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Optimal PV Distributed Generators Allocation using Metaheuristic Algorithm to Enhance Voltage Profile

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Abstract: In this paper, the authors propose a methodology to identify the key locations to install integration of Solar & windbased distributed generators((DG) and the optimal amount of CapacityDGs required to maintain a steady voltage profile and voltage stability. The optimal amount of DG required is obtained via Gorilla troops optimizer(GTO)Metaheuristic algorithm and ,the locations where Integration of DG installation results in maximum benefit are obtained through the voltage stability index. The methodology tested in the Indian28 bus system shows that the proposed technique effectively identifies the critical locations and optimizes the required Integration DG capacity.

Keywords: PV Distribution, Algorithm, Voltage, Metaheuristic algorithm, Distributed generator.

1. INTRODUCTION

1.1 Introduction

In recent years the demand of electricity throughout the globe is increased drastically. But at the same time most of the power generated from the conventional power plants such as thermal, nuclear and etc. In other way the resources availability for generating power using these sources is declined in most parts of the world. So, in this regard it is evident that to generate electricity locally using natural resources such as solar, wind and biomass power plants. Furthermore, because of high R/X ratio the distribution system (DS) losses are more predominant as compared to transmission system. In order to solve the above problem, it is vital to use distributed generators connected to DS optimally. In appropriate allocation of DGs leads to negative impact in terms of high-power loss, degrades the voltage stability and reliability. So, better placement of DGs with proper sizes is an important issue in this era.

With the increasing penetration of DGs in power distribution systems, along with several energy storage devices and embedded customer power devices, the performance of these systems is expected to change in significant ways. Distributed generators play a crucial role in this transition towards a more intelligent electrical power grid. As a result, the allocation of these devices—including the ideal placement and sizing of these devices—has become a difficult problem due to the complex interplay between the advantages and disadvantages of each possible allocation. As more and more features are introduced to the smart grid, optimal allocation of DGs (OADG) has become a pressing issue in the optimisation of the power system. After years of focusing on minimising losses, the OADG problem has evolved into a multi-objective one that also takes into account other factors such as cost, power quality, and dependability. Because of the inherent uncertainty in renewable DGs and smart loads, solving this problem is both difficult and fascinating. Recent years have seen an explosion of published methods for addressing this OADG conundrum. Along with DGs, researchers have developed an algorithm for allocating other optimisation tools, such as network reconfiguration, shunt capacitor placement, D-FACT device deployment, and energy storage devices. An additional noteworthy fact is that several population-based metaheuristic approaches are employed to address these optimisation problems, since these have been shown to yield the best results, in particular when dealing with multi-objectives with Pareto fronts and DG and load uncertainty. Each new improvisation reports new metaheuristic strategies developed to tackle these issues.

1.2 Background

A high R/X ratio and radiality in an electrical distribution system (EDS) with a low voltage profile and high currents is typical. Distribution systems typically supply inductive loads, which leads to a flat voltage profile and substantial losses. An increase in power loss is not only technically inefficient, but also economically costly, as it necessitates more power generation and raises the price at which that power is produced. About twenty percent of India's total electricity production is lost in transmission and distribution.

To solve this issue, it is necessary to incorporate distributed generation (DG) into EDS, which has the potential to boost performance, power quality, stability, and dependability.

Additionally, DG can help boost the utilisation of RE sources like photovoltaic (PV) and wind turbine (WT) to reduce GHG emission in power system operation. According to the definitions, DGs can range in size from 1 kW to 5 MW and can be integrated at even the smallest consumer locations. This could help delay or even prevent the need for building new, larger power plants and transmission lines. Numerous conventional (non-heuristic) and heuristic search algorithms (HSAs) have been applied to the challenge of integrating DG units at suitable sites and their capacities, which is a complicated non-convex optimisation problem with multiple-objectives. HSAs have been identified for many engineering optimisation issues and have grown more popular than traditional approaches due to their reduced complexity and computing time requirements. The basic structure of HSAs may be changed with only a few inputs (such as the size of the search area, the range of the variables, and the maximum number of iterations), making them straightforward to understand and apply. In, the OADG problem for loss minimization is solved using the hybrid grey wolf optimizer (HGWO), which is formed by adopting different operators of evolutionary algorithms (EA). The IEEE 33-bus, 69-bus, and Indian 85-bus real-world systems are used in the case studies to determine the best placement and sizing for the various DG technologies.

