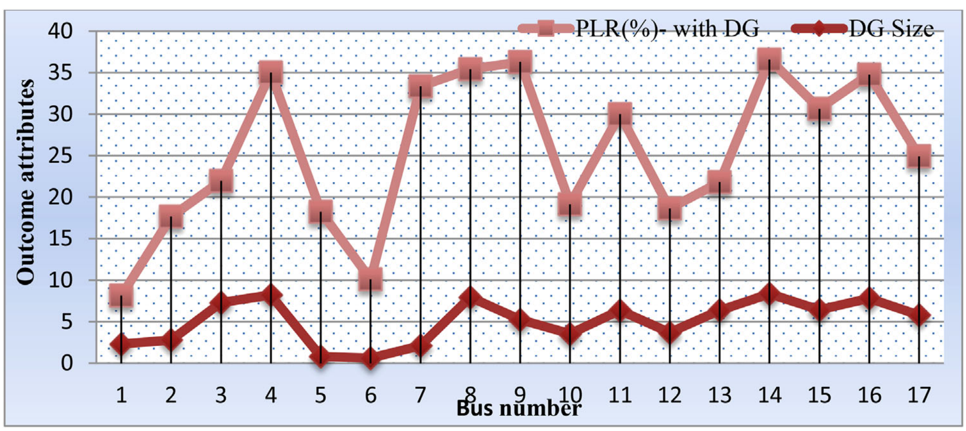

FIGURE 11 Power loss reduction with DG size

TABLE 5 Optimization of DG parameters

5(a) Individual optimization

GA					MGA				
Line	**Device**	**Rated value (MW)**	**MAX TSW (%)**	**PLR (%)**	**Line**	**Device**	**Rated value (MW)**	**MAX TSW (%)**	**PLR (%)**
2	2	5.43	2.43	2.47	2	1	2.93	2.34	3.76
3	1	0.74	6.13	3.94	4	1	1.79	3.23	7.38
4	3	1.83	4.51	4.17	7	2	0.69	16.38	23.59
5	1	1.93	11.47	1.04	8	1	3.29	18.37	14.04
7	3	2.91	13.06	11.65	11	3	2.79	22.41	17.48
9	2	3.51	17.36	8.38	13	3	3.14	4.23	7.99
11	1	1.42	12.37	9.29	17	1	2.63	18.43	12.63
13	3	4.29	19.83	17.27	19	2	1.97	9.82	20.67
17	2	2.58	21.03	28.94					
18	2	2.69	9.17	29.37					
19	1	2.14	20.53	15.78					
20	2	1.68	10.82	21.32					
21	3	3.02	9.64	6.87					

5(b) Proposed hybrid optimization

FL-GA

Line	Device	Rated value (MW)	MAX TSW (%)	PLR (%)
1	3	4.67	3.5	10.57
3	2	3.21	2.4	9.38
4	2	5.83	11.23	21.58
5	3	3.59	14.56	6.59
7	2	0.27	13.33	13.85
8	2	3.59	21.34	15.80
9	3	2.48	6.23	6.37
10	2	3.14	22.34	3.70
12	1	2.87	13.56	12.83
14	3	2.1	17.43	15.94
15	1	3.76	3.21	2.97
16	1	3.12	31.32	32.78
17	3	3.1	24.23	82.89
18	2	3.24	7.86	11.52
19	1	3.09	19.34	23.74
20	3	2.52	22.03	52.21
21	3	3.68	20.13	41.43

suggested hybrid method. However, when the cost of generation is taken into consideration there may be a point of diminishing welfare and hence trade-off considerations will then be applied. Heuristic comparison with respect to generation cost minimization with and without the use of the optimal DG is shown in Figure 12.

DR plays a major role in generation cost minimization. The benefit of DG scheduling based on DR in lowering the generation costs is larger. The effectiveness of the hybrid algorithm compared to the individual optimization algorithm is revealed in Figures 12 and 13.

