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Original Article

An Optimistic Approach with a Distribution Generator for Demand-Side Resource Management Considering a Deregulated Electricity Market

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Abstract *- Distribution Generator (DG) technology mainly uses solar photovoltaics and wind turbines, popular for reducing greenhouse gas emissions. Connecting renewable-based distributed generators offers technical and environmental benefits, leading to their increased adoption over time. Higher penetration of distributed resources negatively affects the distribution system's performance. This makes demand-side management more complex as renewable-based DGs provide variable electricity generation depending on the state of the environment. The excess generation of electricity from DGs causes a harmful impact on the entire system's performance. Therefore, it is necessary to curtail the generation under light loading conditions. The proposed strategy presents an energy management system under a deregulated electricity market for the optimal operation of renewable-based DGs. A Genetic Algorithm (GA) is used to satisfy multiple technical and economic criteria by reducing the weighted objectives to identify the optimal solution to the problem statement. This analysis incorporates the hourly variations in the generation of all four types of renewable (DG) based on environmental data for a single day. The results show good power loss reduction and voltage profile improvement, yielding 50% RE penetration. It has been tested on an IEEE-33 bus standard distribution network with three different load profiles and has shown satisfactory results. Results indicate that considerable line loss reduction and voltage profile improvement have been achieved in each hour due to the energy curtailment of various DG models. The proposed methodology curtails the generation based on each DG's impact on the network performance. Comparative results demonstrate that PV-based SG1 and wind-based WG3 models operate at full capacity throughout the day, while PV-based SG3 and wind-based WG4 operate at their optimal capacity based on the proposed MOF.*

Keywords *- Deregulated electricity market, Distributed Generation, Genetic algorithm, IEEE-33.*

1. Introduction

This Electric energy demands keep increasing day by day. This is due to the increasing population, rising household incomes, industrialization, demand for digitally connected devices, and increasing electric devices in homes and offices. Global electricity demand is expected to rise at a faster rate over the next three years. By 2026, the demand is expected to increase by 3.4% annually. This leads to the depletion of natural resources like fossil fuels and has major impacts on several environmental factors. DG is the most reliable method to tackle the increasing demands by not placing much pressure on the environment. DG produces electricity from several coupled small energy sources. Distributed resources typically supply active and reactive power to the power distribution system via connections located in proximity to the load center. The utilization of DG technology, which primarily integrates solar PV and wind turbines, has gained popularity as a means of reducing greenhouse gas emissions [1], [2]. The restructuring of power systems and advancements in technology have led to a greater focus on DG as an alternate source of electric power that is connected near the load end in order to fulfill the increasing demand.

In addition to alleviating congestion on the current transmission line, establishing additional infrastructure to accommodate increasing demand contributes to revenue savings and facilitates congestion reduction. Currently, the implementation of DG lacks centralized planning and dispatch [3], [4]. Consequently, the integration of DG into the grid presents novel challenges and issues for network operators. These challenges and issues can greatly affect the reliability, power quality, efficiency of the distribution grid, and safety of both customers and electricity suppliers [5]. The distribution network's placement of these distributed resources alters the flow of lines and primarily affects network performance parameters such as network losses and voltage profile.

Network losses and power quality are significantly impacted by the locations and size of these distributed resources [6], [7]. The location and size of renewable-based DGs across distribution networks play a vital role in network performance and power quality. Improper siting and sizing of DGs increase losses and a poor network voltage profile. Optimal sizing and siting problems have been addressed to maximise the benefits received due to DG deployment. Different methodologies based on analytical and heuristic approaches have been used for optimal solutions with various technical and economic objectives and other system considerations. However, the fixed capacity of renewable-based DGs has a stochastic/uncertain generation profile based on environmental conditions.

On the other hand, the network load profile is also an uncertain and variable parameter. According to these facts, the optimal solution may substantially increase the active loss to the network and result in an unacceptable poor voltage profile due to excess generation and light loading conditions. Past research suggested the optimal size and site of DGs across the network. However, supportive government policies encouraging Renewable Energy (RE) based generation attract more private players for investment, further increasing the penetration level across the network and making demand-side management more complex. Renewable-based DG can promptly meet grid demands.

However, its generation is sporadic and contingent upon the availability of solar-wind resources throughout the given time. Given the intermittent and unpredictable characteristics of renewable energy output, it is imperative to ensure the availability of sufficient thermal power generation to effectively address the issue of grid stability. Prior research indicates the necessity of reducing generation and its influence on the stability of the power grid and the performance of the network. Generation curtailment arises from technical factors, resulting in energy loss and eventual revenue loss for the owner of the DG. There is a need to modify the ideal approach for generation curtailment to enhance network performance and mitigate energy losses resulting from curtailment in the deregulated energy market.

The energy price is a variable that is influenced by both demand and generation mismatch. It should balance the interests of the network operator and the owner of the DG, where the utility energy price is constantly tracked to minimize the economic loss from curtailment from the owner's perspective. It is imperative to investigate the performance-based approach of an energy market and network to provide a rationale for the curtailment that aligns the interests of both the network operator and the owner of distributed generation (DG). Various research studies have been conducted in the past. [8] conducted the research based on differential evolution, keeping the load model constant. The main objective is to conserve costs, but uncertainty is not considered. Mahmoud et al. (2015) [9] used a 6-bus system, keeping the load model constant. The main objective was to preserve the power loss. However, even with this method, uncertainty is not considered. Parvaneh (2021) [10] used a 33/69 bus system, keeping the load model constant.

However, even in his method, uncertainty is not considered. To overcome the problems in the above methods, the present analysis has taken into account the IEEE-33 bus standard distribution network. This standard distribution network has numerous advantages, such as voltage profile improvement, reduction of power loss, security improvement, system reliability, and feeder overloading alleviation. The present study aims to provide an optimal energy management strategy for a distribution network that incorporates an adequate amount of renewable-based resources. This approach is intended to enhance the efficiency of the network's operations, particularly in the face of variable loading scenarios.

2. Literature Review

The bus voltage in a conventional unidirectional distribution network is lower than the source voltage. Nevertheless, as a result of the increased adoption of distributed generators (DGs), there is a reversal in power flow during periods of low demand. This leads to a situation where the bus voltage exceeds the source voltage, hence exacerbating the degradation of power quality at the load end [11]. In an extremely penetrated distribution network, the voltage exhibits an inverse relationship with the level of penetration. Active power loss is observed in various line sections and reaches its minimum when the power is supplied by distributed generators.

