

Multi-Objective Hybrid Genetic Algorithms and Equilibrium Optimizer GAEO to **Integrate Renewable Energy Sources with Distribution Networks**

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Graphic Abstract

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Abstract

This paper aims to implement the hybrid Genetic Algorithm Equilibrium Optimizer (GAEO) to enhance the overall performance of radial networks using renewable energy resources (RER) based multi-objective optimization. The GAEO is applied to determine the appropriate location, and capacity of RER unit to reduce the line losses, improve the voltage profile, fuel cost and reduce the pollution emission considering inequality constraints. The suggested hybrid GAEO is tested in three different networks with small, medium and large size. The test systems are IEEE-33 bus, IEEE-69 bus and IEEE-118 bus. A comparative study is performed to judge the accuracy of the proposed hybrid GAEO over GA and or EO in terms of fast conversions, and low RER unit capacity. The suggested RER systems are photovoltaic, fuel cell, and wind energy.

Keywords:— distribution networks; Genetic Algorithms; Equilibrium optimizer; Renewable Energy Sources; Power loss minimization; Voltage profile; fuel cost minimization; pollutant emissions.

1. Introduction

The electric power system is the interconnection of generation, transmission, and distribution systems. The majority of distribution systems are radial in design, with unidirectional power flow. Modern service networks are experiencing a number of issues as a result of ever-increasing demand. With the construction of various distributed power sources including distributed generations, capacitor banks etc, many approaches have been proposed in the literature for the positioning of DGs. The majority of the casualties, about 70%, occur at the distribution level, which comprises main and secondary distribution systems, while 30% occur at the transmission level. As a result, logistics networks are still a major concern. The distribution-level losses are estimated to be about 7.5 percent. By deploying DG units at suitable locations, the losses can be reduced. Photovoltaic (PV) electricity, wind turbines, and other distributed generation plants are usually located in rural areas, necessitating highly integrated transmission and distribution network operating systems. The DG's goal is to combine all generation plants in order to minimize waste, costs, and greenhouse gas emissions [1]. The addition of DG to the distribution system has the potential to dramatically alter power flow and voltage conditions at customers and utility equipment. Depending on the delivery system operating characteristics and the DG characteristics, these influences may be positive or negative [2-4]. Positive effects are referred to as system support advantages and include the following [3, 5, and 6]:

- Loss minimization
- · Increased resiliency of utility systems
- · Improved power quality and voltage support
- Release of transmission and distribution power Transmission and distribution system upgrades are being postponed.
- Because of the prefabricated standardized components, installation is simple and convenient.
- Cost savings by eliminating long-distance high-voltage transmission.
- As renewable resources are used, it is environmentally friendly.

Distributed generation refers to small-scale (typically 1 kW - 50 MW) electric power generators that produce electricity near customers or are linked to an electric distribution grid (or DG). Distributed generators include induction generators, synchronous generators, micro turbines (combustion turbines that run on high-energy fossil fuels like oil, propane, natural gas, gasoline, or diesel), reciprocating engines, fuel cells, solar photovoltaic, combustion gas turbines, and wind turbines [7]. However, in order to have a significant impact on power system operation and regulation, the positions and sizes chosen should be ideal to prevent any negative consequences such as increased power loss and voltage fluctuations [8]. The location and sizing of DG can be considered complex non-linear optimization problem. There are many categories of this problem regarding the solution algorithms, constraints, and considered objectives [9]. Power loss minimization [10–12], voltage profile change, and other objectives are among the researchers' goals. [13–15], fuel cost minimization [16,17], reliability enhancement [18,19], and reduction of environmental emissions [20]. In existing literature, a variety of solution methodologies for the placement and sizing of active and reactive power sources in radial distribution systems have been discussed. Mathematical programming algorithms, heuristics, meta-heuristic methods, and computational approaches are the key categories of solution techniques. GA is considered as an important class of evolutionary algorithms that can improve the performance of radial system [21-23].

In addition to GA, the authors in [24] proposed the loss sensitivity factor (LSF) for sizing optimization and used simulated annealing (SA) to find the best position for DGs. The optimal DGU solution was successfully found by integrating these two suggested methods with the intention of minimising branch losses. This study was carried out with various machine power variables, and the findings were compared to those obtained using other approaches. At various power variables, simulation results showed that this approach was superior to others. is a successful tool, but the most significant drawback is the time-consuming calculation procedure. As a result, it hasn't been commonly used to solve other distribution network issues.

An objective function is a mathematical expression that describes one or more quantities that must be minimised or maximised. When an optimization problem has more than one objective function, multi-objective optimization [25] is the job of finding one or more optimal solutions. In classical search and optimization algorithms, point-by-point search and optimization algorithms are used, resulting in a single optimized solution. Different techniques were applied for optimal allocation of DG as well as Capacitor bank in grid Systems [26-35].

The present work propose a novel multi-objective hybrid Genetic Algorithm and Equilibrium optimizer (GAEO) to enhance the overall distribution system operating behavior. This technique is developed using combination between Genetic Algorithm and Equilibrium optimizer (GAEO) to satisfy the optimal locations and capacities of DG units. The suggested GAEO applied successfully to reduce active power loss, improving voltage stability, minimizing fuel cost, and reduce pollutant emissions. The proposed GAEO has been tested on IEEE 33-bus, IEEE-69 bus and IEEE 118-bus distribution systems. The simulation results approve the superiority of the proposed hybrid GAEO over GA and or EO in terms of fast conversions, lower DG capacities, with evaluation of enhancing the overall performance. The studied system equation is solved and simulated using MATLAB 2014a.

2. **Problem formulation**

The mathematical representation of objective function, F is expressed as follows:

Min. F(x, p)	(1)
Subject to $:h(x, p) = 0$	(2)
And $g(x, p) \ge 0$	(3)

Where x is vector of system state/dependent variables, p is vector of control/independent variables (like generated active and reactive power, generation bus voltage magnitudes, transformer taps etc). F(x, p) is the objective function, h(x, p) is the equality constraints and g(x, p) is the inequality constraints. The optimal power flow problem resides the essence of reducing the objective function and in the same time satisfying the load flow equations (equality constraints) without violation the inequality constraints[36]. The set of variables, which describe the state of the power system, can be defined as follows:

$$\mathbf{x} = \left[\mathbf{P}_{G_1}, \mathbf{V}_{L_1}, \dots, \mathbf{V}_{L_{NL}}, \mathbf{Q}_{G_1}, \dots, \mathbf{Q}_{G_{NG}}, \mathbf{S}_{l_1}, \dots, \mathbf{S}_{l_{nl}} \right]$$
(4)

Where, P_{G1} , Q_G , V_L and S_l are the active power generation at slack bus, reactive power outputs of the generators, the voltage magnitude at load bus and apparent power flow, respectively. NL, NG and nl are the number of load buses (P-Q buses), generators buses (P-V buses) and the transmission lines, respectively.