The efficacy of DRP in reducing the peak load demands is analysed using various computational techniques as shown in Figure 13. Demand reduction has a significant impact on optimization parameters, resulting in maximum benefit to both the end-users and the utility. Reduced peak load demand also

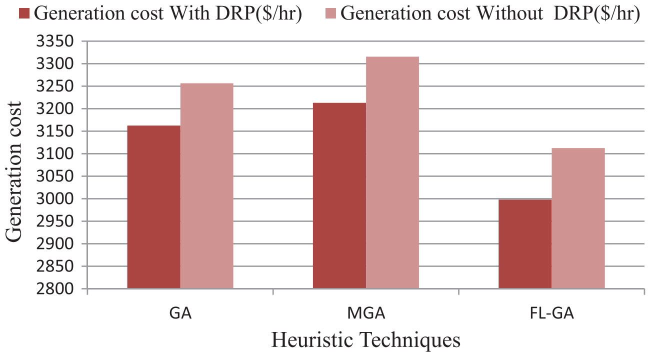

FIGURE 12 Heuristic comparison for generation cost minimization

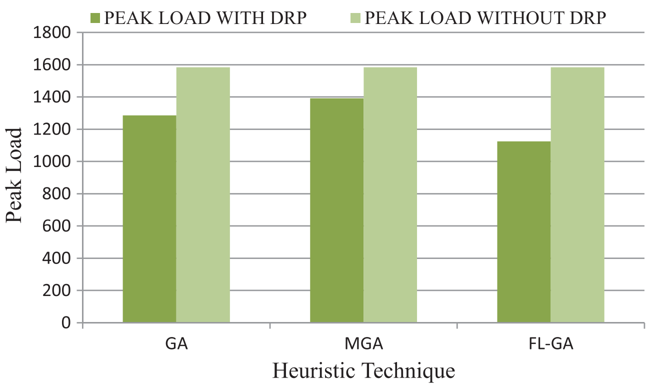

FIGURE 13 Heuristic comparison for peak load reduction

enhances grid sustainability by lowering total costs and carbon emissions.

The consumption pattern is rescheduled using DRP that performs load shifting from peak to off-peak periods. Figures 14 depicts the optimized load distribution pattern of residential, commercial, and industrial consumers to meet the targeted load. Such optimization facilitated proper DG planning which resulted in minimization of generation cost with an increase in TSW. It is observed that the hourly load pattern is optimized to meet the targeted load after shifting the peak loads using the hybrid algorithm (FL-GA). The findings show that generated power is considerably reduced during peak hours, lowering generation costs while increasing overall social welfare. To effectively use the DRP with DG optimization, comprehensive case studies are taken for simulation and a trade-off solution is proposed for all the cases in the IEEE real-time Indian utility network.

- Case (i) Rescheduling of generation (140↑)
- Case (ii) Rescheduling of generation with DG devices (150↑)
- Case (iii) Rescheduling of generation with load shedding (155↑)
- Case (iv) Rescheduling of generation with DG devices and load shedding (155↑)

The DRP–DG methodology simulated above is based on a day-ahead load scheduling and can be applied to large distribution system. The limitation is that forecasted hourly loads and device pattern of consumption should be known in advance so that the next day desired load curve can be obtained by running DRP that may reduce peak load and cost to utilities. Therefore, this research has advantages of simulating the objective function, considering the practical deployment of the distribution system. The results given under base case and comprehensive case prove that prioritization of multi-objective optimization is attained without fully compromising the other objectives. The heuristic rule-based FL-GA algorithm comes very handy in providing this flexibility. Therefore, the proposed DRP-DG strategy can help utilities and consumers to attain a desired optimized result.

The below-simulated results indicate the cost of Generation and reduction in power loss for the above four test cases and the comparison is done with GA and hybrid algorithm which is tabulated in Table 6.

