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MULTI-OBJECTIVE OPTIMIZATION OF DISTRIBUTED GENERATION PLACEMENT WITH DEMAND RESPONSE INTEGRATION IN RADIAL DISTRIBUTION SYSTEMS

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Abstract: *In modern power distribution networks, Distributed Generation (DG) significantly enhances system performance and operational efficiency. Demand Side Management (DSM) serves as a strategic approach to optimize DG deployment. This study introduces a novel optimization framework that integrates DSM with demand response mechanisms and DG placement. The methodology in this paper identifies optimal DG capacities and locations by evaluating real and reactive power losses alongside voltage profiles. To ensure environmentally sustainable and economically viable operations, the system's daily performance is optimized both with and without demand response integration. A Non-Dominated Sorting Firefly Algorithm (NSFA) is employed for multi-objective optimization, while a fuzzy decision-making model selects the most suitable solution from the Pareto front. The proposed approach is validated using the Practical 32-bus test system, demonstrating its effectiveness through simulation results.*

***Keywords*:** Demand side management, Distributed Generation, Demand Response, Non dominated Sorting Firefly Algorithm, fuzzy decision making.

I. INTRODUCTION

In a power network, the distribution system serves as a critical interface between electricity generation and end-user consumption. Enhancing its operational efficiency is largely achieved through Demand Side Management (DSM), which encompasses strategic planning, execution, and oversight of consumer-side activities that influence energy usage. DSM techniques aim to reshape consumption behaviours and load profiles to optimize system performance while maintaining user satisfaction. Distributed Generation (DG) plays a pivotal role in this context, contributing significantly to the improvement of technical, environmental, and economic parameters within the distribution network. DG units supply electricity to the grid using both renewable and conventional energy sources, thereby supporting demand fulfilment. Additionally, Demand Response (DR) mechanisms are essential for aligning consumption patterns with generation availability, ensuring a more balanced and responsive power system [1–3].

Demand Side Management (DSM) comprises a suite of strategic approaches aimed at reshaping electricity consumption patterns to ensure that demand remains within the bounds of available supply. These strategies include techniques such as peak demand reduction, load enhancement, dynamic load shaping, energy conservation, temporal load shifting, and valley filling. DSM initiatives actively promote behavioral changes among consumers, encouraging reduced energy usage during high-demand periods and incentivizing consumption during off-peak intervals [4]. A visual representation of these DSM methodologies is provided in Fig. 1.

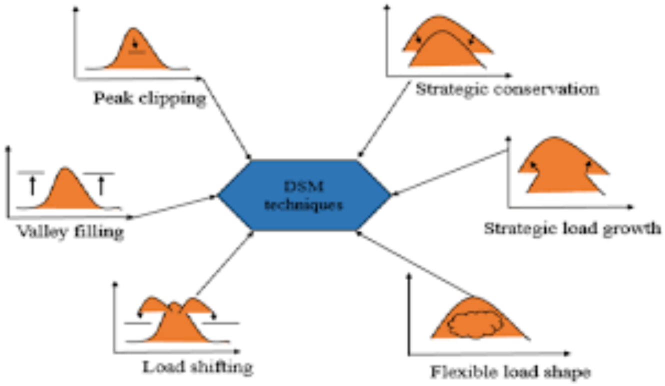

Fig 1 Demand Side Management (DSM) methods

Recent years have witnessed extensive global research efforts focused on advancing Demand Side Management (DSM) strategies. One innovative approach introduces spatial and temporal optimization techniques to reduce daily energy losses and operational expenses [5]. Studies have also explored the integration of rapidly responsive resources—such as electric vehicles and distributed generation units—into DSM frameworks to enhance system flexibility and capacity [6]. In [7], a novel DSM algorithm employing direct load control is presented, specifically targeting peak demand reduction. This method incorporates time-varying renewable DGs during DSM operations. Furthermore, DSM has been applied to building energy systems in conjunction with thermal energy storage solutions [8], considering diverse building typologies and varying levels of renewable energy penetration to improve reliability. These developments culminate in the proposal of an intelligent energy management architecture designed to optimize consumption and resource utilization.

This study presents an optimization framework for identifying the optimal placement and generation capacity of Distributed Generation (DG) units using the Non-Dominated Sorting Firefly Algorithm (NSFA). The methodology incorporates active and reactive power losses, along with voltage profile metrics, to guide the selection process. Additionally, the model evaluates the operational performance of the DG-integrated grid under scenarios both with and without Demand Response (DR) participation. Economic viability and environmental sustainability are treated as primary optimization objectives. To extract the most suitable solution from the Pareto front, a fuzzy logic-based decision-making approach is employed. The proposed strategy is implemented on the IEEE 33-bus test system, and its effectiveness is assessed under varying operational conditions.

II. **DISTRIBUTION GENERATION SYSTEMS**

Distributed Generation (DG) systems utilize two primary categories of energy sources: renewable and non-renewable. Non-renewable sources—such as diesel generators (DGs), micro turbines (MTs), and fuel cells (FCs)—offer controllable power output, as their generation levels can be adjusted by regulating fuel input based on demand. In contrast, renewable sources like photovoltaic (PV) panels and wind turbines (WTs) exhibit variability due to their dependence on meteorological conditions, making their output less predictable. A detailed classification of DG technologies is presented in [15,16]:

A. Diesel Generator

Diesel generators utilize petroleum-based fuels such as diesel and liquefied petroleum gas (LPG) to produce electricity. The generation process involves an electrical generator mechanically coupled to a diesel engine, allowing output to be modulated in response to distribution network demand. For load flow analysis, this type of DG is modeled as a PQ bus, capable of supplying both active and reactive power. In this study, the power factor is maintained at 0.85..

