Uncertainty Based Performance Evaluation of Wind-PV Integrated Distribution Network using MOGWO

Sharmistha Sharma[1], Arup Ratan Bhowmik[2], Sadhan Gope[3] and Diptanu Das[4]

[1,2,3,4]Department of Electrical Engineering, National Institute of Technology, Agartala, Tripura, India

Abstract:- Major problem of distribution network is to allocate Distributed Generation (DG) optimally to enhance the performance of the system. In this research, two types of DG sources are ideally positioned in a 69-bus radial distribution network (RDN) under uncertainty to minimize network real power losses (RPL), maximize voltage control (VC), and improve voltage stability index (VSI). The uncertainty in power availability from photo voltaic (PV) and wind turbine (WT) DG sources along with load demand, have been simulated using the 2m point estimate approach (PEM). From the results obtained it is observed probabilistic approach provides more realistic results considering the uncertainties present in the RDN. In this paper comparative assessment of Grey Wolf Optimization (GWO) with Teaching Learning Based Optimization (TLBO) and Quasi-Oppositional TLBO (QOTLBO) techniques have been performed. Results prove the efficacy of GWO algorithm over other existing techniques.

Keywords*: Distributed Generation, Real power losses, Voltage Control and stability, Uncertainty, Point estimate method, Grey Wolf Optimization.*

1. Introduction

Utilisation of DG sources in RDN is now required to fulfil rising load demand and the fast deployment of fossil fuels. Among the several DG technologies because of their lower operating costs, higher service dependability and enhanced power quality, PV and WT are the most often employed DG sources in power system networks. However, wind and solar energy sources provide variable and unpredictable power because of the fluctuating behaviour of radiation from the sun and air velocity. Besides these, load demand of the network is also uncertain. In the current work, optimal location of PV and WT DG source in RDNs has been determined to reduce RPL, enhance voltage stability and improve voltage profile of the systems considering uncertainties present in DG power output as well as load criterion. The 2m point estimate method (PEM) was used to model the volatility in load demand and electricity supply from both wind and solar DG units.

Allocation of DG sources in optimum places have profoundly impacted on many factors of RDNs. In [1], M.H. Moradi and M.Abedini, in [2] S. Sultana and P.K. Roy, in [3] Sharma et al. determined DG allocation in RDNs to reduce loss and to enhance voltage profile and voltage stability of the networks by applying different optimization techniques. Many other researchers also determined DG allocation in RDNs to improve performance of the networks as depicted in [4-11]. But only few researchers considered uncertainties of DG sources and load in DG allocation problems. In the present work the authors have determined optimal placement of PV-WT based DG sources in RDN recognizing wind uncertainty, solar power output and load demand by applying Multi-objective Grey Wolf Optimization (MOGWO). In comparison to other well-known meta-heuristic techniques, the GWO algorithm [12] is able to deliver better results for various benchmark functions since it is modelled on the organizational hierarchy and hunting process of the grey wolves. Additionally, the GWO algorithm outperforms many previously developed optimization algorithms in terms of exploration and exploitation. The enhanced performance of the GWO method has prompted the present authors to use it to assign DG sources in RDN in the most effective way possible in order to decrease RPL, to control voltage, and preserve voltage stability in the face of uncertainty. To show the usefulness and superiority of the algorithm, the GWO algorithm's findings were compared to the TLBO and QOTLBO algorithms.

2. Problem Formulation

The current study intends to minimise RPL, maximize VC and increase VSI of RDNs by optimally deploying PV and WT-based DG sources in networks while accounting for variability in wind, solar power production, and demand of the load. In this work, variation of power available from WT and PV DG sources are modelled by Weibull and beta distribution, while uncertainty in load demand is modelled as a normal distribution.

2.1 Modeling of wind power

The unpredictable power available from WT is formulated as [13,14]:

$$P_{wind} = \begin{cases} 0, & v \le v_{ci} \\ a_w + b_w v, & v_{ci} \le v \le v_r \\ P_r, & v_r < v \le v_{co} \\ 0, & v > v_{co} \end{cases} \tag{1}$$

$$a_w = P_r v_{ci} / (v_{ci} - v_r), \quad b_w = P_r / (v_r - v_{ci}) \tag{2}$$

where wind speed is v; cut-in wind speed is v_{ci}; cut-out wind speed is v_{co}; rated wind speed is v_r; rated output power of WT is P_r.