DGs is equivalent to the power consumed by the various loads. The network experienced a subsequent rise in penetration, leading to the occurrence of reverse power flow and a progressive escalation in system losses. The utilization of DG technology, which primarily integrates solar PV and wind turbines, has gained popularity [1], [2]. Aman et al. (2012b, 2012a) [12], [13] propose an algorithm for DG placement and sizing. This was based on a novel index. Stable node voltages, referred to as PSI, are used for developing the novel index. In this analytical approach has been proposed to verify the impact of DG on performance, power quality and stability of network.

The 12-bus, modified 12-bus and 69-bus radial distribution networks are used to test the proposed algorithm. The test results are in close agreement with the Golden Section Search (GSS) algorithm. To provide the necessary active and reactive power support, [4] presented a method for optimal location and sizing of DG and capacitor in the distribution network. This is done to reduce the system's real and reactive power loss. The Weight-Improved Particle Swarm Optimization Algorithm (WIPSO) is proposed in the paper.

Table 1. Units for Magnetic Properties

Reference	Test System	Method	Load Model		DG Model	Objectives	Consideration of Uncertainty
[8]	2 Bus	Differential Evolution	PQ	Constant	P	Single Cost	×
[18]	13 Bus	Cuckoo Search	PQ	Constant	P	Multi P_{loss}, Cost, $V_{profile}$	×
[19]	15/33/69 Bus	Dragonfly algorithm	PQ	Constant	PQ	Single P_{loss}	×
[9]	33/69 Bus	EA-OPF	PQ	Constant	PQ	Single P_{loss}	×
[20]	13 Bus	Analytical	P	Constant	P	Single $V_{profile}$	√
[21]	12 Bus	GA	P	Time Varying	P	Single P_{loss}	√
[10]	33/69 Bus	MSSA	P	Constant	P	Single P_{loss}	×
[22]	34/69 Bus	PSO	P	Costant	P	Multi Cost, $V_{stability}$	×

This helps in the preferred sizing and siting of compensating devices. The cost of service provided by the local devices is also tried to be minimized in the paper. The strategic deployment of DG at the recommended penetration level yields favourable outcomes for the network. However, when the penetration level escalates, it exerts adverse effects on the low-voltage distribution grid [14-16]. Kenneth and Folly (2014) stated that the operation of on-load tap changers (OLTC) and automatic voltage regulation are affected by the negative impact of high photovoltaic (PV) penetration [14]. Hence, to curtail the voltage rise issues, communication with PV and voltage control devices is needed.

The paper studies the issue of reverse power flow resulting from high PV penetration and a sudden voltage rise on the LV grid. It also suggests the need for a smarter grid. Miller (2016) [15] presented a case study where he investigated possible maximum limits of solar PV penetration and measured them to alleviate overvoltage problems. Minor overvoltage problems, particularly in urban areas, can be expected in the future. However, the voltage should not be higher than the limit of 1.06 p.u. Given the intermittent and unpredictable characteristics of renewable energy output, it is imperative to ensure the availability of sufficient thermal power generation to effectively address the issue of grid stability [17].

Under conditions of low load, thermal generation operates at its minimum operating limitations. This is because the grid contains a significant proportion of renewable-based output, resulting in a higher penetration level. This higher penetration level has the potential to decrease the energy price (specifically, the unit price of electricity) in a deregulated power system. Nevertheless, under conditions of low load, the surplus generation from renewable sources has a detrimental impact on the power quality and performance of the distribution grid. Consequently, it is imperative to reduce the generation of renewable resources to consistently uphold voltage quality and network performance. Another potential factor contributing to curtailment could be concerns related to system balancing. Wind energy is typically more abundant during nighttime hours when energy demands are low and thermal units are operating at their lowest efficiency. The extent of this curtailment can be diminished gradually by either replacing thermal plants or decreasing the minimum operational restriction [17].

In certain instances, restrictions may be implemented on the amounts of nonsynchronous generation, particularly on small and isolated grids, to preserve frequency control and mitigate system stability concerns. Modern wind and solar generators are connected to the grid using power electronics. Synchronous generators provide characteristics such as inertia and, in certain cases, governor reaction. The frequency responsiveness of a system may be affected if a contingency event occurs during a period of high penetration of nonsynchronous generation, as nonsynchronous generators may be unable to offer synthetic inertia and rapid frequency corrections. In addition, thermal generating offers a rapid service to the power grid for real-time operation reserve. Table 1 shows past research work that deals with optimal planning for demand-side management, considering various renewable-type resources.

Mahmoud et al. (2015) [9] used a 6-bus system, keeping the load model constant. The main objective was to preserve the power loss. However, even with this method, uncertainty is not considered. Ogunjuyigbe et al. (2016) [8] conducted the research based on differential evolution, keeping the load model constant. The main objective is to conserve costs, but uncertainty is not considered. The computation tool used was the intersected mutation differential evolution. Keeping the load model constant, he used the simple DGs and Super Capacitors (SC). The main disadvantage of the system is local minima trapping and unstable convergence. Nadeem Khan et al. (2018) [7] suggested that since a constant-load and generation-model is generally incorporated in studies related to DG, the voltage profile, deferral values, loss reduction, and other related calculations may result in misleading and inconsistent values. So, he investigates the impact of time-varying voltage-dependent load models while planning the DG location planning. He conducted research based on the comparative assessment of different impact indices, active and reactive power loss, penetration level, Mega Volt Ampere support, and active and reactive power intake offered by the installation of photovoltaic-based DG. This is done by time-varying load models. The outcomes revealed that the time-varying load modelling approach has an impact on the DTR.

Suresh and Belwin (2018) [19] used the 15/33/69 bus system. Since he used a combination of three bus systems, a more extensive algorithm is needed. So, he utilized the dragonfly algorithm. This needed more computational time as well as a more efficient networking style. Load modelling is kept constant. A single power loss objective is considered. 13 bus systems were used in this method. An analytic approach was made. Voltage profile was the single objective considered [20]. Saric et al. (2018) [21] used the Genetic algorithm for the analysis. Generally, genetic algorithms produce good results, but with assumptions of many priors. He used the 12-bus standard. The load modelling was done with varying time factors. Power loss consideration was the one single objective. Uncertainty was considered in this case. Aranizadeh et al. (2019) [18] used the 13-bus system.