Tables 7–15 shows the approach in identifying a plan for optimal distribution network operation with generation rescheduling along with DG and load shedding during peak load conditions. Several test cases are used to evaluate the hybrid algorithm's effectiveness. These strategies are expected to aid in effective operational planning and load dispatch.

5.1 | Comprehensive test results for IEEE 33 and Indian utility 17 bus system

Comprehensive case analysis is performed for the real-time and for the IEEE 33 bus system. These outstanding results prove the superiority of the proposed DG with the optimal determination of the DRP on the improvement of any existing power system. Moreover, these results showed a substantial reduction of contingency when using the DG compared to the system that operates without the use of the DG.

In order to obtain reliable results for an optimization algorithm, the optimized solution is chosen based upon the performance over multiple independent runs with random initialization.

The best solution for maximizing the welfare objective is treated as maximum goal ($F2^{max}$,2) and the worst solution is treated as the minimum goal ($F2^{min}$,2). The best solution for minimizing the total real power loss and minimizing the overall cost of the system are treated as ($F3^{min}$,3) ($F1^{min}$,1) and the worst solutions are treated as ($F3^{max}$,3) ($F1^{max}$,1). Thus, the Table 16 gives the best and worst solution obtained for the two-test systems along with their standard deviation.

The results tabulated in Table 17 reveal that hybrid combination overcomes individual computational performance in terms of all aspects. The heuristic optimization comparison was done by taking the time for computation as the measurable parameter and the same is shown in Figure 15. Optimization of DG with DRP places a crucial role in achieving the maximum TSW. The evaluated functions were obtained using the real-time system are presented in Table 18. It indicates the increase in loading

