

AN ADVANCED STRATEGY FOR OPTIMAL SITING AND SIZING OF DISTRIBUTED GENERATORS THROUGH GENETIC ALGORITHM AND D-STATCOM INTEGRATION FOR SUSTAINABLE POWER SYSTEM OPERATIONS

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Abstract

This research article suggests a unique technique for the best placement and size of distributed generators (DGs) which may in the form of solar or wind in a power system network. The objective is to identify the optimum positions and sizes of the DGs that minimize the power losses in addition to fulfill increased load demand in the system. The proposed methodology combines two methods: the Genetic Algorithm (GA) and the Least Power Deprivation (LPL) method. The LPL method is used to determine the optimum positions of the DGs, while the GA is used to determine their optimum sizes. Potentially unstable voltage spots in a power system can be identified by computing the Voltage Stability Index (VSI) of each bus. Installing a Distribution Static Compensators (D-STATCOM) at these sites reduces voltage fluctuations, improving overall system stability and dependability, which is essential for preserving operational effectiveness and averting power network cascade failures. The methodology is validated through extensive simulations on the 30-bus IEEE power network using simulink. The study provides valuable insights into the best positioning and sizing of DGs and D-STATCOMs in power systems, which can help power system operators and planners in enhancing the overall system performance and reliability including reduction in carbon emissions and supplying clean energy. The proposed methodology is also compared with other intelligent techniques reported in literature to determine its versatility and applicability like harmony search algorithm, fire fly algorithm, coyote optimizers and particle swarm optimization; is generic and can be applied to other power systems as well for optimum location and sizing of DGs.

Keywords: Distributed Generators; D-STATCOM; Genetic Algorithm; Least Power Deprivation; Voltage Stability Index

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Introduction

The quest of sustainable and reliable power system operations has become of the utmost importance in the quickly changing global energy landscape. The growing use of renewable energy sources, the urgent need to improve grid stability, and the global commitment to reducing carbon emissions are the driving forces behind this movement. In this regard, Distribution Static Compensators (D-STATCOMs) stand out as a crucial study topic due to their excellent integration with Distributed Generators (DGs) and Dynamic Voltage Support Devices. A power electronic component called a D-STATCOM is used in power distribution systems to improve power quality and voltage stability. By constantly adjusting for imbalances in reactive power, it reduces voltage variations. D-STATCOMs are essential to Distributed Generation (DG) integration because they improve grid reliability, support voltage, and handle power quality problems brought on by DG sources that are intermittent. They are necessary to maintain a stable and effective power distribution network with a variety of decentralized energy inputs because of their quick reaction times and voltage regulation skills. In earlier days, traditional-power system was being used to meet the load demands of a region. This power distribution system consisted of a centralized generating station which then delivered the load demands through the network. Since, this power distribution systems rely on centralized power generation, it requires long-distance transmission and distribution infrastructure. This results in high transmission deprivations and reduced reliability, as any disruption in the transmission lines can lead to widespread outages as stated in Četković and Komen, (2023), Elattar and Elsayed, (2020). As power generation is governed by the centralised power plants, these power distribution systems are not flexible. It is therefore challenging to modify power generation to accommodate variations in demand or the availability of renewable energy sources. Such power distribution systems are prone to voltage instability due to the high variability of power demand and generation. Voltage instability can result in power quality issues and equipment damage as given in Gupta *et al.* (2021), Bagheri Tolabi *et al.* (2015). These systems also have a limited capability to integrate renewable energy sources due to their intermittency and requirement of storage capacity. The limitations mentioned above have led to the adoption of new technologies in the power distribution networks such as distribution generators and smart grid technology as

given in Yang *et al.* (2018). The integration of DGs and D-STATCOMs has been the subject of extensive research, largely because of their potential to improve the efficiency and sustainability of electricity distribution networks. The ideal location and sizing of DGs have been examined using a wide range of optimization techniques, including mathematical programming, heuristic algorithms, and metaheuristic methods proposed in Pushkarna *et al.* (2022). Distribution generators can provide energy based on the localized demands. They also require shorter transmission lines making the system less vulnerable to the environmental conditions and reduces the transmission deprivations considerably. The distribution system also has the capability to integrate renewable energy power sources into the existing power system network. They improve the power quality of the system by reducing the voltage drops that appear between the buses due to transmission depravations. These systems are also able to meet the load growth demands as integration of small generation stations and their integration to the power system network is easy as recommended in Bajaj *et al.* (2020). D-STATCOMs have also drawn a lot of attention for their ability to control voltage profiles and enhance power quality. However, existing literature frequently overlooks the synergistic advantages that might be unlocked through the deployment of DG and D-STATCOM together since it focuses primarily on discrete aspects of their integration. The study solves this gap by offering a comprehensive strategy that simultaneously optimizes DG placement and size while taking into account the tactical deployment of D-STATCOMs as proposed in Arya *et al.* (2016). DG delivers excellent value since it offers a flexible way to choose from a variety of cost and dependability combinations. Researchers in the field have developed a variety of unique algorithms and solutions. These variances frequently result from differences in how problems are phrased, approaches that are chosen, and underlying presumptions. A portion of these techniques are covered in Pushkarna *et al.* (2022) and they are grouped into heuristic methods Purlu and Turkay, (2022), analytical approaches in Mota *et al.* (2011) and numerical programming techniques in Wang *et al.* (2015). Depending on the particular dataset and system features under consideration, each of these approaches has a unique mix of benefits and disadvantages. Typically, the goal function or the constraints are non-linear, stochastic, or even defined by fuzzy functions in the problem formulation for the allocation of dispersed