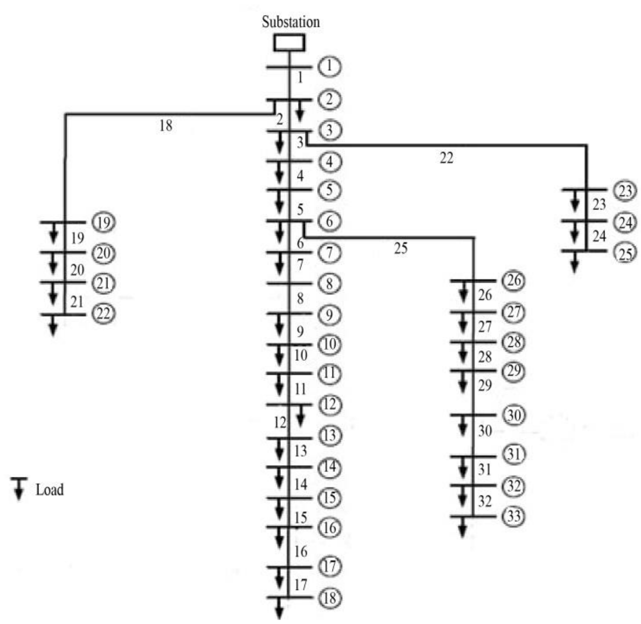

Fig. 1 Network topology of IEEE-33 bus network

This bus system is easy to use but not very reliable for high-load markets. The method used here is the cuckoo search algorithm, and the load model is kept constant. Multiple objectives were used, like power loss, cost, and voltage profile. Uncertain issues were not considered. Ahmed (2020) [4] has used the swarm algorithm to face the electric demand. Multiple objectives, such as voltage deviation, power losses, and voltage stability, were considered. Wind DGs were used with time-varying load models. Local minimum trapping for large systems was the major disadvantage of the system. The 33 and 69 bus systems were used. Parihar and Malik (2020) [22] used the 34/69 bus standard. Keeping the load model constant. Here, he considered multiple objectives like cost and voltage stability. [10] used a 33/69 bus system, keeping the load model constant. However, even in his method, uncertainty is not considered.

3. Methodology

To keep a better voltage profile and reduce line losses, managing the generation of DGs based on renewable energy is crucial. Nevertheless, renewable-based (DGs) introduce variable power generation dependent on the prevailing environmental conditions, hence challenging demand-side management. Given the favourable conditions for renewable energy production, DG plays a crucial role in satisfying the increasing demand. Thus, it is very important to take into account the increasing demand and design a network that can satisfy the needs. The present analysis has taken into account the IEEE-33 bus standard distribution network. The network topology of the IEEE-33 bus network is shown in Figure 1. This system consists of 32 lines and 33 buses and has a load size of 3.715MW and 2.3MVar, with a voltage of 12.66kV. The size of the DG unit is 30% of the total load. The lower voltage is 0. 95p.u, and the upper voltage in the system is set as 1.05p.u.

Figure 2 shows how network losses increase with higher penetration of RE resources under light loading conditions. Higher penetration also results in the number of buses exceeding the rated voltage limit during a lower demand condition, which is caused by the significant reverse power flow from the load side to the source side. The necessity of generation curtailment to maintain consistent network performance in real-time has been demonstrated in Figure 2.

The present study aims to provide an optimal energy management strategy for a distribution network that incorporates an adequate number of renewable-based resources. This approach is intended to enhance the efficiency of the network's operations, particularly in the face of variable loading scenarios. Based on an analysis of voltage stability [12, 13], four potential locations for the placement of renewable energy (RE) based distributed generators (DGs) have been identified. The evaluation of voltage stability analysis was conducted and shown in Equation (1) to identify the weaker buses within the network. Considering probable future load growth, weak buses that are more vulnerable to voltage collapse are identified using the VSI values of network sections and the buses that follow them.

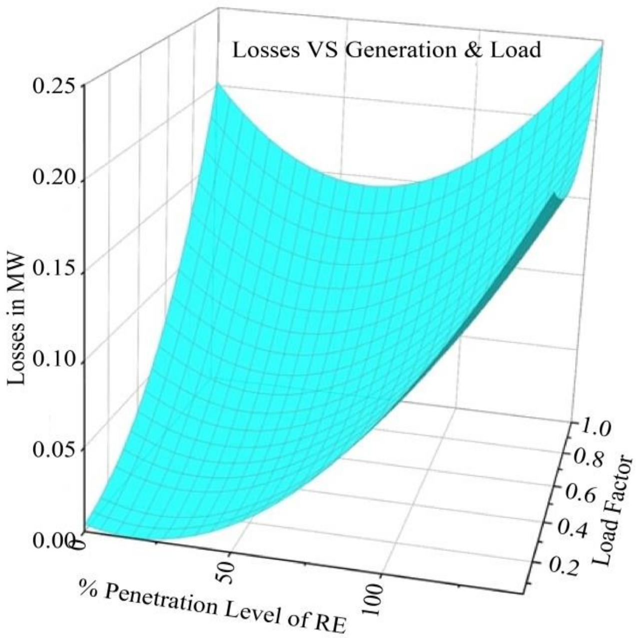

Fig. 2 3D curve shows variation of losses at different RE penetration and LF

$$VSI_{ij} = \frac{4r_{ij}(P_l - P_g)}{[|V_i|\, \boldsymbol{cos}(\theta-\delta)]^2} \leq 1 \quad (1)$$

Figure 3 shows a 3D curve variation of network voltage deviation at different RE penetrations and LF. The results are analysis. The proposed strategy considers hourly variable electricity units. Hourly variations of demand and environmental parameters are shown in Figure 4. Figure 5 shows VSI values of different sections of the IEEE-33 network.

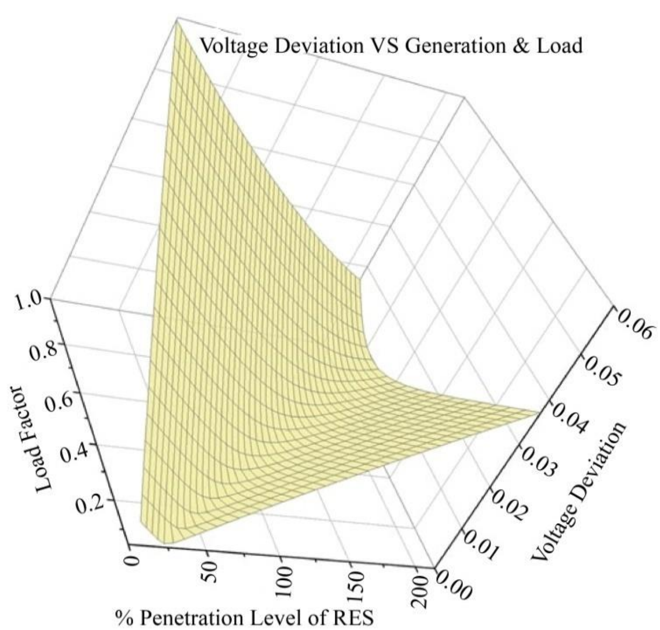

Fig. 3 3D curve shows variation of network voltage deviation at different RE penetration and L