2.1 Constraints

The scheme must meet both inequality and equality constraints. Constraints on power balance are referred to as equality constraints. The functional limits of power system components are referred to as inequality constraints.

2.1.1 Equality constraints:

Equality constraints illustrate the dynamics of the power system as well as the desired voltage set points in the system. The physics of the power system is implemented by the power flow equations, which require that the net injection of actual and reactive power at each bus be equal to zero [37].

$$P_{Gi} - P_{Di} - V_i \sum_{j=1}^{nb} V_j [G_{ij} \cos(\delta_i - \delta_j) + B_{ij} \sin(\delta_i - \delta_j)] = 0 \quad \forall \ i \ \varepsilon \ nb$$
(5)

$$Q_{Gi} - Q_{Di} - V_i \sum_{j=1}^{nb} V_j [G_{ij} \sin(\delta_i - \delta_j) - B_{ij} \cos(\delta_i - \delta_j)] = 0 \quad \forall i \in nb$$
(6)

Where, Q_G is the generator reactive power, nb is the total number of buses, Q_D is the reactive load demand, P_D is the active load demand, G_{ij} and B_{ij} are the transfer conductance and susceptance between bus i and bus j, respectively.

2.1.2 Inequality constraints:

Inequality constraints represent the power system operating limits as follows:

Generation constraints: For stable case, real and reactive power of the generators and the voltages are restricted by the lower and upper limits as follows:

$Q_{Gi}^{min} \leq Q_{Gi} \leq Q_{Gi}^{max}$	∀iεN	(7)
$GP_{Gi}^{min} \le P_{Gi} \le P_{Gi}^{max}$	∀i ε NG	(8)

$$V_{Gi}^{\min} \le V_{Gi} \le V_{Gi}^{\max} \qquad \forall i \epsilon NG$$
(9)

Security constraints: The constraints of load buses voltage magnitudes and transmission line loadings ought to be restricted within their limits as follows:

$$V_{Bi}^{min} \le V_{Bi} \le V_{Bi}^{max} \quad \forall i \epsilon NL$$

$$S_{Li} \le S_{Li}^{max} \quad \forall i \epsilon nl$$
(10)
(11)

Shunt VAR compensator constraints: The shunt VAR compensators are restricted by their limits as follows:

$$Q_{ci}^{\min} \le Q_{ci} \le Q_{ci}^{\max} \quad \forall i \in \mathbb{NC}$$

$$\tag{12}$$

Transformer constraints: The tap settings of the transformers must be restricted by their upper and lower limits as follows:

$$T_i^{\min} \le T_i \le T_i^{\max} \qquad \forall i \in NT''$$
(13)

DG technical constraints

As DG capacity is inherently limited by the energy resources at any given location, it is necessary to constrain capacity between the maximum and the minimum levels[38].

 $P_{gni}^{\min} \le P_{gni} \le P_{gni}^{\max}$ (14)

2. 2 The objective functions

2. 2.1 Minimization of power loss, and voltage deviation

As follows, this feature aims to minimise network power losses and voltage deviation:

 $\boldsymbol{F}_{1} = \boldsymbol{min} \left(\boldsymbol{w}_{1} \cdot \boldsymbol{P}_{L} + \boldsymbol{w}_{2} \cdot \Delta \boldsymbol{V}_{D} \right) \tag{15}$

Where, P_L is the total power losses and can be calculated using Eqs. [16-18]. ΔV_D is the voltage deviation and can be calculated by using Eq. (19). w_1 and w_2 Equal to 0. 6, and 0.4, respectively.

The total power losses to be minimized are given by the sum of line losses.

$$P_{\rm L} = \sum_{\rm K=1}^{N_1} P_{\rm l_k} \tag{16}$$

$$P_{l_k} = g_k [V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j)]$$
(17)

It can now be written as

$$P_{\rm L} = \sum_{i=1}^{N_1} g_k \left[V_i^2 + V_j^2 - 2V_i V_j \cos(\delta_i - \delta_j) \right] [29]$$
(18)

$$\Delta V_{\rm D} = \max\left(\frac{V_1 - V_k}{V_1}\right) \forall \ k = 1, 2, \dots, n \tag{19}$$

During DG installation, if the state of the system has voltage limit violations, the proposed technique will try to minimize ΔV_D closer to zero and thereby improves voltage stability and network performance[39-40].

2. 2.2 Minimizing the total power loss, voltage deviation, and emission produced by DGs and the grid

$$F_2 = \min\left(m_1.P_L + m_2.\Delta V_D + m_3.E_M\right)$$
(20)

Where E_M is the total emission produced by DGs and the grid and can be calculated using Eq. (21) .and m_1 , m_2 and m_3 are equal to 0.4,0.3 and 0.3, respectively .Some of the DGs are releasing pollutant gases into atmosphere. The main polluting gases

are CO_2 , NO_X , SO_2 , CO and PM_{10} The values of the grid and the DG parameters are shown in Table 1. The total annual emission produced by a hybrid energy system and the grid can be expressed as follows:

$$E_M = \sum_{i=1}^{N_{WT}} E_{WT_i} + \sum_{i=1}^{N_{FC}} E_{FC_i} + \sum_{i=1}^{N_{PV}} E_{PV_i} + E_{Grid}$$
(21)

$$E_{WT_i} = (CO_2^{Wind} + NO_x^{Wind} + SO_2^{Wind}) \times P_{WT_i}.$$
(22)

$$E_{FC_{i}} = (CO_{2}^{FC} + NO_{x}^{FC} + SO_{2}^{FC}) \times P_{FC_{i}}.$$
(23)

$$E_{WT_{i}} = (CO_{2}^{PV} + NO_{x}^{PV} + SO_{2}^{PV}) \times P_{PV_{i}}.$$
(24)

 $E_{Grid} = (CO_2^{Grid} + NO_x^{Grid} + SO_2^{Grid}) \times P_{Grid}.$ (25)

where E and P are design emissions produced and active power generation by the ith energy sources including wind turbine ,fuel cell, Photovoltaic and grid. Also, N_{WT} , N_{FC} and N_{PV} is the numbers of the WT,FC and PV units, respectively[37].