generation resources. The two main goals are often shared by all of these formulations: to reduce real power losses and increase voltage. In order to achieve appropriate placement and scale of dispersed generation units within distribution systems, the authors in Lee and Park (2013) provide an approach in which while maintaining an acceptable level of system reliability and voltage profile, their objective is to reduce electrical network losses. The authors in Singh *et al.* (2009) use a hybrid strategy that blends genetic algorithms (GA) with other evaluation techniques to determine how distributed generators affect system dependability, losses, and voltage profiles. By minimizing active power flow in distribution systems, the authors in Siddiqui and Prashant (2022) tackle the optimal sizing problem for single and multiple distributed generators. The authors in Uniyal and Kumar (2016) adopt a hybrid strategy to maximize the power output of distributed generators by combining GA with other meta-heuristic approaches. The ant colony optimization method is suggested by researchers in Raza *et al.* (2023) as a solution to the DG sizing and location issues. Their goal is to reduce the cost of the global network. The optimal positioning of DGs in distribution systems is a multi-objective optimization problem that Ameli *et al.* (2014) addressed. Their goals include reducing power losses, increasing voltage profiles, and enhancing reliability. To tackle this difficult issue, they present a fresh dynamic programming-based strategy. For determining the ideal size and location for DG deployment, the researchers in Devineni *et al.* (2021) create an analytical formula. The reduction of overall power losses in primary distribution systems is their main priority. In order to give a prioritized list of DG locations for compensating reactive power during times of reactive power scarcity, a modified equivalent reactive compensation approach is proposed in Ettehadi *et al.* (2013). The author in Amanifar, (2011) used voltage sensitivity index method to deduce the optimum location for the DG placement and real power deprivation curtail technique was used to determine the size of DG to be placed at the bus. The power deprivation of the system was reduced considerably and load curve of the system showed an increase in the loading capability of the system. In reference Prashant *et al.* (2021) the authors mentions that random selection of DG location in the network may lead to increase in the real power deprivation of the network and optimum size of DG for various buses at various power factor operation was determined. In Almabsout *et al.* (2020), the author used various optimization techniques like genetic algorithm, particle swarm optimizer,

competitive swarm optimizer etc to determine the optimum position of DG placement in order to improve the voltage profile. The author in Shivarudraswamy *et al.* (2016) proposed the use of genetic algorithm which is reliable to obtain the optimum location for DG placement to minimize power deprivation and refine voltage profile of system. The author Prashant *et al.* (2022) proposed the use of multi-DG placement and sizing for reduction in power deprivation to refine the voltage profile of network and to reduce real power deprivations. The author Anuradha *et al.* (2019) determines the ideal placement for the DG using the voltage sensitivity index. The water cycle algorithm (WCA) is suggested in the research of El-Ela *et al.* (2018) for the best positioning and sizing of DGs and CBs. Benefits in terms of technology, economy, and environment are the goals of the suggested approach. Various objective functions are taken into consideration, including reducing power losses, voltage deviation, overall electrical energy cost, total emissions from generation sources, and raising the voltage stability index. In ref Sowmya *et al.* (2017), the deprivation sensitivity factor determines where the DG should be placed, and the Intelligent Water Drop algorithm calculates its size. This approach led to significant improvement in the voltage profile of the network and reduction in active power deprivation. The author in Yammani *et al.* (2015) proposed a novel technique of multi objective shuffled bat algorithm to find out the optimum location and sizing of the DGs. In a 33-bus network they reduced active power deprivations, improved the voltage profile, and reduced the transmission cost of the network. In order to determine the significance of load fluctuations considered in minimizing power losses via DG deployment and network topology change, the article Mahdavi *et al.* (2023) aims to evaluate the impact of consumption patterns on renewable DG allocation and switching plans. A significant research gap exists in the integration of both technologies into a unified framework to accomplish sustainable power system operations, notwithstanding the substantial volume of research on DG and D-STATCOM integration. Power distribution systems are dynamic and multi-objective, making it necessary to simultaneously optimize DG placement, DG sizing, and D-STATCOM allocation. Existing studies usually fall short in this regard. Additionally, nothing is known about how to coordinate these elements in the best way to achieve not just technical but also economic and environmental objectives. By offering a Genetic Algorithm (GA)-based strategy that simultaneously optimizes DG placement, DG sizing, and D-STATCOM allocation, while accounting for several