2. LITERATURE REVIEW

Different authors solved capacitor, DG allocation problem using various heuristic, meta heuristic and nature inspired algorithms. In authors solved power loss reduction problem in DS with placement of capacitors. Best placement of capacitors with suitable sizes minimizes the losses in DS but does not fulfil the load requirement. Next, In authors solved DG allocation problem with an objective of reducing power loss of DS. In this paper a combined approach of voltage stability index (VSI) and cheetah's optimization algorithm is proposed to solve the DG allocation problem in DS. The summary of loss reduction by using different algorithms is illustrated in Table 1

Table 1. summary of different algorithms latestly used

Reference	Objective	Optimisation n Method	Test System	Year
[17]	Minimizing total power loss	MRFO	IEEE33,69,85	2020
[18]	Minimizing power loss	CSA-PSO	IEEE30	2020
[19]	minimizing real power loss and reactive power loss	CSO	IEEE85	2021
[20]	Minimize the power loss, voltage profile improvement	TSO	IEEE33,69	2022
[21]	reducing power loss RDS	IHBO	IEEE33,59	2022
[22]	DG allocation, power loss minimization, voltage profile improvement	MMPO	IEEE39,69	2022
[23]	minimize load losses, load cost ,reduce voltage drop	MOEAD	IEEE30,69	2022
[24]	loss minimization, voltage profile improvement	MINLP	IEEE16,33	2022
[25]	Power loss reduction,Voltage profile	POA	Indian 28	2022
[26]	Reactive power reduction with a capacitor bank	PSO	IEEE15	2023
[27]	Minimizing Real power loss, improving voltage profile	Hybrid SSA-GWO	IEEE123	2023
[28]	reducing power loss RDS	MOGFPA	IEEE33,69,119	2023
[29]	Minimize active power loss, improve voltage profile	EOA	IEEE123	2023
[30]	Minimize the power loss, voltage profile improvement	RSA	IEEE39,69	2023
[31]	Reduction cost of power loss & cost of reliability	ISSA	IEEE39,69	2023
[32]	Reactive power compensation, with fixed capacitor	BHO	IEEE8,IEEE27	2023
[33]	Reduction of annual economic loss, voltage profile improvement	MOWOA	IEEE33,69	2023
[34]	Reduction in power loss in Distribution network	PSO	IEEE34 bus	2023

2.1 LOAD PROFILING AND SOLAR IRRADIANCE MODELLING

2.1.1 Load Profiling

This paper's load profile is modeled following three load patterns, i.e., residential, commercial and industrial, as discussed in [1]. The behavior of the loads is characterized by their consumption cycles, that can be represented by load curves as shown in Figure 1.

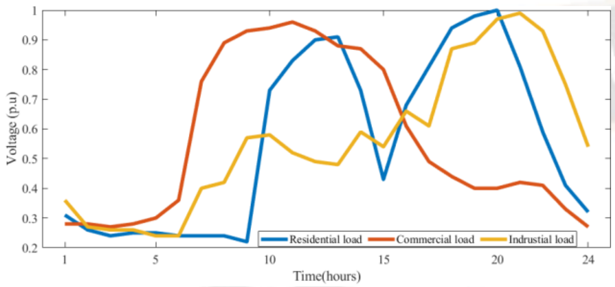

Fig 1 24-hour load profiles for different power consumers

2.1.2 Modelling of the Solar Irradiance

An significant factor is the erratic aspect of solar energy output. The performance of the solar DG modules is determined by solar irradiance. A brief literature analysis indicates that the Beta likelihood density (PDF) function has been been used to accurately model the sun's radioactive irradiance. Reference, is used to obtain historical information of solar irradiance, other metrics like mean and standard deviation are also evaluated from the hourly data.The solar irradiance distribution using Beta PDF can be written as:

$$f_b(s) = \begin{cases} \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} s^{(\alpha-1)}(1-s)^{(\beta-1)} & 0 \le s \le 1, \alpha, \beta \ \ge 0 \\ 0 & otherwise \end{cases}$$

(1)

$$\beta = (1-\mu)\left(\frac{\mu(1-\mu)}{\sigma^2} - 1\right) \qquad (2)$$

$$\alpha = \frac{u\beta}{1-\mu} \qquad (3)$$

where Γ is the gamma function,s is solar irradiance (kW/m^2). α and β are the shape parameters, which can be calculated using mean (μ) and standard deviation (σ) of s. As shown in, the maximum output can be calculated as:

$$P_0(s) = N * FF * V_y * I_y$$

(5)

where P_o is the output of PV module at solar radiance s, N is the number of PV modules.

$$FF = \frac{V_{MPPT} * I_{MPPT}}{V_{OC} * I_{SC}} \qquad (6)$$

$$V_y = V_{OC} - K_v * T_{cy} \qquad (7)$$

$$I_y = s\left[I_{SC} + K_i(T_{cy} - 25)\right] \qquad (8)$$

where FF is the fill factor, N_{OT}, V_{OC} and $I_{SC}$are nominal operating temperature, opencircuit voltage, short-circuit current of the PV module, respectively. T_A and T_y are ambient temperature and PV module temperature, respectively. V_{MPPT} and I_{MPPT} are voltage and current and maximum power point. K_v and K_i are the voltage temperature coefficient and current temperature coefficient, respectively.

2.2 Modeling of Wind turbine

The V162-IEC 5.6mw turbine generator manfucaturing certain specifications,german electric company such specifications listed in below table.The wind generator rotorspeed,wind speed and mechanical power output shown in equation (9),(10),and (11).