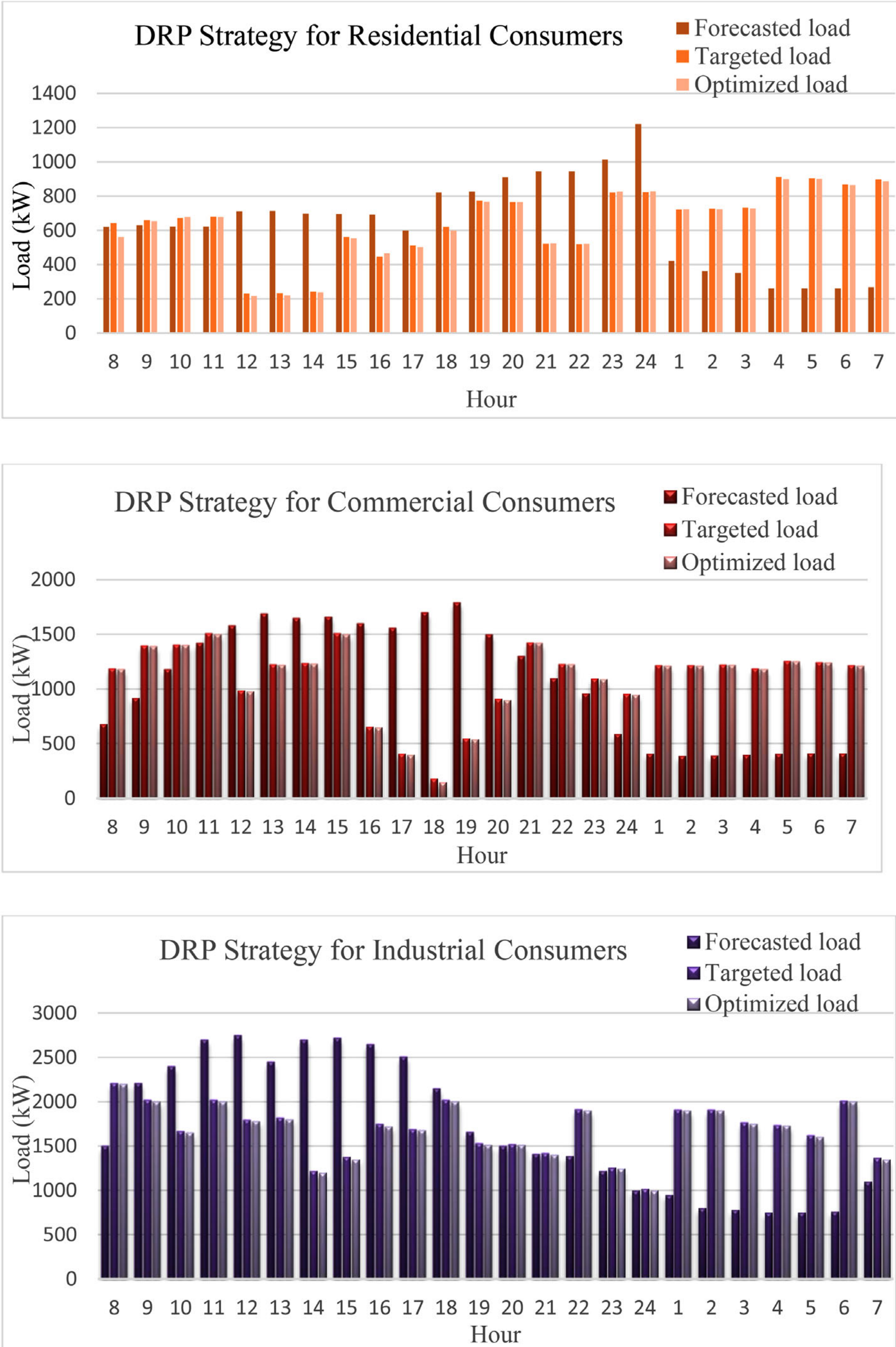

FIGURE 14 Peak load reduction using DRP for residential, industrial, and commercial consumers

TABLE 6 Generation cost and power loss reduction under different test cases- standard IEEE 33 bus system

		Generation cost in ($/h)			Power loss reduction (%)		
Case studies	**Load increased**	**GA**	**MGA**	**FL-GA**	**GA**	**MGA**	**FL-GA**
Case (i)	140%	997.56	957.78	843.56	16.78	21.23	21.49
Case (ii)	150%	995.67	945.33	865.78	23.89	17.78	19.44
Case (iii)	155%	999.23	912.99	872.41	19.27	20.45	25.23
Caase (iv)	155%	1000.23	922.35	843.34	28.11	27.56	24.89

TABLE 7 Generation cost and power loss reduction under different test cases -Indian utility system

		Generation cost in ($/h)			Power loss reduction (%)		
Case studies	**Load increased**	**GA**	**MGA**	**FL-GA**	**GA**	**MGA**	**FL-GA**
Case (i)	140%	983.67	1000.23	898.35	16.78	21.49	32.34
Case (ii)	150%	985.23	995.67	863.56	23.89	19.44	28.34
Case (iii)	155%	984.89	999.23	874.23	19.27	25.23	24.21
Case (iv)	155%	988.78	983.45	824.67	28.11	24.89	22.31

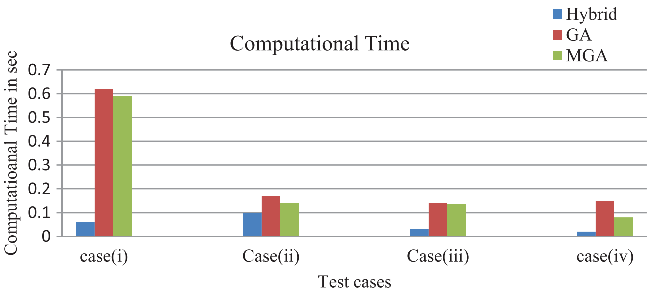

FIGURE 15 Simulation time taken by various case studies

TABLE 8 Comparative analysis of Case (i)—Generation rescheduling-standard IEEE 33 bus system

Bus no.	GA	MGA	FL-GA
Total gen (MW)	237.73	225.78	232.95
Total load (MW)	212.21	201.14	222.73
Objective function	**874.32**	**865.13**	**1087.99**