objectives like voltage management, loss minimization, and environmental considerations, this research intends to address this gap. This study begins a thorough investigation of the best positioning and sizing of DGs in conjunction with D-STATCOMs to address the current issues that power distribution networks are facing. This research work makes several important advances in the field of operating sustainable power systems. In order to improve power systems, it presents a ground-breaking GA-D-STATCOM framework that smoothly integrates the optimization of DG placement, DG sizing, and D-STATCOM allocation inside a unified framework. The proposed method takes into account several, frequently competing goals, such as voltage regulation, power loss minimization, and environmental effect, enabling decision-makers to make well-informed trade-offs in the design of power systems. Additionally, by jointly optimizing DGs and D-STATCOMs, the methodology intends to strengthen the sustainability of electricity distribution networks, thereby lowering greenhouse gas emissions and boosting grid dependability. The suggested approach efficiently handles changes in load demand over time by combining Genetic Algorithm (GA) and Least Power Deprivation (LPL). Using past and future load data, GA optimizes the location and sizing of distributed generators (DGs), dynamically changing configurations to fit different demand patterns. The program can also predict future demand patterns by utilizing load forecasting techniques, which helps to ensure that distributed generators (DGs) are designed and placed strategically to meet variable demand while minimizing power loss. In order to improve grid stability and dependability, the LPL technique prioritizes places where distributed generators (DGs) can reduce system strain during periods of peak demand. By combining these strategies, a framework that is both flexible and adaptable is produced that can adjust to shifting load conditions, maximizing operational efficiency and minimizing the negative effects of load fluctuations on system performance. The suggested approach, which combines Least Power Deprivation (LPL) and Genetic Algorithm (GA), would perform differently in various network topologies, including IEEE n-bus networks. The GA component adjusts by searching the solution space for the best locations and sizes of distributed generators (DGs), taking network restrictions and load changes into account. This is done in complicated topologies such as IEEE networks with different bus configurations. By minimizing power loss and guaranteeing proper placement of DGs, the LPL technique effectively optimizes DG locations throughout the network,

improving system stability and dependability. However, the size, structure, and operational features of the network may have an impact on how effective the method is as because larger networks are more complicated and interconnected, they may demand more processing power and longer optimization times. However, the suggested approach can effectively handle a variety of operational challenges by customizing parameters and algorithms to particular network topologies. This guarantees that DG deployment is in line with network requirements and operational goals across various IEEE n-bus configurations, improving overall grid resilience and performance. This paper is organized as follows: The motivation and history of the study and inferences are thoroughly explored in the introduction section. The methodology is discussed in section 2, the power system network under investigation and simulation results are presented in section 3 and conclusion is discussed in section 4.

Methodology

Optimum location and Sizing of DG

The methodology proposed in the work is to minimize the deprivations which occur in the network. These deprivations occur in the line of the network and are given by:

$$P_{loss} = I^2 R \quad (1)$$

The total power loss P_{loss} in the system is the sum of the losses in all lines. The optimal placement of a distributed generator (DG) is ascertained by assessing the power loss's sensitivity to power injection at various busses. The bus that causes the least amount of power loss (or highest amount of decrease) is thought to be the best spot to put DG. The sensitivity of power loss with respect to the injection of power at a particular bus is given by:

$$\frac{dP_{Loss}}{dP_k} = 2I_{ij} \frac{dI_{ij}}{dP_k} R_{ij} \quad (2)$$

Where k is a particular bus and i and j represent the lines from and to power transfer, R is the resistance of line and I_{ij} is the current flowing in the lines. The total complex power S_i is given as:

$$S_i = S_{ij} + S_D \quad (3)$$

Where S_D is the load demand; real power P_{gi} & reactive power Q_{gi} are given as:

$$P_{gi} = P_{di} + \sum_{j=1}^N |V_i| |V_j| (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij}) \quad (4)$$

Where $i = 1, 2, 3, \dots, N$, and G_{ij} & B_{ij} are the real and imaginary components of the admittance matrix.

where P_{gi} & P_{di} are generations of i^{th} bus and real power demand; $\delta_{ij} = \delta_j - \delta_i$; N represents the total number of buses.

$$Q_{gi} = Q_{di} + \sum_{j=1}^N |V_i| |V_j| (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij}) \quad (5)$$

$$Pl_{ij} \leq Pl_{ij}^{max}; ij \in n_l \quad (6)$$

Pl_{ij} and Pl_{ij}^{max} are the real power flows through line i - j and line maximum capability; n_l is total no. of lines.

$$P_{gi}^{min} \leq P_{gi} \leq P_{gi}^{max}; i = 1, 2, \dots, ng \quad (7)$$

$$\delta_i^{min} \leq \delta_i \leq \delta_i^{max}; i = 1, 2, \dots, N \quad (8)$$

$$V_i^{min} \leq V_i \leq V_i^{max}; i = 1, 2, \dots, N \quad (9)$$

Here P_{gi}^{min} & P_{gi}^{max} are minimum & maximum capacity of the i^{th} generator; $\delta_i, \delta_i^{min}, \delta_i^{max}$ are voltage angle with limits, V_i^{min} & V_i^{max} are maximum and minimum voltages of generator and ng represent a number of total generators.