Mechanical power output

$$P_{mech}(v_{wind}, \omega_{rotor}) = (1/2) \times \rho \times v^3_{wind} \times (\lambda, \theta) \qquad (9)$$

$$\lambda = \frac{\omega_{rotor} \times GR \times R_{rotor}}{v_{wind}} \qquad (10)$$

$$C_p(v_{wind}, \omega_{rotor}, \theta) = C_1\left(C_2 \frac{1}{\propto} - C_3\theta - C_4\theta^x - C_5\right) \times \exp\left(\frac{-C_6}{\propto}\right) \qquad (11)$$

$$\frac{1}{\propto} = \frac{1}{(\lambda + 0.08\theta)} - \frac{0.035}{1+\theta^3} \qquad (12)$$

Here ρ=airdensity,v_{wind}=speed of wind turbine,C_p=non linear function tip speed ratio =λ,pitch angle =θ, ω_{rotor}= generator rotor speed,R_{rotor}=rotor radius wind blades,C_p,C_1,C_2,C_3,C_4,C_5 are x constants from .

$$P_{WTG} = \begin{cases} 0 & ; 0 \le v \le v_{cin} \; or \; V \ge V_{cout} \\ P_{WTG}, rated \times \left(\frac{v - v_{cin}}{v_{rated} - v_{cin}}\right) & ; v_{cin} \le v \le v_{rated} \\ P_{WTG,rated} & ; v_{rated} \le v \le v_{cout} \end{cases}$$

(13)

The detail specifications used in solar and wind turbine shown table 1.1

Discription	Specifications	Rating of unit
Solar panel	Pv panel Ambianet temparature(T_a) Nominal operating temp (N_{ot}) Open circuit voltage Short circuit current	225w 31.76˚C 40 to 65˚C 38.96volts 8.57amp
Wind turbine	Rated output Cut in speed Cut-Out speed Frequency Hub height	5.7MW 3m/s 25m/s 60/50 Hz 119m

Table 1.1 The specifications DG sources as follows

Enhanced raven roosting optimisation, or IRRO for short, is a technique that was employed by the authors of to take advantage of the economical and technical benefits that dispersed generators offer when they are integrated into distribution networks. The minimax-based game theory algorithm was used to make the decision to go with the best compromise solution (BCS). It has been determined that the Pareto optimum front-based artificial bee colony (ABC) optimisation algorithm is the most effective method for determining the ideal size and distribution of DG in RDS. In order to improve the functionality of distribution systems, the problems of total energy loss, power loss, and voltage drop were recast as an optimisation problem including MO. The authors of created an improved Harris Hawks Optimizer (IHHO) in a multi-objective space in order to arrange DG units in distribution networks in the most optimal manner possible. The system's stability was significantly improved by optimising several distinct types of DG units. In order to locate the BCS using the obtained POF, the procedure known as grey relational projection (GRP) was applied. It is important to keep in mind that the GRP is only useful for accomplishing objectives that are very tightly tied to one another. The multi-objective Archimedes optimisation (MOAOA) algorithm has been adopted for the purpose of reducing energy losses incurred by RDSs that are combined with DGs while the RDSs are operating throughout the day. The MOAOA technique is the most effective one for solving the current optimisation issue, beating out both the PSO and ASO approaches. The authors of the article introduced the use of the three new versions of the MO Bonobo Optimizer (MOBO) for the purpose of solving the optimal installation of DG Type-I on the 33-bus and 85-bus distribution systems in order to minimise only the voltage deviation summation and power loss. The POF that was obtained through the use of the MOBO versions was compared with the MOF that was obtained through the use of other well-known multi-objective optimisation techniques such as MOPSO, MOAEO, MOGSA, and MOJAYA utilising MO indicators. Different statistical analyses were performed while the demand load was being applied in order to evaluate the fuzzy best compromise options for each of the offered approaches. It was found that various iterations of the MOBO algorithm performed well in a variety of different contexts.

According to research that was done in the past, a variety of metaheuristic approaches are utilised when solving the DG and SC placement problem by means of weighted MO optimisation. In other words, a few strategies based on Pareto optimal sets were used in order to optimally allocate shunt capacitors, DG Type-I, and DG Type-III considering different load models. These strategies were applied in order to achieve the best possible results. In light of this, the purpose of this research is to offer a basic framework for integrating SCs and multi-type DGs into RDS under numerous different load models in order to improve voltage stability, ameliorate voltage deviation, and minimise active power loss. Both the recently developed and highly effective Multi-objective Lichtenberg Algorithm (MOLA) and the recently developed and physics-inspired Multi-objective Thermal Exchange Optimisation (MOTEO) algorithm are used to accomplish this goal. Both of these algorithms fall under the category of physics-inspired algorithms. In comparison to other well-known methods, the MOLA and MOTEO were able to solve typical optimisation issues in a way that was both successful and expedient. As a result, we shall implement them in order to make the most of the technological advantages offered by DGs and SCs when they are combined with the IEEE 69-bus distribution system.