TABLE 9 Comparative analysis of Case (i)—Generation rescheduling-real time Indian utility system

Bus no.	GA	MGA	FL-GA
Total gen (MW)	268.88	286.77	294.45
Total load (MW)	263.84	281.23	263.82
Objective function	**985.56**	**981.56**	**1056.74**

TABLE 10 Comparative analysis of Case (ii)—Generation rescheduling with DG devices—Standard IEEE 33 bus system

Bus no.	GA	MGA	FL-GA
Total gen (MW)	234.67	224.52	283.42
Total load (MW)	229.34	221.17	278.67
Objective function	**982.07**	**985.45**	**1012.73**

TABLE 11 Comparative analysis of Case (ii)—Generation rescheduling with DG devices—Real time Indian utility system

Bus No	GA	MGA	FL-GA
Total gen (MW)	286.75	268.87	267.73
Total load (MW)	281.23	258.84	261.21
Objective function	**985.34**	**973.10**	**1002.34**

TABLE 12 Comparative analysis of Case (iii)—Generation rescheduling with load shedding—Standard IEEE 33 bus system

Bus no.	GA	MGA	FL-GA
Total gen (MW)	225.67	278.67	276.56
Total load (MW)	213.39	268.42	253.82
Objective function	**912.07**	**996.45**	**1032.43**

TABLE 13 Comparative analysis of Case (iii)—Generation rescheduling with load shedding-real time Indian utility system

Bus no.	GA	MGA	FL-GA
Total gen (MW)	283.62	281.36	272.78
Total load (MW)	277.73	269.32	269.65
Objective Function	**978.45**	**975.34**	**948.88**

TABLE 14 Comparative analysis of Case (iv)—Generation rescheduling with DG devices and load Shedding-standard IEEE 33 bus system

Bus No	GA	MGA	FL-GA
Total gen (MW)	247.83	298.67	269.97
Total load (MW)	245.67	278.90	263.53
Objective function	**952.07**	**1044.879**	**2018.99**

capability limits with the achievement of all fitness functions with load and generation being variable parameters. Generation rescheduling with load shedding can be taken as the last case for maintaining the reliability of the network.

TABLE 15 Comparative analysis of Case (iv)—Generation rescheduling with DG devices and load shedding-real time Indian utility system

Bus no.	GA	MGA	FL-GA
Total gen (MW)	287.72	285.67	293.46
Total load (MW)	283.74	283.74	295.54
Objective function	**989.76**	**982.21**	**998.77**

TABLE 16 Scalability evaluation for the IEEE and real time system

	F1 (US$/h)			F2 (US$/h)			F3 (%)		
Scenario	**$MinF1_{m1}$**	**$MaxF1_{n1}$**	**Standard deviation**	**$MinF2_{m2}$**	**$MaxF2_{n2}$**	**Standard deviation**	**$MinF3_{m3}$**	**$MaxF3_{n3}$**	**Standard deviation**
33 bus system-IEEE	635	879	23.57	894	1034	11.2	32	56	5.32
Indian utility system	529	971	19.34	709	1023	9.32	29	48	13.27

TABLE 17 Computational performance

	Objective functions (With DRP integration)			
Method	**Cost minimization (%)**	**Loss minimization (%)**	**TSW maximization (%)**	**Average CPU time (s)**
FL-GA	9.34	22.13	23.768	1.45
Genetic algorithm	5.56	17.56	18.546	3.12
Micro genetic algorithm	2.15	6.34	11.03	3.26