Where P_{loss} is the active power deprivation of the network and I is the current passing through the network and R is the resistance of the transmission line. The solution given by the network is to be taken as active power deprivation thus the solution which consists of minimum active power deprivation is to be considered for the optimum placement of the DG in the network. The best location for distributed generators (DGs) in a power system can be found using a heuristic technique called the Least Power Deprivation (LPL) method. By giving priority to places where the development of DGs would have the biggest effect on lowering transmission and distribution losses, it seeks to reduce power losses. Potential DG sites are assessed by LPL according to how close they are near nodes with high demand and how well they can relieve pressure on stressed network components. LPL is a useful tool in improving DG deployment methods for sustainable energy integration since it promotes overall network efficiency and reliability by concentrating on reducing power deprivation across the system. The active power deprivations in the network are computed by the Kron's equation (Ameli *et al.*, 2014).

$$Pl = \sum_{n=1}^{ng} \sum_{m=1}^{ng} b_{mn} P_m P_n + \sum_{m=0}^{ng} b_{m0} P_m + b_{00} \quad (2)$$

$$(10)$$

Here, ng represents no. of distributed generators, P_i are the deprivations in the network, and P_m and P_n are the power injected at the buses m and n respectively. The coefficients b_{mn} , b_{m0} , and b_{00} are computed by the standard formula. The process of initializing a population of candidate solutions, each of which represents a potential DG size, is part of the Genetic Algorithm (GA) DG sizing approach. Over the course of several generations, these solutions evolve through selection, crossover, and mutation. Each candidate is assessed by the fitness function, which is based on parameters like power loss. The best solutions are kept and refined repeatedly until a near-optimal or ideal DG size is achieved. The criteria regarding how many candidate solutions (individuals) are taken into consideration in each generation depends on the size of the population. A population with the ideal size converges more quickly while larger populations may need more frequent crossover to maintain convergence speed, smaller populations may benefit from higher mutation rates to preserve diversity. The chance that two parent solutions will mix their genetic material to create offspring is known as the crossover probability. High crossover rates often lead to faster convergence, as the offspring inherit traits from both parents that may increase their performance. The probability that a solution will arbitrarily change a component of its genetic structure in this case, a binary string is determined by the mutation rate. While low mutation rates might not adequately add diversity to the population, high mutation rates can lead to an overwhelming amount of unpredictability. The algorithm stops if the fitness value (such as power deprivation) hits a predetermined optimal value.

The first step in this process is choosing a binary string, for which we have the following assumptions:

Size of population: six

Total length of the string: 5

Probability of Crossover, $P_c = 0.88$ Probability of Mutation, $P_m = 0.05$

The entire methodology is represented in Figure 1.

In order to estimate the size of distributed generators (DGs), the Genetic Algorithm (GA) methodology entails recording DG size as chromosomes in a population. First, fitness criteria are used to evaluate random or specified sizes; the goals are usually to minimize power losses or maximize system reliability. Over generations, the



Figure 1. Flowchart for Optimal Location and Sizing of DG by proposed methodology

method iteratively improves DG sizes through crossover (combining chromosomes), mutation (introducing random changes), and selection. The influence of each DG configuration on system performance is measured through fitness evaluation. By combining renewable resources and improving overall network performance, an ideal DG scale configuration that strikes a balance between energy

efficiency and system stability is produced by this iterative process, which is continued until convergence. In the genetic algorithm as shown in Figure 1, a fitness value is required to determine the ‘fitness’ of the individual or as in this case how good the solution is. The fitness value is set to be the power deprivation obtained. Here, the lesser the power deprivation the more optimum the solution would be, therefore crossover of two individuals with least power deprivation is performed in order to get better results for the next iteration.

Benchmark and Comparative Analysis

Therefore, even though the GA approach requires more resources, its capacity to produce nearly optimal results in intricate DG scaling situations makes the extra computational expense justified, especially where solution robustness and accuracy are valued more highly than speed and resource efficiency as interpreted in Table 1.

Optimum Location of D-STATCOM

The optimum location of the D-STATCOM is calculated by determining the Voltage Stability Index of the all the buses on the network. The system’s capacity to keep voltage within allowable bounds under a variety of scenarios is reflected in the Voltage Stability Index (VSI). High VSI readings suggest possible instability, posing a danger of voltage collapse or interruptions, before installing a D-STATCOM. VSI usually drops when the D-STATCOM is deployed, indicating increased stability as a result of a better reactive power supply. This decrease suggests that crucial buses are less susceptible to variations in voltage, guaranteeing dependable functioning. Following the implementation of D-STATCOM, lower VSI values

Table 1. Comparative Analysis of different optimization techniques for DG Sizing

Optimization Technique	Computational Time	Resource Consumption	Strengths	Weaknesses
GA	High (due to population size, generations, fitness evaluations)	High (due to large population, memory usage)	Robust, flexible, handles complex problems well	Computationally intensive, may require parallel processing
PSO	Moderate (faster convergence for smaller problems)	Moderate (lower memory usage than GA)	Simple, fast for smaller problems	Prone to premature convergence, less effective for large search spaces
Simulated Annealing(SA)	Moderate (depends on cooling schedule)	Low (single solution per iteration)	Good for single-objective problems	Slow convergence, sensitive to parameter tuning
Differential Evolution (DE)	Moderate to High (depends on population size and generations)	Moderate (efficient compared to GA)	Faster convergence than GA in some cases	Requires tuning, may not handle large search spaces well

signify a more robust system that can maintain constant voltage levels, maximize performance, and reduce the likelihood of outages or equipment damage. This enhances overall grid resilience and operational efficiency. The Voltage Stability Index is measured by the eq.11 as given in Hussain *et al.* (2013).