B. Micro Turbine

Micro turbines are cogeneration units that simultaneously produce thermal and electrical energy. They operate on fuels like propane, fuel oil, and natural gas. In power system simulations, micro turbines are represented as constant voltage buses due to their ability to inject both real and reactive power into the grid.

C. Photo Voltaic

Photovoltaic (PV) arrays convert solar radiation into electrical energy, making them a key component of renewable energy integration. PV cells are configured in series-parallel arrangements to achieve desired voltage and current ratings. The output of a PV system is influenced by solar irradiance, conversion efficiency, and array size. In load flow modeling, PV units are treated as P buses since they contribute only active power. The generated power from the PV array is calculated using the following expression

$$P_{PV} = A_{pv}\beta\mu \tag{1}$$

Where P_{PV} is the PV power generated, A_{PV} is area of solar panel, β is efficiency of solar panel and μ is solar irradiance (W/m^2).

D. Wind Turbine

Wind energy stands among the most ancient and inherently clean forms of renewable power. The electrical output of a wind turbine is influenced by several key parameters, including wind velocity, rotor swept area, atmospheric density, and the turbine's power coefficient. In power system analysis, wind turbines are typically modeled as PQ buses, as they contribute active power to the grid while simultaneously absorbing reactive power. The mathematical relationships governing both real and reactive power generation are outlined below:

$$P_{WT} = \frac{1}{2}\rho A_{WT} {V_W}^3 C_P \tag{2}$$

Where P_{WT} is power generated by wind turbine, ρ is Air density, A_{WT} is swept area of wind turbine, V_W is wind speed and C_P is power coefficient of wind turbine.

$$Q_{WT} = -\left(0.5 + 0.04{P_{WT}}^2\right) \tag{3}$$

III. **DEMAND RESPONSE**

Demand Response (DR) is a strategic approach aimed at adjusting consumer load profiles in accordance with the available power supply within the distribution network. Rather than altering generation to meet demand, DR focuses on reshaping demand to align with supply conditions. It typically encompasses two primary mechanisms: time-based strategies and incentive-driven programs. In this study, the time-based approach is adopted due to its simplicity and widespread application in practical DR implementations. The mathematical formulation of the DR model is presented below:

$$d(i) = d_o(i) \times \left[1 + E(i,i) \frac{P(i) - P_o(i)}{P_o(i)} + \sum_{j \neq i}^{24} j = 1\, E(i,j) \frac{P(j) - P_o(j)}{P_o(j)} \right] \quad (4)$$

IV. MULTI OBJECTIVE OPTIMIZATION

The optimization process in this study is structured into two sequential stages:

1. This phase focuses on identifying the optimal placement and sizing of multiple Distributed Generation (DG) units. The evaluation is guided by two key performance indicators—loss index and voltage stability index. These metrics are used to formulate the initial objective function, which is presented below

F$irst\ objective\ function:$ min (I_{ARL}, I_{VP}) (5)

2. In this phase, the optimal scheduling of Demand Side Management (DSM) activities is established by evaluating both economic and environmental performance indicators. These indices serve as the foundation for constructing the second objective function, which is detailed below:

Second $objective\ function:$ min (I_{OC}, I_{PE}) (6)

In this formulation, I_{VP} denotes the voltage stability index, while I_{ARL} represents the index associated with active and reactive power losses. The term. I_{PE} corresponds to the pollution emission metric, reflecting environmental impact, and $\mathrm{I_{OC}}$ signifies the operational cost index, serving as an indicator of economic performance. Together, these indices form the basis for evaluating both economic and environmental objectives within the optimization framework.

A. Loss Index

The power loss index is formulated by aggregating both active and reactive power losses within the distribution network. This composite metric serves as a key indicator for evaluating system efficiency. The corresponding mathematical expressions used to quantify the loss index are presented below.

$$I_{ARL} = C_p P_l + C_q Q_l \quad (7)$$

Where:

$$P_l = \sum_{i=1}^{N_{br}} R_i |I_i|^2 / \sum_{i=1}^{N_{br}} R_i |I_{i_{ins}}|^2 \quad (8)$$

$$Q_l = \sum_{i=1}^{N_{br}} X_i |I_i|^2 / \sum_{i=1}^{N_{br}} X_i |I_{i_{ins}}|^2 \quad (9)$$

B. Voltage Index

The voltage stability index quantifies the extent to which bus voltages deviate from their nominal or rated values. A lower index value—approaching zero—signifies enhanced voltage stability across the network. The mathematical expression used to compute this index is presented below:

$$I_{VP} = \sum_{i=1}^{n} R_i (V_i - V_b)^2 / \sum_{i=1}^{n} (V_{i\_ins} - V_b)^2 \quad (10)$$

C. Economic Index

Operational cost plays a pivotal role in the formulation of the economic performance index. To quantify this aspect, the daily cost index is derived using the equation presented below:

$$I_{OC} = OC_{DG} + OC_{grid} + MC \quad (11)$$

In this context, denotes the operational expenditure associated with Distributed Generation units, while OC_{grid} refers to the cost incurred by the main grid during power delivery. The term MC captures the startup and shutdown costs corresponding to the i th generation unit operating in the h th hour.