TABLE 18 Evaluated functions for 4 cases

	Case(i)		Case(ii)		Case(iii)		Case(iv)	
Evaluated functions ⇩	**Avg of discrete optimization**	**FL-GA**	**Avg of discrete optimization**	**FL-GA**	**Avg of discrete optimization**	**FL-GA**	**Avg of discrete optimization**	**FL-GA**
Total generation (MW)	223.54	262.46	223.47	267.65	284.63	291.24	248.63	267.25
Total load (MW)	246.26	226.37	243.84	268.63	299.85	292.57	286.15	283.73
Power loss reduction (%)	12.45	7.45	36.34	26.54	18.43	13.44	21.33	18.43
Generation cost reduction (%)	4.26	9.58	5.245	7.455	8.24	16.73	7.46	15.435
Computational time (s)	0.18	0.04	0.63	0.02	0.43	0.04	0.56	0.03
Objective function ($/h)	**1045.32**	**1267.67**	**1329.01**	**1845.33**	**1039.87**	**1045.76**	**2016.44**	**2053.42**

6 | CONCLUSION

The proposed strategy shown in this study is introduced to evaluate the performance of the power system with an optimal DG system considering the demand response concepts. Four different case studies were simulated ranging from basic planning to optimal planning.

The following summarizes the research work conducted:

1. The TSW maximization with CI_{Gen} and P_{loss} minimization are taken as objective functions. Also, the proposed optimization algorithm has been performed using three different optimization algorithms to choose the fastest and the most accurate one.
2. The research outcomes give the best location, type and rating of DG devices with DRP for power system problems. The research starts with the analysis of load flow solution by Newton–Raphson method.
3. Power injection model was used in three types of DG devices (PV, Wind and Gas Turbine) under steady state condition.
4. The scheduling pattern of DRP is done at low, medium, and peak load levels with residential, industrial, and commercial consumers.
5. All the test scenarios are first tested with standard IEEE 33 bus system and then implemented in a practical Indian utility system. Critical buses are identified and optimal control parameter settings for DG is determined that enhances the performance of the test systems.
6. The results illustrate the main benefits of DG with DRP and the dominant algorithms are compared with the other algorithms. Also, the extension of the objective function with loading capability is simulated by Generation Rescheduling with and without DG devices and finally by load curtailment.
7. It is concluded that in FL-GA the total number of locations were larger when compared to other algorithms. In Particular this algorithm dominates the other computational methods as each population is given a probability to participate.
8. It is proved that the combination methods will be more efficient when specialized knowledge about the problem was

familiar. Thus, the search space and computational time was reduced and thus the global optimal solution was achieved.
9. All the possible solutions have been assured to achieve the customer benefit and by that the desired trade off solution has been achieved.

The results reveal the achievement of the objective function under all possible scenarios and the overall efficiency and the system performance are proved to be the best. The hybrid DRP-DG optimization is a reliable method for the proper planning of distribution networks.

NOMENCLATURE

P_{dgm}, Q_{dgm}	Real and Reactive power injection at *m*th bus
C_{dg}	DG power generation cost
C_{grid}	Grid power generation cost
$C_{j(t)}$	Operating cost of *j*th DG at time *t*
G_{stc}	Solar insolation at standard test condition
$Mp_{(t)}$	Market price at time *t*
$P^{t}_{T,load}$	Total load at *t*th interval
$P^{t-t'}_{d,\,total}$	Total load that is shifted from *t* to *t'*
P_{dm}, P_{dn}	Real power demand at *m*th and *n*th bus
$P^{min}_{gn} \& P^{max}_{gn}$	Minimum and maximum real power generation limits from the generator *n*
$P_{j(t)} \& P_{grid(t)}$	Powers of *j*th DG and grid at time *t*
P_{level}	Penetration level
$P^{t}_{load\ active}$	Active loads at time *t*
$P^{t}_{load,\,NR}$	Active non responsive load at time *t*
$P^{t}_{load,R}$	Active responsive load shifted to time *t*
P_n, Q_n	Real and Reactive power injection at n^{th} bus.
$P_{pv(t)}$	Power generation from solar at time *t*.
P_r	Rated power of wind turbine
P_{stc}	Solar power at standard test condition.
P_{wt}	Power extracted from the wind turbine
Q_{dm}, Q_{dn}	Reactive power demand at m^{th} and n^{th} bus
$Q^{min}_{gn} \& Q^{max}_{gn}$	Minimum and maximum reactive power generation limits from the generator *n*
S^{max}_{mn} and S^{max}_{nm}	Maximum line flow limits between buses *m* and *n* and between buses *n* and *m*,
T_{stc}	Temperature at standard test condition.
$V_m \angle \delta_m$	Complex voltage at m^{th} bus
V^{min}_n *and* V^{max}_n	Minimum and maximum allowable limits of n^{th} bus voltages
n_{DG}	Total number of DG units
v_a	Hourly wind speed
v_{cin}	Cut-in wind speed
v_{coff}	Cut-off wind speed
v_r	Rated wind speed of wind turbine
$x_{dgm}, y_{dgm}, z_{dgm}$	Scheduled power cost coefficients of DG.
x_{dm}, y_{dm}, z_{dm}	Demand cost coefficients.
x_{gm}, y_{gm}, z_{gm}	Generator cost coefficients.
γ_m	Distribution index
k_{dt}	Number of different device types
m_d	Maximum allowable delay
mn	Elements of impedance matrix, between *m* and *n* buses.
N	Total number of power system buses.
ND	Number of load buses
NDG	Number of buses containing loads and DG units.
NG	Number of generation buses.
Nl	Total number of lines
PLR	Total power loss reduction in the lines
r	Random number between 0 to 1