$$VSI_{n+1} = V_n^4 - 4[P_{n+1,eff} * X_n - Q_{n+1,eff} * R_t]^2 - 4[P_{n+1,eff} * R_n + Q_{n+1,eff} * X_n] * V_n^2 \quad (11)$$

Here, V_n is the magnitude of the voltage at the bus n , X_n and R_n are inductance and resistance between the buses n and $n+1$ respectively. $P_{n+1,eff}$ and $Q_{n+1,eff}$ are the effective active and reactive power that have been transmitted through bus $n+1$ respectively. The lower value corresponds to poor voltage stability of the respective bus. The bus with least VSI is the optimum location for D-STATCOM placement. Placing the D-STATCOM in the best place and adjusting its size to find the one with the reactive power deprivations methodology yields the optimum size of the D-STATCOM as proposed in Zeinalzadeh *et al.* (2019).

Power System Network and Simulation Results

The approach was examined on IEEE-30 bus network which can be represented from the diagram given in Figure 2.

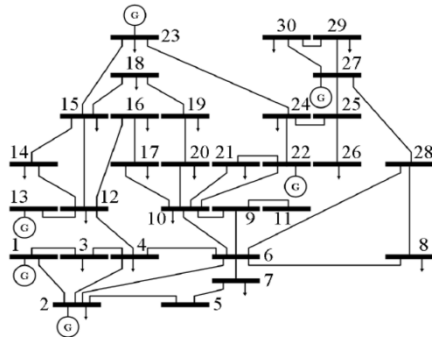


Figure 2. IEEE- 30 bus system

The simulation was done with the help of MATPOWER toolbox, 7.1 version. The initial population for the system is taken to be 20 and the maximum number of iterations was set to 100. One notable feature of MATPOWER is its versatility, offering a wide range of optimization and power flow methods. It is available for extended grid stability and economic dispatch research because to its user-friendly interface and strong community support. These characteristics encourage

cooperation and increase the development of grid technology by enabling researchers to effectively assess and create within the field of power system analysis.

The findings were then recorded as the ideal size of the DG is determined by the least power deprivation approach, followed by the optimum placement for the DG. The results can be obtained by equation 4.

$$P_{DGi} = P_{Di} - \frac{1}{\alpha_{ii}} [\beta_{ii} Q_{ii} - \sum_{j=1, j \neq i}^N (\alpha_{ij} P_j - \beta_{ij} Q_j)] \quad (12)$$

In this case, P_{DGi} denotes the ideal DG size needed at bus i . P_j and Q_j are the active and reactive powers injected at bus j , respectively, and are the coefficients provided by equations 5 and 6. P_{Di} is the power demand at bus i .

$$\alpha_{mn} = \frac{r_{mn} \times \cos(\delta_m - \delta_n)}{V_m \times V_n} \quad (13)$$

$$\beta_{mn} = \frac{r_{mn} \times \sin(\delta_m - \delta_n)}{V_m \times V_n} \quad (14)$$

In the above equations, the terms δ_m and δ_n are the power angles of the bus m and n , respectively. The term r_{ij} is the real part of the z -bus matrix of the network where $z_{mn} = r_{mn} + jx_{mn}$.

Using the above-mentioned methods as shown in Table 2 and Table 3, the ideal placement and size of two DGs were established for the IEEE - 30 bus network. The results obtained are for type 1 DG. The active deprivations of the network before the addition of DG were 2444 KW and total deprivations of the network after addition were 1787 KW. Thus, reduction of 657 KW or 26.88% of active power deprivation was observed. The reduction of active power deprivation across the transmission line can be observed from Table 1. By computing the voltage stability index of the several network buses, the ideal position of the D-STATCOM was found. The bus with the minimum voltage stability index was selected as the optimum location for the D-STATCOM. The voltage sensitivity index was then computed for the buses after the addition of D-STATCOM and the results were obtained as shown in Figure 3. The reactive power deprivations observed in the network are given in Table 3. As per the methodology used the optimum location of D-STATCOM was obtained as bus 8 of size 37 MVar as shown in Table 4. The reactive power compensation before addition of D-STATCOM was 9128 KVar and the reactive power deprivations after inclusion of D-STATCOM were obtained as 7989 KVar. Thus reduction of 1139 KVar or 12.47% of reactive power deprivations were obtained.

Table 2. Comparative Analysis of different optimization techniques for DG Sizing

From Bus	To Bus	Power Loss without DG (MW)	Power Loss with DG (MW)
1	2	0.026293324	1.70E-06
1	3	0.126695201	0.060176879
2	4	0.178005767	0.117374806
3	4	0.018290594	0.007793377
2	5	0.11026491	0.082955561
2	6	0.289202158	0.18865952
4	6	0.066191593	0.04201714
5	7	0.120202674	0.093397471
6	7	0.031418759	0.04496438
6	8	0.128064136	0.118451361
6	9	0	8.88E-16
6	10	-8.88E-16	0
9	11	0	0
9	10	0	0
4	12	0	0
12	13	0	0
12	14	0.036823514	0.031751622
12	15	0.065552771	0.041685792
12	16	0.079537386	0.070423048
14	15	0.003141296	0.004527843
16	17	0.03067166	0.025172179
15	18	0.096813991	0.097113492
18	19	0.022098234	0.022190377
19	20	0.008904309	0.008872211
10	20	0.05236506	0.052235451
10	17	0.023393228	0.023675941
10	21	0.043684641	0.04414688
10	22	0.06216228	0.066650204
21	22	0.09310014	0.100969
15	23	0.109360795	0.109360795
22	24	0.078267431	0.078267431
23	24	0.066278019	0.031550366
24	25	0.034988395	0.034988395
25	26	0.046394189	0.045723135
25	27	0.062563059	0.032491413
28	27	0	-3.55E-15
27	29	0.090096091	0.090096091
27	30	0.171304547	0.171304547
29	30	0.034876316	0.034876316
8	28	0.035624715	0.050261022
6	28	0.001171947	0.015946445