2. 2.3 Minimizing the total power loss, emission produced by DGs and the grid and the total fuel cost (TFC)

$$F_3 = min \left(\mathbf{z}_1 \cdot \mathbf{P}_{\mathrm{L}} + \mathbf{z}_2 \cdot \mathbf{E}_{\mathrm{M}} + \mathbf{z}_3 \cdot \mathbf{TFC} \right)$$
(26)

and z_1, z_2 and z_3 are equal to 0.4,0.3 and 0.3, respectively .The fuel cost of electricity per hour for a power plant or a DG can be formulated by a quadratic curve as follows:

$$TFC = \left(\sum_{i=1}^{NG} a_i P_{Gi}^2 + b_i P_{Gi} + c_i\right) + \text{Penalty}\,(\$/h)$$
(27)

Where, and a_i , b_i and c_i are the cost coefficients of ith generators [41].

DG type	Rated capacity (Mw)	Fuel cost (\$/ Kw h)	Emissi	on factor (II	o/MWh)	Life time (year)
			NO _x	S	CO	2
WT FC PV Grid	3.00 2.00 1.00	0 0.029 0 -	0 0.03 0 5.06	0 0.006 0 11.6	0 1078 0 2031	20 10 20 0

3. Hybrid Genetic Algorithm Equilibrium optimizer (GAEO)

This work present a hybrid optimization technique based on GA and EO algorithm. For optimization problems which are too complex to be addressed through deterministic strategies such as linear programming or gradient (Jacobian) approaches, evolutionary algorithms such as Genetic Algorithms (GA) have become the method of choice. Because of their universality, simplicity of implementation, and parallel computing suitability. GA is based on Darwinian evolutionary theory[42-43], which employs the cross-over principle to generate improved solutions, referred to as offspring, from a collection of fitted solutions, referred to as parents. Cross-over, which happens naturally in nature and aids in the preservation of habitat diversity; or, in this case, to discover the domain. Mutations allow offspring to have different characteristics than their parents. This operator in GA is for local search and result manipulation. Some solutions and their dimensions are subjected to mutation, which is determined by a function and a parameter such as mutation likelihood and percentage. Evolution flow and how genetic algorithm working is shown in Fig. (1) and Fig.(2). Equilibrium optimizer (EO) is a novel optimizer which mixes dynamic mass balance on a control volume firstly proposed by Farmarzi in 2020 [44]. It uses a chunk mass equation to calculate the amount of chunk that step out, take in, and produce in a control volume over time and tries to find the state that will bring the volume to equilibrium [45]. In EO, the search agents are made up of particles (solutions) and their concentrations (positions). And then change their concentration at random in relation to the best-so-far solutions, i.e. equilibrium candidates, in order to arrive at the equilibrium state (optimal result). The term generation rate is used to boost EO's ability to explore, exploit, and avoid local minimas (see Fig.(3)). Figure (4) depicts the collaboration of all equilibrium candidates on a sample particle in 2-D and how they impact concentration updating one by one [46]. The following steps show how to use the EO algorithm model:

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1- The first step in the Equilibrium Optimizer (EO) is initialization: In this step, EO uses a large number of particles, each of which represents a concentration vector containing the solution to the optimization problem. In the search space, the initial concentration vector is generated at random.

2- Candidates and the equilibrium pool: The equilibrium state of the system is sought by EO. As EO enters equilibrium, it will find a solution that is close to optimal. EO has no idea how many concentrations are needed to produce the best results during the optimization process. As a consequence, it selects the ideal four particles from the equilibrium candidate group, as well as the strongest four-particle average from another group. The first four particles enable EO to have a greater degree of diversification, while the standard aids in extraction. The vector that includes these five candidates is the equilibrium pool.

3- adjusting the concentration level: Since the turnover rate contrasts after some time in a good control size, which is presumed to be a random vector between 0 and 1, this concept enables EO to have a fair harmony between concentration and enhancement [47].



Fig (1). Evolution flow of genetic algorithm[43]





To overcome GA's drawbacks and increase its performance, a new hybrid optimization technique is proposed, which combines GA with conventional optimization procedures. GA stands for global quest. When GA is combined with any problem-specific local search process, the overall output and solution quality can be improved. A search algorithm with well-adjusted exploitative capacity will increase the likelihood of generating better solutions from weak ones that have already been found. As a result, most metaheuristics techniques seek to strike a balance between discovery and exploitation by beginning with a high population diversity (high exploration) and gradually decreasing it during the quest process. Since GA's rate of convergence isn't really strong, it's restricted in terms of exploring features. A genetic algorithm can also sample poor representatives of good search regions and good representatives of bad search regions due to the limited population size, necessitating a lengthy generation and population than GA-based algorithms' randomly selected initial population. EO has the ability to be more efficient and effective than GA. On the other hand, the EO algorithm can get trapped in a local optimal solution. The GA algorithm refers to the solutions as chromosomes, and the chromosomes get better with each iteration thanks to the GA operators (i.e., selection, crossover, and mutation). The chromosomes are referred to as particles in the EO algorithm, and with each iteration, the particles get better. The particle with the lowest fitness value is chosen as the initial solution to the optimization problem. The resulting particles are passed to the GA algorithm in the second half of the specified iterations, which then applies EO to the best half solutions.





Fig (4). Equilibrium candidates concentration in 2D dimensions

3.1.1 Mathematical model of GAEO algorithm

The hybrid GAEO algorithm for performance improvement of a radial distribution networks is illustrated in the following subsections:

I. Initialization

Step 1: Assign The data for power system including characteristics of DG units, the network configuration, line impedance, cost coefficients of DGs, prices of substation bus and emission functions.

Step 2: Calculate the fitness of the four particles in equilibrium pool and control parameters of GA and EO as shown in Table 2. Step 3: set the time counter t = 0 and create the initial population of candidate solutions using EO Optimizer in search space $[x_i^{min}, x_i^{max}]$ randomly.

 $P_i^{nitial} = rand_i * (B_{max} - B_{min}) + B_{min}$ i = 1, 2, 3, (28)

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Where P_i^{nitial} is the initial concentration of i particle, B_{max} and B_{min} are the upper and lower bounds respectively. The rand is uniform random value $\in [0,1]$. After initialization, the location and fitness of each particle is sorted and the best solution is selected based on its calculated fitness.

Table 2 The control parameters of GAEO	
a ₁ : controls the exploration quantity (magnitude) of the	2
a_2 : is a constant used to balance the exploitation ability	
	1
GP: controls the participation probability of concentration	
updating by the generation rate.	0.5
Selection	0.5
Max. No. of iterations	100
No. of trails	30

II. Main Loop

Using GA (crossover and mutations) :

Step 4: the first half of the defined population is passed to the GA algorithm . to reduce the complexity of the proposed algorithm we using the first half of population , because the performance of the GA algorithm depends mainly on the size of the population (fitness).