$$OC_{DG} = \sum_{h=1}^{24} [\sum_{i=1}^{n_{DG}} (P_{DG_i}(h) \times C_{DG_i})] \quad (12)$$

$$OC_{grid} = \sum_{h=1}^{24} [(P_{grid}(h) \times MP(h)] \quad (13)$$

$$MC = \sum_{h=1}^{24} [\sum_{i=1}^{n_{unit}} (C_{SS_i} \times |M_{unit_i}(h) - M_{unit_i}(h-1)|)] \quad (14)$$

IV. PROPOSED HYBRID OPTIMIZATION ALGORITHM

The implementation of the proposed optimization algorithm on the IEEE 33-bus distribution system is subject to a set of operational constraints.:

1. Bus voltage levels must remain within the allowable range defined by system standards. These limits ensure voltage stability and reliable operation across all nodes in the network:

$$V_{min} \leq V_i \leq V_{max} \quad (15)$$

2. Distributed Generation (DG) units integrated into the distribution network must operate within

predefined power output boundaries. These constraints ensure system reliability and maintain operational consistency across varying load conditions. The permissible generation limits are specified below:

$$P_{DG}{}^{min} \leq P_{DG\_i} \leq P_{DG}{}^{max} \tag{16}$$

3. The combined power output from both the main grid and the integrated Distributed Generation (DG) units must be sufficient to meet the total load demand within the distribution network, accounting for system losses. This constraint ensures energy balance and operational feasibility throughout the network.

$$\sum_{i=1}^{n_{DG}} P_{DG\_i} + P_{grid} = \sum_{j=1}^{n} P_{demand_j} + \sum_{i=1}^{N_{br}} P_{loss_i} \tag{17}$$

4. The hourly operation of Energy Storage Systems (ESS) must comply with predefined constraints governing both charging and discharging behaviors. These limitations ensure that the ESS units function within safe and efficient boundaries, maintaining system reliability and supporting optimal energy management. The specific operational bounds for each hour are outlined below.

$$W_{ESS}(t) = W_{ESS}(t-1) + \eta_{charge} P_{charge}(t) - \frac{P_{discharge}}{\eta_{discharge}} \tag{18}$$

$$\begin{aligned} &W_{ESS\_min} \leq W_{ESS}(t) \leq W_{ESS\_max} \\ &P_{charge}(t) \leq P_{charge\_max} \qquad (19) \\ &P_{discharge}(t) \leq P_{discharge\_max} \end{aligned}$$

To achieve optimal performance across technical, environmental, and economic dimensions, this study integrates the Non-Dominated Sorting Firefly Algorithm (NSFA) with a fuzzy logic-based decision-making framework. The synergy between these two methodologies enables robust multi-objective optimization and effective solution selection. Detailed descriptions of both techniques are provided in the subsequent sections:

A. Non dominated Sorting Firefly Algorithm

The Non-Dominated Sorting Firefly Algorithm (NSFA), each firefly is characterized by its light absorption capability, which determines its attractiveness to other agents in the search space. Analogous to biological behavior, less luminous agents (referred to here as "worms") are drawn toward fireflies exhibiting higher brightness levels. The firefly that attracts the greatest number of agents is considered the optimal candidate in the solution space.Two dynamic parameters—light intensity and attractiveness—govern the movement and interaction of fireflies. Attractiveness is a relative measure that varies based on the brightness of neighbouring fireflies and their spatial separation. When the j^{th} firefly exhibits greater brightness than the i^{th}, the position of the i^{th} firefly is updated accordingly. The mathematical formulation for this positional update is provided below

$$x_\iota = x_\iota + \beta_o e^{-\gamma r^2}\left(x_\jmath - x_\iota\right) + \alpha\varepsilon_\iota \tag{20}$$

In the NSFA framework represents the baseline attractiveness when the inter-firefly distance r = 0, while r denotes the Euclidean distance between the i and j fireflies. The parameter ɣ is the light absorption coefficient, set to unity in this study, and α introduces stochastic behavior through a randomization factor. For complex optimization scenarios involving multiple conflicting objectives, multi-objective algorithms offer superior performance compared to single-objective approaches. Accordingly, the standard Firefly Algorithm is extended into a multi-objective variant to accommodate the simultaneous optimization of technical, economic, and environmental indices. During the iterative process, candidate solutions with superior fitness values are retained, while suboptimal ones are eliminated through non-dominated sorting and crowding distance evaluation. The flow of the NSFA is illustrated in Fig.2.

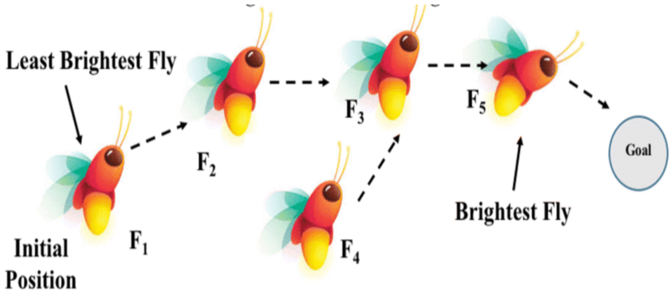

Fig 2 Illustrated diagram of Non Sorted Firefly Algorithm(NSFA)

In the proposed optimization framework, each particle is evaluated against all others using Pareto dominance principles. Through non-dominated sorting, particles are organized into Pareto-optimal fronts, facilitating the identification of superior solutions across multiple objectives.