3. PROBLEM FORMULATION

In this paper, the authors propose a methodology to solve a multi-objective optimization problem, i.e., optimal placement of Integrated Solar & windDG modules, to reduce power loss, to improve voltage stability margin and to improve voltage profile subject to distribution system constraints. So the two objective functions are votlage stabilty index (VSI) and power loss, as shown below:

3.1 Power Loss Minimization

After the potential locations for Integration of DG installation are identified another important aspect of this methodology is, minimization of power loss. In this regard, another objective function is proposed to evaluate the power

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loss in the distribution network. It can be described as follows:

$$f_2 = \sum_{b=1}^{n_b} |I_b|^2 R_b \qquad (15)$$

where I_b and R_b are branch current and resistance, respectively and n_b is total number of branches.

3.2 Problem Constraints

The multi-objective optimization problem described above is solved with respect to the distribution network constraints. They are:

Voltage constraints
$$|V_{min}| \le |V_k| \le |V_{max}| \qquad (16)$$

Thermal constraints
$$I_{ij} \le I_{ij}{}^{max} \qquad (17)$$

DG capacity constraints
$$P_{DG,min} \le P_{DG,k} \le P_{DG,max} \qquad (18)$$

Power balance consraints
Generation= Demand +Losses
$$P_{slack} + \sum_{k=1}^{N_{DG}} P_{DG,k} = \sum_{k=1}^{N_L} P_{D,k} + \sum_{k=1}^{n_b} P_{loss,k} \qquad (19)$$

3.3 Voltage Stability Index Improvement

The stress on distribution system increases with increased loading, faults and equipment malfunction. When the distribution system is stressesd beyond its capacity, The machine voltage stability deteriorates and even can lead to loss of the voltage. For the reliability of the voltage of the system, the VSI (voltage stability index) must be tracked [5, 6].. The objective function can be describes as follows:

$$f_1 = VSI = |V_i|^4 - 4 * \{P_j x_{ij} - Q_j r_{ij}\}^2 - 4 * \{P_j r_{ij} - Q_j x_{ij}\}^2 * |V_s|^2 \qquad (20)$$

As VSI is an index of voltage stability, V_i is a receiving bus voltage, and P_j is an active receipt end load, Q_j is a reactive end load, and r_{ij} is the line resistance i – j and x_{ij} is the line i – j response. VSI will still be greater than zero on all buses.If the VSI is closer to one, the buses become stable, farther the value of VSI from one, the system and the respective buses will become weakest. The values of VSI are sorted in descending order and the buses with weakest VSI will be identified as potential locations for integration of DG installation and VSI is choosen as objective function.

4. GORILLA TROOPS OPTIMIZER (GTO) ALGORITHM

Migration to an unfamiliar place, joining up with other gorillas, migrating in the direction of a predetermined location, trailing behind the silverback, and competing for adult female status are just a few of the methods that GTO takes its cues from in gorilla groups. This is illustrated in figure 1(a) and the respective working flow chart is shown in figure 1.(b).