The following formulation below shows the probability density function (PDF) of wind speed behavior [13,14,15]:

$$f(v) = \frac{k_w}{c_w}\left(\frac{v}{c_w}\right)^{k_w - 1} \exp\left[-\left(\frac{v}{c_w}\right)^{k_w}\right], \quad \text{where } v_{ci} \le v \le v_r \tag{3}$$

$$f(v) = 1 - \exp\left(\left(-\frac{v_{ci}}{c_w}\right)^{k_w}\right) + \exp\left(\left(-\frac{v_{co}}{c_w}\right)^{k_w}\right), \quad \text{where } v \le v_{ci}, \; v > v_{co} \tag{4}$$

$$f(v) = \exp\left(-\left(\frac{v_{ci}}{c_w}\right)^{k_w}\right) - \exp\left(-\left(\frac{v_{co}}{c_w}\right)^{k_w}\right), \quad \text{where } v_r < v \le v_{co} \tag{5}$$

where k_w and c_w are the shape and scale factors of Weibull distribution function; The mean (μ_w) and standard deviation (σ_w) of wind speed are calculated as follows:

$$\mu_w = c_w \Gamma\left(1 + \frac{1}{k_w}\right) \tag{6}$$

$$\sigma_w = c_w^2 \Gamma\left(1 + \frac{2}{k_w}\right) - \mu_w^2 \tag{7}$$

where Γ represents the gamma function.

2.2 Modeling of PV power

The power output from PV is expressed as follows [16]:

$$P^{pv}(s_i) = N_s \times FF \times V(s_i) \times I(s_i) \tag{8}$$

$$FF = \frac{V_{MPP} \times I_{MPP}}{V_{oc} \times I_{sc}} \tag{9}$$

$$V(s_i) = V_{oc} - K_v \times T_c \tag{10}$$

$$I(s_i) = s_a \times \left[I_{sc} + K_i (T_c - 25) \right] \tag{11}$$

$$T_c = T_A + s_a \times \frac{N_{OT} - 20}{0.8} \tag{12}$$

where s_i is the solar irradiance in kW/m^2; s_a is the average solar irradiance; T_c is the cell temperature in ºC; T_A is the ambient temperature in ºC; N_{OT} represent the nominal operating temperature of a PV cell in ºC (Degree Celsius); K_v and K_i are voltage and current temperature coefficients in V/ºC and A/ºC; N_s is the number of PV modules; FF is the fill factor; I_{sc} is the short circuit current in Amp; V_{oc} is the open circuit voltage in Volt; the current and voltage at maximum power point in Amp and Volt are denoted by I_{MPP} and V_{MPP} respectively.

Beta distribution function is used to replicate the stochastic behaviour of solar irradiation, as follows [16]:

$$f(s_i) = \frac{\Gamma(\alpha_s + \beta_s)}{\Gamma(\alpha_s)\Gamma(\beta_s)} s_i^{\alpha_s - 1}(1 - s_i)^{\beta_s - 1}, \qquad 0 \le s_i \le 1, \alpha_s \ge 0, \beta_s \ge 0$$
$$= 0, \qquad otherwise \tag{13}$$

where, α_s and β_s are the shape parameters of the beta distribution function; Γ represents the gamma function.

The mean (μ_s) and standard deviation (σ_s) of solar irradiance are calculated as follows using the aforementioned formulae:

$$\mu_s = \frac{\alpha_s}{\alpha_s + \beta_s} \tag{14}$$

$$\sigma_s = \sqrt{\frac{\mu_s^2 (1 + \mu_s)}{(\alpha_s + \mu_s)}} \tag{15}$$

2.3 Modeling of load demand

The following is a representation of the probability density function for load demand [13,14]:

$$f(P_{load}) = \exp[-(P_{load} - \mu_p)^2 / 2\sigma_p^2] / \sqrt{2\pi}\sigma_p \tag{16}$$

where μ_p and σ_p are the mean and standard deviation of load demand.

2.4 2*m* Point Estimate Method along with spatial correlations between WT, PV sources and load

The present work employs Hong's 2*m* PEM method to model the load demand and the available output power of WT and PV units which are both unpredictable [17,18]. In 2*m* PEM, each random variable in a stochastic situation is replaced with two deterministic points on each sides of the relevant distribution function's mean value. In the case of *m* input random variables (IRVs), the research problem is solved twice for each random variable: once for the point above the mean and again for the point below the mean. Other random variables are held at their mean value in this case. Finally, the output random variable's mean and standard deviation of can be determined by applying 2*m* PEM. The spatial correlations among sources and loads have been taken into account in this study using 2*m* PEM technique. This is accomplished by converting correlated input variables into uncorrelated variables via orthogonal transformation [19].