Step 5: GA algorithm using single point crossover to perform pairing and mating, then the new population Mutate.

Step 6: the position and cost function for each chromosome is evaluated by GA algorithm .

Step 7: the best half population members is selected (selection =0.5) and survive to EO and then using GA crossover in half worse population to updating their location.

Using EO on best half solutions :

Step 8 : EO evaluate the Particles(population members) for their fitness function and then sort to determine the equilibrium candidates .

 $\vec{P}_{eq,pool} = \{ P_{eq(1)}, \vec{P}_{eq(2)}, \vec{P}_{eq(3)}, \vec{P}_{eq(4)}, \vec{P}_{eq(ave)} \}$ (29)

Where $\vec{P}_{eq,pool}$ is the equilibrium state vector, $\vec{P}_{eq(1)}$, $\vec{P}_{eq(2)}$, $\vec{P}_{eq(3)}$ and $\vec{P}_{eq(4)}$ are the four best-so-far particles identified during the whole optimization process . $\vec{P}_{eq(ave)}$ is the mean value of first four candidate solutions . These solutions are assumed as approximated equilibrium states, because no information is available about the equilibrium state, when the optimization process begins. The exponential term \vec{F} make a balance between exploitation and exploration during the search. The expression of vector \vec{F} :

$$\vec{F} = e^{-\vec{\lambda}(t-t_0)} \qquad (30)$$

Where $\overline{\lambda}$ is the turnover rate and t is the time defined as a function of iteration (Iter) and thus decreases with the number of iterations:

$$t = \left(1 - \frac{lter}{Max_iter}\right)^{a_2} \frac{lter}{Max_iter}$$
(31)

Where Iter and Max__iter are the current and the maximum number of iterations. The value of the t₀ is expressed by $t_0 = \frac{1}{\lambda} ln \left(-a_1 sign(\vec{r} - 0.5) \left[1 - e^{-\lambda t} \right] \right) + t$ (32)



Where r is a random vector between 0 and 1 and sign($\vec{r} - 0.5$) effects on the direction of exploration and exploitation. By substitution of Eq. (29) into Eq.(27) The value of exponential term \vec{F} can be expressed by

$$\vec{F} = a_1 \operatorname{sign}(\vec{r} - 0.5) \left[e^{-\vec{\lambda}t} - 1 \right]$$
(33)

EO using a factor name generation rate R_i to improving the exploitation phase and can be calculated using Eq.(31). $\vec{R} = R_0 e^{-\vec{k}(t-t_0)}$ (34)

Where \vec{R}_0 is initial value and can be found using Eq. (35) and k is a constant.

$$\vec{R}_{0} = RCP(\vec{P}_{eq} - \lambda \vec{P})$$

$$\vec{RCP} = \begin{cases} 0.5r_{1} & r_{2} \ge RP \\ 0 & r_{2} < RP \end{cases}$$
(36)

 $\overrightarrow{\text{RCP}}$ is the possibility of contributing the generation term during the position update process, it's the parameter that control the generation rate. So the concentration P can by defined in Eq. (37):

$$\vec{P} = \vec{P}_{eq} + (\vec{P} - \vec{P}_{eq}).\vec{F} + \frac{\vec{R}}{\vec{\lambda V}}(1 - \vec{F})$$
(37)

V is the control volume and considered as unit .

Step 9 : Evaluation. At the end of each cycle, the old population and the new population are evaluated.

Step 10 : sorting the new population and old population based on the values obtained from the cost function and the new population is created .

Step 11 : (time updating): update the time counter t = t + 1.

Step 12: if one of the termination conditions is satisfied then stop, else go to step 5.

Fig. (5) shows the flow chart of GAEO optimization.

For IEEE 33-bus, 69-bus, and 118-bus delivery systems, the latest GAEO algorithm is used to solve multi-objective functions. MatlabR2014, an environment programme, was used to model these systems. The number of iterations that can be done is limited to 100. Based on the form of objective function, there are nine cases for each objective function, as mentioned below:

- 4 Case 1: Minimization of power loss, and voltage deviation for 33 bus system.
- 4 Case 2: Minimizing the total power loss, voltage deviation, and emission for 33 bus system.
- Case 3: Minimizing the total power loss, emission produced by DGs and the grid and the total fuel cost for 33 bus system.
- 4 Case 4: Minimization of power loss, and voltage deviation for 69 bus system.
- Lase 5: Minimizing the total power loss, voltage deviation, and emission for 69 bus system.
- Case 6: Minimizing the total power loss, emission produced by DGs and the grid and the total fuel cost for 69 bus system.
- 4 Case 7: Minimization of power loss, and voltage deviation for 118 bus system.
- 4 Case 8: Minimizing the total power loss, voltage deviation, and emission for 118 bus system

Case 9: Minimizing the total power loss, emission produced by DGs and the grid and the total fuel cost for 118 bus system. and each case is solved for three scenario

- scenario a: with penetration of PV and FC.
- scenario b: with penetration of WT and FC.
- scenario c: with penetration of FC ,WT, and PV .

4.1.1 IEEE 33-bus system test

Total active and reactive loads for the system are 3,715KW and 2,300KVAr, respectively, with a substation voltage of 12.66 kV and a base MVA of 10. The voltage maximum is 0.90 p.u. to 1.0 p.u., with a 208 kW initial active power loss. Figure 1 shows a line diagram of this delivery system (6). This test system's cumulative loads are 3,715 kW and 2,300 kVAr [48].



Fig.(6) Single line diagram for IEEE 33 bus system

4.1.2 IEEE 69 Bus radial distribution test system

As shown in Fig. 1, the IEEE 69 bus radial distribution system consists of 69 buses and 68 branches (7). The cumulative active and reactive loads are respectively 3,800KW and 2,690KVar. The total real power loss at the substation was 225KW, with a voltage of 12.66 kV and a base MVA of 10.0.95 p.u and 1.05 p.u are the lower and upper voltage thresholds, respectively [49].

4.1.3 IEEE 118 Bus radial distribution systems

An IEEE 118-bus system on a wide scale. 22709.72 kW and 17041.07 kVAr are the active and reactive power demands for the system, respectively. There are 54 generators, 9 transformers, and 30 VAR compensators in this system. The lower and upper voltage thresholds are 0.95p.u.V1.1p.u. and 0.95p.u.V1.1p.u., respectively. The limits of the tap setting transformer are 0.9p.u.Ti1.1p.u [50-58]. The single line diagram of IEEE118 is shown in Fig. (8).