3.1. Modelling of PV and Wind-Based Distributed Generators

The study incorporates the aggregate installed capacities of solar and wind-distributed generators (DGs) at a penetration level of 50% relative to the load of the IEEE-33 bus system. The proposed analysis includes the consideration of four distributed generators (DGs) located at different sites. Specifically, two of these DGs are of the Solar-PV type, while the remaining two are of the Wind kind. The identification of all four locations has been conducted through the sensitivity analysis. Table 2 presents the installed capacity of DG (Distributed Generation) and the corresponding bus location numbers that have been taken into account for the analysis provided. The real-time performance of these distributed generation systems that rely on renewable sources is dependent upon a range of environmental factors. A suitable mathematical model. The computation of the hourly variable output of these distributed generators has become a crucial necessity, contingent upon the diverse environmental elements. Researchers have utilized several methodologies to model the Solar-PV and WIND types of Distributed Generators (DGs) in grid-connected distribution networks. Both deterministic and probabilistic approaches can be used to model the performance of individual distributed generation (DG) systems. Solar radiation serves as the main energy source for PV-type DGs, and the amount of effective solar radiation that falls globally onto the PV module's slanted surface has been estimated by,

$$g_T = g_B * r_B + g_D * r_D + (g_B + g_D) * r_R \quad (2)$$

Where g_B and g_D are direct and diffuse solar radiation; r_D and $* r_R$ are the tilted coefficients for diffused and reflected solar radiations. The power output of the PV type of DG can be computed based on total solar radiation and surrounding temperature at the i[th] hour slot.

$$P_{ALS_i} = g_i * n_c * A_m * \frac{\gamma_{mp,ref}}{100}(t_i - 25) \quad (3)$$

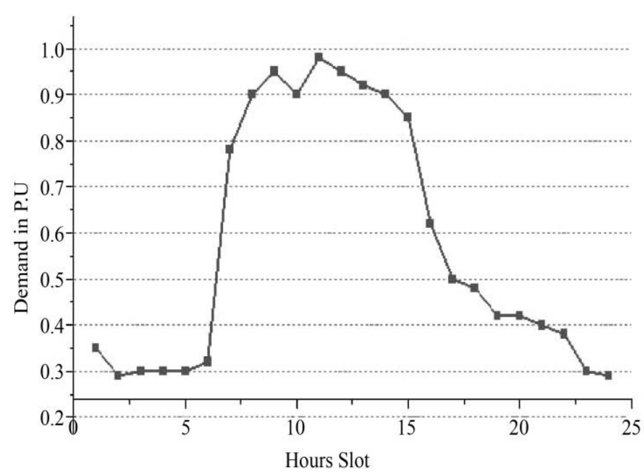

Fig. 4 Hourly variations of demand and environmental parameters for one day

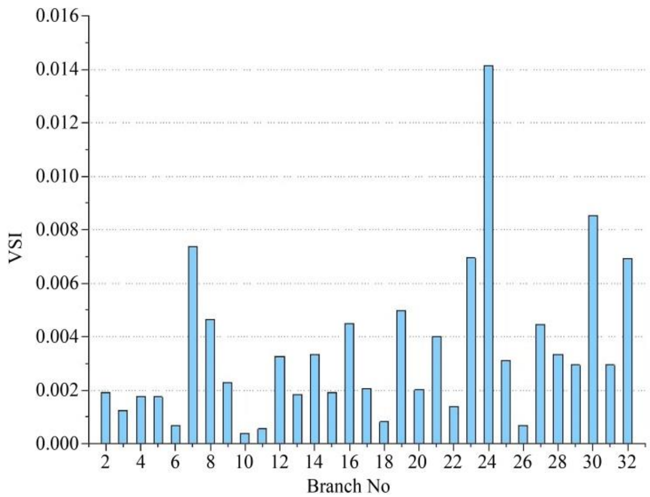

Fig. 5 VSI values of different sections of the IEEE-33 network

Where P_{als_i} is the module conversion efficiency, A_m is the PV module area in m^2, total available radiation at the jth hour shown by g_i, maximum power temperature co-officiant. Following the wind speed availability at the site, the power production from wind-type DG has been calculated. The following is the computation of the hourly power output from wind-type DG.

Table 2. Consideration of the location and size of different DG Models

Sr No	Type of DG-Model	Capacity in MW	Location
1	Solar G-1	0.350	8
2	Solar G-2	0.350	24
3	Wind G-3	0.350	25
4	Wind G-4	0.350	31
Total		1.4	

$$P_{ALW_j} = 0, \quad [V < V_{Ci}] \tag{4}$$

$$P_{ALW_j} = bv^3 - dP_r, \quad [V_{Ci} < V < V_r] \tag{5}$$

$$P_{ALW_j} = bv^3 - dP_r, \quad [V_{Ci} < V < V_r] \tag{6}$$

$$P_{ALW_j} = P_r, \quad [V_r < V < V_{co}] \tag{7}$$

$$P_{ALW_j} = 0, \quad [V > V_{co}] \tag{8}$$

Where Pr is the DG's rated power, VCI, Vr, and VCO are the wind turbine's cut-in, rated, and cut-out speeds, respectively. PALWj is the wind type DG's available power output during the jth hour. The wind turbine's actual power output is provided by Equation (5). The available generation of different DG models, namely G1, G2, G3, and G4, has been computed using time-series datasets collected from the National Renewable Energy Laboratory (NREL) resource dataset.