2.5 Mathematical formulations of the DG allocation problem

2.5.1 Case 1: Minimization of RPL

The objective function for minimizing RPL of the RDN in p.u. is expressed as:

$$f_1 = P_{RPL} = \sum_{i=1}^{Br} I_i^2 R_i \tag{17}$$

where, P_{RPL} is total RPL of Nb - bus RDN; *Br* is the total branch number in the RDN ($Br = Nb - 1$); I_i is the i^{th} branch current; R_i is the i^{th} branch resistance.

Considering uncertainty, the objective function to minimize the mean value of RPL of the network is stated as:

$$Min\ OF_1 = Min\,(m\_\ f_1) = Min\,(m\_\ P_{RPL}) \tag{18}$$

where, $m\_\ f_1$ or $m\_\ P_{RPL}$ is the mean value of RPL in p.u. which is calculated by 2*m* PEM method.

2.5.2 Case 2: Improvement of VC

The objective function to improve VC of RDN in p.u. is expressed as:

$$f_2 = \sum_{j=1}^{Nb} (V_j - V_{rated})^2 \tag{19}$$

where, V_j is the voltage of j^{th} bus; V_{rated} is the rated voltage (1 p.u.).

Considering uncertainty, the objective function to minimize mean value of VC of RDN is expressed as:

$$Min\ OF_2 = Min\,(m\_\ f_2) \tag{20}$$

where, $m\_\ f_2$ is the mean value of VC in p.u. calculated by 2*m* PEM method.

2.5.3 Case 3: Enhancement of VSI

The objective function to enhance VSI of the RDN is expressed as:

$$f_3 = \left(\frac{1}{(SI(n))}\right), \quad n = 2, 3, ..., Nb \tag{21}$$

where, VSI of node *n* given by:

$$SI(n) = |V_s|^4 - 4\left[P_n(n)R_i + Q_n(n)X_i\right]|V_s|^2 - 4\left[P_n(n)X_i - Q_n(n)R_i\right]^2 \tag{22}$$

where, V_s is the voltage of bus *s*; $P_n(n)$ and $Q_n(n)$ are total real and reactive power load fed through bus n ; R_i and X_i are the i^{th} branch resistance and reactance;

Considering uncertainty, the objective function to minimize the mean value of f_3 is expressed as:

$$Min\ OF_3 = Min\,(m\_\ f_3) \tag{23}$$

where, m_f_3 is the mean value of f_3 calculated by using 2*m* PEM method.

2.5.4 Case 4: Minimization of RPL alongwith improvement of VC and VSI

The objective function for minimization of RPL alongwith improvement of VC and VSI is expressed as:

$$f_4 = \{(w_1 \times f_1) + (w_2 \times f_2) + (w_3 \times f_3)\} \tag{24}$$

where, w_1, w_2, w_3 are the weighting factors such that $w_1 + w_2 + w_3 = 1$.

Considering uncertainty, the objective function to minimize mean value of f_4 is expressed as:

$$Min\ OF_4 = Min\ (m\_f_4) \tag{25}$$

where, m_f_4 is the mean value of f_4 calculated by using 2*m* PEM method.

2.6 Equality and inequality constraints

The limitations utilised to solve the cases listed above are as follows:

2.6.1 Load balance constraints

The following equations must be met for each bus:

$$P_{gj} - P_{dj} - |V_j| \sum_{k=1}^{Nb} |Y_{jk}||V_k| \cos(\delta_j - \delta_k - \theta_{jk}) = 0 \tag{26}$$

$$Q_{gj} - Q_{dj} - |V_j| \sum_{k=1}^{Nb} |Y_{jk}||V_k| \sin(\delta_j - \delta_k - \theta_{jk}) = 0 \tag{27}$$

where, P_{gj} and Q_{gj} are generator's active power and reactive power output at bus *j*; P_{dj} and Q_{dj} are active power demand and reactive power demand at bus *j*; V_j is voltage of bus *j*; Y_{jk} admittance of the line connecting bus *j* and bus *k* ; δ_j is phase angle of voltage at bus *j*; Nb denotes total number of buses in a particular RDN; θ_{jk} denotes admittance angle of line connected between bus *j* and *k*.