B. Fuzzy Decision Making

Once the optimal particle is selected from the Pareto front, fuzzy logic is employed to refine the decision-making process. This approach enables the selection of the most balanced solution by interpreting imprecise or overlapping criteria through well-defined membership functions. The fuzzy membership functions used in this study are illustrated below:

$$\mu_i{}^k = \begin{cases} 1 & F_i{}^k \le F_i{}^{min} \\ \dfrac{F_i{}^{max} - F_i{}^k}{F_i{}^{max} - F_i{}^{min}} & F_i{}^{min} < F_i{}^k < F_i{}^{max} \\ 0 & F_i{}^{max} \le F_i{}^k \end{cases} \tag{21}$$

The normalized membership value is computed using the following mathematical expression. This formulation ensures that each criterion within the fuzzy decision-making framework is scaled appropriately, allowing for consistent evaluation across multiple objectives:

$$\mu^k = \frac{\sum_{i=1}^{NO} \mu_i{}^k}{\sum_{k=1}^{NK} \sum_{i=1}^{NO} \mu_i{}^k} \tag{22}$$

The final solution is determined by identifying the particle with the highest membership value, denoted as μ_k . This value reflects the degree of optimality across the defined fuzzy criteria. Among the Pareto-optimal set, the solution corresponding to the maximum μ_k is selected as the most balanced and effective outcome. The graphical representation of the best solution within the Pareto front is illustrated in Fig3.

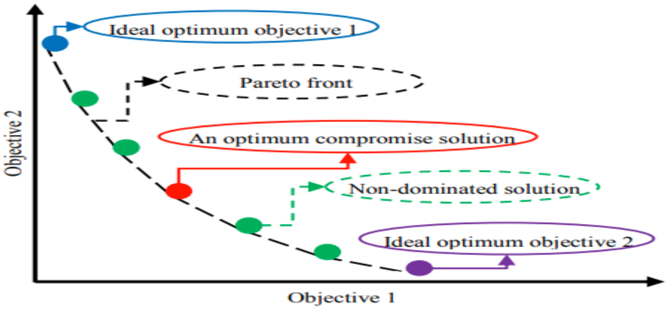

Fig 3 Optimal compromise solution from fuzzy membership functions

The optimization of technical performance indicators namely, the power loss index and voltage stability index is achieved by strategically determining the placement and sizing of Distributed Generation (DG) units. This process leverages the combined strengths of the Non-Dominated Sorting Firefly Algorithm (NSFA) and fuzzy logic-based decision-making, as illustrated in Fig. 4.