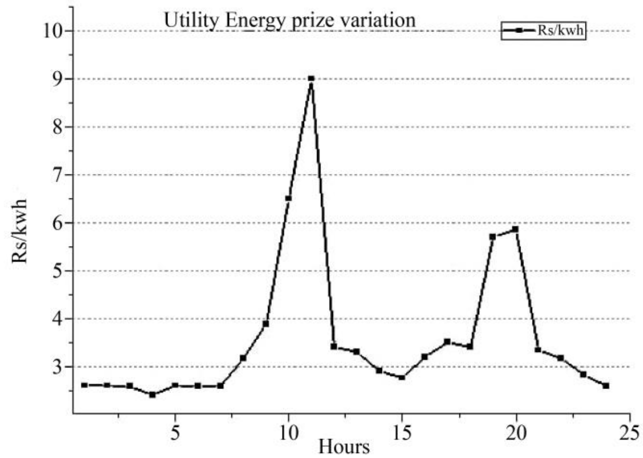

Fig. 6 Hourly variation of energy unit price for one day

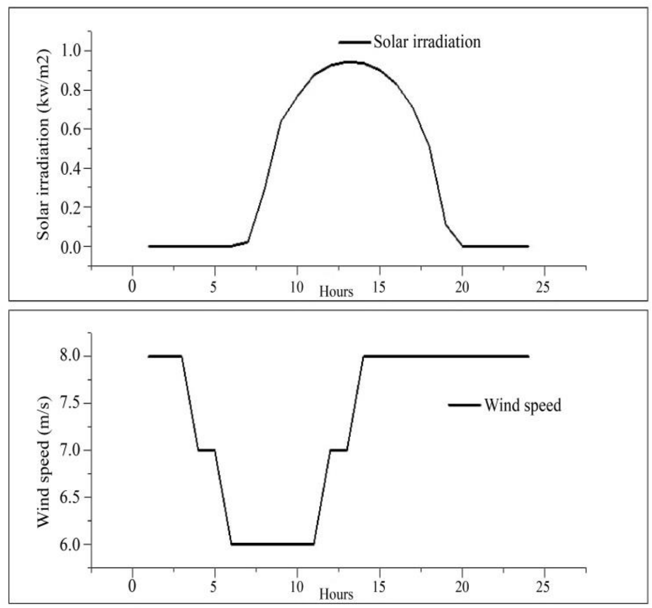

Fig. 7 Hourly Variation of environmental parameters for one day

The analysis considers the hourly variation of wind speed, surrounding temperature, and total solar irradiation. The available generation of various distributed generation (DG) models, namely G1, G2, G3, and G4, has been assessed at different time intervals. This assessment was conducted using mathematical modelling and considering the environmental conditions. The present analysis has been considered a deregulated electricity market. In a deregulated electricity market, various power and distribution utilities participate in the energy market. The electricity market has been managed by an Independent System Operator (ISO) where the electricity unit prize has been no more constant but it is variable based on demand generation at different time slots. Figure 6 shows the hourly variation of the Electricity Utility Unit cost, which has been collected from the Indian Energy Exchange (IES). Figure 7 shows the hourly variation of environmental parameters for one day. Two parts of the figures show the variation of the parameters for solar irradiation and wind speed. The graph shows that as time increases, there is a sharp rise in solar irradiation, and then the drop happens as time further increases. On the other hand, the graph variation with wind speed shows a sharp decrease as the time increases and then a gradual increase as the time moves forward. Figure 8 shows the hourly variation of available Generation of PV/Wind type DG for one day on 21-Jan-2020 based on the wind and solar resource data set. The variation with wind and power graphs is shown together based on the hour slot. This shows that the modelling of PV and wind-based DGs is efficient.

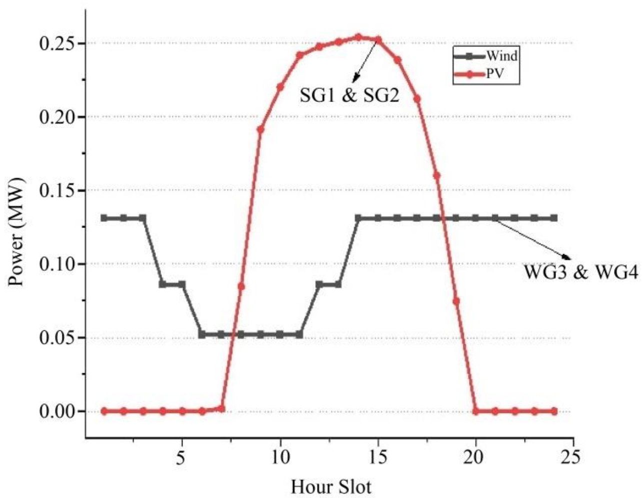

Fig. 8 Hourly variation of available Generation of PV/Wind type DG for one day on 21-Jan-2020 based on wind and solar resource data set

3.2. Problem Formulation for Optimization

The proposed multi-objective index comprises three criteria to enhance network performance in the presence of renewable-based DGs in a deregulated energy market. As seen in Equation (9), the multi-objective index is minimized by the optimization procedure. The framework relies on three main objectives: minimizing losses, minimizing revenue losses, and improving the voltage deviation index. The objectives have been allocated distinct weights, denoted as W1, W2, W3, according to their relative significance compared to other criteria.

$$C_{m_j} = W_1 * C_{l_j} + W_2 * C_{co_j} + W_3 * C_{vd_j} \quad (9)$$

$$C_{l_j} = \left(\frac{P_{loss_j}}{P_{NL_j}}\right) \quad (10)$$

$$C_{co_j} = \left(\frac{(\alpha - Utl_j)}{(Utl_j * P_{G_{avl}})}\right) \quad (11)$$

$$C_{vd_j} = \frac{V_{d_j}}{V_{d_{ref_j}}} \quad (12)$$

$$\alpha = \frac{\sum_{j=1}^{24} \mathrm{Utl_j}}{24} \quad (13)$$

Where,

P_{NL_j} = Network active power loss without distributed generation at jth hour

P_{loss_j} = Network active power loss with optimal generation at jth hour

Utl_j = Distribution utility energy price at jth hour

α = Indice for energy price variation at the jth hour

P_{OG_j} = Optimal distributed generation at jth hour

$P_{G_{avl}}$ = Total available solar and wind generation at jth hour

V_{d_j} = Voltage Deviation Index considering optimal generation at jth hour

$V_{d_{ref_j}}$ = Voltage Deviation Index without DG at jth hour

C_{opt_j} = Multi-objective index value at jth hour

The proposed Cumulative Multi-Objective Index $C_{(m_j)}$ (9) consists of three normalized weighted distributed index parameters. $C_{(l_j)}$ (10) is a normalized loss index parameter that minimizes network losses. Equation (10) shows that the denominator P_{NL_j} is the system loss without considering any generation from DG models with system loading at the jth hour. P_{loss_j} is the network losses considering DG′s generation and the network loading at the jth hour. C_{vd_j} (12) is the voltage deviation index parameter looked after network voltage profile improvement. $V_{d_{ref_j}}$ is the reference value of the voltage deviation index of the network without DGs corresponding to the network loading condition at the jth hour.