2.6.2 Voltage limits

Each bus's voltage must be maintained within its a specified limits i.e.

$$V_j^{\min} \le V_j \le V_j^{\max} \tag{28}$$

where, V_j is voltage of bus *j*; $V_j^{\min}$ and $V_j^{\max}$ are the minimum and maximum voltages at bus *j*;

2.6.3 Line current limit constraint

Each branch's line current must be maintained within branch's maximum current carrying capability limit. It is represented as:

$$I_i \le I_i^{\max} \tag{29}$$

where I_i denotes the i^{th} branch current of the RDN; $I_i^{\max}$ denotes the maximum current carrying capacity of i^{th} branch current of the RDN;

3. Algorithm for optimal placement of DG in RDN considering uncertainties

In the present work locations of DG sources are the decision variables whereas power generated by WT, PV DG sources and active powers of load demand at each bus (except bus no. 1) are the uncertain variables. In this work objective functions are evaluated by using $2m$ PEM technique. In the present work GWO has been applied for optimal placement of DG in a RDN. Fig. 1 depicts below the step-by-step techniques for DG allocation in RDN considering uncertainty using GWO algorithm.

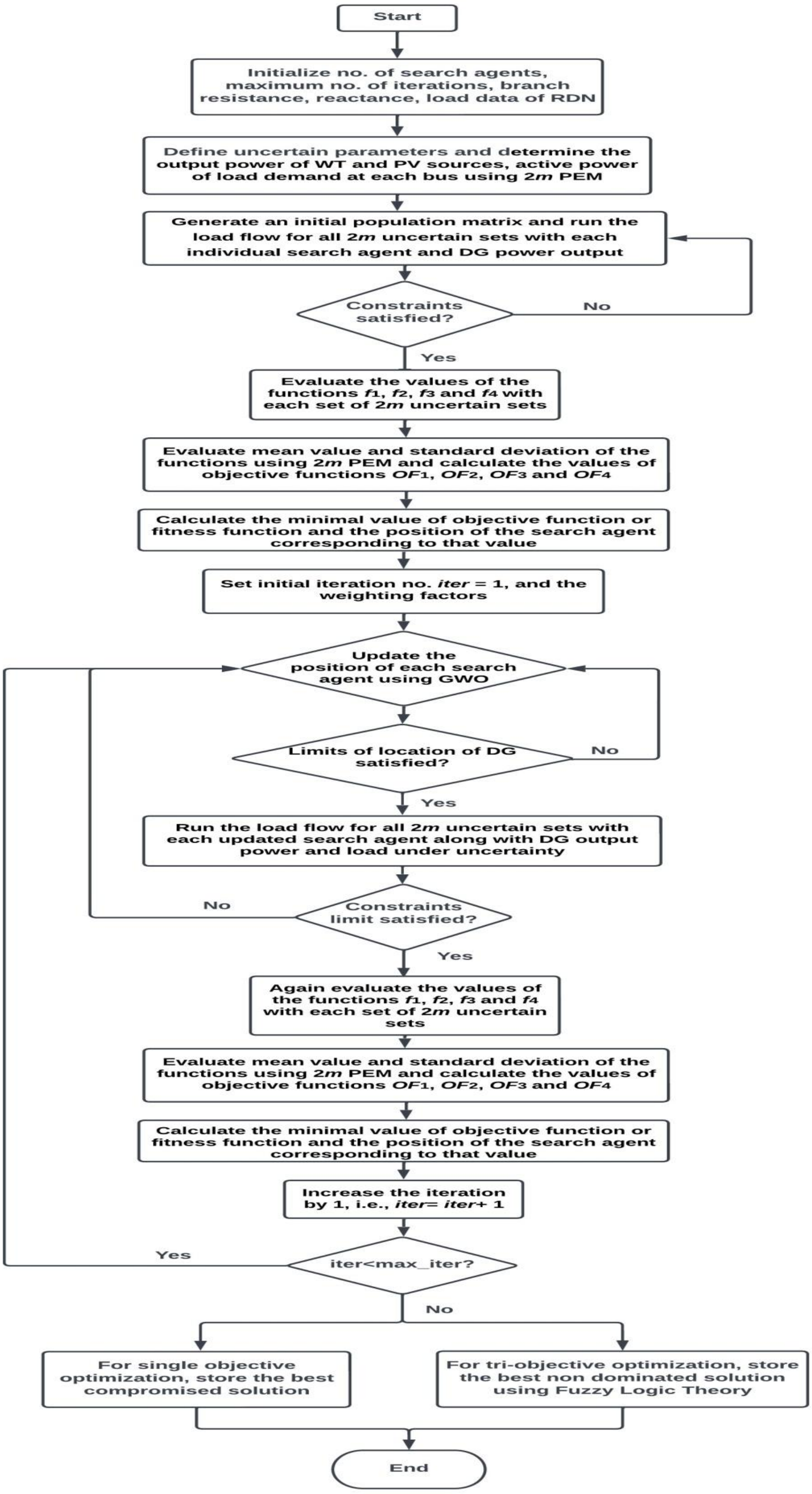


Fig.1 Flowchart for DG allocation in RDN considering uncertainty using GWO algorithm