FUNDING INFORMATION

The authors received no specific funding for this work.

CONFLICT OF INTEREST

There is no conflict of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

ORCID

Punnianathan Sharmila https://orcid.org/0000-0003-1305-9573
Chandrasekaran Nayanatara https://orcid.org/0000-0003-1482-5399

REFERENCES

1. Gampa, S.R., Das, D.: Optimum placement and sizing of DGs considering average hourly variations of load. Int. J. Electr. Power Energy Syst. 66, 25–40 (2015)
2. Akram, U., Khalid, M., Shafiq, S.: Optimal sizing of a wind/solar/battery hybrid grid-connected microgrid system. IET Renewable Power Gener. 12(1), 72–80 (2018)
3. Pakdel, D., Ramezani, M.: Enhancement of distribution network performance in the presence of uncertain parameters. IET Renewable Power Gener. 14(4), 515–525 (2019)
4. Rezaee Jordehi, A.: Optimisation of demand response in electric power systems, a review. Renewable Sustainable Energy Rev. 103, 308–319 (2019)
5. Barik, S., Das, D.: Determining the sizes of renewable DGs considering seasonal variation of generation and load and their impact on system load growth. IET Renewable Power Gener. 12(10), 1101–1110 (2018)
6. Nayanatara, C., Baskaran, J., Kothari, D.P.: Approach of hybrid PBIL control in distributed generation parameters for IEEE and real time Indian utility system. IET Renew. Power Gener. 11(2), 255–263 (2017)
7. Mahmoud, K., Yorino, N., Ahmed, A.: optimal distributed generation allocation in distribution systems for loss minimization. IEEE Trans. Power Syst. 31(2), 960–969 (2016)
8. Li, Y., Feng, B., Wang, B., Sun, S.: Joint planning of distributed generations and energy storage in active distribution networks: A bi-level programming approach. Energy 245, 123226 (2022)
9. Li, Y., et al.: Optimal distributed generation planning in active distribution networks considering integration of energy storage. Appl. Energy 210, 1073–1081 (2018)
10. Hamidpour, H., et al.: Flexible, reliable, and renewable power system resource expansion planning considering energy storage systems and demand response programs. IET Renewable Power Gener. 13(11), 1862–1872 (2019)
11. Combe, M., Mahmoudi, A., Haque, M.H., Khezri, R.: Optimal sizing of an AC-coupled hybrid power system considering incentive-based demand response. IET Gener. Transm. Distrib. 13(15), 3354–3361 (2019)
12. Logenthiran, T., Srinivasan, D., Shun, T.Z.: Demand side management in smart grid using heuristic optimization. IEEE Trans. Smart Grid 3(3), 1244–1252 (2012)