V_{d_j} is the voltage deviation index considering DG penetration across the network at the jth hour. Thus C_{vd_j} (12) and $C_{(l_j)}$ (10) are network performance improvement parameters that have been incorporated into the proposed MOF. However, a network with light loading conditions and favourable environmental conditions, renewable-based DGs inject considerable generation from different buses of the network, which increases the P_{loss_j} and V_{d_j}values and thus also further increases index parameter values, i.e. C_{vd_j} , C_{l_j} , and C_{m_j} . Optimization algorithm under such circumstances proposes curtailment of the generation of different DGs based on their influence on the network performance to optimize the value of MOF. The proposed MOF also incorporated a revenue gain parameter to avoid generation curtailment when the electricity unit cost is higher under the deregulated energy market. It stands to avoid higher revenue loss due to curtailment in terms of exporting the generation to the network by looking at the perspective of the DG′s owner. Under light loading conditions and favourable environmental conditions, renewable-based distributed generators (DGs) inject a significant amount of generation from various buses in the network. This leads to an increase in the values of P_{loss_j} and V_{d_j} , which in turn further increases the values of the index parameters C_{vd_j} , C_{l_j} and C_{m_j} . The optimization technique suggests reducing the generation of various distributed generators (DGs) based on their impact on network performance to optimize the value of the Multi-objective function (MOF). The proposed MOF additionally included revenue gain criteria to prevent the reduction of electricity generation when the cost per unit of electricity is higher in the deregulated energy market looking to the perspective of the DG's owner. The C_{m_j} index is a weighted distributed multi-objective index that utilizes weighting factor values obtained by the Analytic Hierarchy Process (AHP). A relative importance matrix, as shown in Equation (14), has been developed to determine the normalized weighting factor values: w1 = 0.66, w2 = 0.20, and w3 = 0.13.

$$A_{3\times3} = \begin{array}{c} \\ P_{loss} \\ Vd \\ Utl \end{array} \begin{array}{c} \begin{array}{ccc} P_{loss} & Vd & Utl \end{array} \\ \begin{bmatrix} 1 & 3 & 4 \\ 1/3 & 1 & 2 \\ 1/4 & 1/2 & 1 \end{bmatrix} \end{array}$$

$$w_j = \frac{Gm_i}{\sum_{i=1}^{M} Gm_i} \quad (14)$$

$$Gm_i = \left[\prod_{j=1}^{M} b_{ij}\right]^{1/M}$$

$$w_j = \begin{bmatrix} 0.66 \\ 0.20 \\ 0.13 \end{bmatrix} \quad (15)$$

$$B = A * w_j \qquad B = \begin{bmatrix} 2.1097 \\ 0.6789 \\ 0.4182 \end{bmatrix} \quad (16)$$

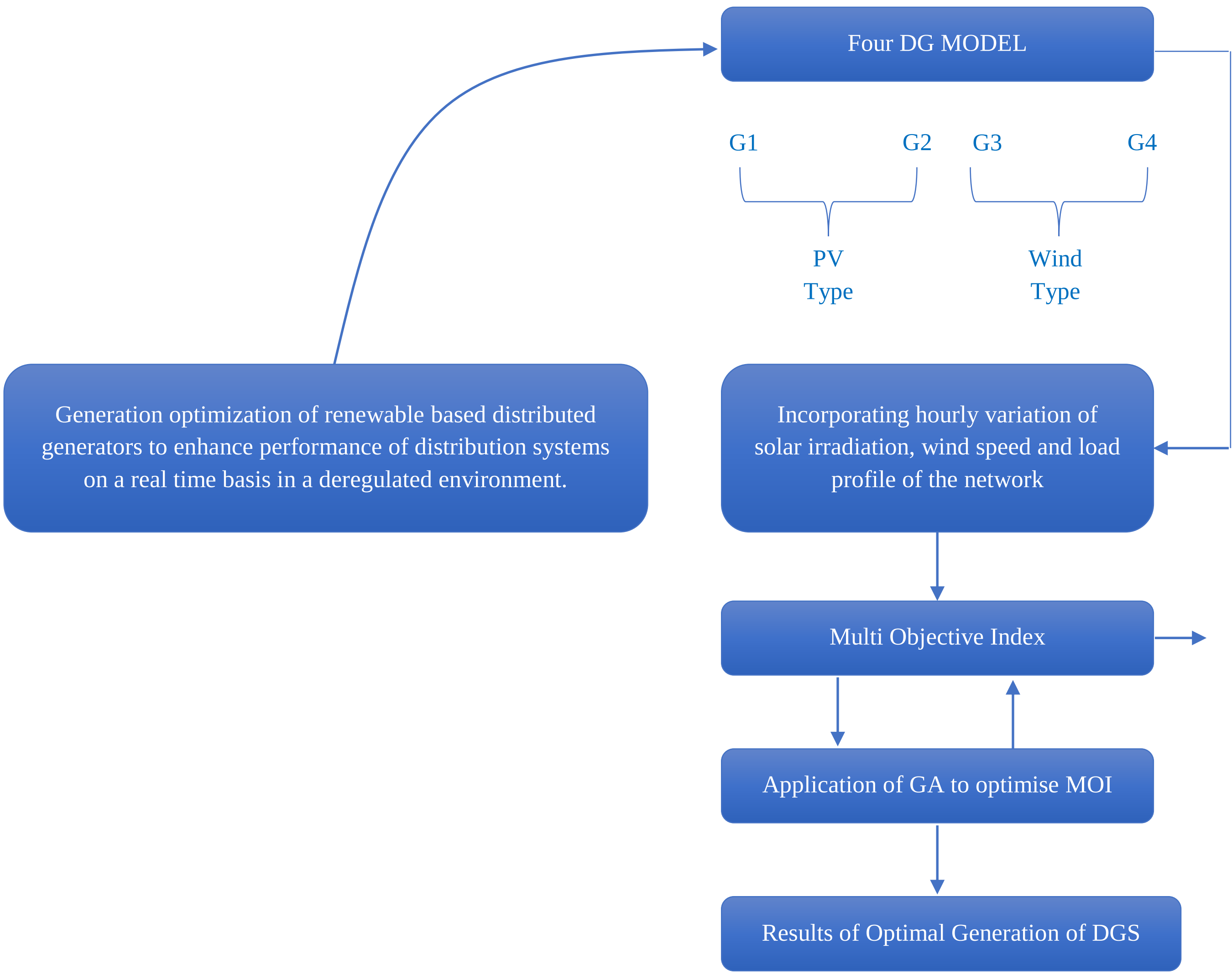

Fig. 9 Block diagram of proposed strategy

$\lambda_{avg} = \frac{B}{w_j}$

$CI = \frac{\lambda_{avg} - N}{N-1}$

Consistency Ratio $CR = \frac{CI}{RI}$ (17)

Take RI=0.52 for three criteria, CR=0.07. The consistency ratio with the proposed relative importance matrix has been evaluated at 0.07 (CR) within the permissible limit. A block diagram of the proposed strategy (P-3) has been shown in Figure 9. Four DG models are considered. Of these, two are PV-based, and two are wind-based. Now, hourly variation is incorporated to evaluate the results. The variables used here are solar radiation, wind speed, and the load profile of the network. Here, multiple objectives are considered. Then the results are fed to the genetic algorithm to optimise MO. Then, the final results are generated efficiently. The proposed MOF optimized on each hour as an hourly variation of demand and DG′s generation has been considered in the present analysis.