4. Simulation Results and Discussion

In this work, allocation of PV and WT DG sources have been determined in 69-bus RDN under uncertainty depending on their area of location as shown in Table 1. Here power factors of DG sources are considered as unity and 0.95 lagging. 69-bus RDN data are given in [20] and maximum line current data of 69-bus RDN are taken from [21]. Real and reactive power losses obtained for 69-bus system are 224.7 kW and 102.13 kVAR with the help of Backward-Forward Sweep load flow method. In the present work 3 nos. of DGs are optimally allocated in the RDN. The maximum active power generation rating of PV and WT is 1.5 MW. Different parameters considered for modelling PV-WT DG sources and correlation coefficients considered between DG sources and loads are presented in Tables 2-4. In the present work performance of GWO algorithm is compared with the performance of TLBO and QOTLBO algorithms. Control parameters utilised in GWO algorithms during simulation are: search agents no.= 40 and maximum iteration no. = 300.

Table 1. Area wise distribution of DG and corresponding type of DG for 69-bus system

Area of DG	Bus no.	Type of DG
Area I	2-8, 28-35	PV
Area II	36-52	PV
Area III	9-17, 53-69	WT
Area IV	18-27	WT

Table 2. Parameters used in Beta distribution of PV DG

Parameter	Value
Shape parameter of beta distribution function, α_s	6.38
Shape parameter of beta distribution function, β_s	3.43
Short circuit current, I_{sc} (A)	5.32
Open circuit voltage, V_{oc} (V)	21.98
Current at maximum power point, I_{MPP} (A)	4.76
Voltage at maximum power point, V_{MPP} (V)	17.32
Voltage temperature coefficient, K_v (V/ºC)	0.0144
Current temperature coefficient, K_i (A/ ºC)	0.00122
No. of PV modules, N_s	20000
Nominal operating temperature of PV cell, N_{OT} (ºC)	43
Ambient temperature, T_A(ºC)	25

Table 3. Parameters used in Weibull distribution of WT DG

Parameter	Value
Cut-in wind speed v_{ci} (m/s)	3
Cut-out wind speed v_{co} (m/s)	20
Rated wind speed v_r (m/s)	11.5

Rated output power of WT P_r (MW)	1.5
Shape parameter of Weibull distribution function, k_w	1.75
Scale parameter of Weibull distribution function, c_w	8.78

Table 4. Correlation coefficients of different DG sources and loads

Area of DG/Load	DG type/Load	Correlation coefficients
Same area	PV-PV	0.75
Different area	PV-PV	0.4
Same area	WT-WT	0.5
Different area	WT-WT	0.3
Different area	PV-WT	0.05
Same area	Load-Load	0.9
Different area	Load-Load	0.5

4.1 Optimal allocation of PV and WT DGs in 69-bus RDN considering uncertainty

4.1.1 Case 1: Uncertainty based allocation of DG for RPL minimization

Table 5 depicts the mean values of RPL and corresponding standard deviation obtained by TLBO, QOTLBO and GWO algorithms with DG operating at p.f. unity and 0.95 under uncertainty for Case 1. The results reveal that mean values of RPL attained by GWO algorithm is significantly less compared to TLBO and QOTLBO algorithms. Besides that simulation time required per iteration for GWO algorithm is also much less. The convergence characteristics of the mean values of RPL shown in Fig. 2 reveal that GWO algorithm converges earlier than other algorithms.

Table 5. Results of RPL reduction attained by different algorithms considering uncertainties

Method	p.f. of DG	Mean value of RPL (MW)	Standard deviation (MW)	Bus no. corresponding to DG position	Simulation time per iteration (sec)
TLBO	1	0.0799	0.0217	69, 61, 62	22.72
QOTLBO	1	0.0789	0.0218	66, 61, 62	21.52
GWO	**1**	**0.0761**	**0.0198**	**61, 62, 12**	**10.05**
TLBO	0.95	0.0405	0.0275	17, 62, 65	23.27
QOTLBO	0.95	0.0356	0.0253	63, 62, 69	22.02
GWO	**0.95**	**0.0310**	**0.0260**	**62, 61, 12**	**11.32**

Fig. 2. Convergence graphs for RPL reduction attained by different algorithms

4.1.2 Case 2: Uncertainty based allocation of DG for VC enhancement

Mean values of VC and corresponding standard deviations obtained by different algorithms for Case 2 are represented in Table 6. Comparison of the results shows that better results are obtained by GWO algorithm compared to TLBO and QOTLBO algorithms for the test system. Table 6 also represents that GWO algorithm takes less simulation times per iteration than other algorithms. Fig. 3 reveals that GWO algorithm converges faster than other algorithms.