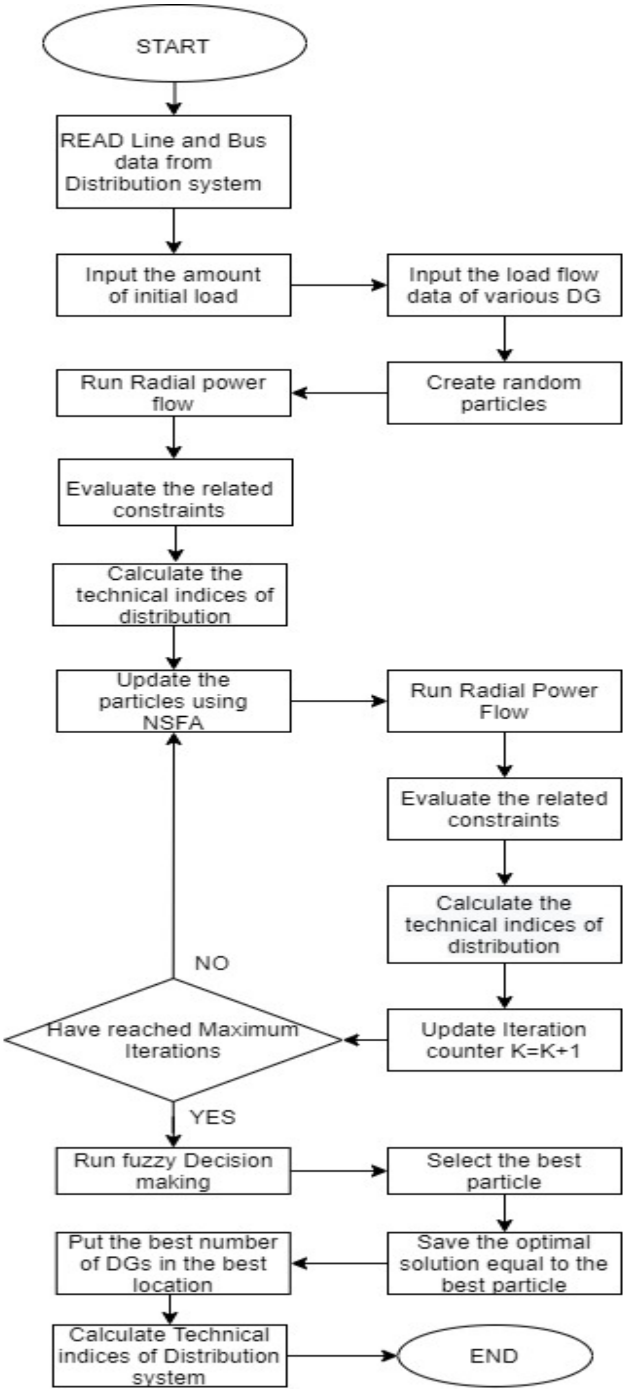

Fig 4 Flowchart to find optimal location and capacity of DGs

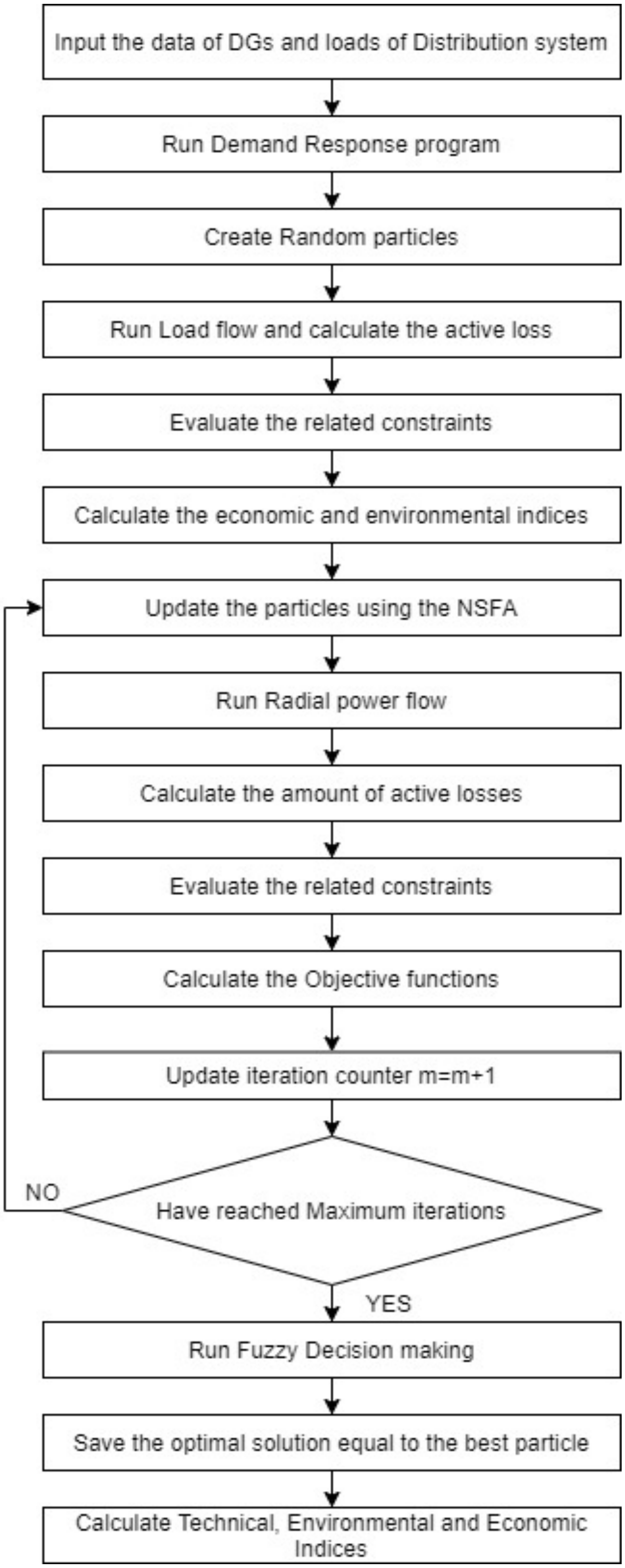

Fig 5 Flowchart to find optimal schedule for the DSM

Similarly, environmental and economic indices are enhanced through the same hybrid optimization framework, ensuring a balanced trade-off among multiple objectives. Demand Side Management (DSM) strategies are implemented for the distribution network under two scenarios: with and without Demand Response (DR) participation. The procedural flow for identifying the optimal scheduling configuration is depicted in the flowchart presented in Fig. 5

V. SIMULATION SETUP & RESULTS

The proposed hybrid optimization framework is implemented on the IEEE 33-bus distribution system. Within this setup, approximately 40% of consumers actively participate in the Demand Response (DR) program, contributing to dynamic load management. The operational boundaries for Distributed Generation (DG) units are defined with a maximum capacity of 4000 kW and a minimum threshold of 100 kW. Each newly integrated DG unit is introduced at the minimum capacity level, serving as the incremental step size for capacity expansion. The temporal variation in system load over a 24 hour Period is illustrated in Fig 6.

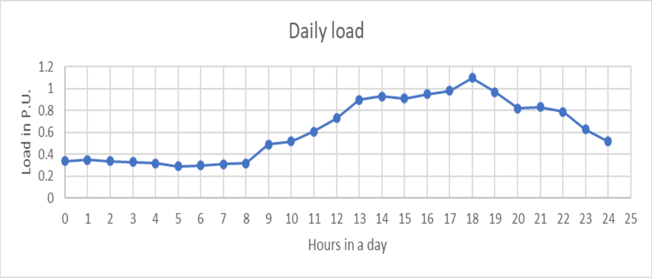

Fig 6 Daily Load graph of Distribution system

The temporal generation profiles of photovoltaic (PV) and wind turbine (WT) systems are illustrated in Fig. 7. This figure presents the hourly variation in output across a 24-hour period, reflecting the stochastic nature of renewable energy sources and their contribution to the overall energy mix within the distribution network.:

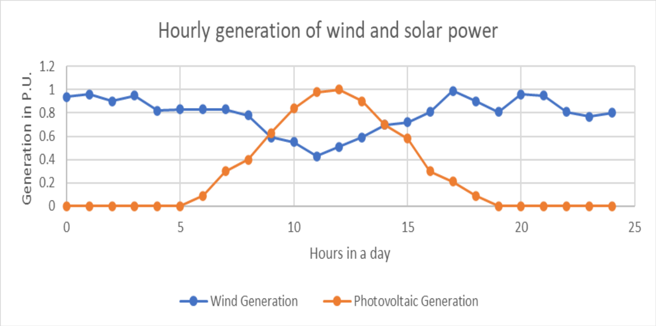

Fig 7 Power Generation of PV and WT per hour

The State of Charge (SOC) for battery energy storage systems is constrained between a minimum of 10% and a maximum of 100%, ensuring safe and efficient operation throughout the scheduling horizon. Table I presents a comprehensive summary of the economic and environmental performance metrics associated with each Distributed Generation (DG) unit. These indices serve as critical parameters for evaluating the sustainability and cost-effectiveness of the proposed configuration.

Table 1 Economic information of all sources

Sl no	DG Type	Power Cost ($/kwh)	Stat-up and shut down cost
1	DIG	1.172	0.35
2	PV	5.168	0
3	WT	2.146	0
4	MT	0.914	1.92

The real time market price in distribution network is shown in Fig 8.

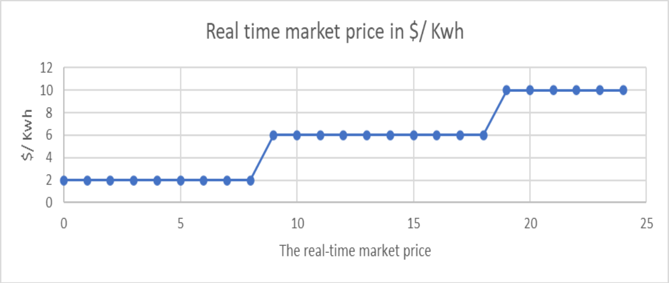

Fig 8 Real time Market Price

IEEE 33 Bus System

The hybrid optimization algorithm is applied to the IEEE 33-bus radial distribution system to evaluate its performance under realistic operating conditions. The structural layout and connectivity of the network are depicted in the single-line diagram presented in **Fig. 9**, which serves as a reference for system topology and node configuration.

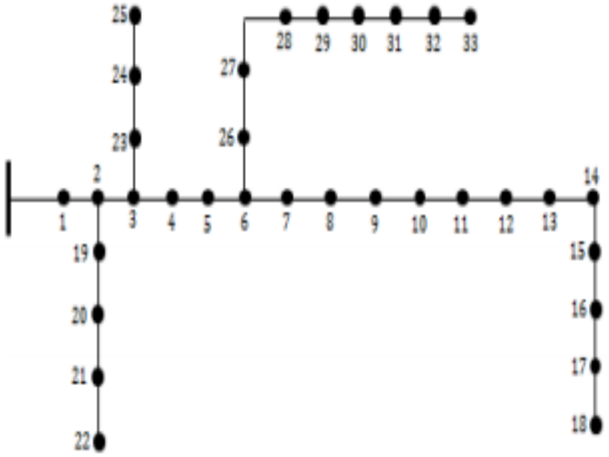

Fig 9 Single line diagram of IEEE 33 bus system

At the initial stage of the optimization process, the proposed hybrid algorithm identifies the most suitable locations and corresponding capacities for the integration of Distributed Generation (DG) units within the IEEE 33-bus system. These optimized parameters are derived to enhance system performance across technical, economic, and environmental dimensions. Table II presents the finalized configuration, detailing the optimal placement and sizing of each DG unit as determined by the algorithm.

TABLE II Optimum Location and capacity of DGs in IEEE 33 bus system

Sl no	DG Type	Location (bus)	Capacity (MW)
1	DIG	30	1.7
2	PV	28	0.9
3	WT	06	1.2

To evaluate the impact of Distributed Generation (DG) integration, key technical performance indicators such as power loss and voltage profile are assessed both prior to and following the placement of DG units within the IEEE 33-bus distribution system. Table 3 presents a comparative analysis of these indices, highlighting the improvements achieved through optimal DG allocation as determined by the proposed hybrid algorithm.

TABLE III Technical Indices of 33 Bus System

Sl no	Indices	Before placement of DGs	After placement of DGs
1	Active power Loss (MW)	0.2025	0.0250
2	Reactive power Loss (MW)	0.1351	0.0189
3	Voltage Profile (Pu)	0.91301 (bus 18)	0.9861 (33)

The comparative analysis presented in the preceding tables confirms that strategic placement of Distributed Generation (DG) units within the IEEE 33-bus system significantly enhances network performance. Notable improvements include reductions in both real and reactive power losses, as well as enhancements in voltage stability across the distribution network .

Following the determination of optimal DG locations and capacities, the proposed hybrid algorithm was employed to perform energy source scheduling. The resulting optimal schedule executed without incorporating Demand Response (DR) mechanisms is illustrated in Fig. 10, showcasing the coordinated dispatch of available resources under baseline operating conditions in Table IV.