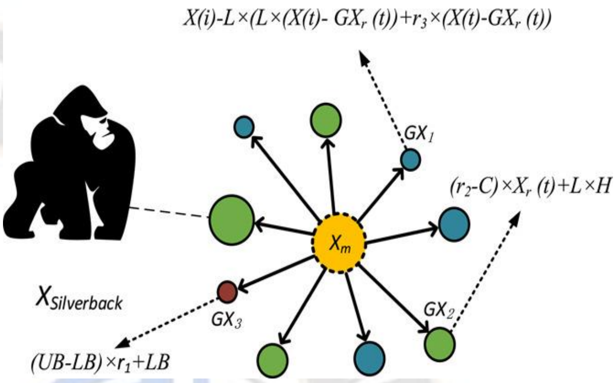

Fig 1a. shows GTO algoritham diagram

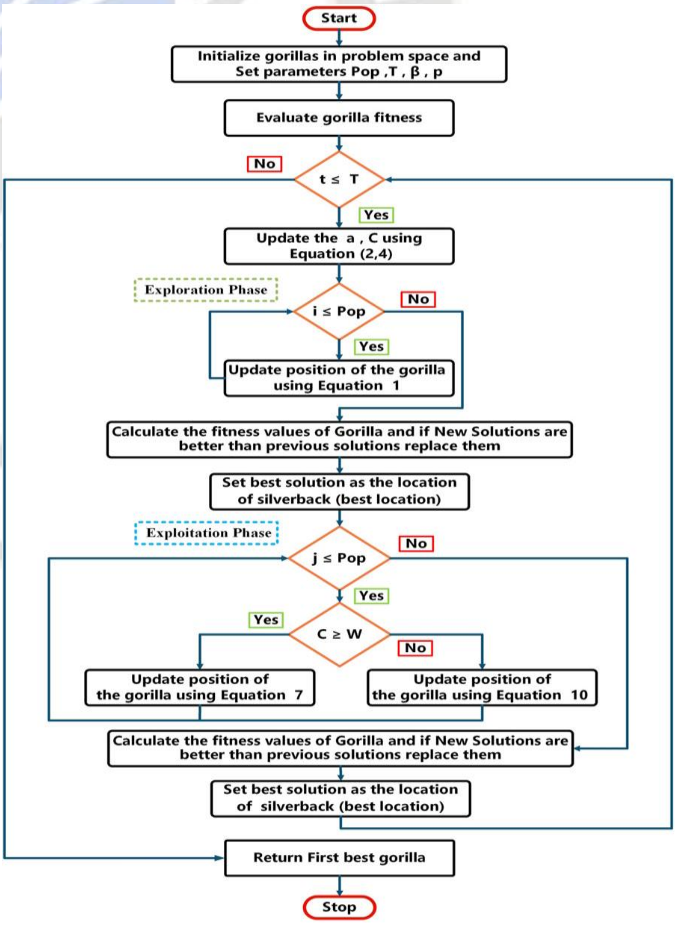

Fig 1b.shows flow chart of GTO algoritham

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5. RESULTS AND DISCUSSION

One research system are tested for the suggeste GTO technique, that isIndian 28 bus system with Three different load profiles, i.e., residential, commercial and industrial are used to check the efficacy of the methodology.Figure 1 shows the hourly load requirement of these load profiles.In this study solar,Wind modules are considered as a source of active power only, also theSolarPV,wind-DGs are modelled using beta PDF as discussed in Section 2,section 3 will be GTO algoritham , to account for their intermittent behaviour. The value of solar irradiance ,wind turbine modeling is considered for The voltage stability index (VSI), is evaluated at base case and the buses with low values of VSI are identified as potential locations for DGs installation. The critical buses for 28-bus system are identified as 13, 24 and 28. seven cases of sequential solar,wind,integration both DGs installation are considered for each system, starting from without DG, after solar, wind ,integration both DG s are installed one by one in the order of their criticality, i.e., the most critical buses are installedSolar, wind and with Both integration first and then the next and so on.

5.1 Results for 28-bus system

The potential locations in Indian 28-bus real time test system are identified as 13, 24 and 28 buses. For Optimal allocation of DG in the network.The results are shown for three load profiles, i.e. residential, commercial and industrial as described in. The single line diagram of Indian 28-bus real time test system shown in below figure2.

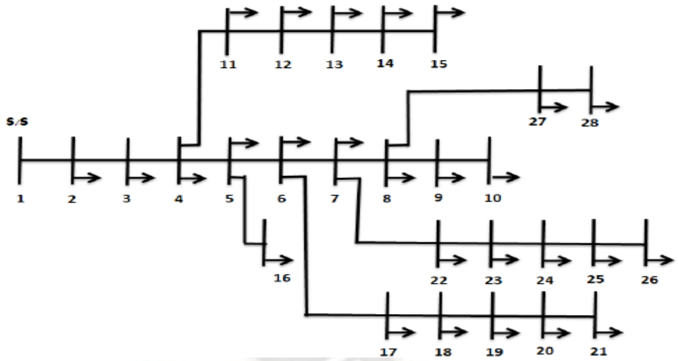

Figure2. One line diagram of 28-bus Indian distribution network

TABLE -2: 28-BUS TEST SYSTEM PERFORMANCE ANALYSIS

Different cases	Bus no	DG sizes (kw)	P_{loss}(kw)	V_{min}(p.u)	VSI_{min}(p.u)	% Redu P_{loss}
Base case	NA	NA	68.8189	0.9123	0.6927	NA
1Solar DG	13	450.47	51.5105	0.9299	0.7470	25.158
2Solar DGs	13 24	265.7533 373.687	38.3096	0.9575	0.8397	44.33
3Solar DGs	13 24 28	228.6199 204.3446 245.6401	36.6885	0.9653	0.8539	46.68
1Solar+1Wind=2DGs	13 13	450.5891 445.5575	35.2987	0.9422	0.7882	48.71
1Solar+2Wind =3DGs	13 13 24	436.2239 266.5497 367.9311	21.1011	0.9617	0.8463	69.33
2Solar+1Wind=3DGs	13 24 13	250.5 399.9 1272.4	21.437	0.9697	0.884	68.85

The results of 28 bus systemis illustrated in table.2.

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5.1.1 Results for 28-bus system for residential load.