13. Zhang, C., Xu, Y., Dong, Z.Y., Po, W.K.: Robust coordination of distributed generation and price-based demand response in microgrids. IEEE Trans. Smart Grid 9(5), 4236–4247 (2018)
14. Chai, Y., Xiang, Y., Liu, J., et al.: Incentive-based demand response model for maximizing benefits of electricity retailers. J. Mod. Power Syst. Clean Energy 7(6), 1644–1650 (2019)
15. Chen, C.-R., et al.: Demand response optimization for smart home scheduling using genetic algorithm. In: *IEEE International Conference on. Systems, Man, and Cybernetics*, Manchester, UK, pp. 1461–1465 (2013)
16. Eltamaly, A.M., Alotaibi, M.A., Alolah, A.I., et al.: A novel demand response strategy for sizing of hybrid energy system with smart grid concepts. IEEE Access 9, 20277–20294 (2021)
17. Shanmugapriya, P., Senthil Kumaran, M., Baskaran, J., et al.: Flexible dispatch strategy adopted by optimizing DG parameters in a real time power system distributed network. J. Electr. Eng. Technol. 17, 847–861 (2021)
18. Dadkhah, A., Vahidi, B., Shafie-khah, M., Catalao, J.P.S.: Power system flexibility improvement with a focus on demand response and wind power variability. IET Renew. Power Gener. 14(6), 1095–1103 (2020)
19. Shayeghi, H., Alilou, M., Tousi, B., DadkhahDoltabad, R.: Multi-objective optimization of demand side management in the presence of DG and demand response. Int. J. Ind. Electron. Electr. Eng. 6(3), 230–242 (2018)
20. Iqbal, S., Sarfraz, M., Ayyub, M., et al.: A comprehensive review on residential demand side management strategies in smart grid environment. Sustainability 13(13), 7170 (2021)
21. Srinivasan, D., et al.: Game-theory based dynamic pricing strategies for demand side management in smart grids. Energy 126, 132–143 (2017)
22. Pothireddy, K.M.R., Vuddanti, S., Salkuti, S.R.: Impact of demand response on optimal sizing of distributed generation and customer tariff. Energies 15(1), 190 (2022). https://doi.org/10.3390/en15010190
23. Singh, S., Namboodiri, A., Selvan, M.P.: Simplified algorithm for dynamic demand response in smart homes under smart grid environment. In: *Proceedings IEEE PES GTD Asia*, Bangkok, Thailand (2019). https://doi.org/10.1109/GTDAsia.2019.8715935
24. Seshu Kumar, R., et al.: Intelligent demand side management for optimal energy scheduling of grid connected microgrids. Appl. Energy 285, 116435 (2021)
25. Yang, H., Zhang, Y., et al.: Reliability evaluation of power systems in the presence of energy storage system as demand management resource. Int. J. Electr. Power Energy Syst. 110, 1–10 (2019)
26. Tan, Z.F., Ju, L.W., et al.: A two-stage scheduling optimization model and solution algorithm for wind power and energy storage system considering uncertainty and demand response. Int. J. Electr. Power Energy Syst. 63, 1057–1069 (2014)
27. Panwar, L.K., K, S.R., Verma, A., Panigrahi, B.K.: Dynamic incentive framework for demand response in distribution system using moving time horizon control. IET Gener. Transm. Distrib. 11(17), 4338–4347 (2017)
28. Kothari, D.P., Singhal, K.C.: Renewable Energy Sources and Energy Technologies, 2nd ed. Prentice-Hall, New Delhi (2011)

How to cite this article: Sharmila, P., Mahadevan, S., Baskaran, J., Nayanatara, C.: Heuristic DRP-DG optimization strategy adopted for maximizing total social welfare in the real time Indian utility network. IET Renew. Power Gener. 16, 3092–3107 (2022). https://doi.org/10.1049/rpg2.12560