TABLE IV Scheduling of Energy Sources without Demand Response

Hrs	DIG	MT	PV	WT	ESS	Grid
1	0	1.101765	0	0	0.19804748	0
2	0.0095025	0.916314	0	0.019033508	0.25686413	0
3	0	1.038345	0	0	0.10872167	0
4	0	1.1055	0	0	-0.0840837	0
5	0	0.54579	0	0	0.44778232	0
6	0.0021	1.1055	0	0	-0.0861805	0
7	0	0.69867	0	0	0.5242125	0
8	0.43134	1.45137	0	0.69277761	-0.0963503	0
9	0.30723	1.46223	0	0.61538169	0.5242125	0
10	0.83853	1.352565	0.5678505	0.494871195	-0.0539939	0
11	1.0330425	1.3526625	0.6087568	0.395917988	0.5242125	0
12	1.610175	1.350675	0.6204293	0.491085525	-0.0863902	0.12829215
13	1.39251	1.570275	0.2208308	0.831795825	0.37952985	0.03154725
14	1.762425	1.502925	0.4143206	0.796042275	0.01803291	0.07781655
15	1.6527525	1.4514675	0.3470198	0.593824403	0.44925011	0
16	1.71087	1.45137	0.1892835	0.69277761	-0.022646	0.3154725
17	1.3256775	1.5728475	0.126189	0.836948543	0.49317912	0
18	1.752975	1.493475	0.0315473	0.777113925	-0.0409934	0.078868125
19	1.163295	1.52775	0.4784666	0.74661825	0.33864128	0.00210315
20	1.760325	1.500825	0	0.791835975	0.13126281	0
21	1.5700125	1.5404025	0	0.771961208	0.33119746	0
22	1.416135	1.44906	0	0.68815068	0.13440809	0.009989963
23	0.9056775	1.4712075	0	0.633363623	0.29974471	0
24	0.335265	1.440765	0	0.671535795	0.1628204	0

In the evaluated scenario, non-renewable energy sources contribute approximately two-thirds of the total system demand, while the remaining one-third is supplied by renewable sources. Among the renewables, wind turbines (WT) generate twice the energy output compared to photovoltaic (PV) systems, reflecting their dominant role in the renewable mix. The utility grid functions as a backup supply, ensuring demand fulfillment in cases where Distributed Generation (DG) units fall short.

The implementation of the proposed scheduling algorithm leads to a notable reduction in operational costs, system losses, and pollutant emissions, thereby enhancing the overall efficiency and sustainability of the distribution network.

Table V presents the technical, environmental, and economic performance metrics under the scenario without Demand Response (DR), serving as a benchmark for further comparative analysis

TABLE V Technical and Economic indices of IEEE 33 Bus system without Demand Response

Hrs	PLI	QLI	VPI	OCI
1	0.070015	0.046607	0.0396055	22.83534
2	0.0644765	0.0429495	0.036366	21.923055
3	0.05225	0.0347985	0.029469	19.791255
4	0.05643	0.03762	0.031768	20.552015
5	0.048279	0.032186	0.02717	19.030495
6	0.0467115	0.031141	0.0262295	18.727445
7	0.0467115	0.031141	0.0262295	18.727445
8	0.0444125	0.0295735	0.0249755	18.269735
9	0.070015	0.046607	0.0396055	22.83534
10	0.1081575	0.0720005	0.0613415	28.16484
11	0.090706	0.060401	0.051414	25.88256
12	0.114323	0.0761805	0.0648945	28.9256
13	0.155496	0.103664	0.0885115	33.491205
14	0.1206975	0.0803605	0.068552	29.687405
15	0.1409705	0.0939455	0.0801515	31.969685
16	0.133969	0.0893475	0.0761805	31.020825
17	0.1081575	0.0720005	0.0613415	28.16484
18	0.133969	0.0893475	0.0761805	31.208925
19	0.1480765	0.0987525	0.084227	32.730445
20	0.090706	0.060401	0.051414	25.88256
21	0.090706	0.060401	0.051414	25.88256
22	0.096349	0.064163	0.054549	26.64332
23	0.096349	0.064163	0.054549	26.64332
24	0.1081575	0.0720005	0.0613415	28.16484

In the enhanced scenario, Demand Response (DR) is incorporated into the Demand Side Management (DSM) strategy to further improve system flexibility and operational efficiency. The scheduling framework now includes Distributed Generation (DG) units from various sources, integrated with Energy Storage Systems (ESS) and supported by the utility grid. This coordinated scheduling ensures optimal resource utilization while maintaining system reliability under dynamic load conditions.

Table VI presents the optimized dispatch schedule of energy sources, reflecting the combined influence of DR, ESS, and grid support within the distribution network.