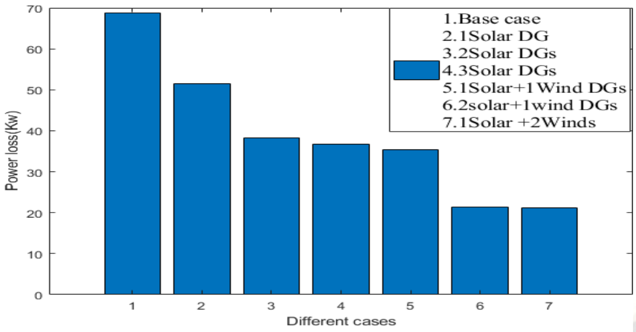

Figure 3a. Different cases of Power loss

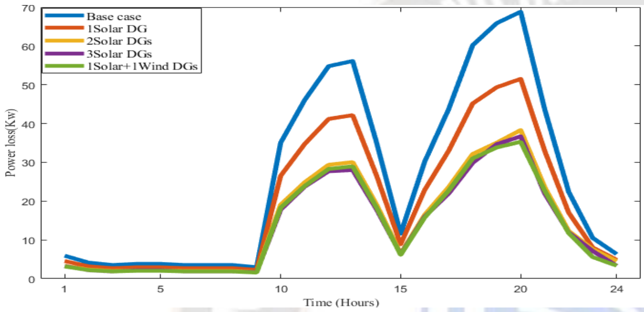

Figure 3b. Different cases of power loss 24 hours

Residential loading results for 28-bus system are can be observed that residential load is maximum at 20th hour. In figure 3a&3b the power loss was maximum without DG installation at 20th hour in 68.8189 kW, after one Solar DG installation power loss reduces to 51.51 kW, after two solar DG installation power loss reduces 38.3096 kW , after three solar DG installations, power loss reduces to 36.6885 kW which is the lowest power loss at 20th hour. And the integration solar and wind DG gets better results compared with only Solar DG connected system of Similar pattern can be observed from 1st hour to 24th hour, i.e. power loss is maximum without any DG installations and it sequentially decreases with every DG installation. The optimal value of DG obtained using metaherastic algorithm and the value of DG required at buses 13, 24 and 28 is also maximum at 20th hour.

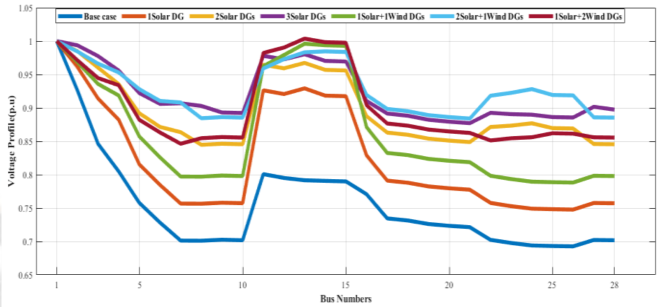

Figure 4.Voltage profile of 28 bus system

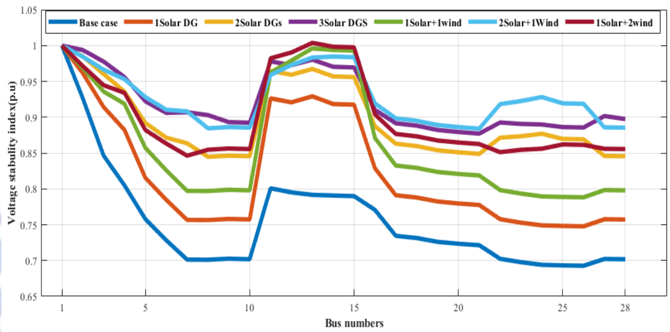

Figure 5.Voltage stability index of 20th Hour.

Figures 4 and 5 represent the voltage profile and VSI of the system at all buses, it can be inferred that without DG results in poor voltage stability and voltage profile, whereas Integration DG will gives better results, i.e. Integration of DGs installed at all three buses results in best voltage stability and voltage profile., it can be observed that the proposed methodology optimizes the total DG value also, resulting in best voltage profile and higher VSI.

Table-3The Power losses are occurring 24hours different cases shown in below

Time (Hour)	Base case ploss (kw)	Ploss 1-solar DG(kw)	Ploss 2-solar DGs(kw)	Ploss 3-solar DG(kw)	Ploss (1-solar+ 1-wind)DGs(kw)
1	5.9219	4.54687	3.325131329	3.232592356	3.1571
2	4.1354	3.18014	2.330156	2.18429	2.2099
3	3.51349	2.70354	1.98246	1.8532	1.8793
4	3.81789	2.93687	2.15273	2.152116	2.0412
5	3.81789	2.93687	2.15273	2.152116	2.0412
6	3.51349	2.70354	1.98246	1.8532	1.8793
7	3.51349	2.70354	1.98246	1.8532	1.8793

8	3.51349	2.70354	1.98246	1.8532	1.8793
9	2.943826	2.2665779	1.71185	1.665	1.576
10	35.038159	26.515143	19.05358	17.79182	18.2734
11	46.048648	34.712	24.8309181	23.7140605	23.8743
12	54.78727	41.182117	29.36317	27.705677	28.2828
13	56.107273	42.156859	30.0439524	28.009509	28.946
14	35.038159	26.515143	19.05358	17.79182	18.2734
15	11.59909	8.871448	6.456787	6.30445	6.1476
16	30.158	22.8649	16.4669	15.9932	15.7731
17	43.7101	32.9754	23.6103	21.9596	22.6892
18	60.1769	45.1579	32.1367	29.8518	30.9865
19	65.8628	49.3405	35.0457	34.6618	33.8268
20	**68.8189**	**51.5105**	**38.3096**	**36.6885**	**35.2987**
21	43.7101	32.9754	23.6103	21.9596	22.6892
22	22.3811	17.0243	12.3084	11.913	11.7638
23	10.5135	8.0465	7.6406	7.1317	5.5778
24	6.3194	4.8505	4.5256	3.3377	3.3674

The power loss of 28 bus system for 24 hours of the residential load illustrated in table3.