Table 3. Reactive Power Loss across transmission line

From	To	Reactive Power Loss without D-STATCOM(MVAR)	Reactive Power Loss with D-STATCOM(MVAR)
1	2	7.89E-02	0.000222273
1	3	0.481441764	0.172833392
2	4	0.504349672	0.253877577
3	4	0.073162377	0.02023369
2	5	0.44105964	0.265161844
2	6	0.867606474	0.408525701
4	6	0.264766371	0.104258067
5	7	0.288486417	0.167668664
6	7	0.083783358	0.152660203
6	8	0.512256544	0.233373046
6	9	9.93E-02	0.028291611
6	10	0.086452429	2.46E-02
9	11	0	0
9	10	0.05200654	0.014819416
4	12	0.018634715	0.058206821
12	13	2.097042949	2.043172538
12	14	0.07978428	0.070683544
12	15	0.121740861	0.078605679
12	16	0.176749748	0.157687702
14	15	0.002855724	0.003536866
16	17	0.072845192	0.061347197
15	18	0.193627982	0.193810329
18	19	0.047879507	0.048491491
19	20	0.02077672	0.021644453
10	20	0.12218514	0.124725243
10	17	0.062381941	0.063543404
10	21	0.101930829	0.053115395
10	22	0.133204886	0.093432184
21	22	0.186200281	0.1696475
15	23	0.21872159	0.272394573
22	24	0.117401147	0.240765405
23	24	0.137654347	0.067982919
24	25	0.060769318	0.412372184
25	26	0.070519168	0.069497356
25	27	0.119438567	0.0557539
28	27	3.13E-01	1.064066876
27	29	0.172001628	0.172001628
27	30	0.321196025	0.321196025
29	30	0.065393092	0.065393092
8	28	0.118749049	0.105103904
6	28	0.003515842	0.054205897

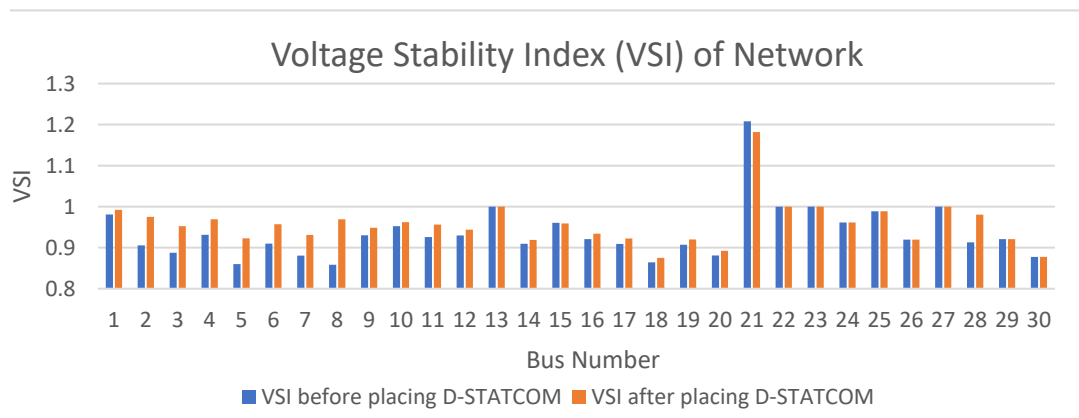
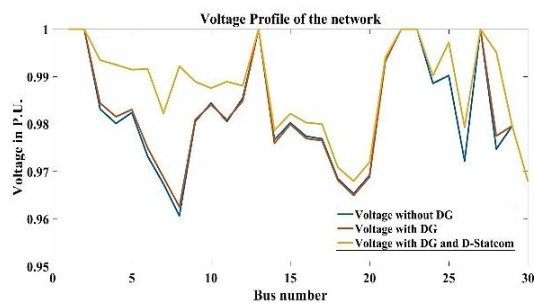
**Figure 3. Voltage Stability Index before and after addition of D-STATCOM**

Table 4. Optimum location and Size of DG and D-SATCOM

Location for DG/D-STATCOM (bus number)	Size for DG/ D-STATCOM (in MW/MVAr)
25 (DG)	9.1 (MW)
27 (DG)	7.6 (MW)
8 (D-STATCOM)	37.1 (MVAr)

With the addition of D-STATCOM along with the DGs to the network, a considerable improvement was observed in the voltage profile of the 30-bus network. The network's voltage profile is represented in Figure 4.