TABLE VI Scheduling of Energy Sources with Demand Response

Hrs	DIG	MT	PV	WT	ESS	Grid
1	0	1.14912	0	0.713493638	0.4321608	0
2	0.212415	1.155	0	0.801615623	0.0349126	0
3	0	1.155	0	0.69572202	0.1387066	0
4	0.000525	1.155	0	0.639988545	0.2700743	0
5	0.15729	1.155	0	0.69277761	-0.1235045	0.0317673
6	0	1.155	0	0.202007558	0.5242125	0
7	0.072345	1.155	0	0.702662415	-0.0561956	0.0090165
8	0	1.139985	0	0.170986095	0.5242125	0
9	0.405405	1.35975	0.4101143	0.643353585	-0.1129154	0
10	0.372435	1.4385	0.5678505	0.494871195	0.5242125	0
11	0.77175	1.28919	0.3575355	0.709813125	-0.1866197	0.0178232
12	0.462	1.47	0.630945	0.445342013	0.5242125	0.0047179
13	1.310925	1.42212	0.6193777	0.6519765	-0.0723413	0.0534697
14	0.501795	1.3755	0.4416615	0.574054793	0.5242125	0.0074438
15	1.3730325	1.3027875	0.2960184	0.593824403	-0.0564053	0
16	0.669585	1.2495	0.1892835	0.69277761	0.5242125	0
17	0.885885	1.218	0.126189	0.84126	-0.1171091	0.0034598
18	0.67914	1.17075	0.0315473	0.762076403	0.5242125	0
19	1.05	1.3314	0.5930883	0.793939125	-0.0870193	0.2014024
20	0.12999	1.155	0	0.791835975	0.5242125	0
21	1.17915	1.08024	0	0.74241195	-0.4078373	0.0083874
22	0.30534	1.155	0	0.69277761	0.5242125	0
23	0.943005	1.155	0	0.633363623	-0.0544133	0.0011533
24	0.55671	1.155	0	0.673008	0.4455806	0

Under the integrated Demand Response (DR) scenario, the distribution network exhibits further improvements across technical, environmental, and economic dimensions. The inclusion of DR enhances load flexibility, reduces peak demand, and enables more efficient utilization of distributed energy resources and storage systems.

Table VII summarizes the key performance indices achieved with DR implementation, highlighting reductions in power losses, operational costs, and pollutant emissions compared to the baseline scenario

TABLE VII Technical and Economic indices of IEEE 33 Bus system with Demand Response

Hour	PLI	QLI	VPI	OCI
1	0.027604	0.0183752	0.0124918	5.62689
2	0.0254204	0.0169332	0.0114701	5.4020925
3	0.0206	0.0137196	0.0092947	4.8767925
4	0.022248	0.014832	0.0100198	5.0642525

5	0.0190344	0.0126896	0.0085696	4.6893325
6	0.0184164	0.0122776	0.008273	4.6146575
7	0.0184164	0.0122776	0.008273	4.6146575
8	0.01751	0.0116596	0.0078774	4.5018725
9	0.027604	0.0183752	0.0124918	5.62689
10	0.042642	0.0283868	0.0193475	6.94014
11	0.0357616	0.0238136	0.0162163	6.37776
12	0.0450728	0.0300348	0.0204682	7.1276
13	0.0613056	0.0408704	0.0279171	8.2526175
14	0.047586	0.0316828	0.0216218	7.3153175
15	0.0555788	0.0370388	0.0252803	7.8776975
16	0.0528184	0.035226	0.0240278	7.6438875
17	0.042642	0.0283868	0.0193475	6.94014
18	0.0528184	0.035226	0.0240278	7.6902375
19	0.0583804	0.038934	0.0265658	8.0651575
20	0.0357616	0.0238136	0.0162163	6.37776
21	0.0357616	0.0238136	0.0162163	6.37776
22	0.0379864	0.0252968	0.0172051	6.56522
23	0.0379864	0.0252968	0.0172051	6.56522
24	0.042642	0.0283868	0.0193475	6.94014

The results presented in the preceding table clearly demonstrate that the implementation of Demand Side Management (DSM) in conjunction with Demand Response (DR) yields significant improvements across technical, environmental, and economic indices when compared to scenarios without DR integration.

The impact of DR on load dynamics is further illustrated in Fig. 10, which depicts the modified load variation profile of the IEEE 33-bus distribution system following the incorporation of the DR program. This graph highlights the enhanced load flexibility and peak shaving achieved through active consumer participation.

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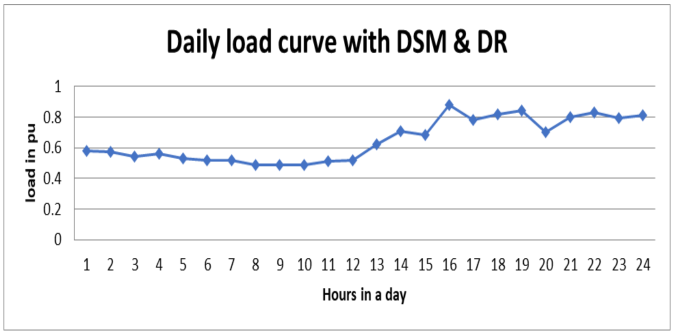

Fig 10 Load variation of IEEE 33 bus system with DR response

VI. CONCLUSION

The optimal sizing and placement of Distributed Generation (DG) units within the distribution network were determined based on the minimization of real and reactive power losses and the enhancement of voltage profiles. To ensure environmentally sustainable and economically efficient operation, the daily performance of multiple DG units and grid parameters was optimized under both Demand Response (DR)-inclusive and DR-excluded scenarios. A hybrid optimization framework was developed, integrating the Non-Dominated Sorting Firefly Algorithm (NSFA) for multi-objective function optimization with a fuzzy logic-based decision-making system to select the most suitable solution from the Pareto-optimal set. This methodology was validated on the IEEE 33-bus radial distribution system.

Within the tested network, DG units powered by non-renewable sources contributed to system stability, while renewable-based DGs significantly improved environmental performance indices. The overall efficiency of the distribution system was further enhanced through the implementation of a DR program, which actively engaged consumers in load modulation and demand shaping.

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