Fig.(7). Single line diagram for the IEEE-69-bus radial distribution system.



Fig.(8). Single line diagram for the IEEE-118-bus distribution system.

Result for IEEE 33-bus system

Case 1: Minimization of power loss, and voltage deviation.

There are two conflicting goals in this case, namely, power loss and voltage deviation. The optimal solution for loss minimization and voltage variance is shown in Table 3. In Scenario, a GAEO has the best power loss and voltage deviation output, while an EO has the worst. In Scenario b, GAEO outperforms EO in terms of power losses, while EO outperforms EO in terms of voltage deviation. In Scenario c, GAEO outperforms EO in terms of both power losses and voltage deviation. Simulation case 1 objective feature and line voltage characteristics are compared in Fig.(9).

Case 2: Minimizing the total power loss, voltage deviation, and emission.

Power loss, voltage variance, and total emissions are all considered multi-objectives in this situation. Table 4 shows the best position and size for DG, as well as the best solution for loss minimization, voltage variance, and total emissions. In Scenario A, EO outperforms GAEO in terms of power losses and voltage variance, while GAEO outperforms EO in terms of total emissions. In Scenario b, GAEO outperforms GA in terms of power losses and voltage variance, while GAEO outperforms GA in terms of total pollution. For Scenario c, EO outperforms GAEO in terms of power losses and total emissions, while GAEO outperforms EO in terms of total pollution. For Scenario c, EO outperforms GAEO in terms of power losses and total emissions, while GAEO outperforms EO in terms of voltage deviation. Simulation case 2 objective feature and line voltage characteristics are compared in Fig.(10).

Case 3: Minimizing the total power loss, emission and the total fuel cost.

As previous type, three competing objectives are considered ,power loss, emissions and fuel cost. Table 5 shows the optimal location and size for DG ,and optimal solution for power loss minimization, emissions and fuel cost. in Scenario a GAEO achieves the best performance for emissions and fuel cost, while GA achieves the best performance for power loss minimization. in Scenario b GA achieves the best performance for fuel cost and EO achieves the best performance for power losses, while

GAEO achieves the best performance for Total emissions. for Scenario c GAEO achieves the best performance for power losses , emissions and fuel cost. the Comparison of objective function and line voltage characteristics of Simulation case 3 are shown in Fig.(11).

Method	DG type	Scer	nario a	Scen	ario b	Scenario c	
		Location (b	Location (bus no.) size Location (bus no.) size Location		Location (bu	s no.) size	
	PV	25	0.09917	-	0	32	0.09785
GA		32	0.09821	-	0	31	0.09612
UA	FC	17	0.19576	15	0.19008	25	0.19822
		14	0.19272	31	0.18440	30	0.19722
	WT	-	0	30	0.28322	16	0.29793
		-	0	18	0.29589	14	0.29680
Plass		0.08603		0.07838		0.07316	
V_D		0.03976		0.02967		0.02639	
	PV	30	0.02827	-	0	32	0.09507
		14	0.07723	-	0	25	0.02562
EO	FC	13	0.16137	18	0.19993	31	0.19824
		10	0.19975	32	0.13595	31	0.20000
	WT	-	0	31	0.27682	14	0.30000
		-	0	14	0.29662	16	0.30000
P _{loss}		0.09405		0.07723		0.08225	
V_D		0.04/6/		0.02758		0.03587	
	PV	14	0.09928	-	0	8	0.09343
GAEO		8	0.08369	-	0	24	0.08774
	FC	32	0.19641	14	0.19622	18	0.18929
		17	0.18173	25	0.18885	30	0.18889
	WT	-	0	30	0.29911	32	0.29826
		-	0	10	0.28990	14	0.24936
P_{loss}		0.08334		0.07611		0.07176	
v _D		0.03946		0.02885		0.02608	

Table 3 Results obtained for MULTI objectives case 1 in the IEEE 33-bus distribution system.

Method	DG type	Scer	nario a	Sce	nario b	Scen	Scenario c		
		Location (b	Location (bus no.) size Location (bus no.) si		us no.) size	Location (bus no.) size			
	PV	25	0.09856	-	0	30	0.09694		
C A		32	0.09967	-	0	31	0.09829		
UA	FC	8	0.19748	32	0.19972	25	0.19944		
		7	0.19746	25	0.18382	32	0.19428		
	WT	-	0	7	0.29830	7	0.29277		
		-	0	24	0.29926	24	0.28495		
Ploss		0.00165		0.00422		0.00400			
V_D		0.09103		0.09452		0.09400			
Emission		3201		0.00132 2514		2134			
LIIIISSIOII		5201		2514		2154			
	PV	7	0.09708	-	0	30	0.0992		
		18	0.09546	-	0	2	0.0600		
EO	FC	32	0.20000	30	0.19806	5	0.1998		
		8	0.19072	25	0.17561	24	0.19122		
	WT	-	0	18	0.29998	7	0.30147		
		-	0	32	0.29472	32	0.29855		
						8			
P _{loss}		0.08588		0.08882		0.07978			
V_D		0.04854		0.05781		0.05224			
Emission		3434		2862		2035.85			
	PV	32	0.09594	-	0	24	0.09204		
GAFO		8	0.09138	-	0	31	0.09984		
Griebo	FC	24	0.19791	8	0.19965	7	0.17312		
		30	0.19161	32	0.19567	8	0.18426		
	WT	-	0	24	0.29627	32	0.29901		
		-	0	31	0.27466	25	0.28948		
Ploss		0 09479		08138		0.08553			
V_D		0.06281		0.04237		0.05093			
Emission		3195		2534		2176			

Table 4	Dogulto	obtained	for MIII TI	Cobiostivos	and 2 in th	a IEEE 22	bug distributio	noutom
Table 4	Results	obtained	IOF MULTI	lobjectives	s case 2 m u	IE IEEE 33	-bus distributio	on system