Table 6. Results for VC improvement attained by different algorithms considering uncertainties

Method	p.f. of DG	Mean value of voltage deviation (p.u.)	Standard deviation (p.u.)	Bus no. corresponding to DG position	Simulation time per iteration (sec)
TLBO	1	0.0074	0.0121	63, 20, 60	22.52
QOTLBO	1	0.0065	0.0129	62, 63, 16	21.33
GWO	**1**	**0.0060**	**0.0122**	**65, 18, 64**	**10.04**
TLBO	0.95	0.0065	0.0134	69, 60, 65	23.26
QOTLBO	0.95	0.0052	0.0118	62, 65, 24	21.72
GWO	**0.95**	**0.0035**	**0.0129**	**65, 63, 14**	**12.08**

Fig. 3. Convergence graphs for VC improvement attained by different algorithms

4.1.3 Case 3: Uncertainty based allocation of DG for VSI enhancement

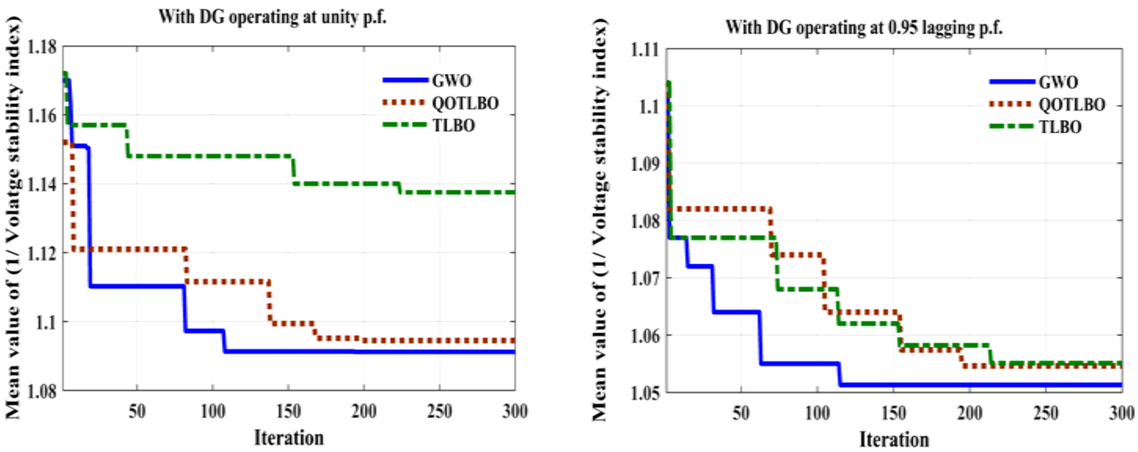
Table 7 represents the mean values of VSI^{-1} and corresponding standard deviations attained by various algorithms for Case 3. Here GWO algorithm shows comparatively better result than TLBO and QOTLBO algorithms. Also GWO takes less simulation time than other algorithms. Fig. 4 demonstrates that convergence of GWO is faster compared to other algorithms.

Table 7. Results for VSI improvement attained by different algorithms considering uncertainties

Method	p.f. of DG	Mean value of VSI^{-1}	Standard deviation	Bus no. corresponding to DG position	Simulation time per iteration (sec)
TLBO	1	1.1375	0.0412	64, 57, 7	23.26
QOTLBO	1	1.0945	0.0622	69, 62, 64	22.04
GWO	**1**	**1.0908**	**0.0545**	**64, 61, 15**	**10.66**
TLBO	0.95	1.0551	0.0605	62, 63, 19	24.21
QOTLBO	0.95	1.0546	0.0593	63, 62, 16	22.82

GWO	**0.95**	**1.0513**	**0.0589**	**64, 61, 16**	**13.12**

Fig. 4. Convergence characteristics for VSI^{-1} obtained by different algorithms



4.1.4 Case 4: Uncertainty based allocation of DG for RPL minimization, VC and VSI enhancement

Table 8 depicts the mean values and standard deviations of RPL, VC and VSI^{-1} obtained for Case 4 by applying diffderent algorithms. Here also the simulation time for GWO algorithm is comparatively less compared to other algorithms. Fig. 5 represents pareto-optimal front graphs achieved by GWO algorithm in Case 4. In this case also GWO represents comparatively better performance than TLBO and QOTLBO.