A genetic algorithm is an evolutionary-based heuristic algorithm that plays an important role in addressing complex engineering optimization problems. The fittest individuals are selected for reproduction in order to create the new variable string of the following iteration, according to the concept of natural selection. The proposed multi-objective function is highly nonlinear and consists of many constraints. GA was applied to find the optimal generation values for different types of DG connected at different locations across the distribution network. Available generations for different types of DGs at the j^{th} hour have been evaluated based on the environmental condition, i.e., solar irradiation and wind speed values. The effect of generation injection of DG at different locations on the network performance is different based on the network loading condition.

Optimal solutions use the full available capacity of the generation of DG, which positively influences network losses and voltage profile. However, under light loading conditions, the proposed approach curtails the generation of DGs, which negatively influences network performance. The proposed MOF also looks after the trade-off price of DG′s generation. The proposed approach uses the total capacity of available generation of DGs when the utility electricity cost at the j^{th} hour is relatively higher than the average deviation index value to reduce revenue loss due to generation curtailment, looking at the DG owner′s perspective. The operational flow chart is shown in Figure 10, and the corresponding algorithm steps have been described below.

Step 1: Read the Network load data as per the load factor at the j^{th} hour.

Step 2: Perform load flow using the NR method to evaluate losses across different sections and bus voltage deviation index values.

Step 3: Generate the initial population of input variables for the generator models G1, G2, G3, and G4.

Step 4: Evaluate the fitness of each chromosome based on the proposed MOF index value.

Step 5: Select the best chromosomes based on the roulette wheel method to generate a new population string.

Step 6: Apply GA operators on the population string (crossover and mutation) to explore the possibility of better solutions across the search space.

Step 7: Check for the termination criteria (Maximum number of generations=100), else repeat the procedure.

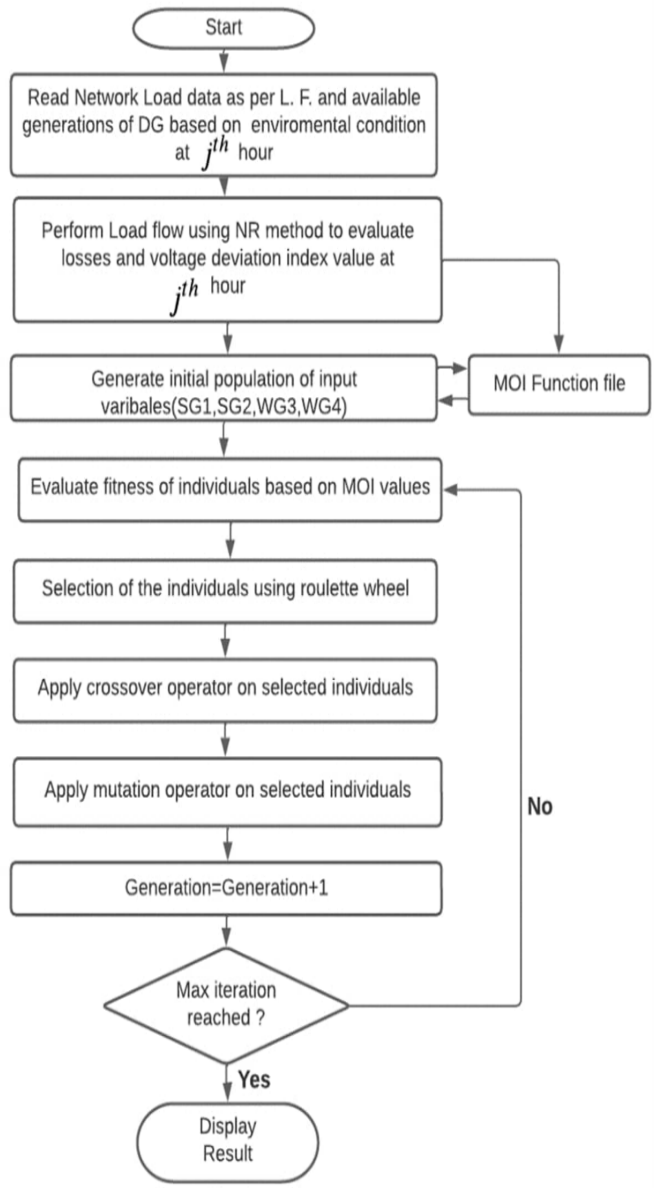

Fig. 10 Operational Flow chart to find optimal generation of DGs using GA

Table 3. Comparative results of OPG problem with CL type load profile

Hour slot (j)	Utility energy cost factor		L.P.		Optimal Generation in KW of various DG Models	
			SG1	SG2	WG3	WG4
1	2.6	0.35	0	0	28.13	131.02
2	2.6	0.29	0	0	38.63	131.02
3	2.57	0.3	0	0	41.12	131.02
4	2.4	0.3	0	0	0	37
5	2.6	0.3	0	0	10.05	65
6	2.57	0.32	0	0	15	40
7	2.58	0.78	0	0	15	51
8	3.16	0.9	83.98	66.21	51.86	51.88
9	3.87	0.95	191.25	191.25	51.86	51.86
10	6.5	0.9	219.88	219.88	51.87	51.87
11	9	0.98	241.62	241.62	51.87	51.87
12	3.39	0.95	247.56	247.56	85.82	85.82
13	3.29	0.92	250.88	209.55	85.67	85.8
14	2.89	0.9	254.02	224.6	127.26	130.89
15	2.76	0.85	252.07	132.77	131	131.02
16	3.19	0.62	238.5	214	130	131.02
17	3.5	0.5	212.14	212.14	131.02	131.02
18	3.39	0.48	160	160	131.02	131.02
19	5.7	0.42	74.76	74.76	131.02	131.02
20	5.85	0.42	0	0	131	131
21	3.33	0.4	0	0	131	131
22	3.16	0.38	0	0	131	131
23	2.82	0.3	0	0	88.96	93
24	2.58	0.29	0	0	36.29	53

4. Results and Discussion

Table 3 shows the optimal solution for all four Dg models at different time slots under varying load profiles and electricity unit prizes with variable environment-dependent available generation. PV-based DG models SG1 and SG2 provide no generation during night hours due to the unavailability of solar radiation. Depending on the wind dataset, wind-based WG3 and WG4 models generate power throughout the day. However, the algorithm considers the generation of the models based on the solar and wind generation at specific time slots. The optimal solution for solar-type DG Models G1 and G2 during the jth hour is depicted in Figure 11.