Method	DG type	Sce	Scenario a		ario b	Scenario c	
	••	Location (bus no.) size		Location (bus	s no.) size	Location (bu	s no.) size
	PV	7	0.09990	-	0	8	0.09448
CA		8	0.09888	-	0	24	0.09739
GA	FC	32	0.19795	25	0.19896	32	0.19962
		30	0.19270	7	0.19810	25	0.19859
	WT	-	0	8	0.29973	7	0.29690
		-	0	30	0.29218	30	0.29408
P _{loss}		0.08004		0.08203		0.08272	
Emission		3205 4		0.08203		1070	
Fuel Cost		3205.4		2371.3		1979.	
		51		25		19	
	PV	22	0.09356	-	0	30	0.02525
		30	0.05115	-	0	8	0.09947
EO	FC	24	0.20000	32	0.16423	24	0.20117
		32	0.19979	7	0.19991	32	0.20083
	WT	-	0	8	0.29765	25	0.30014
		-	0	18	0.29476	14	0.29887
Place		0.10758		0.07416		0.07638	
Emission		3558.8		2646.8		2243.3	
Fuel Cost		34		26		22	
	PV	32	0.09438	-	0	24	0.08391
GAEO		24	0.09863	-	0	30	0.08985
ONLO	FC	30	0.19676	30	0.18414	32	0.19626
		8	0.18821	32	0.19802	8	0.19501
	WT	-	0	25	0.28563	25	0.29114
		-	0	24	0.29450	7	0.29633
P _{loss}		0.00102		0.08504		0.07210	
Emission		2121		0.06594 7254 4		1929 6	
Fuel Cost		3131		2354.4 24 1		1030.0	

Table 5 Results obtained for MULTI objectives case 3 in the IEEE 33-bus distribution system.



Fig (9). Comparison of objective function and line voltage characteristics of Simulation case 1 for 33-bus system.



Fig (10). Comparison of objective function and line voltage characteristics of Simulation case 2 for 33-bus system.



Fig (11). Comparison of objective function and line voltage characteristics of Simulation case 3 for 33-bus system.

Result for IEEE 69-bus system

Case 4: Minimization of power loss, and voltage deviation.

There are two conflicting objectives here, namely, power loss and voltage deviation. Table 6 shows the ideal solution for minimising power loss and voltage variance. In Scenario, a GAEO has the best power loss and voltage deviation output, while an EO has the worst. In Scenario B, EO outperforms GAEO in terms of power losses, while GAEO outperforms EO in terms of voltage variance. GAEO produces the best results for power losses and voltage deviation in Scenario c. In Fig. (12), the objective function and line voltage characteristics of Simulation case 4 are compared.

Case 5: Minimizing the total power loss, voltage deviation, and emission.

Power loss, voltage variance, and total emissions are all called multi-objectives in case 5. Table 4 indicates the best position and size for DG, as well as the best solution for minimising power loss, voltage variance, and pollution. In Scenario, a GAEO performs best in terms of pollution and voltage deviation, while GA performs best in terms of power losses. In Scenario b, GAEO outperforms EO in terms of power losses and voltage variance, while GA outperforms EO in terms of total pollution. For Scenario c, GAEO outperforms GA in terms of power losses and voltage variance, while GA outperforms GA in terms of pollution. Comparison of objective function and line voltage characteristics of Simulation case5 is shown in Fig.(13).

Case 6: Minimizing the total power loss, emission and the total fuel cost.

Three conflicting targets, power loss, emissions, and fuel expense, are viewed in the same way as in case 5. Table 5 demonstrates the best position and size for DG, as well as the best solution for minimising power loss, pollution, and fuel costs. GAEO outperforms the competition in terms of power loss, pollution, and fuel cost in Scenario a,b, and c. In Figure 14, the objective function and line voltage characteristics of Simulation Case 6 are compared.

Method	DG type	Sce	nario a	Scer	nario b	Scenario c	
		Location (b	Location (bus no.) size		is no.) size	Location (bu	s no.) size
	PV	62	0.07705	-	0	59	0.09701
CA		21	0.09859	-	0	61	0.09776
UA	FC	12	0.19922	64	0.19293	64	0.19914
		64	0.19159	50	0.19538	12	0.19290
	WT	-	0	61	0.29040	55	0.29837
P_{loss}		-	0	21	0.29595	17	0.29664
V_D		0.07050		0.07103		0.07253	
		0.01592		0.01013		0.00839	
	ΡV	65	0.09878		0	69	0.08055
	1 V	12	0.09878	-	0	54	0.08033
FO	FC	61	0.15454	12	0 19970	61	0.10000
EO	re	21	0.16127	64	0.19999	12	0.00000
	WT	-	0	18	0.27088	21	0.21176
		-	0	61	0.19961	64	0.29596
Place		0.07076		0.07053		0.07043	
V_D		0.01841		0.01087		0.00937	
2	PV	61	0.09816	-	0	64	0.09987
GAEO		21	0.09938	-	0	12	0.09555
UALO	FC	59	0.19739	61	0.16882	65	0.16495
		12	0.19906	11	0.18525	17	0.13116
	WT	-	0	64	0.29236	61	0.27446
		-	0	21	0.27894	19	0.27779
P _{loss}		0.07037		0.07081		0.07015	
V _D		0.01557		0.00906		0.00573	

Table 6 Results obtained for MULTI objectives case 4 in the IEEE 69-bus distribution system.

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 V_D

Emission

Method	DG type	Scen	nario a	Scen	ario b	Scen	ario c	
		Location (bu	ıs no.) size	Location (bus	Location (bus no.) size		Location (bus no.) size	
	PV	12	0.09115	-	0	61	0.09816	
GΔ		8	0.09603	-	0	12	0.09780	
On	FC	50	0.19922	12	1.86151	64	0.18262	
		61	0.18183	50	1.97259	11	0.19275	
	WT	-	0	61	2.98823	49	0.29391	
		-	0	49	2.88280	50	0.29751	
Ploss		0.07542		0.07201		0.07267		
$V_{\rm D}$		0.07542		0.07291		0.07207		
Emission		1728 65		0.02471 756 79		272 20		
EIIIISSIOII		1758.05		/50./0		572.29		
	PV	49	0.09971	-	0	61	0.09664	
		11	0.09115	-	0	59	0.02356	
EO	FC	8	0.19752	50	0.19474	50	0.17975	
		50	0.19464	49	0.19268	12	0.16299	
	WT	-	0	69	0.29100	49	0.29356	
		-	0	61	0.29689	4	0.29324	
Plass		0.08200		0.07594		0.08032		
1/		0.03955		0.02368		0.03421		
V _D		1953.20		1422.01		1176.37		
Emission								
	PV	12	0.09849	-	0	49	0.09577	
GAEO		49	0.08693	-	0	11	0.09929	
0.120	FC	64	0.19622	49	0.19737	64	0.18228	
		61	0.19826	50	0.19960	61	0.19914	
	WT	-	0	11	0.29986	21	0.29734	
		-	0	21	0.29969	50	0.27347	
P _{loss}		0.07596		0.07021		0.06890		

0.02853

771.30

Table 7 Results obtained for MULTI objectives case 5 in the IEEE 69-bus distribution system.