Table 8. Performance analysis of different algorithms for Case 4

Method	**Objective function value**						**Bus No.**	**Simulation time per iteration (sec.)**
	Mean value of RPL (MW)	**Standard deviation of RPL (MW)**	**Mean value of voltage deviation (p.u.)**	**Standard deviation of voltage deviation (p.u.)**	**Mean value of VSI^{-1}**	**Standard deviation of VSI^{-1}**		
DG operating at p.f. = 1								
TLBO	0.0887	0.0172	0.0069	0.0120	1.0927	0.0545	64,25,62	912.55
QOTLBO	0.0817	0.0213	0.0064	0.0133	1.0943	0.0624	15,62,64	811.95
GWO	**0.0797**	**0.0191**	**0.0063**	**0.0129**	**1.0906**	**0.0545**	**64,61,16**	**472.52**
DG operating at p.f. = 0.95								
TLBO	0.0375	0.0241	0.0044	0.0120	1.0529	0.0602	63,19,64	943.75
QOTLBO	0.0341	0.0245	0.0044	0.0121	1.0554	0.0594	63,62,18	842.16
GWO	**0.0328**	**0.0256**	**0.0035**	**0.0130**	**1.0514**	**0.0600**	**64,61,14**	**494.26**

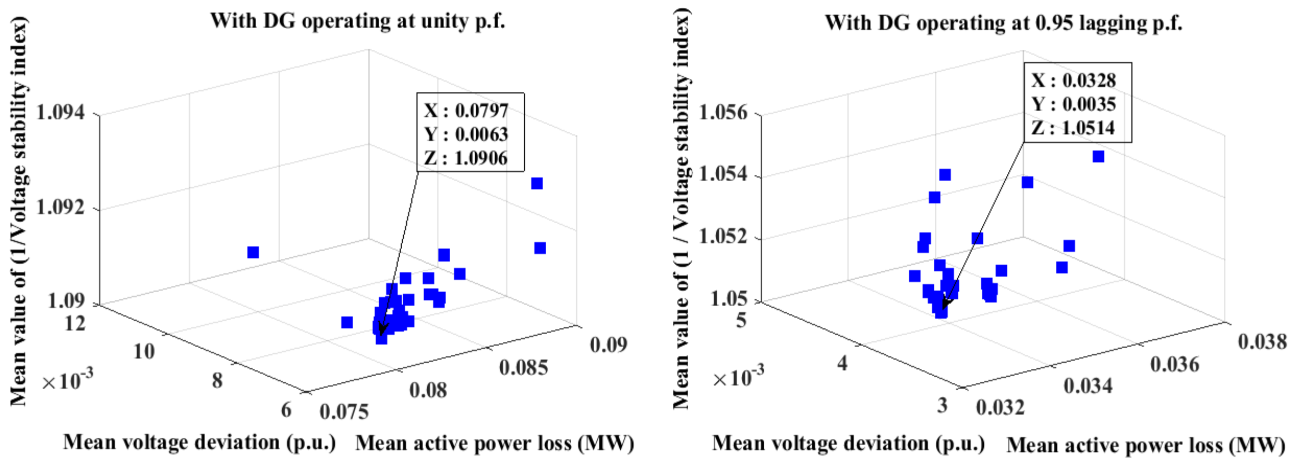


Fig. 5. Pareto-optimal front attained by GWO algorithm for Case 4

5. Conclusion

The ideal positions of PV-WT DG sources in RDN have been found in this study to minimize RPL, to improve system voltage and to enhance the VSI while accounting for uncertainties in PV, WT DG output power and load. In this work, TLBO, QOTLBO and GWO algorithms are used to find the best placements for DG sources in 69-bus test RDN. The results reveal that when DG sources are optimally allocated using the MOGWO, system performance quality is improved along with superior computing efficiency. When uncertainties in the RDNs are taken into account, the simulation results show that the probabilistic method can yield more efficient solutions.

Refrences

[1] M.H. Moradi and M. Abedini, A combination of genetic algorithm and particle swarm optimization for optimal DG location and sizing in distribution systems, Electrical Power and Energy Systems 34 (2012) 66-74.

[2] S. Sultana and P.K. Roy, Multi-objective quasi-oppositional teaching learning based optimization for optimal location of distributed generator in radial distribution systems, International Journal Electrical Power and Energy Systems 63 (2014) 534-545.