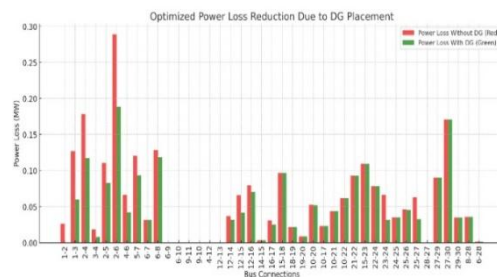
**Figure 4. Voltage Profile of the 30-bus network**

In order to ascertain the power flow, active and reactive power flow violations, as well as voltage generation violations before and after the

deployment of DGs and D-STATCOM to the network using the suggested approach, the load flow analysis of the network was carried out using the Newton Raphson technique.

The results for violations at 10%, 20% and 40% increment of the load from the base case shows the output on command window as shown in Tables 5, 6 and 7 after the addition of DGs and D-STATCOM.

From the above Tables 5-7, it can be concluded that after implementation of the proposed methodology improvement in the loading capability of the network without violation of load flow limits is achieved in addition to improving the voltage profile. Optimized Power Loss Reduction Due to DG Placement is shown in Figure 5, and optimized DG size comparison is shown in Figure 6.

**Figure 5. Optimized Power Loss Reduction Due to DG Placement****Table 5. Power Flow without and with DG & D-STATCOM for 10% load increment**

From	To	Flow without DG and D-STATCOM(MW)	Line Limit	Violation	%-Violation	Flow with DG and D-STATCOM(MW)
24	25	17.23649	16	1.23	7.68	14.42455

Table 6. Power without and with DG & D-STATCOM for 20% load increment

From	To	Flow without DG and D-STATCOM(MW)	Line Limit	Violation	%-Violation	Flow with DG and D-STATCOM(MW)
21	22	33.4194468	32	1.41	4.4	28.46174689
22	24	18.7327565	16	2.67	16.68	14.61895655
24	25	24.5152865	16	8.53	53.31	14.72378659

Table 7. Power Flow without and with DG & D-STATCOM for 40% load increment

From	To	Flow without DG and D-STATCOM(MW)	Line Limit	Violation	%-Violation	Flow with DG and D-STATCOM(MW)
21	22	36.10950215	32	4.05	12.7	29.31200215
15	23	17.23332563	16	1.2	7.5	14.11412563
22	24	22.21821693	16	6.17	38.5	15.52331693
24	25	29.50665388	16	13.53	84.5	15.82095388
25	27	17.82356862	16	1.77	11	14.52836862

From the Tables 8-9 and Figure 5,6 and 7; it can be concluded that the proposed methodology for optimal placement and sizing of DG is better as compared to the other techniques reported in literature. The integration of the Genetic Algorithm (GA) and Least Power Deprivation (LPL) method in simulation tests produced encouraging outcomes for optimizing the placement and sizing of distributed generators (DGs). Using LPL's emphasis on reducing power loss and GA's capacity to investigate intricate solution spaces, the technique successfully determined the best places for DG installation throughout the power system network. The approach's effectiveness in improving network resilience was validated by the results, which showed notable improvements in system voltage stability and a reduction in power losses.

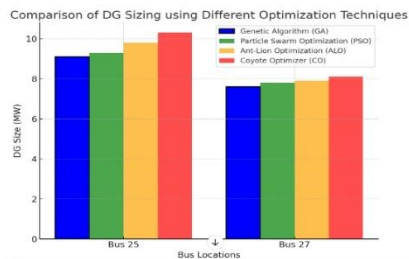


Figure 6. Comparison of DG Size using Different Optimization Techniques

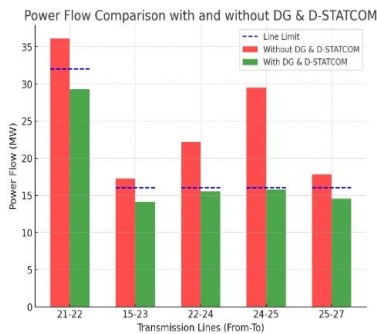


Figure 7. Power Flow improvement with integration of DG and DSTATCOM

The methodology's flexibility to load profile and network conditions was also demonstrated by the simulations, highlighting the methodology's potential for useful application in actual power systems. These findings enable well-informed decision-making for improving overall system performance and reliability by offering insightful information on sustainable energy integration strategies. By applying the GA-LPL methodology to bigger networks like the IEEE 57-bus and 118-bus test systems which more closely resemble distribution networks found in the real world, its scalability may be assessed. For example, a 57-bus system has a far greater number of possible DG placement locations than a 30-bus system, which results in a wider solution search area. Longer convergence periods and more power flow evaluations per candidate solution lead to greater computational complexity. The method's robustness under large-scale settings would be further tested in a real implementation on an IEEE 118-bus system, which contains several generators and voltage control devices. Applying GA alone could result in excessive computation time in a real metropolitan distribution network, such as a 200-bus system with many DGs interconnected at various load centres. This can be addressed by hybrid approaches that speed up convergence, including combining GA with deterministic techniques (like using linear programming for initial candidate selection) or parallel computing. Efficiency can also be increased by dynamic parameter tweaking, such as adaptive mutation rates. It is possible to verify the methodology's efficacy in reducing power loss while maintaining voltage stability in large-scale power systems by contrasting the outcomes with those of other optimization techniques, such as PSO and DE. By employing Genetic Algorithm (GA) and Least Power Deprivation (LPL) to improve Distributed Generator (DG) placement and sizing, the suggested methodology directly supports clean energy and carbon emission reduction objectives. The strategy