0.02696

1664.65

0.01539

459.68

Method	DG type	Scer	Scenario a		ario b	Scenario c	
		Location (bu	ıs no.) size	Location (bus	s no.) size	Location (bu	s no.) size
	PV	50	0.09940	-	0	50	0.09185
CA		12	0.09833	-	0	49	0.09996
GA	FC	49	0.18563	12	0.19474	59	0.19046
		11	0.19873	50	\0.19533	64	0.19268
	WT	-	0	61	0.29100	61	0.29100
		-	0	49	0.29689	12	0.29864
P _{loss}		0.07514		0.07202		0.07780	
Emission		0.07314		0.07292		0.07789	
Fuel Cost		1500.52		7 40		4/1.55	
		13.42		7.49		4.75	
	PV	49	0.07232	-	0	11	0.09973
		21	0.00822	-	0	64	0.09017
EO	FC	61	0.19996	64	0.17317	21	0.08358
		64	0.18946	12	0.19733	12	0.19867
	WT	-	0	61	0.29455	50	0.30000
		-	0	65	0.29722	61	0.29892
P_{local}		0.07625		0.08333		0.06824	
Emission		2153.3		1471.7		1105.2	
Fuel Cost		21.17		14.52		10.9	
	PV	21	0.09853	-	0	61	0.09846
GAEO		61	0.09142	-	0	64	0.09777
ONLO	FC	49	0.19770	49	0.19737	49	0.19737
		12	0.19720	50	0.19960	12	0.19960
	WT	-	0	11	0.29986	21	0.29986
		-	0	21	0.29969	50	0.29969
P _{loss}		0.07050		0.0702		0 06850	
Emission		1514.6		744 3		365.04	
Fuel Cost		1314.0		7 38		3 72	

Table 8 Results obtained for MULTI objectives case 6 in the IEEE 69-bus distribution system.



Fig (12). Comparison of objective function and line voltage characteristics of Simulation case 4 for 69-bus system.



Fig (13). Comparison of objective function and line voltage characteristics of Simulation case 5 for 69-bus system.



Fig (14). Comparison of objective function and line voltage characteristics of Simulation case 6 for 69-bus system.

4.2.1 Result for IEEE 118-bus system

Case 7: Minimization of power loss, and voltage deviation.

Two objectives functions, power loss and voltage deviation, are considered in the same way as in cases 1 and 4. Table 9 shows the ideal solution for minimising power loss and voltage variance. In Scenario, a GA achieves the best power loss efficiency, while a GAEO achieves the best voltage deviation performance. GAEO performs best in Scenario b and c in terms of power losses and voltage variance. Figure (15) depicts the objective feature and line voltage characteristics of Simulation Case 7.

Case 8: Minimizing the total power loss, voltage deviation, and emission.

Power loss, voltage variance, and total emissions are all considered multi-objectives in this situation. Table 4 shows optimal solution for power loss minimization ,voltage deviation and emissions . in Scenario a and b GAEO achieves the best performance for power losses , voltage deviation and emissions . in Scenario c GAEO achieves the best performance for power losses and emissions , while GA achieves the best performance for voltage deviation. Fig .(16) show Comparison of objective function and line voltage characteristics of Simulation case8.

Case 9: Minimizing the total power loss, emission and the total fuel cost.

Power loss, emissions, and fuel cost are all considered multi-objectives in the same way they are in case 6. The best position and size for DG ,and optimal solution for power loss minimization , emissions and fuel cost are shown in Table11. In Scenario, a GA achieves the best power loss performance, while a GAEO achieves the best emissions and fuel cost performance. In Scenario b, GAEO has the best results in terms of power losses, emissions, and fuel cost. In Scenario c, GAEO achieves the best results in terms of power loss minimization and fuel cost, while EO achieves the best results in terms of emissions. Figure 17 depicts the objective function and line voltage characteristics of Simulation Case 9.

Method	DG type	Scer	nario a	Scen	ario b	Scenario c	
		Location (be	us no.) size	Location (bus	s no.) size	Location (bu	s no.) size
	PV	96	0.96302	-	0	111	0.66252
CA		111	0.90434	-	0	50	0.97799
UA	FC	51	1.81015	79	1.98654	32	1.26914
		74	1.69822	70	1.98146	71	1.45053
	WT	-	0	110	2.25817	97	1.96140
P_{loss}		-	0	50	1.53651	107	1.98337
V _D		0.61765		0.60369		0.58527	
		0.05387		0.04566		0.04948	
	PV	108	0.61563	_	0	80	0 99974
	1 1	111	0.61176	-	Ő	50	0.94717
EO	FC	74	1.61542	72	0.40207	96	0.38934
		51	1.89085	50	1.93752	40	1.96668
	WT	-	0	97	2.59416	74	1.77944
		-	0	111	2.07258	109	2.40652
P _{loss}		0.67858		0.61223		0.56864	
V_D		0.04720		0.04417		0.05865	
	PV	50	0.96151	-	0	42	0.79476
GAEO		52	0.93821	-	0	73	0.85284
OTEO	FC	107	1.99407	111	1.83899	70	1.98227
		74	1.75591	80	1.72135	50	1.17950
	WT	-	0	51	1.79888	109	2.13594
		-	0	74	1.67155	97	1.87804
Ploss		0.64156		0 59732		0 53165	
V_D		0.04130		0.04410		0.035105	
		0.04012		017710		0.04500	

Table 9 Results obtained for MULTI objectives case 7 in the IEEE 118-bus distribution system.



Fig (15). Comparison of objective function and line voltage characteristics of Simulation case 7 for 118-bus system.

Method	DG type	Scenario a Location (bus no.) size		Scenario b Location (bus no.) size		Scenario c Location (bus no.) size	
	PV	71	0.96302	-	0	96	0.96030
GA		96	0.94259	-	0	102	0.95001
UA .	FC	109	1.93252	31	1.86151	50	1.99992
		28	1.98297	74	1.97259	31	1.98781
	WT	-	0	111	2.98823	74	2.99211
		-	0	50	2.88280	111	2.93311
P _{loss}		0 70602		0 72711		0.65001	
V_{D}		0.70093		0.72711		0.03091	
Emission		27800		20839.45		16872.03	
	PV	74	0.98149	-	0	102	1.0000
		102	0.97091	-	0	71	0.90509
EO	FC	109	1.99942	34	1.99963	1	1.98065
		50	1.99439	111	1.99870	80	1.99391
	WT	-	0	63	2.99974	110	2.82814
		-	0	96	2.98347	49	2.95924
Place		0.67643		0.71922		0.68877	
1033		0.06194		0.07164		0.08093	
		26837.4		20167.97		20103	
Emission							
	PV	80	0.98492	-	0	50	0.96406
GAEO		111	0.83618	-	0	28	0.91961
	FC	71	1.99407	107	1.99407	80	1.96602
		50	1.75591	74	1.93267	111	1.99011
	WT	-	0	50	2.94325	20	2.90229
		-	0	80	2.93486	74	2.87807
Ploss		0 62729		0 62104		0 64755	
V_D		0.05034		0.04048		0.05858	
Emission		26324.84		19111		15159.87	

Table 10 Results obtained for MULTI objectives case 8 in the IEEE 118-bus distribution system.