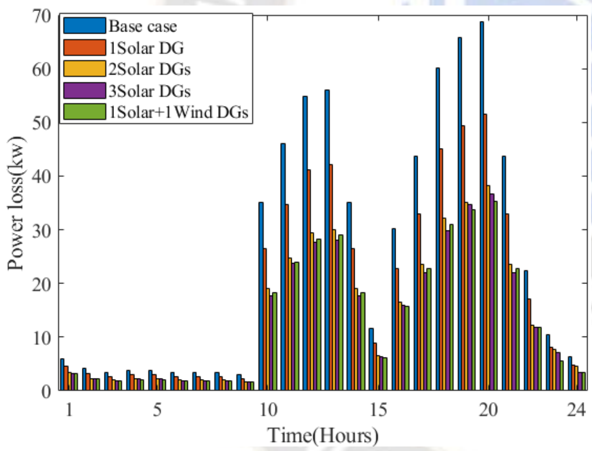

Figure6. Power loss 24hours in different cases Residential Load.

The power loss calculation graphs for 24hours in different cases Residential Load are shown in figure 6.

4.1.2Results for 28 Bus system Commercial loads

In commercial 28Bus system the base case power loss is 62.9824kw for integration of one solar and one wind DG the power loss reduced into 32.38955, & for installing 3Solar DG power loss reduced in to 31.2864.The voltage profile and voltage stability also improved which was shown on figure 7(a) and 7(b).

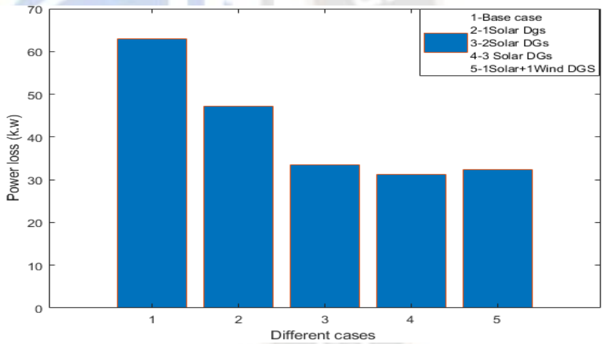

Fig7(a).Commercial power loss Different cases

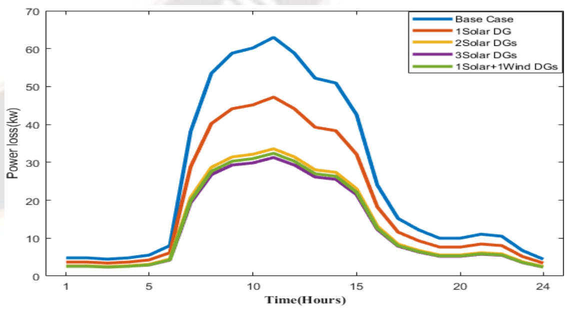

Fig7(b).Commercial power loss 24Hours

4.1.2 Indian 28 bus system for Industrial load

In 28 bus system connected to the industrial load the base case power loss is 67.3313kw for connecting Integration for one solar & one wind DG the power loss reduced in to 34.5584kw and for installing 3 Solar DGs at proper location The power loss reduced in to 33.3459kw.The voltage profile

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and voltage stability index are also improved in this systemwhich was shown on figure 8(a) and 8(b).