Figure 11 also illustrates how, while considering network restrictions, the algorithm attempted to maximize the generation of Model G2 more than Model G1 based on the ideal MOF value at hours. Mitigate the generation of distributed generation (DG), which has a detrimental impact on network losses and voltage deviation and the performance of the network. The results indicate that Model G1 has a more beneficial effect on network performance compared to Model G2, as it incorporates the complete available generation of Model G1 at a distinct time. However, the algorithm limits the production of G1 at various time slabs depending on MOF value to enhance bus voltages and improve network performance in response to unfavourable network loading conditions with lower power unit rates. Figure 12 displays the ideal solutions for the variable load profile for the DG models G3 and G4 wind type. Illustrates the variation in the amount of solar PV generation available for the DG models G1 and G2. The optimal value of generation was determined using GA with the Lower Bound set to zero and the Upper Bounds set to the available generation, considering the total generation of DG based on the environmental condition at the jth hour. Even though each DG was produced with the same generation, its location and network loading condition have a unique impact on network performance, notwithstanding the algorithm-optimized generation based on the proposed MOF value at the jth hour.

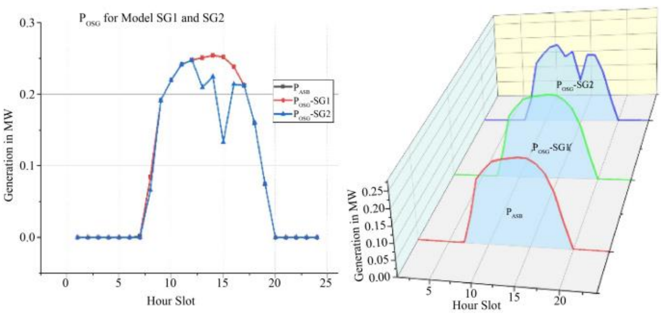

Fig. 11 P_{OSG} for model SGI and SG2 at different time slots

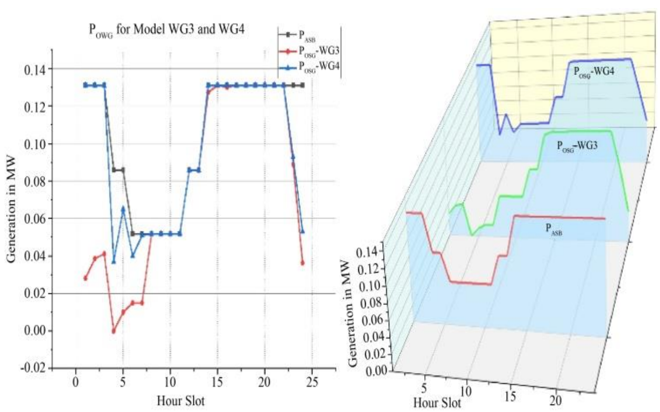

Fig. 12 POWG for model WG3 and WG4 at different time slots

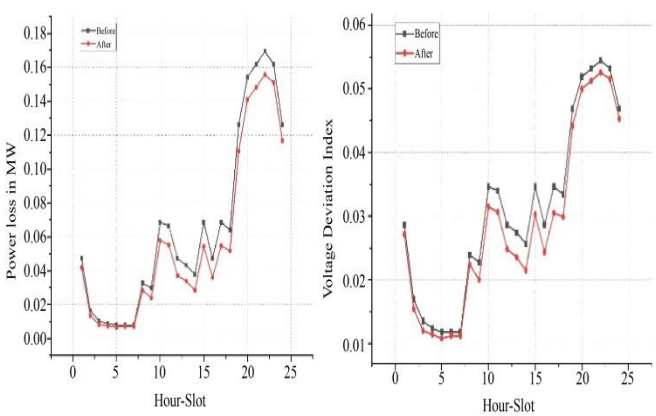

Fig. 13 Comparison chart for power loss and voltage profile with and without the proposed strategy

These DGs supply consistent generation to the network throughout the day, contingent upon the available wind speed. The wind type DG models G3 and G4, which are positioned at various load buses, provide the available generation at different hours as depicted in the 3D graph Figure 12. An algorithm has been used to determine the optimal generation value between the upper limit-which has been determined based on the available generation from DG based on wind speed at the jth hour-and the lowest limit, LB = 0. The algorithm has been used to maximize available generation at different time slabs from model G3, while curtailing the generation of model G4 based on MOF.

The results indicate that the wind-type model G3 has a positive impact on the network performance compared to the wind-type model G4. To minimize the losses incurred by the owner of the distributed generation (DG), the cost of the electricity unit has been integrated into the MOF to prevent any generation curtailment during peak electricity pricing hours. When the electricity unit price exceeds the average utility price deviation index, the MOF value increases and the DG is automatically rejected from the solution string by the optimization algorithm. Figure 13 shows a comparative chart for power loss reduction and voltage profile improvement before and after the implementation of the proposed strategy.

5. Conclusion

The proposed approach yields optimal planning for demand-side renewal-based resource management to guarantee improved network performance in the deregulated energy market. However, the impact of DG varies depending on the precise position inside the distribution grid. The proposed methodology attempts to reduce the generation of distributed generators that have an adverse impact on the network's performance under light-loading conditions.

To minimize revenue loss from energy curtailment on a real-time basis in a deregulated electricity market, the present strategy also aligns with the interests of the owner of DG. This is achieved by integrating utility energy pricing with MOF. The proposed approach helps the utility to mitigate high losses and over-voltage problems due to a highly penetrated distribution network. It suggests requiring generation curtailment of RE-based DG under light loading conditions.

The present analysis yields 50% RE penetration; however, the penetrated distribution grid needs more curtailment on a real-time basis to mitigate losses and power quality. GA has been used to optimize the proposed MOF, and it takes 8 to 9 seconds to find a solution. Looking at its implementation on a real-timse basis, it needs to be further reduced. The proposed work can be extended further to reduce this time lag so that it can be implemented on a real-time basis.

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