Table 8. Comparative analysis for voltage (pu) at bus 8

	VSI based DSATCOM	Harmony Search Algorithm, Yuvaraj <i>et al.</i> (2015)	Fuzzy Fire Fly Algorithm, Kaur <i>et al.</i> (2016)
Voltage Magnitude in pu	0.978	0.964	0.944

Table 9. DG Size Comparison at the two best bus locations

Bus Location	Genetic Algorithm (MW)	Particle Swarm Optimization (MW), El-Zonkoly <i>et al.</i> (2011)	Ant-Lion Optimization Algorithm(MW), Moayedi <i>et al.</i> (2021)	Coyote Optimizer(MW), Kamel <i>et al.</i> (2019)
25	9.1	9.3	9.8	10.3
27	7.6	7.8	7.9	8.1

reduces losses and improves grid performance by carefully integrating DGs. Decreased losses result in less reliance on fossil fuels, which lowers CO₂ emissions. Increased use of renewable energy also improves system stability and resilience, facilitating sustainable energy transitions. The study "Emission-aware Energy Storage Scheduling for a Greener Grid" is a real-world case study that illustrates how the best location for Distributed Generation (DG) may reduce emissions. The strategic scheduling of energy storage to reduce dependency on carbon-intensive power plants is the main emphasis of this work. Through the optimization of distributed energy storage installations, the study was able to reduce annual carbon emissions by nearly 0.5 million kilos, which translates to a 23.3% reduction in grid emissions. This notable decrease highlights how well-thought-out DG integration works to support a more sustainable and environmentally friendly power grid. Therefore, the proposed technique is a feasible solution for contemporary power systems striving for net-zero emissions since it supports cleaner power generation, lower operating costs, and long-term sustainability by aligning with global decarbonisation targets.

Conclusion & Future Scope

From the suggested technique, it can be inferred that by adding DG in an efficient way to the current power system network at strategic locations of optimal sizing, the network's loading capacity has increased plus reduction in power loss has achieved without requiring any changes to the network's architecture and structure. The network's power flow and voltage profile have also improved. By placing and sizing DG in an optimum location, both reactive and active energy deprivations are reduced. The usage of DG which may in the form of wind or solar helps in reducing carbon emissions thereby producing environment friendly clean energy. Also, the allotment of D-STATCOM has improved the voltage profile at specified bus and led to reactive power compensation as well thereby improving the power quality also. It takes extensive modelling and analysis to quantify the decrease in carbon emissions brought about by the deployment of distributed generators (DGs) and D-STATCOMs. The capacity and efficiency of the distributed generation (DGs), the power system's operational profile (including load demand and generation mix), and the efficacy of D-STATCOMs in enhancing system efficiency and lowering losses can all be used to estimate the reduction in carbon dioxide

(CO₂) emissions in simulations. The reduction in CO₂ emissions is often determined by contrasting scenarios with and without D-STATCOMs and DGs. The simulations monitor the amount of generation based on fossil fuels that is replaced by distributed generation (DGs), which typically employ cleaner or renewable energy sources, lowering the overall carbon intensity. D-STATCOMs also lessen distribution and transmission losses, which lessens the requirement for fossil fuel-based power and, as a result, lowering emissions. Simulations would need to include comprehensive data on power generation, load profiles, fuel mix, and environmental conditions in order to produce precise quantitative findings. Researchers can calculate the CO₂ emissions prevented or decreased as a result of the installation of DGs and D-STATCOMs by examining these variables, which provides important information about the advantages these technologies have for the environment in power systems. There are various difficulties in applying the GA-LPL methodology to actual power systems. Since precise load profiles, network setups, and real-time power flow data are necessary for the best possible DG installation, data availability is a major challenge. In real-world situations, utilities might have incomplete or out-of-date data, which would compromise the accuracy of the solution. Another problem is hardware compatibility because DG integration calls for protection systems and inverters that need to be coordinated with the grid's current setup. Large networks increase computational complexity, necessitating parallel computing or high-performance computers. The viability of implementation may also be impacted by regulatory restrictions and renewable energy uncertainties (such as solar PV variability). The integration of machine learning, smart grid technology, and powerful optimization algorithms holds the key to the future of Distributed Generation (DG) deployment and sizing. When choosing the best locations and sizes for distributed generation units (DG) units, optimization methods such as genetic algorithms and ant colony optimization will be crucial in taking load demand and budgetary concerns into account. In order to help in the sizing of DG units to match future demand patterns, machine learning models will make use of past data for predictive analysis. Real-time monitoring and control are made possible by smart grid technologies, guaranteeing dynamic adaptation to grid circumstances. This integration offers a robust, effective, and sustainable DG infrastructure when combined with data-driven decision support systems and decentralized autonomous operation.

Declarations

Availability of data and material: All data generated or analysed during this study are included in this research article, and any relevant information related to the current study are available from the corresponding author on reasonable request.

Competing interests: The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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