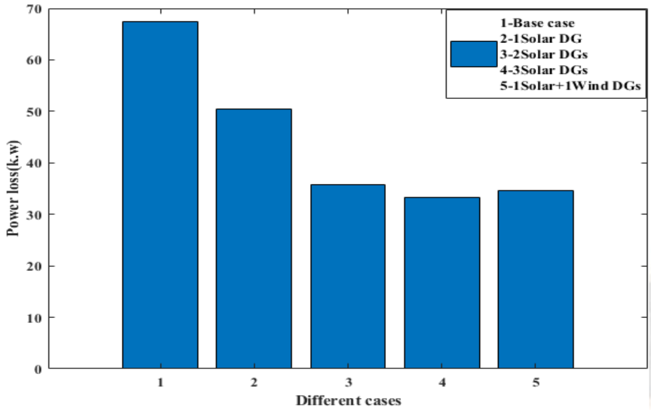

Fig 8(a). Industrial power loss different cases

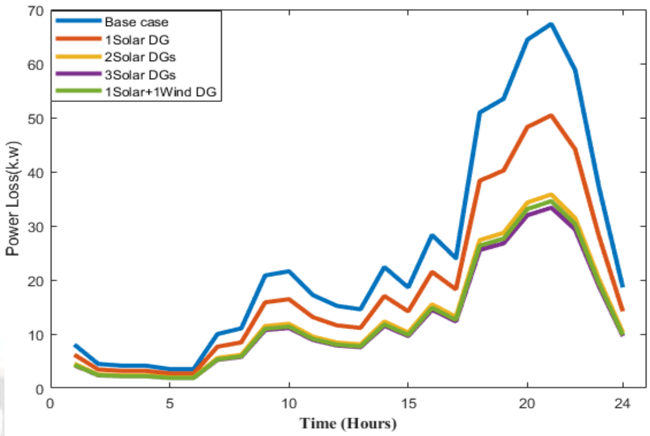

Fig8(b). Industrial power loss 24 Hours

Table-4.DG sizes for power loss reduction at different cases 24 hours

Hour	1-Solar DG(kw)	2-Solar DGs(kw)		3-Solar DGs(kw)			1Solar+1Wind DGs(kw)	
1	131.745	78.7933	112.675	69.8651	63.9706	53.43596	131.7968	133.2454
2	110.0776	65.87133	94.3376	56.6839	51.84355	62.19736	110.1173	111.49
3	101.458	60.7384	87.0058	52.3286	47.7524	57.7008	101.4874	102.8231
4	105.76665	63.29828	90.6579	63.2224	77.13249	13.61426	105.7976	107.1562
5	105.76665	63.29828	90.6579	63.2224	77.13249	13.61426	105.7976	107.1562
6	101.458	60.7384	87.0058	52.3286	47.7524	57.7008	101.4874	102.8231
7	101.458	60.7384	87.0058	52.3286	47.7524	57.7008	101.4874	102.8231
8	101.458	60.7384	87.0058	52.3286	47.7524	57.7008	101.4874	102.8231
9	92.86727	81.32618	64.6189	55.3893	52.45619	26.53735	92.8939	94.1673
10	320.97492	190.519	269.751	163.9138	147.9386	177.411	321.1336	320.4339
11	368.146668	218.0482	307.9763	183.38	78.15614	317.994	368.3088	366.299
12	401.70936	237.5662	334.896	188.7682	173.0804	289.0996	401.8571	398.7332
13	406.544645	240.3611	338.763	206.8005	185.3896	222.7474	406.6916	403.3871
14	320.97492	190.519	269.751	163.9138	147.9386	177.411	321.1336	320.4339
15	184.453402	110.1034	157.02	137.0717	39.71544	153.2962	184.534	185.8897
16	297.7	176.8968	250.7731	191.8112	226.8792	47.4438	297.8669	297.7008
17	358.6	212.5038	300.2997	181.7739	160.7662	203.3308	358.8066	357.078
18	421.1	248.8	350.4	212.1358	182.9326	243.1493	416.3788	412.7218
19	440.6	260.0999	365.9	361.7994	296.5175	77.6914	440.7651	436.1448
20	450.5	427.3523	319.3315	411.4016	138.0633	311.1755	450.5891	445.5575
21	358.6	212.5038	300.2997	181.7739	160.7662	203.3308	358.8065	357.0862
22	256.4	152.6	216.8	147.0702	206.8744	50.5359	256.5076	257.0936
23	175.6	244.0752	109.3863	227.8373	94.0267	136.2361	175.6743	177.0727

24	136.1	176.1	145.8	68.4668	47.1776	95.9464	136.1505	137.6135

Table 4illustrates the size of DGs used for power loss reduction.

Table 5 .The above algorithm results compared the data related 28 bus system.[34]

Different methods	DG size in kw	Ploss (kw)	V_{min}(p.u)	VSI_{min}(p.u)
GOA	334.5565 230.4149 145.4055	33.649	0.9638	0.8614
WOA	182.5130 262.1370 265.0772	33.9388	0.9613	0.8541
DA	332.1820 235.1820 145.1591	33.6512	0.9632	0.8611
POA	222.0523 220.5258 256.781	33.1337	0.9632	0.8612
GTO	228.6199 204.3446 245.6401	34.048	0.9652	0.8538

The compared results of the data related 28 bus system are shown in table 5.

6. CONCLUSION

The proposed GTO methodology addresses two key aspects of Integration Solar and wind -DG installation, firstly the key locations where DG installation can give best results, secondly the amount of DGrequired to address the increased loading in the system. The DG amount required to maintain the voltage profile and voltage stability in the system has been calculated effectively by metaheuristic algorithm.The technique has been tested on 28 bus standard system with different loads and results are in agreement that the proposed methodology can effectively maintain voltage stability and voltage profile in the system with optimum value of DG.

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