Fig (16). Comparison of objective function and line voltage characteristics of Simulation case 8 for 118-bus system.

Method	DG type	Scenario a		Scenario b		Scenario c		
		Location (bu	s no.) size	Location (bu	is no.) size	Location (bu	s no.) size	
	PV	107	0.99663	-	0	50	0.99132	
C A		97	0.92979	-	Ő	111	0.98086	
GA	FC	50	1.95457	32	1.94600	32	1.98105	
		71	1.98719	111	1.97022	28	1.88494	
	WT	-	0	71	2.92215	102	2.99635	
		-	0	20	2.93056	74	2.99282	
P _{loss}		0. (20.45		0 75071		0 (0717		
Emission		0.62945		0.75071		0.68/17		
Fuel Cost		26963.57		19847.43		14886.39		
1 401 0000		264		194		146		
	PV	103	1.00000	-	0	50	0.99948	
		109	0.96001	-	0	74	0.99285	
EO	FC	6	1.98223	55	1.97567	31	1.99090	
		50	1.84511	108	1.98859	111	1.99209	
	WT	-	0	19	2.96057	102	2.99876	
		-	0	71	3.00000	32	2.98533	
P_{loss}		0.78494		0.80354		0.70779		
Emission		30019.72		22771.75		14824.34		
Fuel Cost		293		223		145		
	PV	50	0.94686	-	0	96	0.99213	
GAFO		28	0.92083	-	0	74	0.92448	
UALO	FC	74	1.95897	74	1.97664	50	1.80142	
		111	1.99072	28	1.95649	42	1.97468	
	WT	-	0	107	2.94182	112	2.88049	
		-	0	80	2.71055	80	2.89248	
P _{loss}		0 67210		0 (7012		0 (0777		
Emission		0.07319	0.6/319		U.0/U12 10491 64		U.OU/// 16700.02	
Fuel Cost		20070.727		17401.04		10799.92 1 30		
		203		171		137		

Table 11 Results obtained for MULTI objectives case 9 in the IEEE 118-bus distribution system.





Conclusion

The primary aim of this study is to introduce the novel hybrid GAEO algorithm to improve the overall distribution network performance by implementing the Renewable Energy Reources (RER) by solve several optimization problem. The two algorithms that were subjected to hybridization to form hybrid GAEO. The performance of GA and EO algorithms are compared with GAEO to judge the accuracy of the proposed hybrid GAEO which solved for multi objective function. There are nine cases of the objective function. The comparisons between GA and EO show that GAEO is a better optimization method for dealing with global optimization tasks, making it ideal for solving complex problems. Furthermore, it validates the proposed algorithm's primacy and its ability to find valid and accurate solutions. To authorise the power of the proposed hybrid GAEO, tests were performed on the IEEE 33-bus, IEEE 69-bus, and IEEE 118-bus systems.

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Symbol	Meaning
i	the iteration counter
$f_i(x)$	the objective functions
hj	The equalities constraints
g _k	The inequalities constraints
J	The number of equalities constraints
K	The number of inequalities constraints
G _{ij} & B _{ij}	Transfer conductance and susceptance between buses i and j
PL	line losses
Plk	The Individual line losses
N _B	the total number of transmission lines
δ	the voltage angle of bus
g _k	the conductance at line k
P _{DGi}	The DG active power at bus i
P _{Di}	The load demand active power at bus i
PL	The active power losses
V _{imin} &V _{imax}	upper and lower limits of the voltage
P ^{min} &P ^{max} gni	Active (real) power limit of DG
f _i ^{min} &f _i ^{max}	Limits of the objective function value

1. List of symbol

$E_{WT_i}, E_{FC_i}, E_{PV}$	design emissions produced by the ith energy sources including
&E _{Grid}	wind turbine, fuel cell, Photovoltaic and grid
dilu	
$P_{WT_i}, P_{FC_i}, P_{PV_i}$	active power generation by the ith energy sources including wind
&P _{Grid}	turbine ,fuel cell , Photovoltaic and grid
N_{WT} , N_{FC}	the numbers of the WT,FC and PV units
&N _{PV}	
a_i, b_i and c_i	The cost coefficient of ith generators
penalty	The cost coefficient of the substation bus
NO _x ^{Wind} , NO _x ^{FC} ,	The Emission factor for Nitrogen oxides gas produced by the ith
NO _x ^{PV} &NO _x ^{Grid}	energy sources including wind turbine ,fuel cell , Photovoltaic and
	grid
$CO_2^{Wind}, CO_2^{FC},$	The Emission factor for Carbon oxides gas produced by the ith
$\rm CO_2^{PV}\&CO_2^{Grid}$	energy sources including wind turbine ,fuel cell , Photovoltaic and
Wind EC	grid
SO_2^{WIIIu}, SO_2^{FC}	The Emission factor for Sulphur oxides gas produced by the ith
$, SO_2^{PV} \& SO_2^{GIIU}$	energy sources including wind turbine ,fuel cell, Photovoltaic and
minmax	gild
x _i , x _i	controls the exploration quantity (magnitude) of the algorithm
a_1	is a constant used to belance the exploitation shility
a_2	are the four best-so-far particles identified during the whole optimization process
$\vec{\Gamma}_{eq(1)}, \vec{\Gamma}_{eq(2)}$ \vec{P} and \vec{P}	
$\vec{\mathbf{p}}$	is the equilibrium state vector
F _{eq,pool} →	
$P_{eq(ave)}$	is the mean value of first four candidate solutions.
$B_{max} \& B_{min}$	upper bound and lower bound
$ec{F}$	term tries to maintain a balance between exploitation and exploration during the
\rightarrow	search.
λ	is a random vestor between 0 and 1
ı Gi	is the generation rate
\vec{G}_0	is initial value and can be found.
k	is a constant.
GCP	is the possibility of contributing the generation term
V	is the control volume and considered as unit