[3] S. Sharma, S. Bhattacharjee and A. Bhattacharya, Quasi-Oppositional Swine Influenza Model Based Optimization with Quarantine for optimal allocation of DG in radial distribution network, International Journal of Electrical Power and Energy Systems 74 (2016) 348- 373.

[4] A. Uniyal, A. Kumar, Optimal Distributed Generation Placement with Multiple Objectives Considering Probabilistic Load, Procedia Computer Science 125 (2018) 382–388.

[5] K.H. Truong, P. Nallagownden, I. Elamvazuthi, D.N. Vo, A quasi-oppositional-chaotic symbiotic organisms search algorithm for optimal allocation of DG in radial distribution networks, Applied Soft Computing Journal 88 (2020) 106067.

[6] R. Siddique, S. Raza, A. Mannan, L. Khalil, N. Alwaz, M. Riaz, A modified NSGA approach for optimal sizing and allocation of distributed resources and battery energy storage system in distribution network, Materials Today: Proceedings 47 (2020) doi: https://doi.org/10.1016/j.matpr.2020.05.669

[7] A. Uniyal and S. Sarangi, Optimal network reconfiguration and DG allocation using adaptive modified whale optimization algorithm considering probabilistic load flow, Electric Power Systems Research 192 (2021) 106909.

[8] M.J. Aliabadi and M. Radmehr, Optimization of hybrid renewable energy system in radial distribution networks considering uncertainty using meta-heuristic crow search algorithm, Applied Soft Computing 107 (2021) 107384.

---

[9] A.S. Machava, K.K. Kaberere and G.A. Vilanculo, A Method for Optimal Distributed Generation Allocation Considering Load Demand Uncertainties, International Journal of Electrical and Electronic Engineering & Telecommunications 11 (2022) 210-217.

[10] A. Ramadan, M. Ebeed, S. Kamel et al., Optimal allocation of renewable DGs using artificial hummingbird algorithm under uncertainty conditions, Ain Shams Engineering Journal 14 (2023) 101872.

[11] T. E. Gümüş, S. Emiroglu, M. A. Yalcin, Optimal DG allocation and sizing in distribution systems with Thevenin based impedance stability index, International Journal of Electrical Power & Energy Systems 144 (2023) 108555.

[12] S. Mirjalili, S.M. Mirjalili and A. Lewis, Grey Wolf Optimizer, International Journal of Advances in Engineering Software 69 (2014) 46-61.

[13] P. Li, Z. Zhou and R. Shi, Probabilistic Optimal Operation Management of Microgrid Using Point Estimate Method and Improved Bat Algorithm, IEEE PES General Meeting, Conference & Exposition 2014, National Harbor, MD, USA, 27-31 July 2014.

[14] L. Dong, W. Cheng, H. Bao and Y. Yang, Probabilistic load flow analysis for power system containing wind farms, 2010 Asia-Pacific Power and Energy Engineering Conference (APPEEC), 28th -31st March 2010, pp. 28–31.

[15] R. Roy and H.T. Yadav, Optimal power flow solution of power system incorporating stochastic wind power using Gbest guided artificial bee colony algorithm, Electrical Power and Energy Systems 64 (2015) 562-578.

[16] A. Soroudi, M. Aien and M. Ehsan, A probabilistic modelling of photo voltaic modules and wind power generation impact on distribution networks, IEEE Systems Journal 6 (2012) 254-259.

[17] H.P. Hong, An efficient point estimate method for probabilistic analysis, Reliability Engineering & System Safety 59 (1998) 261-267.

[18] A. Soroudi, M. Ehsan, R. Caire and N. Hadjsaid, Hybrid immune-genetic algorithm method for benefit maximisation of distribution network operators and distributed generation owners in a deregulated environment, IET Generation, Transmission & Distribution 5 (2011) 961-972.

[19] J.M. Morales, L. Baringo, A.J. Conejo and R. Mínguez, Probabilistic power flow with correlated wind sources, IET Generation, Transmission & Distribution 4 (2010) 641-651.

[20] M. Chakravorty and D. Das, Voltage stability analysis of radial distribution networks, International Journal of Electrical Power and Energy Systems 23 (2001) 129–135.

[21] M.M. Aman, G.B. Jasmon, A.H.A. Bakar, H. Mokhlis, “A new approach for optimum simultaneous multi-DG distributed generation Units placement and sizing based on maximization of system loadability using HPSO (hybrid particle swarm optimization) algorithm,” Energy, March 2014, 66, (1), pp. 202-215.